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Socio-ecological Predictors of Social Connection Among Older Adults

Georganna Amateau
Virginia Commonwealth University

Socio-ecological Predictors of Social Connection Among Older Adults

A dissertation submitted in partial fulfillments of the requirements for the degree of Doctor of Philosophy at Virginia Commonwealth University.

by

Gigi Amateau
Master of Science, Gerontology, Virginia Commonwealth University, 2018
Bachelor of Science, Urban Studies and Planning, Virginia Commonwealth University, 1988

Director: Tracey L. Gendron, Ph.D.
Associate Professor, Chair, Department of Gerontology

Virginia Commonwealth University
Richmond, VA
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We all get through life with help from our family and friends who nurture us during critical points in our lives. – **James Lubben**

Dedicated to my sister: We are a river.

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Table of Contents

List of Tables

List of Figures

Abstract

SOCIO-ECOLOGICAL PREDICTORS OF SOCIAL CONNECTION AMONG OLDER ADULTS

By Gigi Amateau, MS

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy at Virginia Commonwealth University.

Virginia Commonwealth University, 2021.

Major Director: Tracey L. Gendron, PhD, Associate Professor, Department of Gerontology

Decades of research has established an unequivocal link between states of social connection and health status. Lack of social connection, whether construed as social isolation or loneliness, negatively influences health and is highly associated with cardiovascular disease, high blood pressure, fall risk, and premature death. Despite extensive research on social isolation and loneliness, evidence relative to the broader construct of social connection suffers. Few studies inform practice standards for community-based organizations. This study aimed to develop a multidimensional, continuous composite variable of social connection and use the composite variable to examine predictors with a socio-ecological lens.

A secondary data analysis was conducted with a sample of 12,116 older adults. The regression results showed that trauma, transition, and loss predicted lower social connection scores with greater strength than any of the other variables. Perceived barriers to access, housing type, and supportive services enrollment significantly predicted social connection, yet were overshadowed by the power of disruptive life events to negatively influence social connection. Additionally, the creation of a two-dimensional social connection measure underscored the criticality of subjective experiences of social connection. In this study, positive social connection scores were highest among the oldest. Missingness in the data rendered it impossible to validly include race or ethnicity, leaving important questions about health equity and racial equity unanswered. Findings can inform data collection, intake and screening processes, referral pathways, student and provider training, early identification, and strategic alliances between community-based service providers and adult protective services and victim assistance services.

Keywords: social isolation, loneliness, older adults, social connection, socio-ecological system

Chapter 1: Introduction

Chapter Overview

This study analyzed social connection among community-dwelling older people seeking long-term services and supports (LTSS) using a multidimensional measure of social connection. An important aspect of this study was the development and use of a multidimensional, continuous dependent variable (DV). The composite DV was used to identify how well housing environment, perceived neighborhood condition, supportive services enrollment, and disruptive life events would predict the extent of social connection. The study used ecological systems theory (Bronfenbrenner, 1977; Bronfenbrenner, 1986; Bronfenbrenner, 2005) to inform how different contexts of older adults' environments influence the extent of social connection. Study findings contribute to the scientific understanding of social connection and health by building upon the existing body of evidence and venturing into territory where the existing evidence is scant or inconclusive.

Chapter 1 begins with definition of terms because several distinct but related constructs inform the umbrella term *social connection*. Confusion and inconsistency among constructs, such as loneliness and social isolation, are limitations in the canon of literature related to social connection – a limitation that the research community aims to address (Holt-Lunstad, 2018; Holt-Lunstad et al., 2017; Hortulanus et al., 2006; Lee et al., 2018; Lubben, 2018; National Academies of Science, Engineering & Medicine [NASEM], 2020; Weldrick & Grenier, 2018). Chapter 1 also includes background on issues related to social connection among older adults, a statement of the problem, and the study purpose. Study significance and an introduction to the theoretical framework are also provided. The data source and delimitations are presented herein, as well. The chapter concludes with a preview of the remaining chapters.

Definition of Terms

Different researchers have studied different aspects of social connection. Most research has focused on a single construct such as social isolation, loneliness, social support, or social inclusion. These terms are sometimes used synonymously, which is both confusing and incorrect (NASEM, 2020). Such fragmented efforts have resulted in inconsistent and inconclusive findings (Holt-Lunstad, 2018; Holt-Lunstad et al., 2017; Hortulanus et al., 2006; NASEM, 2020).

Most research related to the state of social relationships has investigated social isolation or loneliness (NASEM, 2020). Recently, Holt-Lunstad (2018) proposed a *typology of social connection* to establish a way to delineate these common related but distinct constructs. This study is anchored in the umbrella term social connection. Most of the evidence presented herein relates to social isolation, a structural indicator of social connection, and loneliness, a functional indicator of social connection. Terms used frequently in this study are defined here. Unless otherwise noted, the source for the definitions is the recent NASEM consensus report (2020).

Area Agencies on Aging: An area agency on aging (AAA) is a public or private non-profit agency designated by a state or U.S. territory to address the needs and concerns of all older people at the regional and local levels. Area agency on aging is a generic term—specific names of local agencies may vary (Eldercare Locator, n.d.). There are 622 area agencies on aging in the United States and its territories, 25 of which are located in Virginia.

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

Social connection: An umbrella term that encompasses the structural, functional, and quality aspects of how individuals connect to one another.

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

Social support: The actual or perceived availability of resources (e.g., informational, tangible, emotional) from others, typically one's social network.

Neighborhood: A section lived in by neighbors and usually having distinguishing characteristics (Merriam Webster, 2020).

Disruptive life event: A life event that alters a person's interpersonal relations and how they perceive their lives or feelings of isolation and loneliness.

Supportive services: For purposes of this study, the term supportive services is synonymous with the term home- and community-based services (HCBS) and includes varying care models linking housing, health care, and other services that "facilitate aging in place, enabling older individuals to remain in their homes and communities as they age" (Supporting Older Americans Act of 2020 [OAA], 2020, p. 31).

Background

In the midst of government-imposed social distancing to slow the spread of COVID-19, people of all ages began singing in tandem across the balconies of Italian towns and cities in effort to connect with one another (Taladrid, 2020; Thorpe, 2020). A spontaneous public health moment celebrated around the world, the Italian balcony singing aptly demonstrated how social determinants of health, such as social connection, influenced health and well-being amid the biggest global health crisis in a century.

In fact, positive social connection promotes health through a stress buffering role and by directly promoting mental health and subjective well-being (J.T. Cacioppo & Cacioppo, 2014; Feeney & Collins, 2015). Additionally, positive social connection improves vagal nerve functioning (Kok & Fredrickson, 2010). Group singing, for example, acts as "powerful social glue” that helps people feel closer, more socially connected, and a sense of community (Suttie, 2016, n.p.). In Italy, balcony singing positively influenced a strained social environment by entertaining people during a difficult time (Taladrid, 2020; Thorpe, 2020) and also worked as a protective health factor to counteract the unintended health risk of social isolation created by the pandemic lockdown (Taladrid, 2020). Italians who participated in these musical flash mobs cited a desire for unity, connection, and health as their motivation (Taladrid, 2020).

Conversely, lack of social connection, whether labelled as social isolation or loneliness, negatively influences health and is highly associated with cardiovascular disease, high blood pressure, increased fall risk, and premature death (Holt-Lunstad et al., 2010; NASEM, 2020). Strong links have been observed between loneliness or social isolation and mortality and morbidity (Holt-Lunstad, 2018; NASEM, 2020). Relative to mortality, a plethora of evidence exists that, per the Bradford Hill criteria, has established a “potential causal link between social isolation and mortality” (NASEM, 2020, p. 47).

Regarding morbidity, loneliness increases the chance of premature cognitive decline, chronic inflammation, and lowered immunity (J.T. Cacioppo & Cacioppo, 2014). Likewise, social isolation, specifically among older adults, has been linked to poorer health outcomes including high blood pressure, cardiovascular disease, weakened immunity, fragmented sleep, inflammation, and cognitive decline (J.T. Cacioppo & Cacioppo, 2014; S. Cacioppo et al., 2014; J.T. Cacioppo & Patrick, 2008; Holt-Lunstad et al., 2010). Furthermore, social isolation might actually be worse for health than well-established negative health habits such as smoking 15 cigarettes or consuming six alcoholic beverages daily (Holt-Lunstad et al., 2010).

Study Problem

Scientific evidence has informed many topics related to older adults and social isolation or loneliness, particularly individual-level risk and protective factors. Yet reliable, extensive knowledge about contributing factors within the total human environment remains elusive (Holt-Lunstad, 2018; NASEM, 2020), because most of the research related to social connection and its typology has examined individual demographic and lifestyle factors (Holt-Lunstad, 2018; Kim & Clarke, 2015; Portacolone et al., 2018; Samuel et al., 2018). Despite the evidence that positive social connection promotes good health, while lack of social connection negatively impacts health (AARP Foundation, 2018; Holt-Lunstad, 2018) and strongly correlates to premature death (Holt-Lunstad, 2018; Holt-Lunstad et al., 2010; Holt-Lunstad et al., 2015; NASEM, 2020), the available, scientifically supported evidence remains targeted toward individual factors (Holt-Lunstad, 2018; Kim & Clarke, 2015; Portacolone et al., 2018; Samuel et al., 2018; Weldrick & Grenier, 2018) and has failed to identify population-level strategies necessary to address issues of loneliness and isolation as threats to public health.

A systems approach that examines multiple levels of the socio-ecological system among a single sample has remained largely unexplored (Holt-Lunstad, 2018; NASEM, 2020). Furthermore, the influence of environmental factors such as housing (NASEM, 2020), perceived neighborhood conditions (Buffel et al., 2014; Keene & Ruel, 2013; Kim & Clarke, 2015; NASEM, 2020; Portacolone et al., 2018), supportive service enrollment, and disruptive life events (Holt-Lunstad, 2018; Suen et al., 2018; Weldrick & Grenier, 2018), has been overlooked or under-studied.

From a public health perspective, two methodological barriers need to be resolved in order to broaden and deepen the collective ability to effectively prevent, identify, and treat low social connection: 1) adoption of a multidimensional measurement of social connection, incorporating the full spectrum of the distinct constructs of loneliness, social isolation, social inclusion, social integration, and social supports (Holt-Lunstad, 2018; Hortulanus et al., 2006; NASEM, 2020) and 2) an examination of social connection that recognizes that people live within complex and interrelated socio-ecological environments composed of self, family-friends, community, and society (Holt-Lunstad, 2018; Kim & Clarke, 2015; NASEM, 2020; Portacolone, 2018; Weldrick & Grenier, 2018).

Study Purpose

Through the lens of Bronfenbrenner's ecological systems theory, this study employed a multidimensional measure of social connection to retrospectively identify risk and protective factors of social connection among community-dwelling older adults. Specifically, a secondary data analysis furthered understanding of risk and protective factors by examining the predictive ability of housing, perceived neighborhood environment, supportive services enrollment, and disruptive life events. The long-term goal is to design targeted prevention and early intervention strategies that, ultimately, improve social connection among community-dwelling older adults.

Study Significance

The 2020 reauthorization of the OAA — the most comprehensive legislation guiding the provision of services to people ages 60 and older throughout the U.S. (Administration for Community Living [ACL], n.d.a) — expanded the purpose of the OAA to address social determinants of health with an emphasis on social isolation (OAA, 2020). Under the 2020 reauthorization, area agencies on aging and their contracted network partners are now required to conduct screening, assessment, education, and intervention related to social isolation (OAA, 2020).

Exploring linkages between the extent of older adults' social connection and housing, perceived neighborhood environment, supportive services enrollment, and disruptive life events will contribute valuable knowledge as the aging services network pivots to align with the shift in federal policy. Moreover, while social isolation, loneliness, and social support have been extensively researched, no studies have been conducted that examine each of these constructs within the same sample in the United States (NASEM, 2020). By developing a multidimensional measure of social connection and by broadening the analysis beyond individual and lifestyle factors, this study provides new evidence and rationale to improve data collection, implement screening protocol, interpret risk signaling, and guide heat mapping to inform outreach, service provision, and population-level interventions. The combined development of an innovative multidimensional social connection measure and a systems approach to examining risk and protective factors contributes to new pathways for addressing dimensions of social connection, such as loneliness and social isolation, from a public health approach.

Introduction to Theoretical Framework

Social connection is a multi-faceted construct of complexity that expresses various attributes such as loneliness, social isolation, social support, social inclusion, and social activity. These attributes occur as people interact with family and friends, their communities, and with society itself (Holt-Lunstad, 2018; Weldrick & Grenier, 2018). Ecological systems theory provides a theoretical compass with which to undertake this multi-level study and can be summarized as follows: People influence and are influenced by their environments, or ecosystems, composed of multiple levels, which are all connected (Shelton, 2019). As such, this theory can be used as a rubric with which to study the socio-ecological characteristics of social connection among a group of community-dwelling older adults.

Ecological systems theory originated as a multi-level child development theory and is often used to enhance or study conditions such as childcare, child health disparity, family systems, and child intelligence (Bronfenbrenner, 2005). Over the decades, the theory has expanded and evolved to incorporate lifespan development (Rosa & Tudge, 2013; Shelton, 2019). In terms of constructs, ecological systems theory evolved over three decades into a person-process-context-time (PPCT) theory and is composed of multiple connected, interactive context-levels that work in concert with constructs of a developing person and developmental outcomes (Bronfenbrenner, 2005; Rosa & Tudge, 2013; Shelton, 2019).

The full PPCT theory evolved in three distinct phases (Rosa & Tudge, 2013). Phase 1 (1973-1979) introduced nested context levels of the human ecosystem. The Phase 1 context-levels include the microsystem, mesosystem, exosystem, and macrosystem. The microsystem includes activities, structures, and process occurring in the immediate setting (e.g., home, school) of the developing person; whereas the mesosystem links the processes of two or more settings that include the developing person, such as a neighborhood (Shelton, 2019). Another sphere of environmental influence is the exosystem, which links activities and processes of two or more settings where at least one does not ordinarily contain the developing person, such as federal policies and funding that create a service setting where the person engages (Bennett & Grimley, 2001). Additionally, the macrosystem consists of the overarching organizing pattern of a culture or subculture – a societal blueprint (Shelton, 2019). Traits such as age, gender, race, ethnicity, poverty level, and education are related to the makeup of individuals; yet these traits also bind people together via societal norms and cultural patterns. Further in Phase 1, Bronfenbrenner recognized and introduced the construct of an *ecological transition* (Eriksson et al., 2018; Rosa & Tudge, 2013), which later on in the theory's lifecycle became a defining trait of the chronosystem. Throughout life, people go through a multitude of changes, not all of which would be considered ecological transitions, which are defined as occurring, “whenever a person’s position in the ecological environment is altered as the result of a change in role, setting, or both” (Shelton, 2019, p. 51). Also in Phase 1, Bronfenbrenner (1977) argued for operationalizing *ecological validity* as not only referring to the objective attributes of the environment under study but also “the way in which it [the environment] is perceived by the research subjects” (p. 516). The theory’s emphasis on the developing person’s perception of their environment was of particular importance in constructing this study design, research questions, and study variables.

Phase 2 (1980 – mid 1990s) expanded the context levels of the ecosystem to more formally recognize life events that occur with the passage of time (Eriksson et al., 2018; Rosa & Tudge, 2013; Shelton, 2019). The earlier ecological system models consisted of the micro, meso, exo, and macrosystems (Rosa & Tudge, 2013; Shelton, 2019). In Bronfenbrenner’s work, the concept of time and its embeddedness into a formal paradigm and distinct ecosystem level evolved over several iterations (Bronfenbrenner & Morris, 2007; Eriksson et al., 2018; Rosa & Tudge, 2013; Shelton, 2019). Bronfenbrenner noted that “traditionally in developmental science, the passage of time, has been treated as being synonymous with chronological age: that is, a scale for ordering individuals in terms of how long they have lived” (Bronfenbrenner, 2005, p. 82). In the development of this theory, the construct of time expanded beyond the influence of chronological age on development to also encompass “the impact of prior life events and experiences singly or sequentially on subsequent development” (Bronfenbrenner, 2005, p. 83). Bronfenbrenner asserted that chronosystem models can be simple or advanced, incorporating single or multiple ecosystem levels. In his later reflection on chronosystem models, Bronfenbrenner (1986) wrote:

> the simplest form of chronosystem focuses around a life transition. Two types of transitions are usefully distinguished: normative (school entry, puberty, entering labor force, marriage, retirement) and nonnormative (a death or severe illness in the family, divorce, moving, winning the sweep stakes). Such transitions occur through the lifespan and often serve as direct impetus for developmental change" (p. 724).

Many scholars agree that the chronosystem may be represented by the influences of aging and personal and cultural historical events (Bronfenbrenner, 2005; Eriksson et al., 2018; Rosa and Tudge, 2013; Shelton, 2019). Today, the American Psychological Association's Dictionary of Psychology defines the chronosystem as:

> changes and continuities occurring over time that influence an individual's development. These influences include normative life transitions (e.g., school entry, marriage, retirement), nonnormative life transitions (e.g., divorce, winning the lottery, relocation), and the cumulative effects of the entire sequence of transitions over the life course (APA, 2021, n.p.).

The APA's definition incorporates both normative and nonnormative transitions as personal, historical events that impact a person's development throughout their lives.

In Phase 3 (1990s-2006) Bronfenbrenner and colleagues continued to refine the theory as PPCT model with emphasis on proximal process interactions.

In its investigation of social connection among older adults seeking LTSS, this study drew from constructs represented in Phases 1 and 2 and investigated aspects of the micro, meso, exo, and chronosystems, while controlling for aspects of certain individual demographic factors. A more complete depiction of the study's conceptual ecological model is presented in Chapter 2. Table 1 summarizes the elements of Bronfenbrenner's ecological systems theory that are utilized in this study, distinguished by the theory's phases.

Table 1

Key Ecological Systems Theory Constructs by Phase

Study use	Phase 1	Phase 2	Phase 3
Key concepts	Microsystem Mesosystem Exosystem Ecological transitions Ecological validity must incorporate research participants' perceptions of their ecosystem.	Chronosystem Simplest application of chronosystem: life transitions	
Core of analysis	Do factors representing interactions within and between different ecosystem levels (housing, neighborhood perception, supportive services enrollment) predict extent of social connection?	Do disruptive, stressful past life events (ecological transitions) predict the extent of social connection?	
Assumptions relative to social connection	Understanding risk and protective factors related to social connection requires an ecological perspective. Older adults' perceptions of access and safety in their neighborhoods inform experiences of social connection. Enrollment in Title III supportive services acts as a mechanism for forming friendship and connections.	Unexpected, stressful life events such as trauma or transitions experienced within individuals' micro and mesosystems, such as the death of someone close, may negatively affect the extent of social connection.	

Summary of Data Source

The Virginia Uniform Assessment Instrument (UAI) served as the sole data source for this study. Since 1994, health and human services agencies in Virginia have used the UAI to determine needs and eligibility and to create service plans for people seeking LTSS (Virginia Department for Aging and Rehabilitative Services [DARS], 2015). The UAI consists of identification and background, functional status, physical health, psychosocial, assessment summary, and caregiver assessment sections (DARS, 2015). The breadth of the UAI allowed for the creation of a multidimensional composite DV representative of social connection. Likewise, the UAI's extensive and holistic scope made it plausible to examine potential risk and protective influences from multiple ecosystem levels within the same sample. Furthermore, relative to Bronfenbrenner's (1977) definition of ecological validity as inclusive of research participants' perceptions of their environments, the UAI is based on self-reported responses about older adults' lives and living environments. Appendix A contains the full UAI.

Assumptions

A fundamental assumption of this study is that a human being's state of social connection is not only predicted by individual demographic or lifestyle factors, but that aspects of one's environment, surroundings, and life events also contribute to the extent of social connection. This is not to say that individual demographic and lifestyle factors do not influence social isolation or loneliness. On the contrary, the majority of the evidence has exclusively focused on these factors (Holt-Lunstad, 2018; Holt-Lunstad et al., 2017; Kim & Clarke, 2015; NASEM, 2020; Weldrick & Grenier, 2018).

A second set of important assumptions relates to the use of the UAI as the data source. The UAI's first purpose is to conduct a point-in-time assessment of a person's needs and eligibility for publicly funded LTSS. This study assumes that using UAI data for a research study will result in valid findings. Another assumption is that the UAI is reliable even though it is administered by many different raters.

Delimitations

Several choices made at the outset of this study have, no doubt, influenced its findings. For example, the secondary data analysis examined UAI data only for adults ages 60 and older in Virginia who sought LTSS through an area agency on aging during calendar years 2013–2019. Under the OAA, supportive services, known as Title III supportive services, are restricted to people ages 60 and older, so the study was limited relative to age. Also, due to privacy requirements, geographic information was excluded from the data request, so a comparison by rural-suburban-urban was not undertaken. The selection of input variables to develop a continuous DV based on Holt-Lunstad's (2018) typology for a multidimensional social connection measure was limited to UAI data elements that were viably populated in the data set. Finally, as with physical health, social health ebbs and flows over time and across the lifespan. UAIs are typically re-certified at least once annually or when a significant change occurs. However, this study only examined one point in a person's life – that which was captured by an initiating UAI and did not, therefore, capture longitudinal changes.

Chapter Summary and Organization of the Study

Chapter 1 has summarized the need to understand a more complete picture of the nature of social connection among community-dwelling older adults on two fronts: a multidimensional social connection measure and predictive environmental risk and protective factors. The entirety of this dissertation consists of five chapters, a bibliography, and appendices. Chapter 2, a comprehensive literature review, presents an overview of evidence relative to loneliness, social isolation, and health. Chapter 2 also addresses the evidence relative to each independent variable (IV) in the study and provides a deeper explanation of the theoretical framework. Chapter 3 explains the research design and analysis methods that were used. The UAI, procedures, and study sample are also described. Chapter 4 presents the data analysis and findings. Chapter 5 includes the summary, conclusions, and recommendations and implications of findings. Lastly, the bibliography and appendices follow.

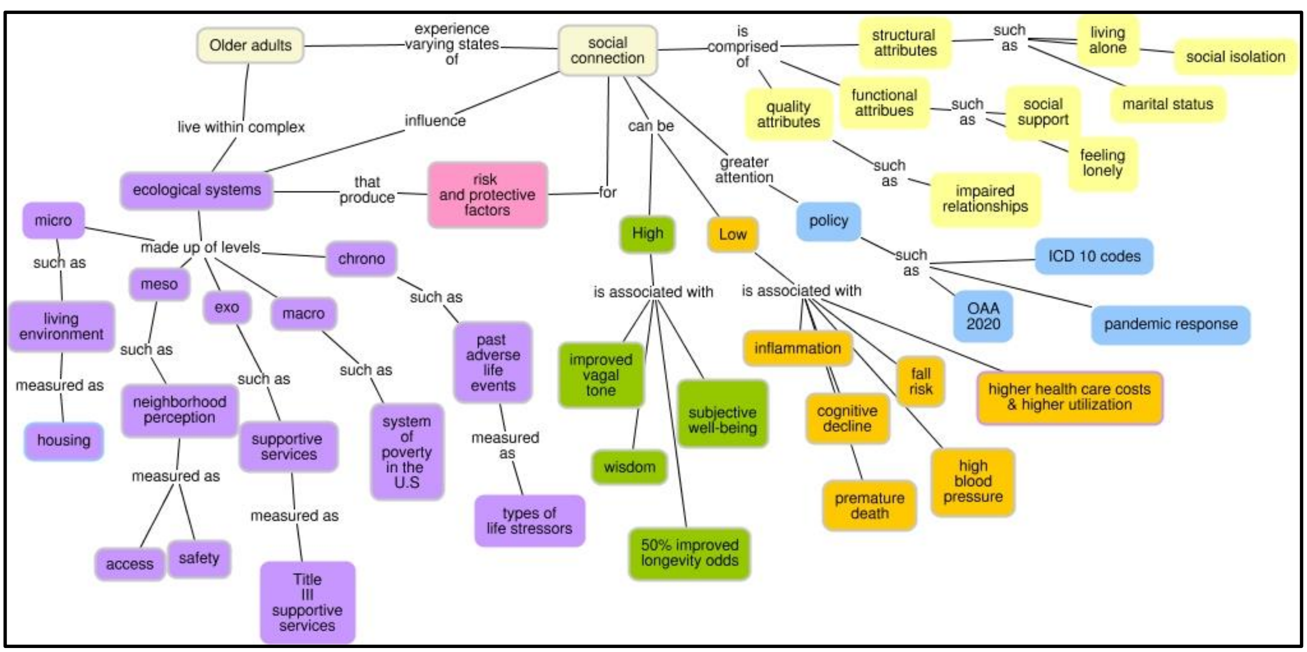
Chapter 2: Literature Review

Chapter Overview

Chapter 2 begins with a visual depiction (Figure 1) and description of the search strategy. Following, the prevalence of loneliness and social isolation is presented. The chapter then discusses the relationship between mortality and social connection. Next, the evidence linking positive and negative health outcomes to social connection is summarized, followed by an overview of risk and protective factors related to social connection among community-dwelling older adults. This chapter also reviews an emergent typology of social connection upon which the DV of this study is based. In addition, Chapter 2 covers evidence relative to each IV in the study and provides a deeper explanation of the theoretical framework used herein. The chapter concludes with delimitations and a summary conclusion.

Figure 1

Visual Representation of Scope of Literature Review



Search Strategy

Preliminary searches of VCU Library's holdings were conducted to gain familiarity with the literature and search terms. Search terms tested in the preliminary searches included general keywords such as older adults, loneliness, social isolation, and social support. As research questions were developed, additional parameters were included such as housing, neighborhood perception, Title III supportive services enrollment, and disruptive life events. Once research questions were finalized, search strategies were developed for each research question in consultation with a research librarian at VCU's Tompkins-McCaw Library for the Health Sciences. The following terms were searched with regard to the population of interest: older adults, senior citizens, and elderly. Relative to the DV, search terms included social isolation, loneliness, social support, social inclusion, and social connection. Search terms were also established for the study IVs including perceived neighborhood environment, housing, neighborhood, physical environment, and built environment. For supportive services enrollment, the keywords included Title III, supportive services, congregate meals, home-delivered meals, adult day services, telephone reassurance, and befriending. For disruptive life events, search terms included adverse life events, disruptive life events, stressors, trauma, transitions, and non-normative transitions.

Search strategies were tailored to the specific requirements of each database, including Ageline, CINAHL, OVID/Medline, PSYCHNET, Project Muse, Sage, and Urban Studies Abstracts. Search parameters were limited to peer-reviewed articles published in English language between 2015 and 2020. Google and Google Scholar were also searched in effort to find important studies outside of the peer-reviewed literature such as those undertaken by philanthropic, non-profit, or governmental organizations. Backward citation chaining via hand searches of reference lists to find additional sources proved especially helpful in locating seminal studies and in defining the evidence base for the IVs of interest. Electronic database search results were exported into .xls format and organized in Microsoft Excel for de-duplication and cross referencing. Where feasible, sources were imported into Mendeley citation management tool for indexing and storage. Mendeley's search algorithm was configured to find and alert to articles of interest, and some sources were added through this strategy.

Toward a Typology of Social Connection

Most social connection research has focused on a single dimension such as social isolation, loneliness, social support, or social inclusion. Often, these disparate efforts have resulted in inconsistent and inconclusive findings (Holt-Lunstad, 2018; Hortulanus et al., 2006; NASEM, 2020). Typically, only single dimension measures have been used, and single dimensions measures only partially explain how, when, and why people flounder or flourish in their social connection (Holt-Lunstad, 2018; Hortulanus et al., 2006; NASEM, 2020). Findings of loneliness and social isolation are related to the broader concept of social connection; yet the most frequently utilized multi-factor instruments only measure a single dimension of social connection, such as loneliness, social isolation, or social support.

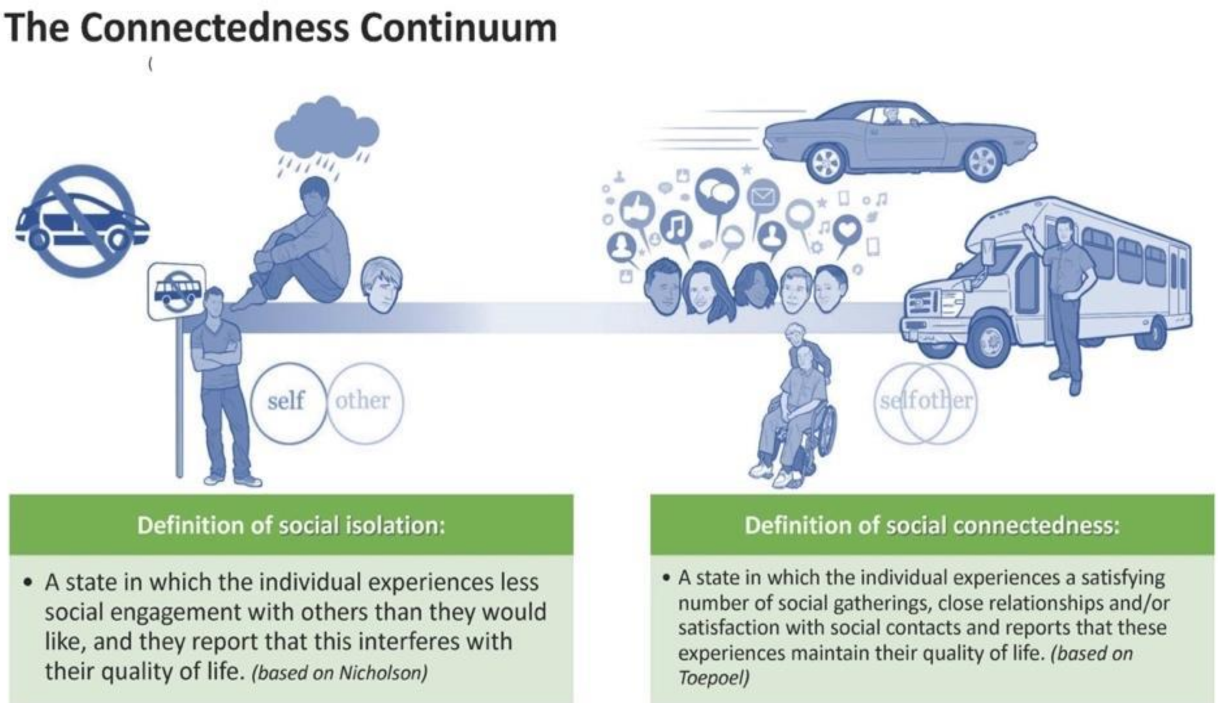
Prior to Holt-Lunstad's (2018) typology of social connection, Hortulanus and colleagues (2006), presented a typology wherein loneliness is subordinate to social isolation. Later, J.T. Cacioppo and Patrick (2008) framed three degrees of social connection as a parallel model to Brewer and Gardner's three-part construct of the self (1996), which consists of personal or intimate self, social or relational self, and collective self. Brewer and Gardner determined that people understand who they are at three levels:

1) the *personal self* includes attributes solely related to you, including physical appearance, abilities, aesthetic, and preferences (Brewer & Gardner, 1996; J.T. Cacioppo & Patrick, 2008)
2) the *social or relational self* is composed of you in relation to “the people closest to you – your spouse, kids, friends, and neighbors” (Brewer & Gardner, 1996; J.T. Cacioppo & Patrick, p. 78, 2008)
3) the *collective self* is defined as who you are relative to group membership, social identity, and societal structures (Brewer & Gardner, 1996; J.T. Cacioppo & Patrick, 2008)

J.T. Cacioppo and Patrick (2008) posited that social connection works in tandem with self-identity and proposed that social connection can be examined through *three degrees of connection* that mirror Brewer and Gardner’s three constructs of the self. The three degrees of connection typology is consistent with the connectedness continuum shown in Figure 2 (MacDonald et al., 2016). The *connectedness continuum* presents individuals in various states of social connection relative to self, others, and community. This visualization of social connection was developed by the social isolation risk index (SIRI) project’s community partners and is frequently referenced and utilized by Richmond, Virginia’s aging services network. It also illustrates the influence of varying aspects of the human environment on states of social connection.

Figure 2

The Connectedness Continuum



Note. From MacDonald, Gendron, Hickey, Watson, & Amateau, 2016. Reprinted with permission.

More recently, Holt-Lunstad (2018) issued a call to action and "presented a framework by which to move social connection into the realm of public health" (p. 437). This framework included two critical turns: 1) broadening the "individualistic approach" (p. 440) of scientific inquiry to consider "the individual, the family and close relationships, the community, and the society" (Holt-Lunstad, 2018, p. 439) and 2) positioning a typology of social connection as an "umbrella term to represent the multiple ways in which individuals connect to others emotionally, behaviorally, and physically" (Holt-Lunstad, 2018, p. 437). Holt-Lunstad (2018) asserted that three primary factors determine "the extent to which an individual is socially connected" (p. 440). These factors relate to "relationships and their roles," "actual or perceived support or inclusion," and the "positive and negative qualities" of connection (Holt-Lunstad, 2018, p. 440). Holt-Lunstad's (2018) social connection typology is illustrated in Table 2.

Table 2

Holt-Lunstad's Social Connection Typology

Social Connection The extent to which an individual is socially connected depends on multiple factors, including:		
1. Connections to others via the existence of relationships and their roles 2. A sense of connection that results from actual or perceived support or inclusion 3. The sense of connection to others that is based on positive and negative qualities		
Structural	*Functional*	*Quality*
The existence of and interconnections among different social relationships and roles ◆ *marital status* ◆ *social networks* ◆ *social integration* ◆ *living alone* ◆ *social isolation*	*Functions provided by or perceived to be available because of social relationships* ◆ *received support* ◆ *perceptions of social support* ◆ *perceived loneliness*	*The positive and negative aspects of social relationships* ◆ *marital quality* ◆ *relationship strain* ◆ *social inclusion or exclusion*

Note. From Holt-Lunstad, J. (2018). Why social relationships are important for physical health: A systems approach to understanding and modifying risk and protection. *Annual Review of Psychology*, *69* (437–458).

Prevalence of Social Isolation and Loneliness

Is loneliness a global public health crisis that can be solved at the population-level? Many among the scientific community, including two U.S. Surgeon Generals, say yes (AARP Foundation, 2018; Dickens et al., 2011; Gerst-Emerson & Jayawardhana, 2015; Holt-Lunstad et al., 2017; Holt-Lunstad et al., 2010; Hudson, 2018; Hyland et al., 2019; Lubben, 2018; McGregor, 2017). Yet, precise prevalence of loneliness is difficult to determine because of inconsistent definitions, varying classification, and unstandardized assessments and measurements of constructs related to social connection (Holt-Lunstad, 2018; Hyland et al., 2019; Lee et al., 2018). Regardless, that many people experience loneliness at some point in their lives is well-established. Among adults ages 60 and older in the U.S., 43% report being lonely (Perissinotto et al., 2012), while among adults ages 18 and older, 27% report loneliness (Cigna, 2018). Likewise, more than one third of American adults ages 45 and older are lonely, as measured by the UCLA Loneliness Scale (AARP, 2018). In response to Cigna's (2018) U.S. loneliness survey, only 53% of respondents reported having meaningful social interactions on a daily basis. Demographic trends such as shrinking household size, decreasing marriage rates, and rising childlessness point toward less familial support, just as decreases in volunteerism and religious affiliation suggest lower community engagement (Holt-Lunstad, 2018). Such trends indicate that existing prevalence estimates may be conservative (Holt-Lunstad, 2018). Recent surveys have found that the incidence of loneliness is consistent across gender and race-ethnicity but differs widely by age (Cigna, 2018; AARP, 2018).

Mortality, Longevity, and Social Connection

Human beings are social beings. Our biological make up, in fact, appears to include numerous traits that predispose our species to seek out social connection with others in order to survive and thrive (Holt-Lunstad, 2018). For four decades, research has consistently indicated that positive social connections hold great power to influence health and longevity (Holt-Lunstad, 2018; NASEM, 2020). Conversely, the evidence also shows that lack of social connection increases the odds of premature death (Holt-Lunstad, 2018; Holt-Lunstad et al., 2010; Holt-Lunstad et al., 2015; NASEM, 2020). The social connection-mortality link has been studied primarily through two lenses: social control and social endocrinology (J.T. Cacioppo et al., 2015;

Holt-Lunstad, 2018). The social control lens hypothesizes that people control their own health behaviors, and that family and friends impact health behaviors as well (J.T. Cacioppo et al., 2015). Alternatively, social endocrinology proposes that brain functioning is key to “forming, monitoring, maintaining, repairing, and replacing” social relationships (J.T. Cacioppo et al., 2015, p. 734).

Berkman and Syme (1979) conducted a seminal study from a social control perspective in a nine-year follow up with a random sample of 6,928 adults in Alameda County, California, which was among the first studies to directly examine factors related to social ties and all-cause mortality. They tested mortality risk against four factors: marriage, contact with close friends and family, church membership, and membership in formal and informal groups and found lower mortality rates among people with social ties (Berkman & Syme, 1979). In fact, each of the four factors independently predicted mortality (Berkman & Syme, 1979). Two factors, marriage and contact with close friends and family, were the strongest predictors of lower predicted mortality (Berkman & Syme, 1979). A later seminal study, which controlled for baseline health status in a review of five prospective studies, found consistently increased risk of death among people with low quantity and low quality of social relationships (House et al., 1988).

Studies that have investigated the social endocrinology approach of examining association between social connection and mortality have focused on how the brain responds to states of loneliness via myriad neural processes including social threat surveillance and aversion, social rewards, and self-preservation in social contexts (J.T. Cacioppo et al., 2015). One such study found that over a six-year period, feelings of loneliness correlated with increased mortality risk (J.T. Cacioppo & Cacioppo, 2014). Moreover, in a review of studies examining neuroendocrine activity and social isolation, researchers found that “a significant body of human research, including longitudinal studies, suggests that perceived social isolation affects the HPA[1] axis, inflammation, and immunity" (J.T. Cacioppo et al., 2015, p. 743).

In their meta-analytic review of 148 studies with a combined 308,849 participants who were followed 7.5 years on average, Holt-Lunstad and colleagues (2010) found evidence among those with stronger social connection indicative of a "50% greater likelihood of survival compared to those with poor or insufficient social relationships" (p.1). In their review, "the overall effect remained consistent across a number of factors, including, age, sex, initial health status, follow-up period, and cause of death, suggesting that the association between social relationships and mortality may be general" (Holt-Lunstad, 2010, p. 14). A later, large meta-analysis of (N = 3,407,134), found that the odds ratio of increased mortality for loneliness was approximately double the odds ratio for increased mortality for obesity and quadruple the odds ratio for increased mortality for air pollution (Holt-Lunstad et al., 2015).

Whether the outcome of interest is social isolation, loneliness, or social support, evidence exists that people "who are more socially connected live longer" (Holt-Lunstad, 2018, p. 438). In fact, "the body of evidence has grown exponentially to now include hundreds of studies, millions of participants, and broader measures" (Holt-Lunstad, 2018, p. 438), all pointing to the same finding that people with strong, positive social connections live longer. Moreover, a plethora of evidence exists, that when viewed through the Bradford Hill criteria, establishes a "potential causal link between social isolation and mortality" (NASEM, 2020, p. 47).

[1] The HPA axis is the hypothalamic-pituitary-adrenal axis, which has a primary role of regulating the stress response through the release of hormones, such as cortisol (Neuroscientifically Challenged, 2014).

Health Outcomes and Social Connection

Various studies examining participants across the lifespan have pointed toward a strong causal association between social relationships and health status (House et al., 1988; S. Cacioppo et al., 2014). However, a causal pathway is difficult to establish when accounting for the biological and neurological associations between social connection and mortality and morbidity in human subjects (J.T. Cacioppo et al., 2015; S. Cacioppo et al., 2014). As a result, experiments of acute and chronic induced social stress on multiple animal species have contributed important evidence to understanding the processes that occur within human beings (S. Cacioppo et al., 2014). Consequently, studies conducted with voles, rats, finches, canaries, and baboons and other non-human primates have shown "psychological and physiologic effects that could, if prolonged, produce serious morbidity and mortality (p. 542)."

As with the social connection-mortality research, the evidence linking state of social connection to health outcomes harkens to the 1970s, when the construct of social support dominated the scientific canon (House et al., 1988). The social support studies, generated from 1976 to 1981, underscored the health buffering role of social relationships, for example, suggesting that being married is beneficial to health (Berkman & Syme, 1979; House et al., 1988).

The negative health impact of social isolation has been demonstrated as worse than smoking 15 cigarettes daily or consuming six alcoholic beverages daily (Holt-Lunstad et al., 2015). Overall among adults, and among older people specifically, social isolation has been linked to poorer health outcomes including high blood pressure, cardiovascular disease, weakened immunity, fragmented sleep, cognitive decline, and inflammation (J.T. Cacioppo & Cacioppo, 2014; S. Cacioppo et al., 2014; Holt-Lunstad et al., 2010; Holt-Lunstad et al., 2015).

Also, J.T. Cacioppo and Cacioppo (2014) found that loneliness impairs, “executive functioning, sleep, and mental and physical well-being” (p. 1). Furthermore, loneliness has been shown to increase the chance of premature cognitive decline, chronic inflammation, decreased resistance to infection, and lowered immunity (J.T. Cacioppo & Cacioppo, 2014; Fakoya et al., 2020).

Social Connection and Health Care Utilization

The body of evidence relative to social connection’s impact on “health care utilization and access is limited, and it has shown mixed results” (NASEM, 2020, p. 125). An association has been found between weaker social support and hospital re-admission and longer hospital stays (Valtorta et al., 2018). In one study examining delayed hospital discharge among people ages 75 or older (*N*= 278), socially isolated patients or those at high risk of isolation spent, on average, 2.6 additional days in the hospital, and moderate risk of isolation added 1.5 additional days (Landeiro et al., 2015). Moreover, the patients who were socially isolated experienced a discharge delay 3.5 times more often than patients who were not socially isolated (Landeiro et al., 2015).

However, a recent consensus report on social isolation stated that other studies have discovered no evidence of impact on health care utilization or have even found evidence of decreased utilization (NASEM, 2020). Contradictory evidence also has resulted when examining health care utilization and social isolation versus loneliness. For example, findings have noted an increase in Medicare costs among socially isolated people (NASEM, 2020) and a decrease in Medicare costs among lonely people (NASEM, 2020).

Future evidence relative to economic impact on health care costs, utilization, and reimbursement seems likely to emerge, considering that as major health care actors seek to control rising costs, greater attention is being paid to the social determinants of health as drivers of health status. Notably, half of Medicare Advantage payers have incorporated a social isolation-loneliness intervention into their plans (Aging2.0, 2019). Moreover, in partnership with UnitedHealthcare, the American Medical Association (AMA) has advocated for the inclusion of 23 additional social determinants of health codes to the 10th revision of the International Statistical Classification of Diseases and Related Health Problems (ICD-10), which would allow for more specific diagnosis, treatment, and, thus, reimbursement for loneliness, social isolation, and other social determinants of health (Aging2.0, 2019). Additionally, in an effort to formalize these diagnostic-treatment-reimbursement pathways related to the social determinants of health, the American Hospital Association (AHA) (2018) advises hospital and health systems to make full use of the existing ICD-10 Z55-65 codes. Pertinent to social connection, code Z60 pertains to problems related to social environment, adjustment to life-cycle transitions, living alone, acculturation difficulty, social exclusion and rejection, and target of adverse discrimination and persecution (AHA, 2018).

Risk and Protective Factors of Social Connection Among Older Adults

The literature has traditionally examined risk and protective factors through the lens of individual traits, when, in reality, people live in complex and layered environments where there may be many other levels of risk and protection (Holt-Lunstad, 2018; Hortulanus et al., 2006; NASEM, 2020; Weldrick & Grenier, 2018). Researchers estimate that between 37% and 55% of the state of loneliness is heritable (Gao et al., 2017; Holt-Lunstad et al., 2017). Regarding modifiable risk, a gap exists in that we do not yet fully understand how the socio-ecological system influences risk or offers protection (Weldrick & Grenier, 2018). This is critical, because when a health issue reaches the level of public health concern, the best approach is to respond on multiple fronts in order to help the whole population by adopting a systems approach (Holt-

Lunstad, 2018; Holt-Lunstad et al., 2017; NASEM, 2020). Examples of population-level interventions could include targeted livability and public safety improvements (Portacolone et al., 2018), precisely directed interventions and services (Cotterell et al., 2018; Portacolone et al., 2018) and widespread early intervention screening Cotterrell et al., 2018).

Risk and protective factors for social connection can be categorized through a bio-psycho-socio-spiritual (BPSS) lens. Biological factors for low social connection include chronic conditions and functional limitations (NASEM, 2020). Also, the evidence suggests that hearing loss, particularly when untreated, increases the risk of social isolation (NASEM, 2020). It is important to note that physical factors, such as chronic health conditions, may increase the risk of social isolation or loneliness, and the opposite is true as well that "social isolation or loneliness may increase the chances of developing a chronic health condition" (NASEM, 2020, p. 64). A recent consensus report identified "robust evidence" (NASEM, 2020, p. 65) that cardiovascular disease and stroke can be risk factors for both loneliness and social isolation. Functional impairments, sometimes labelled geriatric syndromes, also appear to increase social isolation and loneliness, due in part to stigma surrounding limitations such as incontinence or limited mobility (NASEM, 2020).

Interestingly, aging is not independently associated with social isolation or loneliness (NASEM, 2020), although prevalence of loneliness appears to rise among certain age groups. For example, Lee et al. (2018) found an increased chance of loneliness occurred at the mid-twenties, mid-fifties, and late eighties. Recent national studies have also found higher proportions of loneliness exist in adults ages 18-22 (Cigna, 2018) and 45-49 (AARP, 2018). The AARP study (2018) found that loneliness decreased as age increased.

Mental health conditions such as depression, anxiety, and cognitive impairment raise the risk of low social connection (NASEM, 2020; Weldrick & Grenier, 2018). From a social perspective, roles such as informal caregiver or widowhood (NASEM, 2020) also increase the risk of social isolation and loneliness. Being single, does not equate to a destiny of loneliness or social isolation; however, the prevalence of low social connection among unmarried people has been shown as higher than among married people (AARP, 2018; Cigna, 2018; NASEM, 2020). Thus, marriage can help to protect against social isolation and loneliness if the relationship quality is positive (NASEM, 2020). Very little research has examined spiritual aspects of social connection; however, the construct of wisdom appears to have a protective benefit over social isolation and loneliness (Lee et al., 2018). In their seminal study on social support, House et al. (1988) examined religious participation and found a protective aspect.

Theoretical Model

The complexity of social connection as a phenomenon requires a theoretical framework that acknowledges this level of complexity in order to better understand social connection and develop strategies to mitigate low social connection. Attributes of social connection play out as individuals influence and are influenced by family and friends, their communities, and society itself (Holt-Lunstad, 2018; Weldrick & Grenier, 2018). Ecological systems theory provides a useful theoretical compass with which to undertake this multi-level study and can be used as a rubric to study the socio-ecological characteristics of social connection among a group of older adults.

As described in Chapter 1, ecological systems theory originated as a multi-level child development theory and has most often been used to enhance or study conditions such as childcare, child health disparity, family systems, and child intelligence (Bronfenbrenner, 2005).

Since its introduction in the late 1970s, however, the theory has evolved to incorporate lifespan development (Eriksson et al., 2018; Rosa & Tudge, 2013; Shelton, 2019).

To recap, over a span of several decades, Bronfenbrenner's ecological systems theory evolved into its current complete PPCT model (Rosa & Tudge, 2013). Its evolution occurred in three distinct phases. Phase 1, typically labelled as an ecology of human development, defined four contexts, or levels, of the ecosystem that influence and are influenced by human beings: microsystem, mesosystem, exosystem, and macrosystem (Bronfenbrenner, 2005; Rosa & Tudge, 2013; Shelton, 2019). This phase can be summarized as: People influence and are influenced by their environments, and the environment – or ecological system – comprises multiple levels, which are all connected (Shelton, 2019).

Phase 2 expanded upon the contexts by adding the consideration of time, known as the chronosystem (Rosa & Tudge, 2013). In adding a fifth essential dimension – time – Bronfenbrenner recognized with his theory that "the developing person changes over time" with particular emphasis on biological changes across the lifespan (Shelton, 2019, p. 14-15).

In its third and final phase, ecological systems theory expanded beyond a model of the ecosystem levels into its final expression as a PPCT theory, comprising multiple connected, interactive context-levels that work in tandem with constructs of developing persons and developmental outcomes (Bronfenbrenner, 2005; Rosa & Tudge, 2013; Shelton, 2019). The construct of time within the theory continued to evolve in Phases 2 and 3 (Rosa & Tudge, 2013).

Researchers have utilized chronosystem models to examine personal, cultural, and historical life events occurring within one or more of the other ecosystem levels. For example, in their review of elder abuse research, Schiamberg & Gans (2000) observed that the chronosystem can be understood through one or more of the "multiple time clocks" (p. 337) that represent the temporal contexts of ontogenic time, generational time, and macro time. They wrote that:

> These temporal contexts all affect human development. Ontogenic time refers to events in the biography of a person—a person's development or life course. It is indexed by chronological age or by age periods, stages, or levels. Generational time refers to the position of the individual in the rank descent within the biosocial family (e.g., grandparent, parent, grandson) and to familial events—the family development or life course. Historical time refers to the macro social dimension of time—events in the broad social context that affect families (Schiamberg & Gans, 2000, p.337).

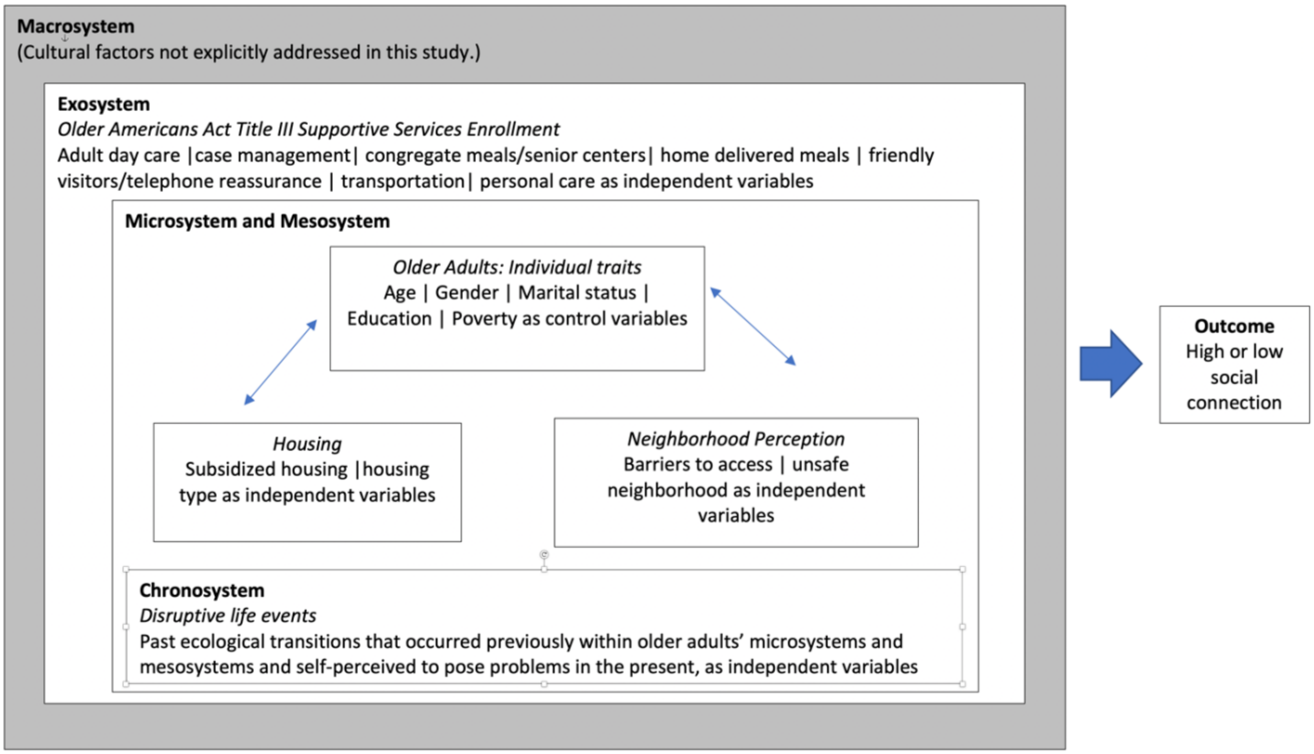
Application of Ecological Systems Model

At all ages and stages of human development, people actively engage in and respond to the world around them; yet a conceptual model describing the ecosystem of social connection among older adults remains underdeveloped (Holt-Lunstad, 2018). Prior research has emphasized individual traits with limited attention directed at community and societal factors (Holt-Lunstad, 2018; Portacolone et al., 2018; Kim & Clarke, 2015; Weldrick & Grenier, 2018). On the whole, the current evidence base relative to social connection does not "explicitly target" (Holt-Lunstad, 2018, p. 441) multiple levels of the human ecosystem.

In designing research questions to understand risk and protective factors of social connection as a multidimensional construct, this study formulated six hypotheses that examined aspects of the same individuals' microsystems, mesosystems, exosystems, and chronosystems. Further, the central research question asserted that each represented ecosystem level would contribute to the extent of social connection. This study mostly drew from Phase 1 and Phase 2 aspects of ecological systems theory. Figure 3 reflects the theoretical model as it applies to this study.

Figure 3

Theoretical Model of the Study



At the center of the theoretical model resides the developing person – an older adult seeking LTSS. Within the developing person's microsystem, or immediate setting, the study controlled for personal traits of age, gender, education level, poverty, and marital status. Arguably, in a different type of study these variables could well have been operationalized to represent other contexts such as the chrono (e.g., age) and macrosystems (e.g., age, gender, marital status, education). In this study, however, the research questions considered only the presence of those traits and not the longitudinal or cultural implications of those variables.

Indeed, while multiple individual traits are associated with a state of low social connection, the influence of environmental and societal factors, such as housing type is not entirely understood (NASEM, 2020). Therefore, expanding beyond personal traits, the theoretical model places housing within the microsystem, since the closest activity to the developing person may well be where they live (e.g., home). Housing characteristics are operationalized as living environment and subsidized housing. While housing is not a social factor, Bronfenbrenner (1977) argued early on that "environmental influences on development are of course not limited to human beings" (p. 522). He further elaborated that ecological research must "take into account aspects of the physical environment as possible indirect influences on social processes taking place within the setting" (Bronfenbrenner, 1977, p. 523).

Relative to mesosystem traits, the theoretical model situates older adults' perceptions of the neighborhoods in which they live within the mesosystem. Specifically, older adults reported on their perceptions of problems where they live related to perceived barriers to access or a perceived unsafe neighborhood. Neighborhood condition and perceived neighborhood condition are also understudied in the literature (Buffel et al., 2014; Keene & Ruel, 2013; Kim & Clarke, 2015; Portacolone et al., 2018).

The exosystem trait of interest in this study focused on the delivery of federally mandated services within the social services system. Specifically, utilization of supportive services offered via the exosystem may factor into developmental outcomes relative to social connection. The UAI records enrollment into these services at the time of the initial assessment.

Likewise, the theoretical model recognizes the importance of time by hypothesizing that past disruptive life events, which continue to cause stress in the present, may contribute to social connection or lack thereof. A few examples of such events include the loss of someone close, crime victimization, or a recent housing relocation. In experimental research, the chronosystem is often operationalized longitudinally. This study is cross-sectionally designed, yet the UAI assesses disruptive life events in a manner that inherently acknowledges a before-after state of mind. With regard to older adults' experiences and impact of past disruptive life events, the UAI question about life stressors ("Are there any stressful events that currently affect your life?") ascertains two important characteristics that help to index these events as temporal ecological transitions: 1) certain life events have/have not occurred (past) 2) indication that the event continues to have a stressful impact at the time of the initial assessment (present).

In the context of the chronosystem, the theoretical model driving this study does not examine cultural or historical life events but restricts its scope to biographical events. Operationalizing the chronosystem solely on disruptive life events, theoretically defined as non-normative ecological transitions, positioned the study as making simplest use of the chronosystem (Bronfenbrenner, 1986; Bronfenbrenner, 2005).

Finally, the theoretical model shown in Figure 4 includes variables that are both observed and perceived. Bronfenbrenner (1977) recognized that both are equally critical measures of ecological validity.

In summary, for older adults seeking LTSS in order to avoid institutionalization, factors such as housing, neighborhood perception, enrollment in supportive services, and disruptive life events may externally influence one's perceptions and experiences of positive social connection. Table 3 summarizes the context levels of ecological systems theory relative to the current study.

Table 3

Ecological Systems Theory Constructs and Dissertation Focus

Level	Definition	Representation
Microsystem	Structures and processes occurring in the immediate setting of the developing person	-Housing environment -Subsidized housing - Individual traits: age, gender, education level, marital status, poverty
Mesosystem	Linkage or processes of two or more settings including the developing person	-Perceived barriers to access -Perceived unsafe neighborhood
Exosystem	Linkage or processes of two or more settings where at least one does not ordinarily contain the developing person	-Enrollment in Title III supportive services
Chronosystem	The influence of events in time across any or all ecosystem levels. This study examines ecological transitions in time within the micro and mesosystems.	-Past disruptive life events self-identified as a present-day life stressor
Developmental outcome	A multidimensional construct that considers the influence of people, processes, contexts, and time (PPCT) on characteristics susceptible to development.	Degree of social connection measured via social connection score
Ecological validity	Objective and self-perceived measures are necessary to understand the influence of the developing person’s ecosystem.	Study variables include objective measures (e.g., has Medicaid) and subjective (e.g., unsafe neighborhood)

Study Independent Variables

Housing

There is surprisingly little conclusive evidence on how the built environment, housing type particularly, predicts the extent of social connection. Researchers who have examined the links between aspects of social connection and the built environment have noted that in primarily focusing on personal traits and social isolation, external pathways have been overlooked (Kim & Clarke, 2015; Portacolone et al., 2018). As a result of the aforementioned SIRI project, Suen et al. (2018) found a weak association between the built environment and satisfaction with social support among older adults. In discussing their secondary data analysis, Suen and colleagues (2018) called for additional research in this area, a call to action echoed by numerous researchers (Buffel et al., 2014; Keene & Ruel, 2013; Kim & Clarke, 2015; NASEM, 2020; Portacolone et al., 2018).

Neighborhood Perception

Similar to housing, the influence of neighborhood environment as a manifestation of the built environment is also understudied (Buffel et al., 2014; Keene & Ruel, 2013; Kim & Clarke, 2015; NASEM, 2020; Portacolone et al., 2018). As an example of objectively examining the built environment's influence over social support, Suen et al. (2018) find an association between social satisfaction and observable traits of the built environment such as proximity of resources including grocery stores and public transportation. Likewise, Kim and Clarke (2015) conducted a three-year secondary data analysis of Medicaid home- and community-based services waiver data on community-dwelling older adults in Detroit (N=965), which combined on-the-ground neighborhood observation. Results from their "multilevel multinomial analyses indicated that the presence of neighborhood watch signs was associated with increased chance of social withdrawal and social isolation" (Kim and Clarke, 2015, p. 414).

In their cross-sectional study, Buffel and colleagues (2014) examined how perceived neighborhood conditions may hinder or encourage social participation, defined as formal and informal. They found that the most significant indicator of formal social participation was perceived accessibility (Buffel et al., 2014).   In, another cross-sectional study (*N*=647), Hong et al. (2018) examined the role of perceived safety relative to perceived and observed green space and social cohesion and social interaction among older adults. They found that perceived personal safety was statistically significantly associated with social cohesion but less so for social interaction (Hong et al. 2018).

In a longitudinal, qualitative study of older adults (*N*= 20) living in high-crime areas in Richmond, California, Portacolone et al. (2018) aimed to investigate the lived experiences of older adults, giving specific consideration to how neighborhood structures influenced social connection and social isolation. Their study found that a social environment perceived as rampant with crime and drug activity "hampered the creation and maintenance of social ties" (Portacolone et al., 2018, p. 83). One study participant with limited mobility explained why fear of neighborhood crime caused him to withdraw socially, saying, "If I had a motorized scooter I could get on public transportation, I could go to the movies, I can go out and have a nice dinner out, I can go to the marina and fish ... I don't have to be a sitting duck" (Portacolone et al., 2018, p. 85). Portacolone and colleagues (2018) encouraged further research on structural influences of social isolation to avoid blaming older adults as solely responsible for their social connection challenges (p. 86).

For this study, the condition of older adults' neighborhoods was measured by individuals' perceived barriers to access or a perceived unsafe neighborhood. Table 4 summarizes the findings of contemporary studies relative to neighborhood condition and social connection.

Table 4

Summary of Literature Regarding Social Connection and Neighborhood

Study	Subjects	Results	Study design
Buffel et al., 2014	1,877	The most significant indicator of formal social participation was perceived accessibility.	Cross-sectional study that surveyed residents of a single neighborhood in Belgium.
Hong et al., 2018	647	Perceived personal safety associated with social cohesion,	Cross-sectional study using observed and perceived measures.
Kim & Clarke, 2015	965	Presence of neighborhood watch signs was associated with reduce social engagement and increased social isolation.	Secondary data analysis of Medicaid waiver participants in Detroit combined with built environment observation
Portacolone et al., 2018	20	Structural barriers (high crime, poor walkability, poor access) exacerbate and lead to social isolation in older adults, even those who desire greater connection	Qualitative, longitudinal study
Suen, et al., 2018	819	Weak association between observable attributes of the built environment and satisfaction with social support	Secondary data analysis measuring social support satisfaction

Title III Supportive Services Enrollment

There is no existing literature that analyzes Title III supportive service enrollment as a protective factor. Existing literature has examined post-intervention effects of supportive services interventions (such as friendly visiting and home-delivered meals) and found mixed results. These studies are limited by a possible bias since participants are typically identified as lonely or isolated prior to study enrollment. Authors of systematic reviews of loneliness and social isolation interventions agree that more research and more rigor are needed to provide reliable data on effective interventions (Dickens et al., 2011; Gardiner et al., 2018). While the canon of evidence has heretofore investigated supportive services as intervention or treatment for low social connection once detected, community-based providers also need to know which services may be most effective to prevent social isolation and loneliness among older adults. In other words, do supportive services play a protective role by buffering older adults from the risk of becoming socially isolated or lonely?

Broadly, interventions for community-dwelling older adults are indexed either as group interventions occurring outside of an individual's home or one-to-one interventions occurring in-home. Group and in-home approaches tend to rely on community-based organizations (CBOs) and community volunteers working through CBOs (Gardiner et al., 2018). The evidence regarding the efficacy of different interventions is still emerging and suggestive that group interventions organized by interest area or affinity have the most success (Aging2.0, 2019; Dickens et al., 2011). Interestingly, group interventions designed solely to address social isolation have yet to demonstrate that they work (Aging2.0, 2019; Dickens et al., 2011); the evidence does suggest, however, that appealing to people's interests, hobbies, and cultural experiences is the best way to meaningfully connect people in group settings (Aging2.0, 2019;

Gupta, 2021). However, not all older people can or want to participate in community-based group activities. No studies have been identified wherein supportive service enrollment has been tested as protective of strong social connection, so this section presents evidence on how well supportive services work to improve existing states of loneliness and social isolation.

The OAA provides significant funding for in-home and group interventions targeting older adults most at risk of social isolation under the Title III Nutrition Services and Title III B Supportive Services provision. In part, programs such as home-delivered meals, friendly visiting/telephone reassurance, companion services, personal care, adult day care, and congregate meals are designed to reduce social isolation and improve socialization.

Community-based Group Interventions. Two types of group interventions that strive to improve socialization are part of the OAA's Title III provision: adult day care and congregate meals. There is limited peer-reviewed evidence on the effectiveness of these programs as social connection interventions and no evidence was identified in the literature that addresses the protective role of these services, relative to social connection. In a case-control study (*N*=817) where the vast majority of participants scored as moderately or highly lonely, Iecovich and Biderman (2012) found no significant difference between the loneliness scores of participants in adult day care versus non-participants. The most recent evidence that examined a link between congregate meals and socialization is the National Program Evaluation Survey (*N*= 766) conducted by the ACL (ACL, 2018), which found that 84% of congregate meals participants surveyed reported that participation resulted in seeing their friends more often. In the same survey, 60% of congregate meals participants responded that their social opportunities have increased since they became involved with the local area agency on aging (ACL, 2018).

In their systemic review, Dickens and colleagues (2011) did not include any studies specific to congregate meals, adult day care, personal care, or companion services, but they did observe that group social activities were associated with a self-reported increase in new friendships.

In-Home Supportive Services. Relative to home-delivered meals, one randomized control trial (RCT) has been conducted on the association between home-delivered meals and perceived loneliness (Thomas et al., 2016). In a three-armed RCT, Thomas and colleagues (2016), found statistically significant differences in loneliness score averages between three groups. In that study, participants who received daily meals had lower loneliness scores, on average, than participants who received weekly meals and lower than participants who received no meals (Thomas et al., 2016).

Befriending services, such as friendly visiting and telephone reassurance, are an evaluated intervention demonstrating mixed results relative to social isolation, loneliness, social supports, and social connection (Dickens et al., 2011; Gardiner et al., 2018; Wiles et al., 2019). Most often, research studies on both friendly visiting and telephone reassurance services have been conducted with small samples without control groups (Dickens et al., 2011; Gardiner et al., 2018; Roberts, 2015). Regarding friendly visiting, some studies have found little to no change in social connection or perceived loneliness, (Dickens et al., 2011; Wiles et al., 2019), while other studies have shown positive changes (Dickens et al., 2011; Roberts, 2015; Wiles et al., 2019).

Telephone reassurance services offer personal interaction to a lesser degree than friendly visiting. Telephone reassurance shares some attributes with friendly visiting, such as use of volunteers. However, the nature of telephone reassurance typically is not centered around friendship development, shared interests, reciprocity, or community engagement (Roberts, 2015).

A meta-analysis that examined social support interventions found little change occurred in older adults' perceived loneliness, social connection, or social isolation as a result of telephone peer support (Dickens et al., 2011). A different systematic review, however, found evidence that telephone reassurance "alleviates loneliness through making life worth living and generating a sense of belonging" (Gardiner et al., 2018, p.152). Interestingly, telephone reassurance interventions appear more successful at achieving positive outcomes when the service is conducted by a staff member rather than a volunteer (Dickens et al., 2011; Gardiner et al., 2018). As with friendly visiting, telephone reassurance studies have typically been conducted with small sample sizes (Roberts, 2015). Table 5 summarizes the evidence presented in this section relative to social connection and supportive services enrollment.

Table 5

Summary of Literature Regarding Social Connection and Supportive Services

Study	Subjects	Results	Study design
ACL, 2018	766	84% of respondents indicated congregate meals participation helped them see their friends more often.	Telephone survey for internal program evaluation
Dickens et al., 2011	4,061	Group participatory interventions demonstrated most significant outcomes.	Systemic review of 32 studies
Gardiner et al., 2018	39 studies	Group interventions showed the most success. Telephone reassurance showed improved loneliness. Befriending showed limited success and a number of ongoing challenges.	An integrative review
Iecovich & Biderman, 2012	817	Enrollment in adult day care did not	Case-control study comparing two

Study	Subjects	Results	Study design
		significantly relate to lower loneliness scores compared to non-enrollment.	groups: adult day participants and non-participants
Thomas et al., 2016	626	Participants receiving daily meals were three times more likely than people receiving weekly delivered meals to indicate that receiving home-delivered meals helped them feel less lonely.	First RCT of home-delivered meals Measured improved loneliness

Disruptive Life Events

Research shows that experiences of trauma, loss, and stressful transitions that occur across the lifespan may hold particular influence over the extent of social connection as people grow old (Holt-Lunstad, 2018; NASEM, 2020). Ecological transitions such as retirement, loss of a loved one, health problems (Holt-Lunstad, 2018; Suen et al., 2018), and childhood and adult trauma (S. Cacioppo & Cacioppo, 2012; Hyland et al., 2019; Suen et al., 2018) are also associated with decreases in social connection.

Numerous studies have emphasized a need to better understand the relationship between disruptive life events and social connection (AARP, 2018; Holt-Lunstad, 2018; Hortulanus et al., 2006; NASEM, 2020; Suen et al., 2018). Suen et al. (2018) conducted a risk-protective factor regression study (N = 819) using UAI data, colloquially known as the social isolation risk index (SIRI) project, with a sample focused on a single geographic region and a single factor, binary DV of satisfaction with frequency of contact with children, family, and friends. Findings from the SIRI project (Suen et al., 2018) indicated that a recent transition or trauma event decreased the odds of being socially satisfied by 24.7%; specifically, family conflict decreased the odds of being socially satisfied by 66.1%, financial problems by 49.3%, and failing health by 33.3%. Similar to Suen et al. (2018) and Hortulanus et al. (2006), Holt-Lunstad (2018) observed a social isolation-disruptive life event linkage and called for additional research in this area.

In 2013, Keene and Ruel conducted a qualitative study of public housing demolition and relocation among older adults in Atlanta. Study participants described a range of benefits to living in housing communities "that were 'like families' and where they often held important roles as respected elders" (Keene & Ruel, 2013, p. 359). The study found that older adults described the social networks within their public housing developments as communities of "kinship, belonging, security, and support" (Keene & Rule, 2013, p. 361). Post-relocation narratives revealed that while some participants were satisfied with their relocation, others experienced the dispersal of decades-long social bonds as a deeply felt loss (Keene & Ruel, 2013, p. 361). Keene and Ruel (2013) concluded that "this loss of social ties may be an unintended consequence of public housing demolition that has profound health implications for relocated older adults" (p. 363).

In an observational study of lifetime experiences of community violence among adults 18 and older, Tung et al. (2019) found an association between the personal experience of community violence and reduced frequency of social network interaction, reduced perceived social support, and increased perceived loneliness, suggesting that "living in an unsafe neighborhood may be an important risk factor for social isolation and loneliness" (Tung et al., 2019, p. 1670). Tung and colleagues (2019) noted that, "although rich qualitative and conceptual research suggests that people living in high crime neighborhoods may be at higher risk for social isolation, there is a paucity of quantitative data to confirm and assess the extent of these relationships" (p. 1671).

The studies described in this section demonstrate how disruptive life events can temporally alter the social well-being of older adults even after those events have occurred. There are many types of life events, or ecological transitions, that may impact feelings of loneliness or social isolation, including death of someone close, failing personal health, and change in employment (NASEM, 2020). A recent consensus study called for more research in this area and stated, "although research on these topics is sparse, it provides insight into how these experiences can disrupt people's lives and how they could lead to social isolation or feelings of loneliness" (NASEM, 2020, p. 77). Table 6 depicts the results of the evidence discussed in this chapter relative to social connection and disruptive life events.

Table 6

Summary of Literature Regarding Social Connection and Disruptive Life Events

Study	Subjects	Disruptive life events	Results	Study design
Keene and Ruel, 2013	25	Public housing relocation	The disruption of social networks resulting from public housing relocation experienced as a loss for older adults.	Qualitative, small sample
Suen et al., 2018	819	Life stressors included in Virginia UAI	A recent transition or trauma event decreased the odds of being socially satisfied by 24.7%	Secondary data analysis, single region, single dimension measure, binary outcome
Tung et al., 2019	504	Exposure to community violence	Prior exposure to community violence associated with reduced social interaction, reduced perceived social support, and increased loneliness.	Observational

Research Question and Hypotheses

Central research question: To what extent do housing (microsystem), neighborhood perception (mesosystem), supportive services enrollment (exosystem), and disruptive life events (chronosystem) predict the extent of social connection among community-dwelling older adults, after controlling for age, gender, poverty, marital status, and educational attainment?

The breadth of the UAI as the data source allowed for the creation of a multidimensional DV of social connection informed by Holt-Lunstad's (2018) typology of social connection. Uri Bronfenbrenner's ecological systems of human development theory (ecological systems theory) (Bronfenbrenner, 1977; Bronfenbrenner, 1986: Bronfenbrenner, 2005; Rosa and Tudge, 2013; Shelton, 2019) provided the theoretical scaffolding for this study. The hypotheses tested heretofore understudied variables representing four ecological levels: microsystem, mesosystem, exosystem, and chronosystem. Individual traits of age, gender, educational attainment, poverty, and marital status were used as control variables.

Aim 1

Construct a multidimensional measure of social connection composed of input variables representing structural, functional, and quality attributes of social connection.

Hypothesis 1. Each attribute of social connection (structural, functional, and quality) will uniquely contribute to the ability to detect predictive influences on extent of social connection via the composite variable social connection.

Aim 2

Determine the most robust predictors from among those variables representing the microsystem, mesosystem, exosystem, and chronosystem.

Hypothesis 2 (Microsystem). Older adults' housing environments predict higher social connection, after controlling for age, marital status, gender, poverty, and educational attainment.

Hypothesis 3 (Mesosystem). Older adults' negative perception of neighborhood environment predicts lower social connection, after controlling for age, marital status, gender, poverty, and educational attainment.

Hypothesis 4 (Exosystem). Older adults' enrollment in Title III supportive services predicts a higher social connection score after controlling for age, marital status, gender, poverty, and educational attainment.

Hypothesis 5 (Chronosystem). Older adults' experiences of disruptive life events predict lower social connection scores after controlling for age, marital status, gender, poverty, and educational attainment.

Aim 3

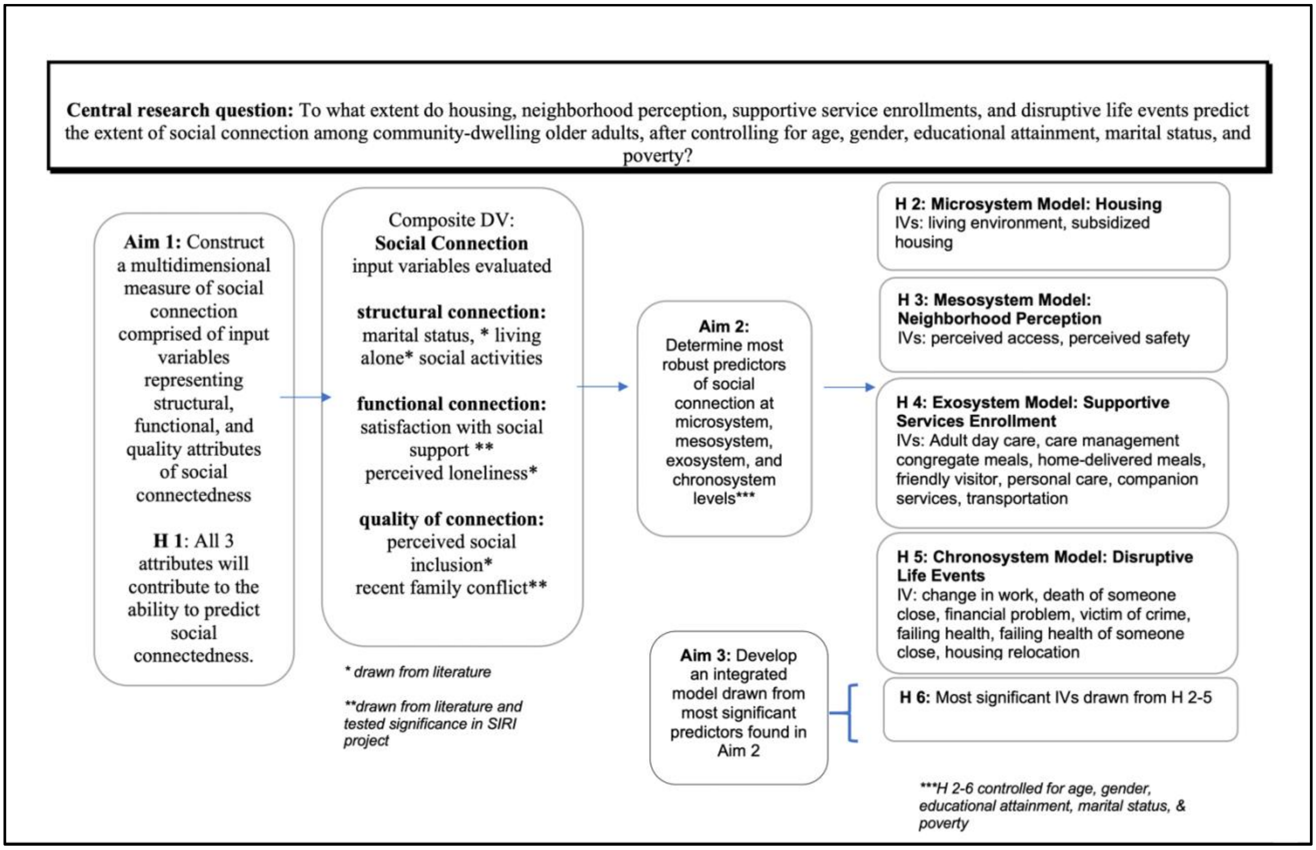
Develop an integrated model drawn from the most significant predictors found in Aim 2.

Hypothesis 6 (All Levels). The best predictors of older adults' extent of social connection will include housing, neighborhood perception, supportive services enrollment, and disruptive life events, after controlling for age, marital status, gender, poverty, and educational attainment.

Figure 4 depicts the relationship among the central research question, ecosystem levels, aims, and hypotheses.

Figure 4

Relationship Among Central Research Question, Ecosystem Levels, Aims, and Hypotheses



Delimitations

Though it is generally accepted that socio-economic status, or poverty, negatively influences social connection (AARP, 2018; NASEM, 2020; Samuel et al., 2018), the evidence relative to poverty and social connection has primarily focused on income (Samuel et al., 2018). However, dimensions of poverty other than income also appear to relate to perceived social inclusion and social exclusion, but this relationship has been drastically understudied (Samuel et al., 2018). As an initial exploratory step toward a deeper investigation of poverty and its various dimensions, this study uses Medicaid (has/does not have) as a control variable.

Conclusion

This chapter described the findings of seminal and contemporary studies that have examined the concepts of social connection, loneliness, and social isolation. Collectively, these studies have contributed to the conceptualization of a composite social connection DV that was developed in this study. As a result of the aforementioned SIRI project, for example, Suen et al. (2018) noted varying definitions of social isolation, called for further study of societal factors such as the built environment, and encouraged urban planning-gerontological collaboration in the study of social isolation among older adults.

Both loneliness and social isolation are associated with higher blood pressure, increased depressive symptoms, compromised immunity, increased fall rate, and early mortality (J.T. Cacioppo & Patrick, 2008; Holt-Lunstad et al., 2010). The evidence supports that positive social relationships play an important role in health and well-being (Holt-Lunstad, 2018) by offering safe havens, encouragement, and assistance (Feeney & Collins, 2015). Myriad single dimensional measurements point conclusively toward a risk-protective effect of social connection, yet the lack of a multidimensional social connection measure inhibits the ability to effectively intervene at the individual, family-friends, community, and societal levels (Holt-Lunstad, 2018; NASEM, 2020; Veazie et al., 2019). While many in the health care sector now recognize both loneliness and social isolation as constituting a public health crisis (J.T. Cacioppo & Patrick, 2008; Fakoya et al., 2020; Holt-Lunstad, 2018; Holt-Lunstad et al., 2010; Hudson, 2018; Lubben et al., 2018; McGregor, 2017; Veazie et al., 2019), the response to this crisis has not matured into a public health approach (Holt-Lunstad, 2018; NASEM, 2020).

Individual demographic and lifestyle risk factors have been extensively studied (Holt-Lunstad, 2018). However, the literature is quiet, and intermittently silent, on the interrelated environmental and societal mechanisms by which people thrive or fail to thrive in their connections with other people (Holt-Lunstad, 2018; NASEM, 2020). Systems approaches to public health issues represent the essential means by which the broader health care system transforms its response protocol from treating individuals to treating the public (Holt-Lunstad, 2018; NASEM, 2020). Preeminent scientific organizations (NASEM, 2020) and community-based actors (AARP Foundation, 2018; Cigna, 2018; Veazie et al., 2019;) have joined Holt-Lunstad (2018) in calling for measuring across environmental levels, developing more predictive, complex measures, and taking multidimensional measurement approaches.

In summary, the timely and unprecedented access to a large data set from the UAI enables this study to address the following gaps:

1. The vast majority of research studies in the social connection realm have examined a single dimension, most often the structural dimension.
2. No studies have been identified that explicitly and quantitatively examined socio-ecological system risk and protective factors within the same sample.
3. No studies have been identified that examine a potential protective role of Title III supportive services and nutrition services enrollment.
4. A paucity of evidence exists relative to congregate meals, specifically.
5. The relationship between housing environment and social connection is understudied.
6. The relationship between neighborhood perception and social connection is understudied.
7. The relationships between disruptive life events and social connection are understudied.

Chapter 3: Methodology

Chapter Overview

The purpose of this study was to analyze social connection among community-dwelling older adults seeking LTSS, using a multidimensional measure of social connection comprising structural, functional, and quality attributes. To accomplish this purpose, the study devised a continuous composite dependent variable and conducted eight regression analyses to test six hypotheses. This chapter describes the study's research methodology, including the research questions, target population, and sampling methods. Descriptions of variables, the instrument, data collection, and data analysis procedures are included as well. Lastly, study limitations are addressed, and the chapter concludes with a brief summary.

Aims and Hypotheses

The study pursued the aims and hypotheses shown in Table 7.

Table 7

Aims and Hypotheses

Aims	Hypothesis
Aim 1: Construct a multidimensional measure of social connection composed of input variables representing structural, functional, and quality attributes of social connection.	**H1:** Each attribute of social connection (structural, functional, and quality) will uniquely contribute to the ability to detect predictive influences on extent of social connection via the composite variable social connection.
Aim 2: Determine the most robust predictors at the microsystem, mesosystem, exosystem, and chronosystem levels.	**H2 (Microsystem):** Older adults' housing environments (subsidized housing or housing type) predicts higher social connection, after controlling for

Aims	Hypothesis
	age, gender, poverty, marital status, and educational attainment.
	H3 (Mesosystem): Older adults' negative perception of neighborhood environment predicts lower social connection, after controlling for age, gender, poverty, marital status, and educational attainment.
	H4 (Exosystem): Older adults' enrollment in formal supportive services predicts a higher social connection score after controlling for age, gender, poverty level, marital status, and educational attainment.
	H5 (Chronosystem): Older adults' experience of disruptive life events predicts lower social connection score after controlling for age, gender, poverty, marital status, and educational attainment.
Aim 3: Develop an integrated model drawn from the most significant predictors found in Aim 2.	**H6 (Mixed Levels):** The best predictors of older adults' extent of social connection will include neighborhood influences, supportive services enrollment, and disruptive life events, after controlling for age, gender, poverty, marital status, and educational attainment.

Research Design

This quantitative study utilized a retrospective, cross-sectional design with data related to older people who sought services through the 25 area agencies on aging in Virginia from 2013 to 2019. Researchers often use retrospective designs to "identify risk factors for differing amounts of an outcome" (Polit & Beck, 2017, p. 204). Additionally, retrospective studies are often cross-sectional "with data on both the dependent variable and the independent variables collected at a single point in time" (Polit & Beck, 2017, p. 204). This study conformed to each of those traits.

There are three typical approaches to retrospective studies: secondary data analysis, ancillary study, and systemic review (Grady et al., 2013). Secondary data analysis "makes use of an existing data set to investigate research questions other than the main ones for which the data were originally gathered" (Grady et al., 2013, p. 192). A strong rationale for selecting a secondary data analysis approach is that research questions can be answered quickly and efficiently – an especially appropriate strategy for new researchers with limited experience and limited funding. This design allows early researchers to study important questions while growing their research skills (Grady et al., 2013). Moreover, this type of design is ideally suited to test assumptions of new measures and methodology in describing relationships among variables at a point in time (Polit & Beck, 2017).

Some compelling reasons motivated the decision to use a secondary data analysis approach: The data set is not publicly available and has no assigned principal investigator; therefore, it is understudied and largely unexplored. One exception, which works to the advantage of this study, is that researchers from VCU's Departments of Gerontology and Urban Planning undertook the SIRI project in 2015 and 2016 using a subset of data from the Virginia UAI for a single jurisdiction (Suen et al., 2018). Two of the three university researchers and one of the community-based partners who worked on the SIRI project served on this dissertation committee, which offered the student-researcher access to specialized guidance.

Population and Sample

Target Population

The study examined older adults seeking LTSS as the population of interest. LTSS services empower community tenure: choosing to live in a community setting by garnering supports in order to avoid residential placement in an institution such as a nursing facility. By the fact of inclusion in the data set of UAIs conducted, all participants in the study had functional, mobility, or health limitations that impacted their well-being at the time of the initial assessment.

Virginia is home to 25 area agencies on aging, which collectively served 61,105 older Virginians in FY2018 (DARS, 2019, p. 13). While there is no financial means test in order to receive area agency on aging services, through its state agency plan Virginia's area agency on aging network prioritizes "older individuals with greatest economic and social need, with special emphasis on low-income minority individuals, older individuals with limited English proficiency, older persons residing in rural or geographically isolated areas, and older individuals at risk for institutional placement" (DARS, 2019, p. 13), which is consistent with the population of people completing a UAI assessment through an area agency on aging in Virginia.

Sampling Strategy

This study used a nonprobability consecutive sampling method, which is a form of convenience sampling that minimizes "selection biases by consecutively selecting subjects who meet the criteria" (Hulley et al., 2013, p. 27). This method is "desirable when it amounts to taking the entire accessible population over a long enough period of time to include seasonal variations or other temporal changes" (Hulley et al., 2013).

Throughout Virginia, organizations other than area agencies on aging conduct UAIs, such as local adult protective services offices, home care agencies, and assisted living facilities.

Moreover, not all older adults seeking LTSS require a complete UAI to access the services they need or desire. Some connect with services through information and referral channels such as No Wrong Door Virginia, VirgniaNavigator, and 2-1-1 Virginia. Therefore, the accessible population was identified as older adults seeking LTSS with UAIs completed by area agencies on aging over the seven years spanning 2013-2019. Individual UAI records from calendar year 2020 were excluded because the year was incomplete at the time of data transfer. Because geographic area is considered protected health information (PHI) (HIPAA Journal, 2017; Office for Civil Rights, 2015), this project did not examine city, county, or ZIP code but rather studied the entire state.

Eligibility Criteria

Table 8 depicts the inclusion-exclusion criteria.

Table 8

Study Inclusion-Exclusion Criteria

Inclusion criteria	Exclusion criteria
● Participated in a full Virginia UAI between January 1, 2013 and December 31, 2019	
● UAI Parts A and B completed	● Parts A and B of the UAI not completed
● UAI social status and emotional status sections completed	● UAI social status and emotional status sections not completed
● Age 60 or older	● Under age 60

The study excluded individuals under 60 because Title III of the OAA stipulates a minimum age of 60 in order to receive certain services at no cost through an area agency on aging. These services include home-delivered meals, congregate meals, adult day care, and in-home care — all critical to community tenure for older people throughout the nation (ACL, n.d.a). As part of the exosystem analysis, Hypothesis 4 examined the effect of enrollment into these supportive services. The rationale for requiring completion of the social and emotional status sections of the UAI was that a majority of the potential input variables for the composite DV (H1) originated from these two sections.

Data that did not meet these criteria were excluded. The criteria were applied in two steps. In preparing the raw UAI data for data transfer, DARS applied three of the four criteria: 1) participation in the full UAI originally collected between 2013 and 2019, 2) completion of UAI Parts A and B, and 3) age 60 or older at the time of an initiating UAI. The final criteria — UAI social status and emotional status sections completed — was applied by the researcher prior to data screening and cleaning.

Power Analysis

This study was powered to a small effect size, significance level of .01, and power of .90. Using a web-based sample size calculator resulted in a sample size estimate of 1,389 (10 predictors) necessary for an effect size of .14, a significance level of .01, and power of .90 (Stats Kingdom, n.d.).

Instrumentation and Variables

Instrument

The Virginia UAI is the instrument that provided all data for the IVs, CVs, and the DV. Therefore, the instrument is discussed first, in order to provide context for the source of the variables. The complete UAI can be found in Appendix A. The UAI is required for use with all publicly funded LTSS in Virginia but is not limited to public services. Beginning in 1994, after several years of pilots, revisions, and testing, health and human services agencies in Virginia began using the UAI to "gather information for the determination of individuals' care needs, for service eligibility, and for planning and monitoring client care needs across agencies and services" (DARS, 2015, p. 2). The short assessment, known as the quick form, is used for intake and screening. The full assessment is "designed to gather sufficient information about the client, his or her needs, and his or her strengths in order to begin a service plan" (DARS, 2015, p. 3). The full assessment consists of the following sections: identification/background, functional status, physical health, psychosocial, assessment summary, and caregiver assessment (DARS, 2015).

Typically, the quick form is conducted by phone and the full assessment during a face-to-face interview. The data originated from 25 different agencies, which at any given time employed one or more care coordinators who are responsible for assessment. An extensive UAI user guide and UAI assessor training mitigate the threat to interrater reliability.

Dependent Variable

Aim 1, Hypothesis 1 developed the continuous variable that served as the outcome variable for Hypotheses 2 – 6. The development of the continuous, composite DV was guided by Holt-Lunstad's (2018) multidimensional umbrella typology of structural, functional, and quality social connection. Holt-Lunstad (2018) posited that three primary factors determine "the extent to which an individual is socially connected" (p. 440). These factors relate to "relationships and their roles," "actual or perceived support or inclusion," and the "positive and negative qualities" of connection (Holt-Lunstad, 2018, p. 440). The composite DV resulted in an overall social connection score, generated for each record in the data set.

As depicted in Table 9, the UAI includes numerous possible input variables that represent Holt-Lunstad's (2018) typology of social connection. Each variable in Table 9 was evaluated for inclusion in the composite DV. Specifically followed steps for devising the DV are discussed in the data analysis section of this chapter.

Table 9

UAI Data Elements Evaluated for Inclusion in Composite DV

Component	Attribute	Variable name	UAI element(s)	UAI location
Structural	Marital Status	Marital Status	Marital Status	Demographics
Structural	Living alone	Lives_With	Does anyone live with you?	Physical Environment -
Structural	Social integration	Solitary Groups_Clubs Friends_Fam Religious_Act	Are there some things you especially enjoy?	Social Status
Structural	Social isolation	Talk_Children, Talk_Family, Talk_Friends	How often do you talk with your children, family or friends either during a visit or over the phone?	Social Status
Functional	Perceived social support	Soc_Satisfied	Are you satisfied with how often you see or hear from your children, other family, and/or friends?	Social Status
Functional	Perceived loneliness	Feel_Alone	In the past month, how often did you feel alone and that you don't have anyone to talk to?	Emotional Status
Quality	Relationship strain	Family_Conflict	Family Conflict	Life Stressors
Quality	Social exclusion	Bad_Harm	Feel afraid that something bad was going to happen to you and/or feel that others were trying to take things from you or trying to harm you?	
Quality	Social inclusion	Introvert	In the past month, how often did you feel like you didn't want to be around other people?	Emotional Status

Control Variables

Planned control variables included educational attainment, age, race-ethnicity, gender, and poverty. Due to a high rate of missingness, race and ethnicity were not included in the univariate analysis or regression analysis. Additionally, when analyzing the input variables for their unique contribution to the composite DV, marital status did not meet the threshold for inclusion into the composite DV, therefore, was not included. However, the canon of evidence strongly suggests that marital status is a protective factor against social isolation and loneliness (AARP, 2018; Berkman & Syme, 1979; J.T. Cacioppo et al., 2015; Cigna, 2018; Cudjoe et al, 2020; House et al., 1988; Lee et al., 2018; NASEM, 2020; Veazie et al., 2019). With respect to previous research findings, marital status was kept in the study but shifted into the role of a control variable. For purposes of this study, poverty was represented by Medicaid enrollment, a proxy for poverty used in prior research (Thomas et al., 2016). The variable age was used as a continuous variable in the regression models. For descriptive purposes and to aid in data interpretation, a new variable age_group was created and examined. The study's final control variables are shown in Table 10.

Table 10

Study Control Variables for Hypotheses 2 - 6

Variable	UAI element(s)	UAI location	Measure
Educational attainment	Education	Demographics	1 = less than high school, 2 = some high school, 3 = high school graduate, 4 = some college, 5 = college graduate
Marital Status	Marital status	Demographics	1 = widowed, 2 = single/divorced/separated, 3 = married
Age	Age	Demographics	Continuous
Age Group			1 = 60 – 64, 2 = 65- 74, 3 = 75-84, 4 =85 – 94, 5 = 95 and older
Gender	Gender	Demographics	1 = female, 2 = male
Poverty	Has Medicaid	Financial resources	1 = No, 2 = Yes

Independent Variables

Aim 2, Hypotheses 2 – 6 introduced the devised composite DV into a series of regression models designed to test the ability of variables representing the micro, meso, exo, and chronosystem levels of the human ecosystem to predict social connection scores. Study variables were informed by the literature and specific aspects of ecological systems theory. To aid in data analysis, a new variable was created, total life events, which amounted to a sum of how many disruptive life events had been experienced. Table 11 shows the IVs for Hypotheses 2-6.

Table 11

Study Independent Variables

Variable	UAI element(s)	UAI location	Measure
Hypotheses 2: microsystem: living environment			
Living environment	Where do you usually live?	Physical Environment	1 = Own or rent house, 2 = Rent room or apartment 3 = other
Subsidized housing	Subsidized housing	Financial Resources	1 = No 2 = Yes
Hypothesis 3: mesosystem: neighborhood perception			
Perceived neighborhood safety	Unsafe neighborhood (defined as the individual lives in an area which is unsafe with frequent crime problems)	Physical Environment	1 = No 2 = Yes
Perceived access	Barriers to access (defined as features which make the living arrangement inaccessible)	Physical Environment	1 = No 2 = Yes
Hypothesis 4 exosystem: supportive services enrollment			
Supportive Services	Adult day care Adult Protective Services Chore/Companion/Homemaker Case Management Congregate meals/senior center Personal Care Chore/Companion/Homemaker Transportation Volunteer/tele reassurance	Current formal services	1 = No 2 = Yes

Variable	UAI element(s)	UAI location	Measure
Hypothesis 5 chronosystem: disruptive life events			
Disruptive life events	Change in employment Death of someone close Financial problems Major illness of family or friend Recent move/relocation Victim of crime Failing health Other	Life stressors	1 = No 2 = Yes
Total Life Events			Discrete number between 0 and 8.
Hypothesis 6 included the most significant variables from H2-5. These variables were determined after regression was completed.			

Data Collection

In May 2020, VCU and DARS executed a data sharing agreement (Appendix B) to allow a one-time data extraction of Virginia UAI data collected by area agencies on aging between January 1, 2013 and December 31, 2019. Typically, UAI assessments are completed annually to certify continued eligibility or when there is a change in status. Due to its cross-sectional design, this study only examined data collected at the point of initial assessment. Per the agreement, the data set was de-identified by DARS and electronically transferred to VCU Gerontology via file transfer protocol (FTP), where it resided on a secure, password protected server. Secure remote access to the data was granted via VCU's secure, encrypted virtual private network (VPN) and restricted to the principal investigator/committee chair, Tracey L. Gendron, PhD; the student-researcher, Gigi Amateau, MS; and statistical consultant Derick L. Rivers, PhD. Verbal permission was secured from DARS, per the data sharing agreement, to share data with the statistical consultant.

Research Ethics and Human Subjects Protection

Ethical and human protection considerations guiding the use of secondary data were followed in this study, which was submitted to VCU's Institutional Review Board (IRB) on October 9, 2020. IRB approval was granted as an exempt study. A most important ethical consideration in the use of a secondary study is protection of information about people's lives, their health, their finances, and other private details (Office of Civil Rights, 2015). Because participants in a secondary study cannot viably be consented, it was important to thoughtfully examine whether any present or future harm could come from using personal information without that person's explicit consent (Office of the Vice President for Research and Innovation, n.d.). Multivariate statistical analysis conducted on individuals' health information propelled this study, thus it was necessary to ascertain the precise nature of the data and assure that ethical guidelines and human protections were followed. As a result, this study followed the safe harbor method (HIPAA Journal, 2017) of de-identifying the data set of all protected health information (PHI) before the data was transferred to VCU.

Data Analysis

This was a retrospective study of UAI data collected over seven years from 25 different area agencies on aging and stored at a single state agency. SPSS 27.0 was used for data evaluation and analysis. Before importing the raw data into SPSS, a codebook was created in Microsoft Excel to label each variable, identify its purpose in the study, and its measures. Coding instructions and inclusion-exclusion rules were also recorded in the codebook as were variable names, descriptions, and measures, and decisions about each variable (Polit & Beck, 2017). The data set included a unique record id (contact_id), which was preserved.

Data Screening and Cleaning

During the pre-analysis phase, the data file received from DARS was inspected for duplication, completeness, accuracy, errors, and irregularities. Records were examined for duplicates based on the contact_id field. Before deleting duplicates, the researcher conferred with DARS information technology (DARS IT) staff to ensure accurate interpretation of the contact_id field. Next, data were screened using SPSS Frequencies to check range, missing values, normality, and assumptions relative to each variable's role (Tabachnick & Fidell, 2013). Data were also checked for outliers and "wild" code, or "code which is not possible" (Polit & Beck, 2017, p. 428). The variable age was the only continuous variable in the original data set; all other variables under study were either nominal or ordinal. Age was evaluated using SPSS Frequencies to check range and standard deviation. A histogram was also examined. Records containing values determined to be "wild code" were deleted rather than transformed.

After conferring with DARS IT and the UAI users' manual, all variables that included values of unknown, unable to assess, or refused to answer were recoded as missing. To understand the extent and patterns of missingness, the SPSS Missing Values analysis function, frequency distributions, and other tasks were performed (Polit & Beck, 2017). Several steps were taken to accommodate missing data. Per Fox-Wasylyshyn and El-Masri (2005), "no empirical guidelines are present to suggest what constitutes excessive missingness" (p. 489). Historically, different statisticians have recommended remediation ranging from treating up to 10% as not extensive to deleting variables with 15% or more missingness to deleting variables with 40% or more missing (Fox-Wasylyshyn & El-Masri, 2005). For this study, the centrality of the variable was evaluated before deciding whether to impute or remove the variable from consideration (Fox-Wasylyshyn & El-Masri, 2005). For race, ethnicity, and lives_with, SPSS determined the missingness pattern to be Missing Not at Random (MNAR). All other variables were determined to be Missing at Random (MAR).

Based on the MAR pattern of missingness the Fully Conditional Specification (FCS) was selected for imputation as it can easily handle the MAR pattern (Liu & De, 2015). For this study, 20 imputed (*i.e*., complete with no missingness) datasets were created. For each of the 20 imputed datasets, the FCS method fit a linear regression model with a single dependent variable using all other available variables in the model as predictors then imputed missing values for the variable being fit. At the end of the 20 imputations, the imputed values were saved to a new, imputed dataset.

Table 12

Data Cleaning Checklist

Data Cleaning Steps
● Evaluate descriptive statistics for out-of-range values, means, standard deviations, and outliers
● Assess amount and distribution of missing data; resolve issues
● Plot for nonlinearity and heteroscedasticity
● Evaluate for normality, skewness, kurtosis, and transform if necessary
● Identify and resolve outliers
● Assess for multicollinearity and singularity

Note. Adapted from Using Multivariate Statistics by B.G. Tabachnick and L.S. Fidell, (6^{th} edition), 2013, Boston, MA: Pearson

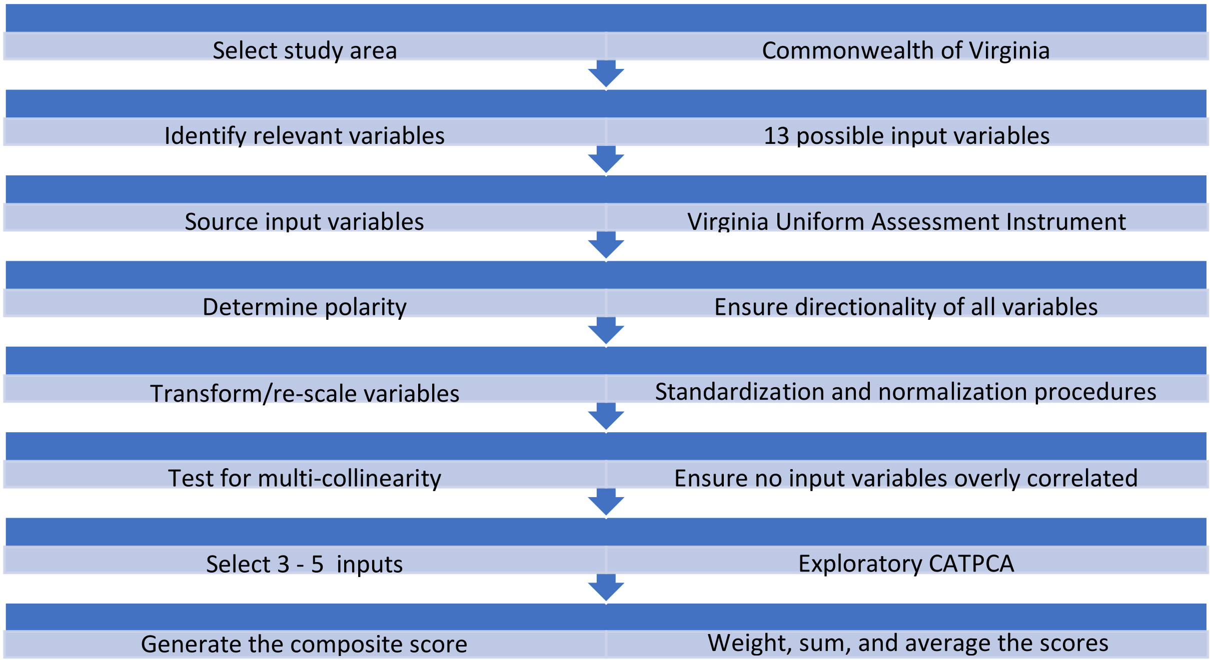
Dependent Variable Transformation

Composite indices have been broadly applied in many areas and are especially useful, “when attempting to analyze phenomena that are difficult to quantify and may encompass multiple dimensions” (Lucy & Burns, 2017, p. 2). To guide the development of the composite

DV, a multi-step process was adapted from a model used in the United Kingdom to develop a composite spatial loneliness index (Burns & Lucy, 2018; Lucy & Burns, 2017). In their study, Lucy and Burns (2017) drew solely from publicly available risk factors present in UK census data. They then plotted hot spots at geographic levels comparable to U.S. census tracts. While the data sources and rationale for input variables in this study differed from Lucy and Burns, each study aimed to predict loneliness or social connection in order to better serve and support older people.

Notably, Lucy and Burns also sought to establish an easily replicable approach to predicting loneliness (Burns & Lucy, 2018; Lucy & Burns, 2017). Replication ease motivated this study's use of their process, since the UAI data hold mission-critical information for local area agencies on aging as well as local, state, and federal government agencies serving older adults. Figure 5 presents the process that was followed in this study to create a continuous, composite DV for social connection.

Figure 5
Steps Followed for Creating the Composite Variable



Note. Adapted from Burns, L. & Lucy, L. (2018) Locating and measuring loneliness in the United Kingdom through the creation of a composite index. *Sage Research Methods Cases in Sociology*.

At the outset, it was critical to analyze, then select the best input variables to represent the broader construct, social connection, before transformation into the composite DV (Polit & Beck, 2017). Before final selection of the input variables, the polarity of each was determined. Some input variables differed in directionality. For example, a yes response for a disruptive life event signaled greater risk, while a yes response for social satisfaction signaled lower risk.

Following directionality resolution, the candidates for the composite DV in Table 9 were evaluated for inclusion in building the composite DV. When desiring to reduce many variables into fewer variables with minimal loss of information, researchers are confronted with the challenge that traditional principal components analysis (PCA) suffers from being a poor fit for data where variables are categorical or interval or where the relationships between variables may be non-linear (Linting et al., 2007; Linting & van der Kooij, 2012). Categorical Principal

Components Analysis (CATPCA), also called nonlinear principal components analysis or optimal scaling, offers an alternative statistical technique that simultaneously transforms nominal or ordinal variables into a numeric expression and reduces variables into components that represent variance accounted for (VAF) (Linting et al., 2007; Linting & van der Kooij, 2012). To do so, CATPCA uses dynamic, algorithmic decision-making (Linting et al., 2007; Linting & van der Kooij, 2012).

CATPCA has often been used in the social sciences to study broad constructs such as social capital (Saukani & Ismail, 2019), maternal depression (Eastwood et al., 2012), and socio-economic vulnerability (Rajesh et al., 2018). The purpose of using CATPCA in this study was to reduce the number of input variables for the DV from 13 possible inputs to no more than six. The results of the CATPCA helped to select the input variables with the most VAF and to weight the selected variables accordingly in devising the composite DV. In the CATPCA for this study, the following variables were treated as nominal: lives_with, social_satisfied, family_conflict, religious_active, solitary_active, family_friends, group_club, talk_family, talk_children, talk_friends. The variables bad_harm, feel_alone, and introvert were treated as ordinal. To aid in decision-making, Chronbach's alpha, VAF, and component loadings were examined. The CATPCA was conducted with the SPSS Optimal Scaling function.

Next, the normalized values for each of the selected variables were weighted per the CATPCA loadings, summed, and averaged to create a social connection score. Each record was then assigned a score reflecting the extent of social connection. When creating their composite index score, Lucy and Burns (2017; Burns & Lucy, 2018) calculated the score from among five input variables using the following formula:

$$IS_j = \sum_{i=1}^{5} \frac{V_i}{5}$$

where IS_j represented the index score for local area j and V_i represented the normalized value for input variable i, "effectively creating an average across all inputs" (Lucy & Burns, 2017, p. 6).

In their 2018 study, Burns and Lucy asserted that it may be helpful to go beyond a simple summation and averaging of the input variables: "Weighting is a useful addition to composite indices, when there is clear intelligence to support this" (p. 12). They, in fact, provided a formula for a weighted composite variable (Burns & Lucy, 2018). In this study, the CATPCA loadings determined the weightings for the five input variables drawn from the UAI. A new variable, sc_score, was created and a composite score generated for each case using the following formula:

$$SC_j = \frac{\sum_{i=1}^{5} w_i V_i}{\sum_{i=1}^{5} w_i},$$

where SC_j represented the social connection score for subject j and V_i represented the normalized value for input variable i and w_i represents the weighting of V_i.

Data Splitting

Prior to conducting statistical tests, the data set was split into two subsets: a primary (training) data set and a validation (test) data set. The sample was divided using the SPSS Split File command. Data splitting is a technique using the larger share of data for training or fitting the models, while reserving part of the data for validation at the end of analysis (Lin & Li, 2021). Data splitting allowed for an adequately powered sample size on which to run the predictive tests (Lin & Li, 2021). While "there is no standard rule for split ratio and number of repetitions," it is common practice to set 20%, 30%, and 40% of the data aside as the test set if the sample size allows" (Lin & Li, 2021 p. 7.21.). This study utilized a data split of 80% primary (training) and 20% validation (test).

After parsing out the primary (training) set by randomly selecting 80% of the records via SPSS, the remaining 20% were set aside as the validation (test) data set. The primary (training) data set served as the set for imputation, diagnostics, model fitting, and statistical analysis. Once the regression models for H2-5 were conducted on the primary (training) data, the accuracy of the final regression models for H6 were was compared to the accuracy of the controls-only model using the validation (test set). To perform the validation, cases with missing values were removed from the validation (test) set. Next, a social connection score was generated for each case in the validation (test set) before calculating and analyzing the root mean square error for the controls-only model and the two final mixed-level regression models.

Descriptive Statistics

Univariate statistics were used to calculate distribution and frequencies (*n*), percentages, mean, median, standard deviation, and range, as appropriate for the demographics, IVs, CVs, and DV.

Multivariate Analyses: Regression Techniques

In this study, multiple linear regression techniques were used to examine the relationship between micro, meso, exo, and chronosystem level IVs and the extent of social connection among older adults seeking LTSS, after controlling for educational attainment, age, gender, marital status, and poverty. Multiple linear regression was the best test for the composite DV (sc_score), because it is a continuous measure. Multiple regression, or multiple correlation, "is used to analyze the effects of two or more independent variables on a continuous dependent variable" (Polit & Beck, 2017, p. 403). Eight regression models were constructed to test Hypotheses 2 – 6. In each, the DV was sc_score, in its normalized and weighted expression.

With all statistical tests, there are two types of assumptions to accommodate: study design assumptions and data assumptions (Laerd Statistics, n.d.). Study design assumptions relate to the sample size and types of variables functioning in the IV and DV roles. Study design assumptions were met. Data assumptions relate to the nature of the data itself. To examine the presence of outliers, Cook's Distance (Cook's D), studentized residuals, and leverage values were used diagnostically. Ultimately, outliers were removed if the Cook's D value was larger than .00041195 because that value detected extreme outliers in both the X and Y directions. Homogeneity of variance was examined via Levene's Test and by plotting the standardized residuals vs. the standardized predicted values. The normality of residuals assumption was assessed by examining Q-Q plots of standardized residuals. The Durbin-Watson statistic was used to identify whether the errors associated with one observation were correlated with the errors of any other observation. Since DVs that are highly related to each other and both predictive of the IV can cause problems in estimating the regression coefficients, for each of the five regression models, multicollinearity was assessed through an observation of the variance inflation factors (VIF), condition index, and the variance proportions. Multicollinearity was considered an issue if the VIF was greater than 10, a condition index was above 15, and two or more predictors had variance proportions above 0.90.

The regressions were conducted using the SPSS General Linear Model (GLM) function. In GLM in SPSS, all variables are entered at once. The normalized, weighted social connection score was entered as the DV. The CVs and IVs were entered as fixed factors, with the exception of age and total life events, which were entered as covariates since both were continuous. Before conducting the regression tests, assumptions were evaluated, as depicted in Table 13.

Table 13

Regression Assumptions and Diagnostics

Study design and data assumptions
● One DV at continuous level ● Two or more IVs at continuous or nominal levels ● Minimum of 30 cases per IV ● Independence of observations ● Absence of significant outliers ● Absence of multicollinearity ● Linearity ● Normal distribution of residuals ● Homoscedasticity of residuals

Note. Adapted from Using Multivariate Statistics by B.G. Tabachnick and L.S. Fidell, (6^{th} edition), 2013, Boston, MA: Pearson and Laerd Statistics.

Limitations

The design of the study as a secondary data analysis, a pre-experimental design, relinquished some control over internal and external threats to validity (Polit & Beck, 2017). Still, it was important to consider potential threats and mitigate their potential impact where possible.

Predetermined Parameters

A limitation of a secondary data analysis study is that the researcher holds no control over the data characteristics: The population and data elements are all predetermined (Grady et al., 2013; Young & Ryu, 2012). As a result of predetermined data elements, a possible threat to reliability is that the measures extracted from the data set only approximate the study concepts (Young & Ryu, 2012). This threat was mitigated to some extent by confining selected proxy measures strictly to those apparent in the evidence base. Relative to social connection, the UAI is remarkably nuanced and fairly complete.

Fixed Population Sample

Another notable limitation in secondary data analyses is that there is a fixed population sample, rendering the researcher unable to control recruitment into the study (Young & Ryu, 2013). As a result, both bias and non-random variance may be present in samples parsed from any data set or data collection instrument (Stephens & Sukumar, 2020), including data from the UAI. However, this limitation was somewhat offset by a large population sample size (Young & Ryu, 2013).

Interrater Reliability

Interrater reliability poses a threat when two or more assessors administer the same instrument among different people (Polit & Beck, 2017). While the UAI is largely self-reported, LTSS staff also use professional observation to complete the tool. In conducting the UAI, many different assessors, or raters, administer the instrument, which could lead to bias and variance in scoring by posing a threat to the consistency of scores and results (Polit & Beck, 2017). This study, being a secondary data analysis, could not avoid the possible threat of interrater reliability; however, “an excellent means of enhancing reliability for observational measures is through observer training” (Polit & Beck, 2017, p. 307). To the point of reliability, all UAI assessors must complete the same training and follow the UAI assessors’ guidebook (DARS, 2015).

External Validity

This study was conducted with a data set composed of information about community-dwelling older adults seeking LTSS in Virginia. The sample, therefore, may not be representative of community-dwelling older adults seeking LTSS beyond Virginia or of the general population of older people. A threat to external validity "concerns whether inferences about observed relationships will hold over variations in person, setting, time, or measures of outcomes" (Polit & Beck, 2017, p. 216-17). There was no tactic to mitigate this threat because the data was collected between 2013 and 2019, so the limitation will be reported in the results.

Despite the single-state focus of the study, the results may have national relevance and present an opportunity for further study, because the LTSS network is similar in structure and funding throughout the United States and its territories. Virginia's home- and community-based services system for older people, like the rest of the nation's, largely draws its authority and scope from the OAA, which is managed at the federal level by the Administration for Community Living. Admittedly, there are differences in geography, population demographics, and how programs are carried out from state-to-state, but No Wrong Door, from which this data set originated, operates within the same four pillars and aims in all states and territories (No Wrong Door, n.d.). Thus, generalizability of the research questions, processes, and approach may hold beyond Virginia.

Time

A consideration for any secondary data analysis is the age of the data and its present-day relevance. This study examined the most recent seven-year capture of all UAI data collected in Virginia through area agencies on aging. Area agencies on aging are the codified lead agencies for No Wrong Door Virginia, as local hubs of aging and disability services (NWD, n.d.). Notably, the COVID-19 pandemic disrupted the typical manner of UAI administration and introduced a seismic element into the chronosystem, which could bias the analysis. Since entering into the pandemic, the aging and disability services network of providers have become increasingly aware of the impact of social isolation and loneliness (DARS, 2020). Additionally, service delivery mechanisms have changed: More older adults are being served via telephone and telehealth modalities (DARS, 2020). This limitation cannot be addressed in this study but will be reported in the results. A future study of interest could compare pre- and post-pandemic UAI data relative to social connection.

Cohort Effect

As noted earlier, data were collected at 25 different area agencies on aging over the course of seven years and pooled into a single source. This study data set did not include any elements such as assessment date, ZIP code, or agency code that might have allowed for analysis by organization, location, or year of UAI assessment. As a result, undetected cohort effects may exist—patterns related to changes in certain communities, protocols at certain agencies, or regional chronological events (Polit & Beck, 2017). The influence of any cohort effect would; however, likely be mitigated by the long period over which the data were collected.

Summary

This chapter summarized the study's overall research plan. The secondary data analysis design was described, along with explanations of how the study approached ethics and protections. Additionally, the study population sample and sampling, instrumentation, variables, data collection, and data analysis procedures were described. Study limitations were addressed, as well. Despite the intrinsic limitations when conducting secondary data analyses, several strengths of this study were also noted. The large sample allowed the study to be powered to detect small effects with confidence. The VCU Gerontology-DARS partnership presented an opportunity to research a unique and underexamined data set for the purposes of improving services and outcomes for community-dwelling older people.

Chapter 4: Results

Chapter Overview

The purpose of this study was to identify risk and protective factors that predict extent of social connection among older people seeking long-term services and supports (LTSS). This chapter presents the study findings. First, data collection procedures are reviewed, followed by the results of data screening and pre-analysis data cleaning. Aim 1, Hypothesis 1 of this study created and tested a composite DV to measure the three dimensions of social connection (Holt-Lunstad, 2018). The procedures and results of the composite DV development are discussed. Univariate statistics then describe the data set relative to the study variables prior to regression diagnostics and regression analysis. Next, the assumptions of multiple regression and results of the regression tests related to Aims 2 and 3 (H 2 – 6) are presented. The results of the final regression models using the validation (test) data set are reviewed, and the chapter concludes with a brief summary of hypotheses conclusions.

Review of Data Collection

In November 2020, DARS IT securely transferred a data set containing 46,861 records to VCU via encrypted FTP to a secure VCU server. Prior to data transfer, DARS applied three of four inclusion-exclusion criteria. DARS did not, however, de-duplicate the data. Two requested open text fields were excluded by DARS due to possibly containing identifying information. All other requested fields were included in the data set.

Review of Data Screening and Cleaning

Upon receipt, the data were examined for duplication, errors, and accuracy. The data review revealed 10,183 cases of a duplicate contact_id. After conferring with DARS that the data query included initial UAI assessments and UAI re-assessments, the duplicate cases were deleted using SPSS Delete Cases command, keeping those records with the youngest age as representative of the first UAI conducted for any given individual and removing subsequent records with an older age, as representative of a UAI re-assessment. Next, the final inclusion-exclusion criterion was applied. As a result, 23,960 cases where the social and emotional status elements were not completed were removed, also using SPSS Delete Cases function.

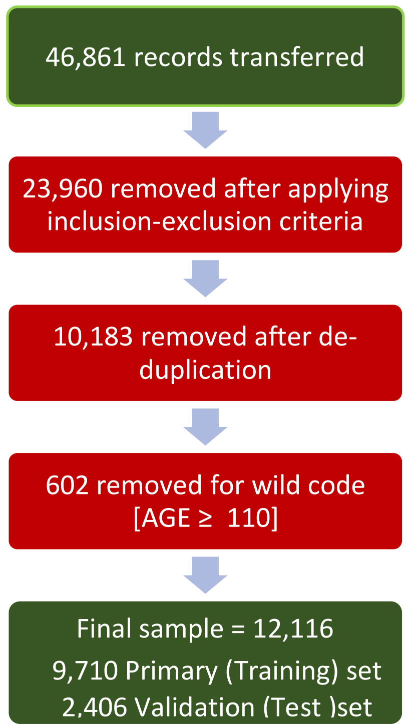
Among the variable age, some records were determined to include wild code (Polit & Beck, 2017), where the age values were impossible. In the raw data, age ranged from 60 to 1,074. A total of 602 records indicated an age of 116 years old or higher at the time of initial UAI assessment. DARS IT confirmed that there is no field validation for year of birth in the data entry system. The values in question were considered erroneous. Based on the estimation that only one in five million people live beyond 110 (Boston Medical Center, 2021), the ceiling for age was set by the researcher as 110 years old. As a result, the 602 records were excluded where age was greater than or equal to 110.

Final Sample

After applying the inclusion-exclusion criteria, removing duplicate records, and removing erroneous age records, the data set was reduced from 46,861 to 12,116 records – a decrease of 74.13%. While this reduction in records was considerable, it was not surprising. Based on the null values experienced in the SIRI project (Suen et al., 2018), high data loss due to attrition after applying eligibility criteria was expected. The study needed to retain at least 1,389 records in the sample in order to reach the power analysis requirements. The final sample of 12,116 was substantially higher than the 1,389 required. The sample was then randomly split into two data sets: a primary (training) set and validation (test) set. Figure 6 shows the adjusted, final sample size.

Figure 6

Consort Flow Chart of Final Sample Size



Missing Data

Before conducting the SPSS Missing Values Analysis, response values were reviewed by variable. Where completed values indicated unknown, refused to answer, or unable to assess, these values were recoded as missing. For example, the variable Medicaid included 61 cases with a value of R. After conferring with DARS IT and the UAI instruction manual, the value R in the Medicaid field was interpreted as refused to answer. Records containing the response R were then recoded as missing. After likewise recoding appropriate responses as missing for other variables, the data were evaluated by variable using the SPSS Frequencies and Missing Values Analysis, which determined the pattern and extent of missingness.

Variable missingness ranged from 0.6 to 64.4%. Of the 41 variables analyzed, four variables contained notable rates of missing data. For example, after deduplication and data cleaning, the variable race was missing a response in 64.4% of cases. Likewise, the variable lives_with was missing a response in 40% of the cases. The variable ethnicity was missing a response in 15.9% of the cases. The variable education was missing a response in 10.9% of cases. The missingness pattern for all other variables was found to be Missing at Random (MAR) per SPSS analysis. Race and ethnicity were removed from the study. Due to its expected central role as a likely input variable, lives_with was retained and imputed. Ultimately, however, lives_with was not utilized in the study. Because many studies have found that lower educational attainment predicts higher loneliness and higher social isolation, education was retained as a control variable.

Data Analysis

H1 Key Findings: Composite Variable

As described in Chapter 3, the process for devising the DV expanded upon the steps outlined by Lucy and Burns (2017; Burns & Lucy, 2018) by conducting CATPCA to help select and weight no more than six input variables to devise the composite DV. Variance accounted for (VAF) is the test statistic best positioned to assist with variable selection (Saukani & Ismail, 2018). In performing CATPCA, the SPSS Optimal Scaling function was configured to create the best possible single-dimension solution to explain the most possible variance.

The CATPCA produced a two-dimension solution, with Dimension 1 explaining the most variance. The top six input variables ranged in VAF from .093 to .499 and included at least one variable from each of the three social connection dimensions. Those variables were feel_alone (.499), social_satisfied (.365), bad_harm (.353), introvert (.283), family_conflict (.241), and talk_family (.093).

In evaluating the CATPCA results, a cut-off of ≥ .20 served as the minimum amount of variance for selecting which input variables would best represent social connection in the devised DV. Notably, no input variables representing the structural aspect of social connection met the threshold cut-off of ≥ .20. The highest explained variance of the structural components was observed in the variable talk_family, but the VAF (.093), did not meet the ≥ .20 cut-off in Dimension 1, thus it was not included among the final input variables.

Among the five variables that did meet the threshold, two input variables represented the functional aspect of social connection (feel_alone, social_satisfied) and three represented the quality aspect of social connection (bad_harm, introvert, and family_conflict). Each of the variables is subjective in nature. Together, these variables share aspects of *perceived social connection*. The second CATPCA dimension showed a set of variables that relate to each other around a more objective construct of the presence of a *social network*. While these variables together revealed the structural presence of social roles and relationships; they were not selected for inclusion in the DV because they did not meet the ≥ .20 threshold for Dimension 1.

One note of caution, the CATPCA model summary also presented the internal consistency coefficient (Cronbach’s Alpha) for each dimension of the analysis. Dimension 1, which determined the input variables, resulted in a Cronbach’s Alpha of .553, which is considered poor for internal consistency, a limitation that is reported. The CATPCA model summary is presented in Table 14.

Table 14

Categorical Principal Components Analysis Model Summary

Dimension	Cronbach's Alpha	Variance Accounted For	
		Total (Eigenvalue)	% of Variance
1	0.553	2.016	15.506
2	0.457	1.697	13.054
Total	0.792b	3.713	28.56

Note. a Rotation Method: Varimax with Kaiser Normalization. b Total Cronbach's Alpha is based on the total Eigenvalue.

The CATPCA loadings determined how the input variables would be weighted in the derived DV. Table 15 shows the average loadings and weights for the five selected input variables. The weights for each variable represent the percent that variable contributed to the DV and range from .17 to .24 and combine to equal 1.0.

Table 15

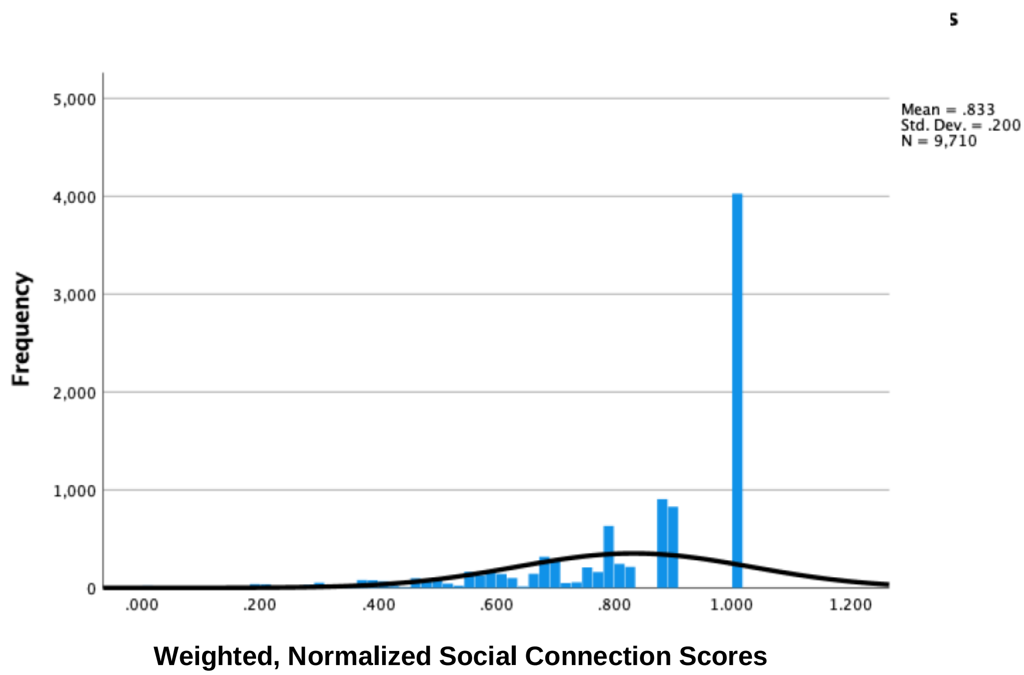
Weightings for Selected Input Variables

Input variable	Average Loadings	Weights
Feel_Alone	.7	.24
Social_Satisfaction	.61	.21
Bad_Harm	.60	.20
Introvert	.53	.18
Family_Conflict	.5	.17
Total	2.94	1.0

Once the DV was devised, a normalized, weighted social connection score ranging from 0 to 1 was calculated for each case, with a score of 0 representing the lowest possible social connection and a score of 1 representing the highest possible social connection. Subjectively, scores closer to zero would indicate lower social connection and higher risk, whereas scores closer to 1 suggest higher social connection and lower risk. Overall, social connection scores ranged from .00 to 1.0 with a raw mean score of .833 (SD = .200). Figure 7 shows the distribution of the social connection scores.

Figure 7

Distribution of Raw Social Connection Scores



In summary, Holt-Lunstad's 2018 social connection typology informed the development of the single continuous, composite DV to predict the extent of social connection among the cases. Aim 1 constructed a multidimensional measure of social connection composed of five input variables from the UAI. Hypothesis 1 asserted that each aspect of social connection (structural, functional, and quality) would uniquely contribute to the ability to detect predictive influences on extent of social connection via the composite variable social connection.

Thirteen possible input variables were evaluated to respectively represent the structural, functional, and quality dimensions of social connection. The possible input variables were weakly correlated, suggesting that each variable would uniquely contribute to the composite DV, sc_score. Further analysis suggested a factor analysis would be very helpful in selecting the best input variables. After conducting CATPCA, the final input variables were selected based on their VAF contribution. These were representative of the functional and quality dimensions of the typology of social connection (Holt-Lunstad, 2018). The structural dimension of social connection did not meaningfully contribute to the composite DV. Therefore, with a DV representing two of the three social connection dimensions, H1 was rejected. The analysis continued, having devised a continuous DV, sc_score, representative of the functional and quality aspects of social connection.

Descriptive Statistics

This section first describes the frequency and percentages of sample characteristics using the control variables of gender, age, marital status, education level, and poverty (Medicaid). Next, the average social connection scores are presented for the sample by the individual traits represented by the control variables. Before turning to the regression analysis results, IVs are described within the context of the ecological level represented. All descriptives are reported from summary statistics derived from across the 20 imputed data sets prior to adjustment for extreme outliers. Demographics and analysis findings are presented on the primary (training) set. In descriptives, age is reported by age group for ease of interpretation, though age was regressed continuously in the models.

Demographic Profile. Table 16 presents the demographic profile of the primary (training) set portion of the sample. Of note, 65.6% (*n*=6,370) of the sample were female. Age was fairly normally distributed with the mean age of the sample at 78.36 (SD = 9.48) and a range of 60 to 106. Notably, 22.5% (*n* = 2,806) of the cases were ages 85 or older, with 321 of these cases being between ages 95 and 106. With regard to marital status, a variable initially considered as a possible proxy for structural connection in the devised DV, 41.5% (*n* = 4,030) were widowed. The distribution of educational level revealed that 37.3% (*n* = 3,621) of the sample had attained an education level of some college or college graduate. Finally, 29.7% (*n* = 2,887) of the sample was insured by Medicaid, the variable representing poverty.

Table 16

Pooled Demographic Characteristics and Control Variables for Training Set (N = 9,710)

Control variable	Frequency (*n*)	Percentage/Mean (*SD*)
Gender		
Female	6,370	65.6%
Male	3,340	34.4%
Age		78.36 (9.48)
60 to 64	921	9.5%
65 to 74	2,437	25.0%
75 to 84	3,555	36.6%
85 to 94	2,485	25.6%
95 to 106	321	3.2%
Marital Status		
Widowed	4,030	41.5%
Singe/Divorced/Separated	2,798	28.8%
Married	2,882	29.7%
Education		
Less than high school	1,860	19.1%
Some high school	1,109	11.4%
High school graduate	3,120	32.1%
Some college	1,651	17.0%
College graduate	1,970	20.3%
Has Medicaid		
No	6,823	70.3%
Yes	2,887	29.7%

Raw Social Connection Scores. As reported previously, the raw mean social connection score for the sample was .833 (.200). The 0 to 1 scale compressed the variability into a small but continuous range. Table 17 presents the raw weighted, normalized social connection score means by demographic characteristics.

Table 17

83.

Variable	Frequency (*n*) 9,710	SC Score Mean (SD) .833 (.200)
Gender		
Female	6,370 (65.6)	.830 (.201)
Male	3,340 (34.4)	.851 (.185)
Age		
60 to 64	921 (9.5)	.750 (.239)
65 to 74	2,437 (25)	.801 (.218)
75 to 84	3,555 (36.6)	.843 (.188)
85 to 94	2,485 (25.6)	.872 (.168)
95 to 106	321 (3.2)	.902 (.153)
Marital Status		
Widowed	4,030 (41.5)	.842 (.190)
Sing/Div/Sep	2,798 (28.8)	.795 (.224)
Married	2,882 (29.7)	.857 (.183)
Education		
Less than high school	1,860 (19.1)	.817 (.203)
Some high school	1,109 (11.4)	.822 (.207)
High school graduate	3,120 (32.1)	.838 (.195)
Some college	1,651 (17.0)	.828 (.207)
College graduate	1,970 (20.3)	.850 (.193)
Has Medicaid		
No	6,823 (70.3)	.845 (.194)
Yes	2,887 (29.7)	.804 (.209)

The lowest mean score appears among the age group 60 to 65 at .750 (.239), followed by marital status of single/divorced/separated at .795 (.224). The highest mean score of .902 (.153) appears within the age group 95 to 106 followed by age group 85 to 94 with a mean score of .872 (.168).

Independent Variables. Independent variables were grouped together based on the theoretical model presented in Chapter 2. Tables 18-22 present frequencies and raw social connection score means for the variables represented in H2-6.

H 2: Microsystem. This study investigated housing as an environmental trait of an individual's microsystem. Housing was represented by two IVs: living environment and subsidized housing, as shown in Table 18. At the microsystem level, cases where living environment equaled renting a room or apartment had a mean of .798 (.215), the lowest mean score among three different types of housing environments. While only 1.3% of the sample lived in subsidized housing, those who did had a mean social connection score of .789 (.219).

Table 18

Microsystem: Housing Frequencies and Raw Social Connection Score Means (N = 9,710)

Variable	Frequency (*n*)	SC Score Mean (SD)
Living Environment		
Own-rent house	5,193 (53.5)	.843 (.194)
Rent room-apartment	2441 (25.1)	.798 (.215)
Housing: other	2076 (21.6)	.847 (.192)
Subsidized Housing		
No	9570 (98.7)	.840 (.197)
Yes	131 (1.3)	.789 (.219)

Note. Housing: other is defined in the UAI as "individual lives in a house owned by family/friends and does not pay rent, or the individual lives in a house for which he or she has lifetime rights, but does not pay rent" (DARS, 2015).

H3: Mesosystem. This study investigated how individuals perceive barriers to access and neighborhood safety as representative of an individual's mesosystem. Neighborhood perception is represented by two IVs: perceived barriers to access and perceived unsafe neighborhood. Table 19 summarizes the frequencies and raw social connection score means for these IVs.

Table 19

Mesosystem: Neighborhood Perception Frequencies and Raw Social Connection Score Mean (N = 9,710)

Variable	Frequency (*n*)	SC Score Mean (SD)
Barriers to Access		
No	7,461	.840 (.197)
Yes	2,240	.808 (.212)
Unsafe Neighborhood		
No	9,579	.834 (.198)
Yes	131	.760 (.245)

H4: Exosystem. In examining the influence of an individual's exosystem on social connection, this study analyzed enrollment in Title III supportive services enrollment. In the analysis, Title III supportive services encompassed nine dichotomous (No/Yes) IVs: adult day care, adult protective services, case management, chore/homemaker services, congregate meals/senior centers, volunteer/telephone reassurance, home-delivered meals, personal care, and transportation. Table 20 summarizes the frequencies and raw social connection score means for these IVs. In two cases, adult day care (.877/.164) and personal care (.834/.191), the mean social connection score was higher for those enrolled than for those not enrolled. In all other cases, the average social connection score was lower for those cases enrolled versus those not enrolled. The most commonly utilized services were case management (*n* = 1,624, 26.7%), transportation (*n* = 1,620, 16.7%), and personal care (*n* = 1,539, 15.8%).

Table 20

Exosystem: Supportive Services Enrollment Frequencies and Raw Social Connection Score Mean (N = 9,710)

Supportive services	No		Yes	
	Freq. (%)	Mean (SD)	Freq. (%)	Mean (SD)
Adult Day Care	8,928 (92.0)	.829 (.202)	781(8.0)	.877 (.164)
Adult Protective Svs	9,480 (97.6)	.836 (.196)	230 (2.4)	.711 (.264)
Case Management	8,086 (83.3)	.838 (.197)	1,624 (16.7)	.809 (.215)
Chore/Homemaker Svs	8,573 (88.3)	.834 (.200)	1,137 (11.7)	.827 (.199)
Cong Meals/Sen Center	9,096 (93.7)	.833 (.201)	614 (6.3)	.832 (.199)
Vol/Tele Reassurance	9,553 (98.4)	.834 (.199)	157 (1.6)	.771 (.206)
Home Delivered Meals	8,531 (97.9)	.834 (.200)	1,179 (12.1)	.825 (.198)
Personal Care	8,171 (84.2)	.833 (.201)	1,539 (15.8)	.834 (.191)
Transportation	8,090 (83.3)	.837 (.197)	1,620 (16. 7)	.811 (.213)

H5: Chronosystem. The analysis of the chronosystem was confined to historical life events of a personal, biographical nature. The life stressors section of the UAI represents a point-in-time snapshot of how individuals perceived past disruptive life events as presently challenging. The construct of interest, disruptive life events, is represented by eight dichotomous (No/Yes) IVs: change in work/employment, death of someone close, financial problems, major illness: family/friend, recent move/relocation, victim of a crime, failing health, and other.

Of note, for each disruptive life event, the average social connection score for a response of no was higher than the overall sample mean social connection score of .833. Conversely, a yes response for each event yielded an average social connection score well below the sample mean. The lowest mean social connection score among the chronosystem IVs appeared among those cases where an individual had been a victim of a crime. With a raw mean score of .624, this was also the lowest mean social connection score among all IVs at all ecosystem levels. The most commonly experienced disruptive life event was failing health (*n* = 5,385, 55.5%), followed by financial problems (*n* = 2,198, 22.6%). Table 21 summarizes the frequencies and average raw social connection scores for disruptive life events by type of event.

Table 21

Chronosystem: Disruptive Life Event Frequencies and Raw Social Connection Score Means (N = 9,710)

Disruptive life event	No		Yes	
	Freq. (%)	Mean (SD)	Freq. (%)	Mean (SD)
Change in work/employ	9,375 (96.5)	.837 (.196)	335 (3.5)	.709 (.249)
Death of someone close	8,180 (84.2)	.849 (.189)	1,530 (15.8)	.747 (.230)
Financial problems	7,512 (77.4)	.864 (.175)	2,198 (22.6)	.726 (.237)
Major illness – fam/friend	8,323 (85.7)	.845 (.191)	1,387 (14.3)	.759 (.232)
Recent move/relocation	8,722 (90)	.843 (.191)	988 (10)	.742 (.244)
Victim of a crime	9,424 (97)	.839 (.194)	286 (3.0)	.624 (.266)
Failing health	4,325 (44.5)	.878 (.169)	5,385 (55.5)	.797 (.215)
Other	8,322 (85.7)	.845 (.193)	1,388 (14.3)	.761 (.229)

Next, Table 22 presents disruptive life events in the form of total life events, a new variable that was created to examine the total number of disruptive life events experienced for each case in the sample. This variable assigned a value between 0 and 8, representing the number of disruptive life events observed in each record. Among the sample, 72.6% (*n* = 7,050) of cases had experienced one or more disruptive life events. In cases where disruptive life events totaled 2 or more, the raw mean social connection score dropped to below the sample average score of .833 (.200) with a mean range between .802 (.203) for two events to .446 (.222) for seven events.

Table 22

Chronosystem: Total Life Event Frequencies and Raw Social Connection Score Means (N = 9,710)

Total life events	Frequency (%)	Mean (SD)
0	2,660 (27.4)	.910 (.138)
1	3,305 (34.0)	.859 (.177)
2	2,037 (21.0)	.802 (.203)
3	1,037 (10.6)	.737 (.221)
4	436 (4.4)	.680 (.245)
5	163 (1.7)	.588 (.265)
6	57 (.59)	.496 (.249)
7	11 (.11)	.446 (.222)
8	4 (.04)	.572 (.256)

Assumptions of Multiple Linear Regression

The diagnostics and corrective plan for the assumptions of multiple regression (MLR) using general linear model (GLM) were similar for each model. As a general indicator, the lack of fit test was undertaken for each model, where the desired *p* value was larger than .05. Initially, the lack of fit tests resulted in *p* values of less than .05 for each model, signaling the need for corrective action.

To detect extreme outliers, the Cook's D, studentized residuals, and leverage values were examined. Cook's D offered the most promising method of detecting outliers in both directions; therefore, cases with a Cook's D value of more than $\frac{4}{9{,}710} \approx$ .00041195 were removed. This step improved each model's lack of fit statistic to a more desirable value. As a result, a new data set was created, inclusive of each imputed data set with cases that violated the Cook's D threshold removed. Table 23 presents the improved lack of fit test *p* value ranges among the imputed sets for each model after removal of extreme outliers in both directions.

Table 23

Post-Cook's D Lack of Fit Test Results Across Pooled Data

Model	Min.	Max.	N
Controls only	.036*	.602	9,710
Model 1 Microsystem	.549	.967	9,180
Model 2 Mesosystem	.346	.992	9,193
Model 3 Exosystem	1.000	1.000	9,168
Model 4a Chronosystem – disruptive life events	.038*	.891	7,877
Model 4b Chronosystem – total life events	.149	.924	8,527
Model 5a Mixed levels – disruptive life events	.112	.848	7,910
Model 5b Mixed levels – total life events	.252	.775	9,116

Note. * $p < .05$

Tests for nonlinearity and homogeneity of variance were examined with scatterplots for each model. In each, the line appeared through the center near zero suggesting unbiased residuals. Normality of residuals was examined visually with Q-Q plots of standardized residuals. As the distribution of the social connection scores was skewed, so too were the residuals. Consequently, the models may violate the assumption of homogeneity of variance. In this study, the models appeared to perform better with cases of higher scores. To analyze multiple regression output for multicollinearity, the variance inflation factor (VIF) statistic was examined for all predictors. When VIF values are above 10 a collinearity problem exists (Laerd Statistics, n.d.). The data set did not show multicollinearity. Regarding the assumption of independence of observations, given the cross-sectional study design and the variables drawn from the UAI, there was no basis to believe this assumption would be violated. The Durbin-Watson statistic was included in diagnostics and confirmed no violation of the assumption of independent observations.

Hypothesis Testing: Results of Regression Models

Each model was regressed on the 20 imputed data sets with extreme outliers removed for each model. Tables 24 – 48 show the pooled regression and validation results. Prior to conducting regression on the ecosystem models, the control variables were regressed. For the control-only model among the 20 imputed data sets, the adjusted *R* squared, which explains the percent of variance explained by the model, ranged from a minimum of .050 to a maximum of .055. The low adjusted *R* squared suggests that the control variables explain 5.5% of the variance in social connection scores, at most. In the control-only model, differences in social connection score were statistically significant for gender, age, education, poverty (Medicaid), and marital status. Table 24 presents the regressed control variables.

Table 24

Regression Model for Study Control Variables N = 9,710

Parameter	β	Std. Error	Sig.
Intercept	0.545	0.02	< 0.001
Gender=Female	-0.019	0.005	< 0.001
Age	0.004	0	< 0.001
Medicaid=No	0.021	0.005	< 0.001
Education=Less than HS	-0.029	0.007	< 0.001
Education=Some HS	-0.018	0.008	0.029
Education=HS graduate	-0.006	0.006	0.279
Education=Some college	-0.01	0.007	0.178
Marital_Status=Widowed	-0.023	0.006	< 0.001
Marital_Status=Sing/Sep/Div	-0.034	0.006	< 0.001

Note. Reference categories have been removed.

H2 Key Findings: Microsystem. For the microsystem model, 9,180 cases were included in the model after the Cook's D adjustment. The ANOVA summary for the overall model returned a *p*-value of < 0.001; hence, the model is statistically significant. Among the 20 imputed data sets with extreme outliers removed, the adjusted *R* squared ranged from a minimum of .043 to a maximum of .049. The low adjusted *R* squared indicates that in the presence of the control variables, the microsystem variables (living environment, subsidized housing) explain 4.9% of the variance in social connection scores – a decrease in variance explained from the control-only model. Table 25 shows the ANOVA summary for the model, drawn from across the 20 imputed data sets with extreme outliers removed.

Table 25

Model 1 Microsystem: Analysis of Variance Results Based on 20 Imputed Datasets

	F(df1, df2)	*p*-value	*R*-squared	adj. *R*-squared
Minimum	*F*(12, 9178) = 35.232	< 0.001	.044	0.043
Maximum	*F*(12, 9159) = 40.186	< 0.001	.050	0.049

Regarding the significance of specific IVs, for living environment, results suggested that those who own or rent a house and those who rent a room or apartment are likely to have lower social connection scores to a statistically significant degree than those who live in another type of housing. Subsidized housing did not appear to predict social connection to a statistically significant degree. In summary, H2 was partially accepted for living environment but rejected for subsidized housing. Table 26 depicts the regression results for the microsystem variables. Table 27 presents the estimated means for the microsystem model variables.

Table 26

Regression for Model 1: Microsystem Variables (Housing) N = 9,180

Parameter	β	Std. Error	Sig.
Intercept	0.675	0.019	< 0.001
Gender=Female	-0.014	0.004	< 0.001
Medicaid=No	0.01	0.004	0.023
Education=Less than HS	-0.028	0.006	< 0.001
Education=Some HS	-0.009	0.007	0.196
Education=HS graduate	-0.011	0.005	0.026
Education=Some college	-0.006	0.006	0.283
Marital_Status=Widowed	-0.021	0.005	< 0.001

Parameter	β	Std. Error	Sig.
Marital_Status=Sin/Sep/Div	-0.022	0.005	< 0.001
Housing=Own/rent house	-0.014	0.005	0.003
Housing=Rent room/apt	-0.024	0.006	< 0.001
Subs_Housing=No	0.002	0.006	0.77
Age	0.003	0	< 0.001

Note. Reference categories have been removed. Housing: other is defined in the UAI as "individual lives in a house owned by family/friends and does not pay rent, or the individual lives in a house for which he or she has lifetime rights, but does not pay rent" (DARS, 2015).

Table 27

Estimated Means for Model 1: Microsystem Variables (Housing) N = 9,180

Variable	Variable categories	N	Mean SC_SCORE	Std. Dev.
Gender	Female	6,003	0.861	0.310
	Male	3,177	0.875	0.225
Age_Groups	60 - 64	816	0.815	0.171
	65 - 74	2,268	0.841	0.190
	75 - 84	3,393	0.868	0.233
	85 - 94	2,402	0.891	0.196
	95 and older	302	0.924	0.174
Medicaid	No	6,518	0.873	0.323
	Yes	2,662	0.863	0.206
Education	Less than High School	1,749	0.851	0.209
	Some High School	1,023	0.869	0.192
	High School Graduate	2,987	0.868	0.219
	Some College	1,548	0.872	0.236
	College Graduate	1,873	0.879	0.216
Marital_Status	Widowed	3,849	0.862	0.248
	Single/Sep/Divorce	2,577	0.859	0.203
	Married	2,755	0.882	0.262
Housing	Own or rent house	4,984	0.866	0.282
	Rent room or apt.	2,239	0.856	0.189
	Housing: Other	1,957	0.882	0.221
Subszd_Housing	No	7,920	0.869	0.267
	Yes	1,260	0.867	0.213

H3 Key Findings: Mesosystem. This model included 9,193 records after adjusting for extreme outliers. Because the ANOVA summary for the overall model returned a *p*-value of < 0.001, the model is recognized as statistically significant. In examining the adjusted *R* squared for the mesosystem model among the 20 imputed data sets, the adjusted *R* squared ranged from a minimum of .045 to a maximum of .049. The low *R* squared indicates that in the presence of the control variables, the mesosystem variables (perceived barriers to access, perceived unsafe neighborhood) explain no more than 4.9% of the variance in social connection scores, which is less than the variance explained by the control-only model. Therefore, the mesosystem variables did not improve the model. Table 28 presents the ANOVA summary for the model, drawn from across the 20 imputed data sets with extreme outliers removed.

Table 28

Model 2 Mesosystem: Analysis of Variance Results Based on 20 Imputed Datasets

	F(df1, df2)	*p*-value	*R*-squared	adj. *R*-squared
Minimum	*F*(11, 9166) = 40.456	< 0.001	.046	0.045
Maximum	*F*(11, 9205) = 44.284	< 0.001	.050	0.049

Relative to the significance of specific IVs, the regression analysis indicated that perceived barriers to access predicted extent of social connection among older people seeking LTSS to a statistically significant degree. Perceived unsafe neighborhood did not appear to predict social connection to a statistically significant degree (*p*=.422). In summary, H3 is partially accepted for perceived barriers to access but rejected for perceived unsafe neighborhood. Table 29 shows the summary model for the mesosystem variables. Table 30 presents the estimated means for the variables included in the mesosystem model.

Table 29

Regression for Model 2: Mesosystem Variables (Neighborhood Perception) N = 9,193

Parameter	β	Std. Error	Sig.
Intercept	0.593	0.061	< 0.001
Gender=Female	-0.016	0.004	< 0.001
Medicaid=No	0.013	0.004	0.002
Education=Less than HS	-0.028	0.006	< 0.001
Education=Some HS	-0.01	0.007	0.158
Education=HS graduate	-0.012	0.005	0.023
Education=Some College	-0.007	0.006	0.242
Marital_Status=Widowed	-0.021	0.005	< 0.001
Marital_Status =Sin/Sep/Div	-0.024	0.005	< 0.001
Access_Barrier=No	0.014	0.004	<0.001
Unsafe_Hood=No	0.048	0.059	0.422
Age	0.003	0	< 0.001

Note. Reference categories removed.

Table 30

Estimated Means for Model 2: Mesosystem Variables (Neighborhood Perception) N = 9,193

Variable	Variable categories	N	Mean SC_SCORE	Std. Dev.
Gender	Female	6,020	0.830	2.250
	Male	3,173	0.846	1.634
Age_Groups	60 - 64	817	0.783	0.829
	65 - 74	2,270	0.811	1.429
	75 - 84	3,399	0.837	1.691
	85 - 94	2,407	0.861	1.472
	95 and older	300	0.898	0.520
Medicaid	No	6,519	0.845	2.341
	Yes	2,674	0.831	1.499
Education	Less than High School	1,760	0.821	1.216
	Some High School	1,026	0.840	0.961
	High School Graduate	2,987	0.838	1.585
	Some College	1,550	0.842	1.142
	College Graduate	1,871	0.850	1.254
Marital_Status	Widowed	3,859	0.834	1.801

Variable	Variable categories	N	Mean SC_SCORE	Std. Dev.
	Single/Sep/Divorce	2,580	0.827	1.473
	Married	2,754	0.853	1.522
Access_Barrier	No	7,125	0.845	2.448
	Yes	2,068	0.831	1.319
Unsafe_Hood	No	9,127	0.861	0.287
	Yes	66	0.815	0.469

H4 Key Findings: Exosystem. In this model, 9,168 cases were regressed after removal of extreme outliers. The ANOVA summary for the overall model returned a *p*-value of < 0.001; hence, the model is statistically significant. The exosystem model showed an adjusted *R* squared range from a minimum of .058 to a maximum of .063, after extreme outlier removal. This result indicates that in the presence of the control variables, the exosystem variables (supportive services enrollment) explain no more than 6.3% of the variance in social connection scores, a modest improvement over the variance explained by the control-only model. Therefore, the exosystem variables did improve the model. The ANOVA summary for the model is presented in Table 31.

Table 31

Model 3 Exosystem: Analysis of Variance Results Based on 20 Imputed Datasets

	F(df1, df2)	*p*-value	*R*-squared	adj. *R*-squared
Minimum	$F(18, 9161) = 32.403$	< 0.001	.060	0.058
Maximum	$F(18, 9140) = 35.593$	< 0.001	.065	0.063

Regarding the positive predictive strength of specific IVs, regression analysis results suggested utilization of adult day care, congregate meals/senior centers, and personal care services positively predicted extent of social connection among older adults seeking LTSS to a statistically significant degree. Case management, chore/homemaker services, home-delivered meals, and transportation services did not appear to predict social connection to a statistically significant degree. Adult protective services and friendly visiting/telephone reassurance negatively predicted extent of social connection to a statistically significant degree. In summary, H4 is partially accepted for adult day care, congregate meals/senior centers, and personal care services but rejected for adult protective services, friendly visiting/telephone reassurance, case management, chore/homemaker services, home-delivered meals, and transportation. Table 32 shows the summary model for the exosystem variables. Table 33 presents the estimated means for the variables included in the exosystem model.

Table 32

Regression for Model 3: Exosystem Variables (Title III Supportive Services) N = 9,168

Parameter	β	Std. Error	Sig.
Intercept	0.531	0.036	< 0.001
Gender=Female	-0.016	0.004	< 0.001
Medicaid=No	0.019	0.004	< 0.001
Education=Less than HS	-0.03	0.006	< 0.001
Education=Some HS	-0.012	0.007	0.115
Education=HS graduate	-0.011	0.005	0.044
Education=Some college	-0.01	0.006	0.131
Marital_Status=Widowed	-0.02	0.005	< 0.001
Marital_Status=Sing/Sep/Div	-0.02	0.005	< 0.001
Adult_Day_Care=No	-0.038	0.007	< 0.001
Adult_Protect=No	0.108	0.017	< 0.001
Case_Manage=No	-0.001	0.005	0.821
Chore_Home=No	0.003	0.006	0.614
Meal_Seniorcenter=No	-0.016	0.008	0.041
Visitor_Telephone=No	0.067	0.022	0.003
Home_Meals=No	-0.01	0.006	0.071
Pers_Care=No	-0.01	0.005	0.045
Transport=No	-0.005	0.005	0.313
Age	0.003	0	< 0.001

Note. Reference categories removed.

Table 33

Estimated Means for Model 3: Exosystem Variables (Title III Supportive Services) N = 9,168

Variable	Variable categories	N	Mean SC_SCORE	Std. Dev.
Gender	Female	5,998	0.795	1.162
	Male	3,170	0.811	0.845
Age_Groups	60 - 64	822	0.747	0.459
	65 - 74	2,258	0.779	0.760
	75 - 84	3,393	0.807	0.874
	85 - 94	2,394	0.832	0.734
	95 and older	301	0.870	0.312
Medicaid	No	6,481	0.813	1.208
	Yes	2,687	0.794	0.778
Education	Less than High School	1,755	0.786	0.670
	Some High School	1,032	0.804	0.546
	High School Graduate	2,972	0.805	0.818
	Some College	1,546	0.806	0.629
	College Graduate	1,862	0.816	0.647
Marital_Status	Widowed	3,845	0.797	0.992
	Single/Separate/Divorce	2,563	0.796	0.759
	Married	2,760	0.816	0.841
Adult_Day_Care	No	8,442	0.784	1.378
	Yes	726	0.822	0.431
Adult_Protect	No	9,037	0.857	1.141
	Yes	131	0.749	0.241
Case_Manage	No	7,711	0.803	1.317
	Yes	1,457	0.804	0.572
Chore_Home	No	8,128	0.805	1.352
	Yes	1,040	0.802	0.516
Meal_Seniorcenter	No	8,623	0.795	1.393
	Yes	545	0.811	0.397
Visitor_Telephone	No	9,059	0.837	0.952
	Yes	109	0.770	0.250
Home_Meals	No	8,091	0.798	1.349
	Yes	1,077	0.808	0.525
Pers_Care	No	7,756	0.798	1.321
	Yes	1,412	0.808	0.564
Transport	No	7,715	0.801	1.317

Variable	Variable categories	N	Mean SC_SCORE	Std. Dev.
	Yes	1,453	0.806	0.572

H5 key findings: Chronosystem (Disruptive Life Events and Total Life Events).

The chronosystem model was examined from the dual perspectives of the impact of each distinct event and then via cumulative disruptive life events (total life events). The findings are presented first for distinct disruptive life events, where each event was considered an IV. Next, the analysis for total life events is presented, as a way of examining the cumulative influence of disruptive life events.

For the disruptive life events model, which introduced each distinct life event into the model, the Cook's D outlier correction was performed thrice to improve the lack of fit test. In the disruptive life events model, 7,877 cases were regressed. Among the 20 imputed data sets representative of the chronosystem model, the adjusted *R* squared ranged from a minimum of .165 to a maximum of .187. The result indicated that in the presence of the control variables, total life events explained up to 18.7% of the variance in social connection scores, .132 more variance than was explained by the control-only model. Table 34 shows the ANOVA summary for the model, drawn from across the 20 imputed data sets with extreme outliers removed.

Table 34

Model 4a Chronosystem (Disruptive Life Events): Analysis of Variance Results Based on 20 Imputed Datasets

	F(df1, df2)	*p*-value	*R*-squared	adj. *R*-squared
Minimum	*F*(17, 7882) = 92.192	< 0.001	.166	0.165
Maximum	*F(*17, 7838) = 110.043	< 0.001	.188	0.187

In considering the performance of eight IVs representing disruptive life events, analysis indicated statistically significance ($p < 0.001$) for each of these events: death of someone close, financial problems, major illness of family/friend, recent move/relocation, victim of a crime, failing health. A change in work/employment was not statistically significant ($p = .149$). Most notably, this model's unstandardized beta (β) values indicated that having not experienced crime victimization increased the social connection score by .149, compared to having experienced crime victimization. Table 35 shows regression results for the chronosystem disruptive life events variables. Table 36 presents the estimated means for disruptive life events.

Table 35

Regression for Model 4a Chronosystem Variables (Disruptive Life Events) N = 7,877

Parameter	β	Std. Error	Sig.
Intercept	0.489	0.02	< 0.001
Gender=Female	-0.004	0.003	0.172
Medicaid=No	0.011	0.003	0.002
Education=Less than HS	-0.015	0.005	0.001
Education=Some HS	0.002	0.005	0.677
Education=HS graduate	-0.005	0.004	0.159
Education=Some college	0.001	0.004	0.798
Marital_Status=Widowed	-0.012	0.004	0.001
Marital_Stat=Sing/Sep/Div	-0.014	0.004	< 0.001
Environ_Change=No	0.017	0.012	0.149
Death_Close=No	0.038	0.004	< 0.001
Financial_Problems=No	0.054	0.004	< 0.001
Illness_Fam_Friend=No	0.022	0.004	< 0.001
Move_Relocate=No	0.024	0.005	< 0.001
Victim_Crime=No	0.149	0.012	< 0.001
Failing_Health=No	0.027	0.003	< 0.001
Other=No	0.04	0.004	< 0.001
Age	0.001	0	< 0.001

Note. Reference categories removed.

Table 36

Estimated Means for Model 4a: Chronosystem Variables (Disruptive Life Events) N = 7,877

Variable	Variable categories	N	Mean SC_SCORE	Std. Dev.
Gender	Female	5,122	0.754	0.573
	Male	2,755	0.758	0.420
Age_groups	60 - 64	608	0.734	0.222
	65 - 74	1,847	0.748	0.344
	75 - 84	2,961	0.755	0.435
	85 - 94	2,177	0.764	0.420
	95 and older	284	0.777	0.185
Medicaid	No	5,661	0.761	0.602
	Yes	2,216	0.751	0.424
Education	Less than High School	1,487	0.744	0.347
	Some High School	847	0.761	0.262
	High School Graduate	2,603	0.754	0.459
	Some College	1,313	0.760	0.326
	College Graduate	1,628	0.759	0.323
Marital_Status	Widowed	3,351	0.752	0.463
	Single/Sep/Divorce	2,089	0.751	0.411
	Married	2,438	0.764	0.444
Environ_Change	No	7,743	0.764	0.616
	Yes	135	0.748	0.139
Death_Close	No	6,885	0.775	0.664
	Yes	992	0.737	0.252
Financial_Problems	No	6,503	0.790	0.645
	Yes	1,374	0.721	0.334
Illness_Fam_Friend	No	6,942	0.764	0.667
	Yes	935	0.747	0.275
Move_Relocate	No	7,276	0.772	0.682
	Yes	601	0.739	0.221
Victim_Crime	No	7,784	0.828	0.618
	Yes	93	0.683	0.126
Failing_Health	No	3,776	0.775	0.553
	Yes	4,101	0.737	0.512
Other	No	6,942	0.776	0.667
	Yes	935	0.736	0.275

Relative to the chronosystem model for total life events, the Cook's D correction was performed twice to improve the lack of fit test. As a result, 8,527 cases were regressed in this model. The ANOVA summary for the overall model returned a *p*-value of < 0.001. Regression analysis suggested the cumulative effect of total life events predicts extent of social connection among older adults seeking LTSS to a statistically significant degree ($p < 0.001$). Among the 20 imputed data sets representative of the chronosystem model, the adjusted *R* squared ranged from a minimum of .183 to a maximum of .200, indicating that in the presence of the control variables, the chronosystem variables explained up to 20% of the variance in social connection scores, an improvement of .154 over the control-only model. The ANOVA summary for the model, drawn from across the 20 imputed data sets with extreme outliers removed, is presented in Table 37.

Table 37

Model 4b Chronosystem (Total Life Events): Analysis of Variance Results Based on 20 Imputed Datasets

	F(df1, df2)	*p*-value	*R*-squared	adj. *R*-Squared
Minimum	$F(10, 8534) = 192.248$	< 0.001	.184	0.183
Maximum	$F(10, 8497) = 213.931$	< 0.001	.201	0.200

For this model, total life events variable was the single IV introduced with the CVs. The model's unstandardized beta (β) values indicated that for each additional life event experienced, the social connection score decreased by .046. Therefore, the total life events variable improved the model. Given the results of the regression models that examined life events from two perspectives, H5 is accepted: Experiencing disruptive life events negatively predicts social connection scores.

Table 38 shows the summary model for the total life events variables. Table 39 presents the estimated means for total life events.

Table 38

Regression for Model 4b: Chronosystem Variables (Total Life Events) N = 8,527

Parameter	β	Std. Error	Sig.
Intercept	0.865	0.014	< 0.001
Gender=Female	-0.007	0.003	0.034
Medicaid=No	0.008	0.004	0.024
Education=Less than HS	-0.021	0.005	< 0.001
Education=Some HS	0	0.006	0.985
Education=HS graduate	-0.013	0.004	0.002
Education=Some college	-0.004	0.005	0.35
Marital_Status=Widowed	-0.016	0.004	< 0.001
Marital_Status=Sing/Sep/Div	-0.02	0.004	< 0.001
Age	0.001	0	< 0.001
Total_Life_Events	-0.046	0.001	< 0.001

Note. Reference categories removed.

Table 39

Estimated Means for Model 4b: Chronosystem Variables (Total Life Events) N = 8,527

Variable	Variable categories	N = 8,527	Mean SC_SCORE	Std. Dev.
Gender	Female	5,591	0.881	0.150
	Male	2,935	0.888	0.163
Age_Groups	60 - 64	702	0.728	0.397
	65 - 74	2,049	0.741	0.634
	75 - 84	3,187	0.748	0.790
	85 - 94	2,297	0.759	0.719
	95 and older	292	0.779	0.274
Medicaid	No	6,106	0.889	0.156
	Yes	2,420	0.880	0.148
Education	Less than High School	1,606	0.871	0.120
	Some High School	914	0.892	0.151
	High School Graduate	2,830	0.879	0.160

Variable	Variable categories	N = 8,527	Mean SC_SCORE	Std. Dev.
	Some College	1,428	0.887	0.151
	College Graduate	1,750	0.892	0.125
Marital_Status	Widowed	3,623	0.880	0.181
	Single/Separate/Divorce	2,325	0.877	0.145
	Married	2,578	0.896	0.152
Total_Life_Events	0	2,485	0.938	0.150
	1	2,993	0.904	0.164
	2	1,805	0.860	0.170
	3	854	0.803	0.146
	4	276	0.753	0.133
	5	80	0.682	0.134
	6	27	0.630	0.136
	7	5	0.582	0.143
	8	2	0.607	0.142

Note. Covariates appearing in the model are evaluated at the following values: Age = 79 and Total_Life Events = 1.3.

H6 Key Findings: Mixed Level Models. Two final regression models were conducted from among the 20 imputed data sets with extreme outliers removed in order to examine the most significant variables from the microsystem, mesosystem, and chronosystem models in the presence of the control variables. Independent variables were selected and combined for this model based on the *p* values of each variable from its particular ecosystem model. Table 40 presents the selected IVs and their *p* values.

Table 40

Independent Variables Selected for H6 Mixed Level Models

Ecosystem level	Independent variable	*p* <
Microsystem	Housing	.01
Mesosystem	Access_Barrier	.001
Exosystem	Adult day care	.001
	Adult protective services	.001

Ecosystem level	Independent variable	*p* <
Chronosystem	Death of someone close [a]	.001
	Financial problems [a]	.001
	Major illness – family/friend [a]	.001
	Recent move/relocation [a]	.001
	Victim of a crime [a]	.001
	Failing health [a]	.001
	Other event [a]	.001
	Total life events [b]	.001

Note. [a] denotes the chronosystem variables included in Model 5a: Mixed Levels w/disruptive life events. [b] denotes the chronosystem variable included in Model 5b: Mixed Levels w/ total life events.

Two final models were produced rather than one in order to examine the predictive strength of both single events and cumulative events. Furthermore, introducing distinct life events and total life events into the same model would have violated independence of observations. First, Model 5a (Mixed Levels w/ Disruptive Life Events) regressed the control variables along with the following IVs: housing, barriers to access, adult day care, adult protective services, and seven distinct disruptive life events. The event change work/employment was excluded based on its weak performance in Model 4a. In Model 5a, 7,910 cases were regressed after extreme outlier removal. The ANOVA summary for the overall model returned a *p*-value of < 0.001. Among the 20 imputed data sets representative of the model, the adjusted *R* squared ranged from a minimum of .188 to a maximum of .205. This result suggested that in the presence of the control variables, the IVs explained up to 20.5% of the variance in social connection scores. The ANOVA summary for Model 5a (Mixed Levels w/ Disruptive Life Events), drawn from across the 20 imputed data sets with extreme outliers removed, is presented in Table 41.

Table 41

Model 5a Mixed Levels w/ Disruptive Life Events: Analysis of Variance Results Based on 20 Imputed Datasets

	F(df1, df2)	*p*-value	*R*-squared	adj. *R*-squared
Minimum	*F*(20, 7915) = 90.993	< 0.001	.192	0.188
Maximum	*F*(20, 7854) = 102.688	< 0.001	.207	0.205

With regard to the contributions of specific IVs, barriers to access was removed due to its *p*-value in the mixed model (.482). All other variables contributed at a statistically significant level. Tables 42 and 43 present the results for Model 5a.

Table 42

Regression for Model 5a Mixed Levels w/ Disruptive Life Events N = 7,910

Parameter	β	Std. Error	Sig.
Intercept	0.476	0.004	0
Gender=Female	-0.003	0.001	0
Medicaid=No	0.007	0.001	0
Education=Less than HS	-0.021	0.001	0
Education=Some HS	-0.006	0.001	0
Education=HS Graduate	-0.009	0.001	0
Education=Some College	-0.006	0.001	0
Marital_Stat=Widowed	-0.008	0.001	0
Marital_Stat=Sing/Sep/Div	-0.01	0.001	0
Housing=Own/rent house	0.002	0.001	0.001
Housing=Rent apt/room	-0.016	0.001	0
Adult_Day_Care=No	-0.019	0.001	0
Adult_Protect=No	0.055	0.003	0
Death_Close=No	0.042	0.001	0
Financial_Problems=No	0.057	0.001	0
Illness_Fam_Friend=No	0.021	0.001	0
Move_Relocate=No	0.037	0.001	0
Victim_Crime=No	0.131	0.002	0
Failing_Health=No	0.028	0.001	0

Parameter	β	Std. Error	Sig.
Other=No	0.04	0.001	0
Age	0.001	0.00003298	< 0.001

Note. Reference categories removed.

Table 43

Estimated Means for Model 5a Mixed Levels w/ Disruptive Life Events N = 7,910

Variable	Variable categories	N	Mean SC_SCORE	Std. Dev.
Gender	Female	5,142	0.739	0.789
	Male	2,768	0.742	0.579
Age_Groups	60 - 64	646	0.717	0.305
	65 - 74	1,864	0.734	0.475
	75 - 84	2,962	0.742	0.599
	85 - 94	2,155	0.748	0.511
	95 and older	283	0.760	0.219
Medicaid	No	5,663	0.744	0.828
	Yes	2,248	0.737	0.569
Education	Less than High School	1,489	0.728	0.425
	Some High School	874	0.742	0.355
	High School Graduate	2,598	0.740	0.561
	Some College	1,324	0.743	0.437
	College Graduate	1,626	0.749	0.444
Marital_Status	Widowed	3,331	0.738	0.693
	Single/Sep/Div	2,123	0.736	0.507
	Married	2,456	0.746	0.545
Housing	Own or Rent Home	4,322	0.747	0.723
	Rent Room or Apt.	1,884	0.729	0.477
	Housing: Other	1,704	0.745	0.454
Adult_Day_Care	No	7,271	0.731	0.938
	Yes	639	0.750	0.303
Adult_Protect	No	7,826	0.768	0.619
	Yes	85	0.712	0.184
Death_Close	No	6,872	0.761	0.912
	Yes	1,038	0.719	0.387
Financial_Problems	No	6,491	0.769	0.967
	Yes	1,419	0.712	0.414
Illness_Fam_Friend	No	6,971	0.751	0.918
	Yes	939	0.730	0.368

Variable	Variable categories	N	Mean SC_SCORE	Std. Dev.
Move_Relocate	No	7,337	0.759	0.942
	Yes	573	0.722	0.287
Victim_Crime	No	7,800	0.806	0.883
	Yes	111	0.675	0.158
Failing_Health	No	3,754	0.754	0.674
	Yes	4,157	0.726	0.709
Other	No	6,951	0.760	0.917
	Yes	960	0.720	0.341

Next, Model 5b (mixed levels w/ total life events) regressed the control variables along with the following IVs: housing, barriers to access, adult day care, adult protective services, and total life events. In this model, 9,116 cases were regressed. The ANOVA summary for the overall model returned a *p*-value of < 0.001. Among the 20 imputed data sets representative of the model, the adjusted *R* squared ranged from a minimum of .187 to a maximum of .203. This result suggested that in the presence of the control variables, the IVs explained up to 20.3% of the variance in social connection scores. Table 44 presents the ANOVA summary for Model 5b (mixed Levels w/ total life events), drawn from across the 20 imputed data sets with extreme outliers removed.

Table 44

Model 5b Mixed Levels w/ Total Life Events: Analysis of Variance Results Based on 20 Imputed Datasets

	F(df1, df2)	*p*-value	*R*-squared	adj. *R*-Squared
Minimum	*F(14, 9110)* = 152.133	< 0.001	.189	0.187
Maximum	*F*(14, 9092) = 161.125	< 0.001	.204	0.203

With regard to the contributions of specific IVs, barriers to access was removed due to its *p*-value (.139) in the mixed model. All other variables contributed to a statistically significant level. Tables 45 and 46 present results for Model 5b.

Table 45

Regression for Model 5b Mixed Levels w/ Total Life Events N = 9,116

Parameter	β	Std. Error	Sig.
Intercept	0.770	0.024	< 0.001
Gender=Female	-0.008	0.004	0.036
Medicaid=No	0.009	0.004	0.028
Education=Less than HS	-0.028	0.006	< 0.001
Education=Some HS	-0.008	0.007	0.236
Education=HS graduate	-0.010	0.005	0.032
Education=Some college	-0.008	0.006	0.163
Marital_Stat=Widowed	-0.016	0.005	0.001
Marital_Stat=Sing/Sep/Div	-0.023	0.005	< 0.001
Housing=Rent/Own home	-0.005	0.005	0.279
Housing=Rent/Room apt	-0.025	0.005	< 0.001
Adult_Day_Care=No	-0.021	0.006	0.001
Adult_Protect=No	0.082	0.016	< 0.001
Age	0.002	0.000	< 0.001
Total_Life_Events	-0.049	0.001	< 0.001

Note. Reference categories removed.

Table 46

Estimated Means for Model 5b Mixed Levels w/ Total Life Events N = 9,116

Variable	Variable categories	N = 9,116	Mean SC_SCORE	Std. Dev.
Gender	Female	5,973	0.677	1.468
	Male	3,143	0.685	1.065
Age_Groups	60 - 64	808	0.651	0.569
	65 - 74	2,244	0.670	0.900
	75 - 84	3,376	0.683	1.104
	85 - 94	2,391	0.693	0.929
	95 and older	297	0.718	0.362

Variable	Variable categories	N = 9,116	Mean SC_SCORE	Std. Dev.
Medicaid	No	6,463	0.685	1.527
	Yes	2,654	0.676	0.979
Education	Less than High School	1,737	0.664	0.792
	Some High School	1,020	0.684	0.639
	High School Graduate	2,965	0.682	1.035
	Some College	1,545	0.684	0.786
	College Graduate	1,849	0.692	0.817
Marital_Status	Widowed	3,825	0.678	1.175
	Single/Sep/Div	2,553	0.671	0.960
	Married	2,738	0.694	0.994
Housing	Own or Rent Home	4,939	0.686	1.335
	Rent Room or Apt.	2,236	0.665	0.898
	Housing: Other	1,941	0.692	0.837
Adult_Day_Care	No	8,397	0.670	1.741
	Yes	719	0.692	0.509
Adult_Protect	No	8,987	0.722	1.612
	Yes	129	0.640	0.273
Total_Life_Events	0	2,584	0.886	0.457
	1	3,150	0.847	0.505
	2	1,905	0.801	0.393
	3	949	0.746	0.308
	4	360	0.697	0.228
	5	121	0.602	0.187
	6	39	0.521	0.186
	7	7	0.502	0.178
	8	2	0.526	0.197

Note. Covariates appearing in the model are evaluated at the following values: Age = 79 and Total_Life Events = 1.3.

Validation of Final Models. To test the accuracy of models 5a and 5b, regression was performed on the unadjusted validation (test) data set (N=2,406). First, cases with missing values were removed (*n*=1,444). Table 47 compares the characteristics of three subsets: the primary (training) (*N* = 9,710) data set, the validation (test) data set with missing values (*N* = 2,406), and the validation (data set) with missing values removed (*N* = 1,444).

Table 47

Sample Characteristics Compared by Data Subsets

Variable	Levels	Primary set		Validation set			
		N	%	N	%	N	%
Gender	Female	5,142	65.0	1,518	64.8	929	64.3
	Male	2,768	35.0	824	35.2	515	35.7
Age_Groups	60 - 64	646	8.2	234	9.7	138	9.6
	65 - 74	1,864	23.6	643	26.7	385	26.7
	75 - 84	2,962	37.4	884	36.7	540	37.4
	85 - 94	2,155	27.2	588	24.4	353	24.4
	95 and older	283	3.6	57	2.4	28	1.9
Medicaid	No	5,663	71.6	1,537	69.2	971	67.2
	Yes	2,248	28.4	685	30.8	473	32.8
Education	Less than HS	1,489	18.8	400	19.2	266	18.4
	Some HS	874	11.0	220	10.6	157	10.9
	HS Graduate	2,598	32.8	704	33.9	486	33.7
	Some Coll	1,324	16.7	333	16.0	229	15.9
	College Grad	1,626	20.6	422	20.3	306	21.2
Marital_Stat	Widowed	3,331	42.1	881	39.6	569	39.4
	Sing/Sep/Div	2,123	26.8	656	29.5	437	30.3
	Married	2,456	31.0	686	30.9	438	30.3
Housing	Own/Rent Home	4,322	54.6	1,260	54.7	760	52.6
	Rent Room/Apt.	1,884	23.8	581	25.2	407	28.2
	Housing: Other	1,704	21.5	462	20.1	277	19.2
Adult_Day	No	7,271	91.9	2,188	92.8	1,367	94.7
	Yes	639	8.1	169	7.2	77	5.3
Adult_Prot	No	7,826	98.9	2,274	97.0	1,407	97.4

Variable	Levels	Primary set		Validation set			
		N	%	N	%	N	%
	Yes	85	1.1	71	3.0	37	2.6
Death_Close	No	6,872	86.9	1,976	84.6	1,217	84.3
	Yes	1,038	13.1	360	15.4	227	15.7
Fin_Probs	No	6,491	82.1	1,768	75.6	1,082	74.9
	Yes	1,419	17.9	572	24.4	362	25.1
Illness_Fam_ Friend	No	6,971	88.1	1,997	85.3	1,220	84.5
	Yes	939	11.9	344	14.7	224	15.5
Move_Reloc	No	7,337	92.8	2,086	89.2	1,309	90.7
	Yes	573	7.2	253	10.8	135	9.3
Vict_Crime	No	7,800	98.6	2,289	97.7	1,416	98.1
	Yes	111	1.4	53	2.3	28	1.9
Fail_Health	No	3,754	47.5	1,019	43.4	615	42.6
	Yes	4,157	52.5	1,328	56.6	829	57.4
Other	No	6,951	87.9	1,908	86.7	1,247	86.4
	Yes	960	12.1	293	13.3	197	13.6
		N = 7,910		N = 2,406		N = 1,444	

In order to evaluate the predictive power of the final models (5a and 5b), the root mean squared error (RMSE) of each model was calculated and compared against the RMSE of the control variables only. Often utilized to measure goodness of fit of regression models, RMSE offers a way to measure "the quality of the fit between the actual data and the predicted model" (Li, 2012, p. 2). The difference between the predicted fit and the actual value are the "prediction errors or residuals" (Li, 2012, p. 2). RMSE, which can be considered as the standard deviation of unexplained variance, is a way of estimating "the fit between the estimate and real data points" (Li, 2012, p. 3). While there are no strict rules for the best RMSE value, in general a "smaller RMSE reflects greater accuracy" (Li, 2012, p. 3). The RMSE and percent change in RMSE are presented in Table 48.

Table 48

Evaluation of Predictive Power of Final Model Compared to Control Only Model

	Evaluation metrics		
Model	Mean squared error	Root mean squared error	% Change in RMSE
Controls Only	0.033	0.183	
Final Model 5a	0.031	0.176	-3.6
Final Model 5b	0.002	0.042	-77.1

These results suggest that both Final Models 5a and 5b improved in predictability over just the control variables. Final Model 5b (total life events) indicated the smallest RMSE and the greatest decrease in RMSE compared to the controls only model and Final Model 5a. Despite finding that both of the final, mixed-level models explained more variance and predicted sc_score more powerfully than the controls only, H6 was ultimately rejected because the mesosystem variables did not reach statistical significance when introduced with micro, exo, and chronosystem variables.

Summary of findings

Table 49 summaries study findings related to Hypotheses 1-6. After analysis, H1 and H6 were rejected. H2, H3, and H4 were partially accepted. H5 was accepted.

Table 49

Summary of Findings: Hypotheses Conclusions

Hypothesis	Outcome	Conclusion
H1 (Composite DV): Each attribute of social connection (structural, functional, and quality) will uniquely contribute to the ability to detect predictive influences on extent of social connection via the composite variable social connection.	**Rejected**	No structural input variables met the >.20 VAF threshold.
H2 (Microsystem): Older adults' housing environments (subsidized housing or multi-family housing) predicts higher social connection, after controlling for age, gender, poverty, marital status, and educational attainment.	**Partially accepted** for living environment**. Rejected** for subsidized housing**.**	Subsidized housing did not predict social connection scores to a statistically significant level.
H3 (Mesosystem): Older adults' negative perception of neighborhood environment predicts lower social connection, after controlling for age, gender, poverty, marital status, and educational attainment.	**Partially accepted** for perceived barriers to access. **Rejected** for perceived unsafe neighborhood.	Perceived unsafe neighborhood did not predict social connection scores to a statistically significant level.
H4 (Exosystem): Older adults' enrollment in formal supportive services predicts a higher social connection score after	**Partially accepted** for adult day care, congregate meals/senior centers, and personal care services. **Rejected** for case	Case management, companion/chore services, home-delivered meals, and transportation did not

controlling for age, gender, poverty level, marital status, and educational attainment.	management, chore/homemaker services, home-delivered meals, adult protective services, friendly visiting/telephone reassurance, and transportation.	predict social connection scores to a statistically significant level. Adult protective services, friendly visiting/telephone reassurance negatively predicted social connection scores.
H5 (Chronosystem): Older adults' experience of disruptive life events predicts lower social connection score after controlling for age, gender, poverty, marital status, and educational attainment.	**Accepted**	Tested by event and by number of events, disruptive life events predicted social connection scores.
H6 (All Levels): The best predictors of older adults' extent of social connection will include housing, neighborhood perception, supportive services enrollment, and disruptive life events, after controlling for age, gender, poverty, marital status, and educational attainment.	**Rejected**	The mesosystem variable perceived barriers to access did not persist as significant when introduced into the mixed level regression models.

Chapter 5: Discussion

Chapter Overview

Chapter 5 first summarizes the study problem and briefly reviews the study's methodology. Next, a discussion of research findings is presented for the control variables and each ecosystem level, followed by implications for future directions and future research. Finally, study limitations are noted, after which the chapter closes with a brief conclusion.

Summary of Problem and Methodology Review

From infancy through elderhood, strong and positive relationships contribute to longer, healthier, happier lives. Like trees (Wohlleben & Billinghurst, 2018) and many animals (J.T. Cacioppo & Hawkley, 2009), human beings (J.T. Cacioppo & Henry, 2009; Holt-Lunstad et al. 2010; Holt-Lunstad et al., 2015; NASEM, 2020; Thomas et al., 2016) need social connection to survive and to flourish. Increasingly over several decades, lack of social connection has been found to predict premature death (Holt-Lunstad et al., 2010; Holt-Lunstad et al., 2015). Whether constructed as a single dimension of overall social connection – loneliness, social isolation, or social support – the scientific evidence is unequivocal in its message to us: We need each other for our very survival. In fact, a recent consensus study argued that based on the Bradford Hill criteria, a causal pathway between social isolation and mortality has been established (NASEM, 2020).

Science has made remarkable progress in understanding the health consequences of low social connection and the individual risk factors for social isolation, loneliness, or low social support. Whereas individual protective factors have been extensively researched, social connection is just beginning to be examined through an ecological lens (Holt-Lunstad, 2018; Holt-Lunstad et al., 2017; Kim & Clarke, 2015). This study builds upon the vast body of knowledge about social connection among older adults and breaks new ground by examining a multidimensional typology of social connection (Holt-Lunstad, 2018) through a socio-ecological lens, both of which are emergent turns in the research. The intent of this study was to overlay a new typology of social connection with factors representing different environmental contexts within the same sample of older adults.

As an initial foray into Holt-Lunstad's (2018) typology of social connection, a cross-sectional, retrospective secondary data analysis was conducted with a sample of 12,116 older adults seeking long-term services and supports in Virginia between 2013 and 2019. Virginia's Uniform Assessment (UAI) Instrument served as the instrument for devising a continuous composite social connection variable. The UAI was also the source for the independent variables and control variables. Drawing from aspects of Bronfenbrenner's ecological systems theory, a series of regression models, representative of the microsystem, mesosystem, exosystem, and chronosystem, tested the predictive ability of factors related to housing, neighborhood perception, supportive services enrollment, and disruptive life events and a multidimensional social connection score.

Findings From Hypotheses Testing

Hypotheses 2 – 6 examined ecological factors in the presence of key demographic variables. Each hypothesis was tested with a set of variables representing an ecological location as either microsystem, mesosystem, exosystem, or chronosystem. Age, gender, marital status, educational attainment, and poverty (Medicaid) were controlled for in each regression model.

Age

As previously described, in this sample age ranged from 60 to 106 and was fairly normally distributed with the raw mean age of the sample at 78.4 (SD = 9.48), just slightly lower than the life expectancy at birth of 78.7 in the U.S. (Xu et al., 2020). In this study, social connection increased with age, which is consistent with the AARP's (2018) loneliness survey of American adults ages 45 and over, which found that loneliness decreased with age. The finding in this study that social connection increased with age is also consistent with prior findings relative to social isolation and mortality. In their meta-analysis (N = 3,407,134), Holt-Lunstad and colleagues (2015) observed that the risk for premature death associated with social isolation was higher for middle-aged adults than older adults. The evidence base is not uniformly reflective of this pattern; however. Some researchers have found no age-related differences (Lee et al., 2018). Others have founded that those ages 90 and older are more socially isolated (Cudjoe et al., 2020). These differences may be partly explained by the constructs that were measured in each study. For example, Cudjoe et al. (2020) measured social isolation, a more objective state related to quantity and presence of social connections. This study measured functional and quality social connection, which are best understood from how people perceive their social connections. The finding merits further into social life in elderhood.

Gender

As the UAI does not offer a non-binary construction of gender, the sample was composed of 65.6% female and 34.4% male. Overall, the evidence base linking gender and social connection is mixed, with some studies finding no difference between males and females (AARP, 2018; Cigna, 2018; Lee et al., 2018), while other studies have found that males were less socially connected than females (Cudjoe et al., 2020; J.T. Cacioppo et al., 2015; Veazie et al., 2019). In fact, in their secondary analysis of the National Health and Aging Trends Study (*N* = 6,649), Cudjoe and colleagues found that males were four times more likely than females to experience severe social isolation (p. 111). With regard to gender, the results of this study did not conform with prior research findings: To a statistically significant degree, males in the sample had higher social connection scores than females. The original and adjusted samples in this study included an overrepresentation of females, who comprised 65.6% of the sample, which may partially account for this finding.

Marital Status

Consistent with the strong evidence base (AARP, 2018; Berkman & Syme, 1979; J.T. Cacioppo et al., 2015; Cigna, 2018; Cudjoe et al, 2020; House et al., 1988; Lee et al., 2018; NASEM, 2020; Veazie et al., 2019), the analysis in this study found higher social connection scores among those who were married than those who were not married. In cases where marital status was single, divorced, or separated the average raw and adjusted social connection scores were lower than the overall sample social connection score. In each of the regression models, being married predicted higher social connection scores than being widowed or single, separated, or divorced. These findings align with the research base.

Education Level

The findings from this study were fairly consistent with the evidence base that lower educational level is associated with increased social isolation and loneliness (Cudjoe et al., 2020; NASEM, 2020; Suen et al., 2018; Veazie et al., 2019) and higher educational attainment is associated with strong social connection (J.T. Cacioppo et al., 2015). In each regression model, less than high school education was found to predict statistically significantly lower social connection scores than the reference category of college graduate.

Poverty

The UAI does not offer a method of determining poverty without calculating income and number of people in the household. The federal poverty thresholds change each year and the study spanned seven years, but dates of assessment were not included, so it was not possible to calculate an accurate poverty variable based on annual federal poverty thresholds. Therefore, Medicaid was used as a proxy for poverty because qualifying income and asset requirements in Virginia are either at or near the federal poverty thresholds. The literature asserts that poverty and social connection are associated (Cudjoe et al., 2020; Lee et al., 2018; Veazie et al., 2019). This study's findings were consistent with prior evidence and found that social connection scores among those with Medicaid as insurance were lower to a statistically significant level than those without Medicaid. Moreover, in each regression model, not having Medicaid as insurance statistically significantly predicted higher social connection scores than having Medicaid as insurance.

Microsystem Findings

The relationship between housing and social connection was investigated via a regression model that tested two independent variables: type of living environment and subsidized housing. The regression model that examined housing variables found that type of housing predicted extent of social connection but that living in subsidized housing did not. However, the levels of the variable living environment (own/rent house, rent apt/room, housing: other) may not have been specific enough to meaningfully or practically interpret this finding, since housing: other is not well-defined in the UAI assessors' guide. The effect of housing on social connection is understudied (NASEM, 2020), and this study affirms that housing-specific research is needed.

Mesosystem Findings

Scientists who have examined neighborhood influence on social connection have either constructed objective or subjective measures. Urie Bronfenbrenner (1977) emphasized that how people perceive their environments essentially defines their reality. How people perceive access and neighborhood safety was examined in this study.

In their study that objectively measured neighborhood access and density, Suen and colleagues (2018) found no overall relationship between the built environment and social satisfaction, but they did find a positive relationship between access to services and amenities and social satisfaction. Buffel and colleagues (2014) found that perceptions about neighborhood barriers to access predicted a decrease in formal social activity such as volunteering.

Consistent with Bronfenbrenner's principles, this study analyzed perceived barriers to access as a predictor of social connection and found that perceived access barriers statistically significantly predicted a negative impact on social connection scores. However, perceived barriers to access failed to persist as statistically significant in the final mixed-level models. While this result expands upon findings related to neighborhood perception and social connection, there is still much to be learned. One explanation for the low amount of variance explained by perceived barriers to access could be that the composite DV did not include structural attributes of social connection, and these may be more tied to neighborhood structure.

Perceived neighborhood safety as a predictor of social connection was also examined in this study, but not found to predict extent of social connection. This is inconsistent with the literature, although the evidence base on this topic is limited and early in its life cycle. In a mixed methods study involving a sample of older adults receiving home and community-based waiver services, perceptions of neighborhood safety and actual presence of Neighborhood Watch signs were studied relative to social isolation (Kim and Clarke, 2015). The researchers found that the presence of Neighborhood Watch signs increased the odds of social withdrawal and social isolation (Kim & Clarke, 2015).

Perhaps narrowing the research question would reveal a pattern embedded more deeply in the sample. For example, in a qualitative study of elder abuse victims (N = 66), Portacolone et al. (2018) found that neighborhoods perceived as high in criminal activity were associated with social withdrawal and social isolation among older adults who had been abused. A clue to inform further exploration of this question may be present in the exosystem and the chronosystem models. For example, the exosystem model show the lowest social connection scores were present among older people who were receiving adult protective services. Similarly, the disruptive life events chronosystem model showed the lowest social connection scores were present among older people who were victims of a crime. By examining the relationship between perceived neighborhood safety and social connection among a narrower target population, more precise findings may emerge.

Exosystem Findings

The exosystem regression model analyzed the ability of enrollment in federally funded, federal-mandated services, known as Title III Supportive Services, to predict social connection. With regard to effectiveness of interventions, the evidence base consists mostly of small studies drawn from convenience samples (Dickens et al., 2011; Gardiner et al., 2018). The research base on supportive services has most often evaluated an intervention's ability to remedy social isolation or loneliness, once detected.

By contrast, this study explored whether supportive services may buffer loneliness and social isolation. By examining cases where people were enrolled in supportive services, the hypothesis tested whether such enrollment would predict higher social connection than for those who were not enrolled. The general direction of raw and adjusted mean social connection scores demonstrated that for those enrolled in supportive services, their social scores were either higher or not significantly lower than those who were not enrolled. For adult day care, congregate meals/senior centers, and personal care, a statistically significant positive changes in social connection scores were observed for non-enrollment vs enrollment. Whereas, for adult protective services and friendly visiting/telephone reassurance, a statistically significant negative change in social connection scores was observed for non-enrollment vs enrollment. The finding of much lower social connection scores among recipients of adult protective services reinforces the chronosystem findings relative to experiences of trauma, transition, or loss (disruptive life event).

These results suggest that there may well be a protective aspect to Title III Supportive Services enrollment. This finding breaks new ground, as little attention has been given specifically to the role of Title III Supportive Services in improving social connection or preventing social isolation or loneliness. Relative to the finding of lower social connection among those receiving adult protective services, this result provides an immediately actionable insight for practitioners working directly in or with adult protective services.

Chronosystem Findings

In 2018, Suen and colleagues initiated a study of UAI data that used social satisfaction as a proxy for social isolation. Their research found a clear and compelling relationship between social satisfaction and experiences of trauma, transition, and loss (Suen et al., 2018). The trauma-transition variables in their study were the same variables operationalized as disruptive life events in this study. The results of this study advance the work of Suen, Gendron, Gough (2018), and the community partners involved in the SIRI project.

Among researchers, it is generally viewed that "adjusted *R*-square values ≥ .10 are interpreted as the beginnings of an important proportion of the variance explained between the dependent and independent variables" (Coolidge, 2013, p. 202). In each of four regression models that included either the disruptive life events or total events variable, the adjusted R-square values exceeded .10 and approached or exceeded .20. Considering that heritability may explain a moderate amount of loneliness (Gao et al., 2016; Holt-Lunstad et al., 2017), disruptive life events appear to dramatically impact people's social connection. Researchers have called for a deeper study of the impact of disruptive life events such as trauma, transition, and loss experiences (Holt-Lunstad, 2013; NASEM, 2020). The findings in this study improve upon the current evidence base and offer pathways forward to immediately improve practice standards for community-based service providers.

Major Finding Themes and Implications

Measuring Social Connection

Aim 1 of this study aspired to build a composite DV inclusive of structural, functional, and quality components of social connection. The utilization of composite indices to inform outreach, planning, expansion, and evaluation is a strategy increasingly employed by researchers, data managers, and service providers (ACL, n.d.b; Advancing States, n.d.; Cotterrell et al., 2018). This study replicated the formula employed by Lucy and Burns (2017; Burns and Lucy, 2018), who created a composite spatial index for loneliness in the United Kingdom.

This study attempted to devise a single, continuous DV intended to express the structural, functional, and quality dimensions of social connection (Holt-Lunstad, 2018). In using CATPCA to evaluate 13 input variables for inclusion in the DV, five variables contributed meaningfully to Dimension 1. These five variables represented the functional and quality components, but not the structural component, of social connection. The input variables selected and weighted for inclusion into the single DV clustered around subjective and perceived experiences, representing constructs indexed within the functional and quality dimensions of Holt-Lunstad's typology (2018). The structural input variable candidates, all more objective and observable traits related to the presence of and roles with a social network, did not signal strong contributions and, therefore, were discarded from consideration into the DV. Despite the construction of a DV with only two of the three social connection dimensions represented, the devised DV was multidimensional (functional and quality) and did detect statistically significant associations, as described in Chapter 4.

With the stated intent of replicating the composite index process described by Lucy and Burns (2017; Burns & Lucy 2018), Aim 1 aspired to devise an approach easily replicable by community-based organizations that may not have the resources nor capacity to engage in complex analysis and testing. Lucy and Burns (2017; Burns & Lucy, 2018) used UK census data in their work. This approach could be replicated and quickly deployed in applied settings using U.S. Census data; however, Census data lacks information about perceived experiences in favor of collecting observable facts about Americans' lives. The sc_score composite DV demonstrated how important self-perception is in understanding the extent of social connection among human beings.

Potentially, the aging services network could develop a data visualization dashboard that incorporates subjective and objective attributes of social connection. For example, it is technically possible to overlay UAI data with Census data and then to offer access to such a dashboard to providers who are part of the aging services network. In fact, in their recent prevention-focused ecological analysis of the literature related to social isolation, Cotterrell et al. (2020) cited the Lucy and Burns approach as an example to emulate and suggested that indexing and visualization of social isolation and loneliness risk at the neighborhood level could play an important role in prevention policies that promote social connection.

Lucy and Burns (2017; Burns & Lucy, 2018) created an approach to a composite loneliness score with an aim that it could be easily replicated. This study followed the path set by their study and successfully created a composite social connection score based on UAI data from No Wrong Door Virginia. The weighted social connection score created in this study could be incorporated into a statewide, local-level data dashboard alongside Census data, providing administrators the ability to better understand the extent of social connection among their communities served.

Despite the absence of structural social connection, this study's DV advanced the evidence in two key ways: 1) rarely has the same study examined more than one dimension of social connection within the same sample (Holt-Lunstad, 2018; Holt-Lunstad et al., 2017), and 2) most often researchers have addressed either structural or functional social connection (Holt-Lunstad, 2018; Holt-Lunstad et al., 2017). Quality social connection is rarely studied (Holt-Lunstad, 2018). Still, that the construct of the structural component of social connection was not captured in the study's DV warrants further study to understand how the three dimensions work together to represent a complete picture of social connection or lack thereof.

Elderhood

A hallmark of this study was the presence in the primary (training) data set of 2,806 (29%) people between the ages of 85 and 106 – a rare occurrence in health research, which typically either caps inclusion at age 65 for technical reasons or utilizes wide-ranging age group categories that hold no practical meaning (e.g., 65 and older, 50 and older) (Rosales & Fernández-Ardèvol, 2019). Explicit biases in research such as samples that exclude, dilute, or ignore the experiences of very old people are one form of structural ageism (Rosales & Fernández-Ardèvol, 2019). The overrepresentation of the oldest old in this sample, combined with the DV's emphasis on subjective attributes of social connection, offered a rare glimpse into one aspect of elderhood — how elders perceive their state of social connection.

Of particular note, is the striking pattern of statistically significant social connection score increases with age. Among the age group 60-64, the mean raw social connection score was .750 (.239). The raw social connection score increased at each age group interval, peaking at .902 (.153) among those ages 95 and older. This finding is precedented in the evidence (AARP, 2018; Holt-Lunstad, 2015).

For gerontologists, the clear and compelling pattern of increasing social connection scores across age might evoke socio-emotional selectivity theory (SST) and its construct of positivity effect (Reed & Carstensen, 2012). The theory posits that humans possess an intimate relationship with time that influences choices and decision-making as people age and realize that time left to live is finite, and, therefore, a precious commodity that must be used wisely (Carstensen et al., 1999). For many, this realization prompts a sort of social pruning, as people elect to live in ways and with people that make them happier (Carstensen et al., 1999; Reed & Carstensen, 2012). An important concept in SST, which may also explain part of the pattern of higher social connection among the oldest in this study, is positivity effect – a tendency to see the good over the negative (Reed & Carstensen, 2012).

Another perspective on the increasingly high social connection scores observed among the oldest old in this study, speaks to resilience across the lifespan. Everyone in this sample has one resilience trait in common: They or someone on their behalf reached out to the service system for help. The decades-deep evidence base relative to resilience and post-traumatic growth has long heralded positive social relationships as a key to bouncing back from adversity, overcoming trauma and living a longer, healthier life (van der Kolk, 2015).

Trauma and Transition Experiences

Returning to a consideration of resilience, despite a high correlation between trauma exposure and poor health outcomes, trauma is not destiny (Felitti et al., 1998; van der Kolk, 2015). An emergent movement within health and human services is a growing awareness of the impact of trauma across the lifespan and the need for health care and other services to care for and serve people with sensitivity and knowledge of the impact of trauma, transitions, and loss, in order to improve health outcomes (Kusmaul & Anderson, 2018). Herein, a key awaits to unlocking a prevention-early intervention framework for social isolation and loneliness: The aging services network could turn to the early childhood and youth services sectors for prevention-early intervention models to emulate.

More than 20 years ago, the adverse childhood experiences (ACE) study (Felitti et al., 1998) identified a direct association between early childhood trauma and long-term health outcomes in adults. The ACE study propelled childhood trauma into a prevention framework that has become a driving model in the provision of health and human services, particularly for children and youth (Fallot & Harris, 2008; Kusmaul & Anderson, 2018). By comparison, little attention has been directed toward the study of older adults' experiences of trauma (Kusmaul & Anderson, 2018). Regardless, the impact of ACEs among older adults has been linked to higher prevalence of social isolation, higher prevalence of high blood pressure, and accelerated shortening of telomeres (Norman et al., 2013).

The ACE Study has positioned childhood trauma at the vanguard of prevention and resilience efforts for children. Findings relative to trauma, transition, and loss among elders – such as discovered in this study and others – could be similarly elevated to stop loneliness and social isolation before they take root. Providers charged with treating and serving older adults need the cultural competence not only to understand the persistent nature of trauma, but also how experiences of trauma and disruptive life transitions influence coping, resilience, and vulnerability into old age (Danzinger & Welfel, 2000; Brown, 2009).

Ageism presents a challenge to transforming the evidence of trauma, transition, and loss in elderhood into a prevention-early intervention framework – a challenge not present in the early childhood or youth services sectors. The evidence shows that a pattern exists among providers of not recognizing trauma or its impact in older adults that is recognized in children, adolescents, and adults (Bourassa, 2009; Brown, 2009; Danzinger & Welfel, 2009; Duffy & Healy, 2011; Iverson et al., 2015; Kosberg, 2009; Kusmaul & Anderson, 2018; São José et al, 2017). For example, when providers omit questions about trauma, transitions, and loss in the treatment of older adult clients, they fail to recognize that, for many people, elderhood may be the first time they feel empowered, free, or safe enough to examine traumatic or difficult aspects of their lives (Brown, 2009). Consequently, if providers hold biased, ill-informed views that trauma-transition-loss related outcomes such as depression or chronic loneliness are normal parts of the aging process, they fall prey to harmful ageist stereotypes, which may prevent individuals from getting help and recovering (Brown, 2009).

No Wrong Door's Person-Centered Options Counseling (Options Counseling) is ideally suited to pilot the use of life events screening and appropriate referral and supports, as indicated, to prevent or detect lack of social connection. As an intervention that is activated when a person experiences certain *situational events*, Options Counseling is inherently concerned with how life transitions and loss threaten community tenure (No Wrong Door Virginia, n.d.). Next steps to consider for research and application could be to:

- Infuse the literature with examples of post-traumatic growth through positive social connection in elderhood with the voices of older trauma survivors of diverse ages, race, cultures, and from along the gender and sexual orientation continuums.
- Expose students and professionals in health and human services (social workers, counselors, physicians, nurses, etc.) to gerontological content, age-bias training, and trauma-informed care principles for older adults.
- Train students and professionals in health and human services as advocates, skilled in identifying and disrupting ageism within organizations, communities, and cultures.
- Develop mechanisms by which aging network service providers prioritize screening for trauma and transitions and assessing for resilience factors in older adults.
- Review and enhance, as appropriate, specific protocol for supporting and advocating for elder victims of crime.

Data Integrity, Health Equity

The most common warning about secondary analysis stems from the condition when data sets are asked to deviate from their original, intended purpose (Grady et al., 2013; Polit & Beck, 2017). In the case of UAI data, its intended purpose at collection is to assess one person at a time for eligibility for LTSS in any number of settings. Yet, UAI and No Wrong Door data increasingly respond to distal demands from federal, state, and local policymakers. As the aging and disability services network matures, No Wrong Door initiatives around the country are being called upon to measure return on investment, to examine the influence of social determinants of health, and to populate dashboards and reports that describe and explain what is occurring with the broader population (ACL, n.d.b; Advancing States, n.d.).

As is often the case when conducting secondary analysis, challenges emerged related to the data set. For example, a problematic extent and pattern of missingness was apparent with the variables race, ethnicity, and lives_with. Race and ethnicity suffered from high and non-random missingness. Likewise, lives_with, which included a key response value of living alone, suffered from a 40% missing rate. Though the variable was imputed, due to its centrality to the question of social isolation, it was not ultimately utilized. Also, upon initial inspection, the variable AGE ranged from 60 to 1,074 in the original data set. In all, 602 cases in the original data set were observed to have age values that were impossible.

While these conditions impacted this study, there is a more urgent implication and opportunity. Increasingly, the UAI data set is being called into the realms of policy, research, and evaluation. Therefore, it is essential that the full continuum of stakeholders have reliable and complete data about race – DARS and local area agencies on aging, first and foremost. With 64.4% missingness for the variable race, for example, administrators and policymakers would not be able to accurately answer basic questions about who is receiving and benefitting from services and whether service delivery and service impact are racially equitable. This is true for ethnicity, as well. Likewise, it is crucial that age is captured accurately.

Some of the data issues encountered in this study could be remediated through an intentional, coordinated effort. One remediation strategy that could improve reliability of UAI data would be to design a training strategy to reach stakeholders who are invested in the UAI data at different levels (e.g., administrators, UAI assessors, and data entry staff) with a purpose to engage the aging services network in an exploration of the relationship between complete, accurate data and racial and health equity. Another remediation strategy would be to work with DARS staff to identify tactical modifications to the electronic case management system. For example, adding a field validation to the year of birth field would eliminate wild code errors that result in impossible birth years.

Limitations

A number of threats to validity and reliability may have influenced the results of this study. Any conclusions and inferences drawn should be considered in the context of these limitations.

Study Design

As a secondary data analysis, this study makes no claims to causality or longitudinal evidence. Relinquishment of control over internal and external threats to validity and reliability is inherent to secondary data analyses, particularly when the study deviates from the original intended purpose of the data collection (Polit & Beck, 2017), which was the case with this study. These threats largely manifest from fixed population sample, data elements, and measures in the data (Grady et al., 2013; Young & Ryu, 2012). As a result, pre-determined constraints can introduce both bias and non-random variance, as was the case with the high proportion of missingness among the race variable. While a large population sample size can offset some of these threats (Young & Ryu, 2013), bias and non-random variance may still exist; therefore, caution should be used in interpretation.

Interrater Reliability

The data set examined in this study may suffer from bias due to inconsistent interrater reliability (Polit & Beck, 2017). The UAI is conducted by many different assessors, which threatens the consistency of results (Polit & Beck, 2017). Universal UAI training and a UAI assessors' guide are efforts to mitigate this threat (DARS, 2015).

External Validity

The study population was restricted to community-dwelling older adults seeking LTSS in Virginia. The sample, therefore, may not be entirely representative of community-dwelling older adults seeking LTSS beyond Virginia or of the general population of older people. However, the LTSS network is similar throughout the United States and its territories. Additionally, as part of the national No Wrong Door system, every state and territory utilizes some form of LTSS assessment similar to the UAI, thus findings may benefit the aging services network beyond Virginia.

Time

Although this study examined the most recent seven-year capture of all UAI data collected in Virginia through area agencies on aging, the COVID-19 pandemic dramatically disrupted three processes important to this study: the lived experiences of older adults relative to their own social connection, the demand for LTSS services, and a shift in how the UAI is typically administered. While this study revealed important pre-COVID patterns of social connection among older adults, all indications suggest that social isolation and loneliness have increased during the pandemic (DARS, 2020; NORC, 2021).

Cohort Effect

The 12,116 cases analyzed in this study were assessed at 25 different area agencies on aging over the course of seven years and pooled into a single data set, which resides electronically at DARS. Data elements that would have allowed for analysis by organization, location, or year of UAI assessment were excluded from the data request to DARS. Consequently, undetected cohort effects may exist relative to unique trends, protocol, or events that could have occurred within certain communities or agencies. The influence of possible cohort effects may be mitigated by the seven-year data collection period.

Internal Validity

The extent and patterns of missingness among variables such as race, ethnicity, and lives_with amount to a bias present in the original data that could not be corrected. As such, internal validity was threatened. Consequently, and despite consistent findings in the literature that race, and ethnicity do not independently predict lack of social connection (AARP, 2018; Cigna, 2018; NASEM, 2020), no such claim can be made from the findings in this study.

Researchers generally accept that between 37% and 55% of loneliness is heritable (Gao et al., 2017; Holt-Lunstad et al., 2017), which suggests that while genetics does assume a large role, a considerable portion of risk is modifiable (Holt-Lunstad et al., 2017). In examining the proportion of variance explained by the five regression models, it is evident that the larger share of modifiable variance in predicting extent of social connection was left unexplained. The chronosystem models and mixed-level models explained about 20% of variance. The controls, microsystem, mesosystem, and exosystem models respectively explained no more than 5.5%. Given that the DV accounted for two of three components of the social connection typology that it attempted to capture, more people in the sample may have lower social connection than were observed. This study's DV favored subjective measures of social connection (e.g., feeling lonely, feeling fearful of being around people, satisfaction with social support) over objective measures (e.g., participation in social activities, presence of social network).

Statistics strives to manage trade-offs between variance and bias. In this study, the regression assumption diagnostics encountered and mitigated bias in the form of extreme outliers. Remediation via the Cook's D correction sought to reduce bias and improve variance consistency, however in some cases the social connection scores appeared notably higher after outlier removal.

Future Research Questions

Poverty and Social Connection

Researchers (Kim & Clarke, 2015; Samuel et al., 2018) have argued that poverty itself is a multidimensional construct that has been systemically fabricated in the U.S. with meaning that extends to education, housing, neighborhood, and social capital – an argument akin to Bronfenbrenner's placement of socio-economic status within the macrosystem level of the human ecosystem. As this study considered but one economic attribute of poverty (Medicaid), an opportunity exists to examine a broader construct of poverty relative to social connection.

In the sample overall, 29.7% of cases were insured by Medicaid at the time of their initial UAI assessment. Proportionally, this is more than quadruple poverty rate of 7% in Virginia among people age 65 or older (U.S. Census Bureau, 2019). The U.S. Census measures poverty in two different ways using 1) federal poverty thresholds and 2) the supplemental poverty measure (Cubanski et al., 2018). Federal poverty thresholds consider income and household size. The supplemental poverty measure is a more all-encompassing approach that takes into consideration "geographic area and homeownership status, and the SPM reflects financial resources and liabilities, including taxes, the value of in-kind benefits (e.g., food stamps), and out-of-pocket medical spending" (Cubanski et al., 2018, n.p.). These definitions, however, only consider poverty from a single dimension: economic.

The UAI data includes data elements that, in a future study, may allow for a deeper exploration of poverty and social connection by examining not only income but also enrollment in the system of benefits under which poverty is organized in the United States including Medicaid, General Relief, food stamps, and auxiliary grants. Such a complex undertaking is beyond the scope of this study but will be an important future endeavor.

Experiences of Elderhood

As described previously, the finding related to social connection among elders who have reached longevity is an important contribution to the larger narrative arc about growing old in America. Given the unusual overrepresentation of people ages 85 to 106 in this study (n = 2,806) and access to UAI data that is largely self-reported experiences of daily life from a holistic lens (biological, psychological, social, spiritual), a study designed to explore experiences of elderhood is an opportune future step.

Extreme Experiences of Lack of Social Connection

Research into extreme experiences of social isolation and loneliness rarely occurs and is much needed (Holt-Lunstad et al., 2017). As noted, in removing the extreme outliers in order to address assumption violations, a portion variance was sacrificed. However, the experiences and characteristics of extreme lack of social connection are critical to learning how to prevent and amend lack of social connection. A future study of characteristics of people who may be extremely lonely or isolated could improve understanding in this area.

Geographic Analysis

A future area of study, under a different or modified data agreement, could include geographic area (e.g., address, ZIP code, city-county), in which case stratified sampling might be useful in comparing rural, suburban, and urban characteristics of social connection.

Post-COVID-19

A consideration for any secondary data analysis is the age of the data and its present-day relevance. Notably, the UAI data set offered a glimpse only at the pre-COVID-19 environment. Across the lifespan, the stressors experienced during the COVID pandemic have challenged people’s social well-being, particularly among older adults who have reported feeling more cut-off from their communities and supports and unsure how to stay connected (Skerrett et al., 2021). Yet, providers and researchers also report that older adults have faced COVID-19 with incredible resilience (DARS, 2020; Luchetti et al., 2021). Since entering into the pandemic, the aging and disability services network of providers have become increasingly aware of the impact of social isolation and loneliness (DARS, 2020). Additionally, service delivery mechanisms have changed: More older adults are being served via telephone and telehealth modalities (DARS, 2020). A future study of interest could compare pre- and post-pandemic UAI data relative to social connection.

Final Conclusions

This study examined the central research question: To what extent do housing (microsystem), neighborhood perception (mesosystem), supportive services enrollment (exosystem), and disruptive life events (chronosystem) predict the extent of social connection among community-dwelling older adults after controlling for age, gender, poverty, marital status, and educational attainment? The results showed that experiences of trauma, transition, and loss predicted lower social connection scores with greater strength than any of the other variables introduced. While traits such as perceived barriers to access, housing type, and supportive services enrollment did significantly statistically predict social connection, those contributions were overshadowed by the power of difficulties in life to negatively influence social connection. This finding underscores the often corrosive nature of trauma and transition experiences relative to social connection.

Additional important findings resulted from this study. First, the creation of a two-dimensional composite DV underscored the criticality of subjective experiences of social connection and perceived social support and inclusion. Secondly, the large representation of people between the ages of 85 and 106 offered a unique glimpse into the lives and environments of elders who, at the time of their initial UAI assessment, had exceeded life expectancy at birth. Consistent with prior large studies (AARP, 2018; Holt-Lunstad et al., 2015), this study found social connection showed strongest among the oldest. Finally, patterns and extent of missingness in the data rendered it impossible to validly include race or ethnicity, leaving important questions about health equity and racial equity unanswered. The extent and pattern of missingness also stand as a call to action for the aging network to prioritize the relationship between complete, accurate data and racial and health equity.

Several short- to mid-term next steps were identified that could enhance the aging services network's capacity and ability to prevent and remedy lack of social connection, including:

- Design data training and data entry standards relative to the intersection of data collection and racial and health equity,

- pilot life events trauma-transition screening and supports with the statewide person-centered options counseling network,
- strengthen relationships between service providers and adult protective services,
- review protocol to identify and support elder crime victims and their social health,
- develop of data dashboard and data visualizations that integrate UAI data with U.S. Census data to better understand neighborhood patterns of social connection, and
- examination of how childhood trauma has been mobilized as a prevention model in the early childhood sector with an eye toward replication for elders.

Ultimately, the study of social connection among elders is an immersion into the possibility of and hope for longevity. While this study intentionally prioritized consistency in variance over the bias of extreme outliers, the patterns observed prior to outlier removal persisted. Yet, the voices of elders at either end of the positive-negative social connection continuum have much to teach us about living healthier, happier, and longer lives. Housing, neighborhood perception, and supportive services enrollment each predicted social connection in this study, but their power to do so dwindled when examined in the shadow of disruptive life events. Just as the need for social connection unites us as humans, so too do experiences of trauma, transition, and loss. Community-based providers and academics cannot prevent these experiences, and nor would we want to, but armed with knowledge and practice standards, providers and researchers can work together to ensure that when elders do face such difficult moments, they do not do so alone.

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Appendix A: Virginia Uniform Assessment Instrument

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VIRGINIA UNIFORM ASSESSMENT INSTRUMENT

Dates:
Screen: _______ /______/ _______

Assessment: /______/ _______ _______

Reassessment: /______/ _______ _______

IDENTIFICATION/BACKGROUND

Name & Vital Information

Client Name: Client SSN: _______
(Last) *(First)* *(Middle Initial)*
Address:
(Street) *(City)* *(State)* *(Zip Code)*
Phone: City/County Code:
Directions to House: Pets?

Demographics

Birthdate: _____ /______/ _______ Age: __ Sex: _______ Male 0 _______ Female 1

(Month) *(Day)* *(Year)*
Marital Status: _ Married 0 _______ Widowed 1 _______ Separated 2 ____ Divorced 3 ____ Single 4 _______ Unknown 9

Race: Education: Communication of Needs:

Race	Education	Communication of Needs
White 0	Less than High School 0	Verbally, English 0
Black/African American 1	Some High School 1	Verbally, Other Language 1
American Indian 2	High School Graduate 2	Specify:
Oriental/Asian 3	Some College 3	Sign Language/Gestures/Device 2
Alaskan Native 4	College Graduate 4	Does Not Communicate 3
Unknown 9	Unknown 9	Hearing Impaired?
Ethnic Origin: _____	Specify: _	

Primary Caregiver/Emergency Contact/Primary Physician

Name: _______ Relationships: _
Address: ______ Phone: (H) (W)
Name: Relationship:
Address: ______ Phone: (H) (W)
Name of Primary Physician: Phone:
Address: ______

Initial Contact

Who called: _______
(Name) *(Relation to Client)* *(Phone)*

Current Formal Services

Do you currently use any of the following types of services?

No 0	Yes 1	(Check All Services That Apply)	Provider/Frequency:
________	________	Adult Day Care	________
________	________	Adult Protective	________
________	________	Case Management	________
________	________	Chore/Companion/Homemaker	________
________	________	Congregate Meals/Senior Center	________
________	________	Financial Management/Counseling	________
________	________	Friendly Visitor/Telephone Reassurance	__
________	________	Habilitation/Supported Employee	________
________	________	Home Delivered Meals	________
________	________	Home Health/Rehabilitation	________
________	________	Home Repairs/Weatherization	________
________	________	Housing	________
________	________	Legal	________
________	________	Mental Health (Inpatient/Outpatient)	________
________	________	Mental Retardation	________
________	________	Personal Care	________
________	________	Respite	________
________	________	Substance Abuse	________
________	________	Transportation	________
________	________	Vocational Rehab/Job Counseling	________
________	________	Other:	________

Financial Resources

Where are you on the scale for annual (monthly) family income before taxes?

D... or manage your business?

$2... Yes 1 *Names*

$15,000 - 19,999 ($1,250 - $1,666) 1 — Legal Guardian ________ ________ ________

$11,000 - 14,999 ($ 917 - $1,249) 2 — Power of Attorney ________ ________

$ 9,500 - 10,999 ($ 792 - $ 916) 3 — Representative Payee ________ ________

$ 7,000 - 9,499 ($ 583 - $ 791) 4 — Other ________ ________ ________

$ 5,500 - 6,999 ($ 458 - $ 582) 5

$ 5,499 or Less ($ 457 or Less) 6

Unknown 9

Do you receive any benefits or entitlements?

No 0 Yes 1

Number in Family unit: ________ Auxiliary Grant ________

*Optional: Total monthly family income:*____ ________ Food Stamps ________

________ Fuel Assistance

General Relief

Do you currently receive income from…?

____

No 0 Yes 1 *Optional: Amount* Subsidized Housing ________ ________

No 0	Yes 1		Optional: Amount	
________	________	Black Lung	________	________ Tax Relief
________	________	Pension	________	
________	________	Social Security_		
________	________	SSI/SSDI	________	
________	________	VA Benefits	________	________
________	________	Wages/Salary	________	________
________	________	Other ________	________	________
________	________	*QMB/SLMB:*___No 0	________Yes 1	
________	________	All Other Public/Private:	________	

What types of health insurance do you have?

No 0 Yes 1

________Medicare, # ________

________Medicaid, # ________

Pending:________No 0 ________Yes 1

Physical Environment

Where do you usually live? Does anyone live with you?	Alone 1	Spouse 2	Other 3	Names of Persons in Household
________ House: Own 0				
________ House: Rent 1				
________ House: Other 2				
________ Apartment 3				
________ Rented Room 4				

	Name of Provider *(Place)*	Admission Date	Provider Number *(If Applicable)*
Adult Care Residence 50			
Adult Foster 60			
Nursing Facility 70			
________ Mental Health/Retardation Facility 80			
Other 90			

Where you usually live are there any problems?		
No 0	Yes 1 *(Check All Problems That Apply)*	Describe Problems:
________	________ Barriers to Access	
________	________ Electric Hazards	
________	________ Fire Hazards/No Smoke Alarm	
________	________ Insufficient Heat/Air Conditioning	
________	________ Insufficient Hot Water/Water	
________	________ Lack of/Poor Toilet Facilities (Inside/Outside)	
________	________ Lack of/Defective Stove, Refrigerator, Freezer	
________	________ Lack of/Defective Washer/Dryer	
________	________ Lack of/Poor Bathing Facilities	
________	________ Structural Problems	
________	________ Telephone Not Accessible	
________	________ Unsafe Neighborhood	
________	________ Unsafe/Poor Lighting	
________	________ Unsanitary Conditions	
________	________ Other: ____________________	

FUNCTIONAL STATUS *(Check only one block for each level of functioning.)*

ADLS	Needs Help?		MH Only 10 Mechanical Help	HH Only 2DHuman Help		MH & HH 3 D		Performed Dby Others 40			Is Not D .Performed 50
	No 00	Yes		Supervision 1	Physical Assistance 2	Supervision 1	Physical Assistance 2				
Bathing											
Dressing											
Toileting											
Transferring											
								Spoon Fed 1	Syringe/ Tube Fed 2	Fed by IV 3	
Eating/Feeding											

Continence	Needs Help?		Incontinent Less than Weekly 1	Ext. Device/ Indwelling/ Ostomy Self Care 2	Incontinent D Weekly or More 3	External D Device Not Self Care 4	Indwelling D Catheter Not Self Care 5	Ostomy D Not Self Care 6
	No 00	Yes						
Bowel								
Bladder								

Ambulation	Needs Help?		MH Only 10 Mechanical Help	HH Only 2 D Human Help		MH & HH 3 D		Performed D by Others 40	Is Not D Performed 50
	No 00	Yes		Supervision 1	Physical Assistance 2	Supervision 1	Physical Assistance 2		
Walking									
Wheeling									
Stairclimbing									
								Confined Moves About	Confined Does Not Move About
Mobility									

IADLS	Needs Help?	
	No 0	D Yes 1
Meal Preparation		
Housekeeping		
Laundry		
Money Mgmt.		
Transportation		
Shopping		
Using Phone		
Home Maintenance		

Comments:

Outcome: Is this a short assessment?

No, Continue with Section 3 (0) ____ Yes, Service Referrals (1) ____ Yes, No Service Referrals (2) ____

Screener: ______________________ Agency: ______________________

PHYSICAL HEALTH ASSESSMENT

Professional Visits/Medical Admissions

Doctor's Name(s) *(List all)*	Phone	Date of Last Visit	Reason for Last Visit

Admission: In the past 12 months have you been admitted to a . . . for medical or rehabilitation reasons?

No 0	Yes 1		Name of Place	Admit Date	Length of Stay/Reason
		Hospital			
		Nursing Facility			
		Adult Care Residence			

No 0 Yes 1 *Location*

Do you have any advance directives such as… (Who has it…Where is it…)?

_______________ Living Will, __

_______________ Durable Power of Attorney for Health Care, ______

_______________ Other, ________

Diagnoses & Medication Profile

Do you have any current medical problems, or a known or suspected diagnosis of mental retardation or related conditions, such as … (Refer to the list of diagnoses)?

Current Diagnoses | Date of Onset

______________________________ ______________

______________________________ ______________

______________________________ ______________

______________________________ ______________

Enter Codes for 3 Major, Active Diagnoses: ________ None 00 ________ DX1 ________ DX2 ________ DX3

Current Medications (Include Over-the-Counter)	Dose, Frequency, Route	Reason(s) Prescribed
1.		
2.		
3.		
4.		
5.		
6.		
7.		
8.		
9.		
10.		

Total No. of Medications: (If 0, skip to Sensory Function) Total No. of Tranquilizer/Psychotropic Drugs: ________

Do you have any problems with medicine(s)…?

No 0 Yes 1

______ ________ Adverse reactions/allergies

______ ________ Cost of medication

______ ________ Getting to the pharmacy

______ ________ Taking them as instructed/prescribed

______ ________ Understanding directions/schedule

How do you take your medications?

________ Without assistance 0

________ Administered/monitored by lay person 1

________ Administered/monitored by professional nursing staff 2

Describe help: ______________________

Name of helper: ______________________

Diagnoses:
Alcoholism/Substance Abuse (01)
Blood-Related Problems (02)
Cancer (03) Cardiovascular Problems
Circulation (04)
Heart Trouble (05)
High Blood Pressure (06)
Other Cardiovascular Problems (07) Dementia
Alzheimer's (08)
Non-Alzheimer's (09) Developmental Disabilities
Mental Retardation (10) Related Conditions
Autism (11)
Cerebral Palsy (12)
Epilepsy (13)
Friedreich'a Ataxia (14)
Multiple Scierosis (15)
Muscular Dystrophy (16)
Spina Bifida (17)
Digestive/Liver/Gall Bladder (18) Endocrine (Gland)Problems
Diabetes (19)
Other Endocrine Problem (20) Eye Disorders (21)
Immune System Disorders (22)
Muscular/Skeletal
Arthritis/Rheumatoid Arthritis (23)
Osteoporosis (24)
Other Muscular/Skeletal Problems (25)
Neurological Problems Brian Trauma/Injury (26) Spinal Cord Injury (27) Stroke (28)
Other Neurological Problems (29) Psychiatric Problems
Anxiety Disorder (30)
Bipolar (31)
Major Depression (32)
Personality Disorder (33)
Schizophrenia (34)
Other Psychiatric Problems (35) Respiratory Problems
Black Lung (36)
COPD (37)
Pneumonia (38)
Other Respiratory Problems (39)
Urinary/Reproductive Problems
Renal Failure (40)
Other Urinary /Reproductive (41) All Other Problems (42)

Sensory Functions

How is your vision, hearing, and speech?

	No Impairment $_0$	Impairment *Record Date of Onset/Type of Impairment*		Complete Loss $_3$	Date of Last Exam
		Compensation $_1$	No Compensation $_2$		
Vision					
Hearing					
Speech					

Physical Status

Joint Motion: How is your ability to move your arms, fingers, and legs?

Within normal limits or instability corrected $_0$

________ Limited motion $_1$

________ Instability uncorrected or immobile $_2$

Have you ever broken or dislocated any bones … Ever had an amputation or lost any limbs … Lost voluntary movement of any part of your body?

Fractures/Dislocations	Missing Limbs	Paralysis/Paresis
None 000	None 000	______ None 000
Hip Fracture 1	Finger(s)/Toe(s) 1	______ Partial 1
Other Broken Bone(s) 2	Arm(s) 2	______ Total 2
Dislocation(s) 3	Leg(s) 3	Describe: ____________
Combination 4	Combination 4	
Previous Rehab Program?	Previous Rehab Program?	Previous Rehab Program?
No/Not Completed 1	No/Not Completed 1	________ No/Not Completed 1
Yes 2	Yes 2	________ Yes 2
Date of Fracture/Dislocation?	Date of Amputation?	Onset of Paralysis?
1 Year or Less 1	1 Year or Less 1	________ 1 Year or Less 1
________ More than 1 Year 2	________ More than 1 Year 2	________ More than 1 Year 2

Nutrition

Height: Weight: Recent Weight Gain/Loss: No $_0$ Yes $_1$

(Inches) (lbs.) Describe: _____

Are you on any special diet(s) for medical reasons?

________ None 0

________ Low Fat/Cholesterol 1

________ No/Low Salt 2

________ No/Low Sugar 3

________ Combination/Other 4

Do you take dietary supplements?

________ None 0

________ Occasionally 1

________ Daily, Not Primary Source 2

________ Daily, Primary Source 3

________ Daily, Sole Source 4

Do you have any problems that make it hard to eat?

No $_0$	Yes $_1$	
________	________	Food Allergies
________	________	Inadequate Food/Fluid Intake
________	________	Nausea/Vomiting/Diarrhea
________	________	Problems Eating Certain Foods
________	________	Problems Following Special Diets
________	________	Problems Swallowing
________	________	Taste Problems
________	________	Tooth or Mouth Problems
________	Other: ____________	

Current Medical Services

Rehabilitation Therapies: Do you get any therapy prescribed by a doctor, such as…?

No 0	Yes 1		*Frequency*
____	____	Occupational	
____	____	Physical	
____	____	Reality/Remotivation	
____	____	Respiratory	
____	____	Speech	
____	____	Other	

Do you have pressure ulcers?

		Location/Size
____	None 0	
____	Stage I 1	____
____	Stage II 2	____
____	Stage III 3	____
____	Stage IV 4	____

Special Medical Procedures: Do you receive any special nursing care, such as …?

No 0	Yes 1		*Site, Type, Frequency*
____	____	Bowel/Bladder Training	
____	____	Dialysis	
____	____	Dressing/Wound Care	
____	____	Eye care	
____	____	Glucose/Blood Sugar	
____	____	Injections/IV Therapy	
____	____	Oxygen	
____	____	Radiation/Chemotherapy	
____	____	Restraints (Physical/Chemical)	
____	____	ROM Exercise	
____	____	Trach Care/Suctioning	
____	____	Ventilator	
____	____	Other:	____

Medical/Nursing Needs

Based on client's overall condition, assessor should evaluate medical and/or nursing needs.

Are there ongoing medical/nursing needs? ____ No 0 ____ Yes 1

If yes, describe ongoing medical/nursing needs:

Evidence of medical instability.
Need for observation/assessment to prevent destabilization.
Complexity created by multiple medical conditions.
Why client's condition requires a physician, RN, or trained nurse's aide to oversee care on a daily basis.

Comments:

PSYCHO-SOCIAL ASSESSMENT

Cognitive Function

Orientation *(Note: Information in italics is optional and can be used to give a MMSE Score in the box to the right.)*

Person: Please tell me your full name (so that I can make sure our record is correct).
Place: Where are we now (*state, county, town, street/route number, street name/box number*)? *Give the client 1 point for each correct response.*
Time: Would you tell me the date today *(year, season, date, day, month)*?

Optional: MMSE Score
(5)
(5)

_____ Ori ented 0 Spheres affected: ____________
_____ Dis oriented – Some spheres, some of the time 1 ____________
_____ Dis oriented – Some spheres, all the time 2
_____ Dis oriented – All spheres, some of the time 3
_____ Dis oriented – All spheres, all of the time 4
_____ Co matose 5

Recall/Memory/Judgment

Recall: I am going to say three words. And I want you to repeat them after I am done (House, Bus,Dog). * Ask the client to repeat them. *Give the client 1 point for each correct response on the first trial.* * Repeat up to 6 trials until client can name all 3 words. Tell the client to hold them in his mind because you will ask him again in a minute or so what they are.

(3)

Attention/
Concentration: *Spell the word "WORLD". Then ask the client to spell it backwards. Give 1 point for each correctly placed letter (DLROW).*

(5)

Short-Term: * Ask the client to recall the 3 words he was to remember.

Total:

Long-Term: When were you born (What is your date of birth)?

Judgment: If you needed help at night, what would you do?

Note: Score of 14 or below implies cognitive impairment.

No 0	Yes 1	
_____	_____	Short-Term Memory Loss?
_____	_____	Long-Term Memory Loss?
_____	_____	Judgment Problems?

Behavior Pattern

Does the client ever wander without purpose (trespass, get lost, go into traffic, etc…) or become agitated and abusive?

Appropriate 0
Wandering/Passive – Less than weekly 1
Wandering/Passive – Weekly or more 2
Abusive/Aggressive/Disruptive – Less than weekly 3
Abusive/Aggressive/Disruptive – Weekly or more 4
Comatose 5

Type of inappropriate behavior: _________ Source of Information: _______

Life Stressors

Are there any stressful events that currently affect your life, such as …?

No 0	Yes 1		No 0	Yes 1		No 0	Yes 1	
_____	_____	Change in work/employment	_____	_____	Financial problems	_____	_____	Victim of a crime
_____	_____	Death of someone close	_____	_____	Major illness- family/friend	_____	_____	Failing health
_____	_____	Family conflict	_____	_____	Recent move/relocation	_____	_____	Other: ____________

Emotional Status					
In the past month, how often did you …?	Rarely/ Never 0	Some of the Time 1	Often 2	Most of the Time 3	Unable to Assess 9
Feel anxious or worry constantly about things?					
Feel irritable, have crying spells or get upset over little things?					
Feel alone and that you don't have anyone to talk to?					
Feel like you didn't want to be around other people?					
Feel afraid that something bad was going to happen to you and/or feel that others were trying to take things from you or trying to harm you?					
Feel sad or hopeless?					
Feel that life is not worth living … or think of taking your life?					
See or hear things that other people did not see or hear?					
Believe that you have special powers that others do not have?					
Have problems falling or staying asleep?					
Have problems with your appetite … that is, eat too much or too little?					

Comments:

Social Status

Are there some things that you do that you especially enjoy?

No 0   Yes 1   *Describe*

_________ _________ Solitary Activities, _________

_________ _________ With Friends/Family, _________

_________ _________ With Groups/Clubs, _________

_________ _________ Religious Activities, _________

How often do you talk with your children family or friends either during a visit or over the phone?

Children	Other Family	Friends/ Neighbors
_________ No Children 0	_________ No Other Family 0	_________ No Friends/Neighbors 0
_________ Daily 1	_________ Daily 1	_________ Daily 1
_________ Weekly 2	_________ Weekly 2	_________ Weekly 2
_________ Monthly 3	_________ Monthly 3	_________ Monthly 3
_________ Less than Monthly 4	_________ Less than Monthly 4	_________ Less than Monthly 4
_________ Never 5	_________ Never 5	_________ Never 5

Are you satisfied with how often you see or hear from your children other family and/or friends?

_________ No 0   _________ Yes 1

Hospitalization/Alcohol – Drug Use

Have you been hospitalized or received inpatient/outpatient treatment in the last 2 years for nerves emotional/mental health alcohol or substance abuse problems?

No $_0$ ________ Yes $_1$ ________

Name of Place	Admit Date	Length of stay/Reason

Do (did) you ever drink alcoholic beverages?

________ Never 0

________ At one time, but no longer 1

________ Currently 2

How much: ________

How often: ________

Do (did) you ever use non-prescription, mood altering substances?

________ Never 0

________ At one time, but no longer 1

________ Currently 2

How much: ________

How often: ________

If the client has never used alcohol or other non-prescription, mood altering substances, skip to the tobacco question.

Have you, or someone close to you, ever been concerned about your use of alcohol/other mood altering substances?	Do (did) you ever use alcohol/other mood-altering substances with …	Do (did) you ever use alcohol/other mood-altering substances to help you …
No $_0$ Yes $_1$ ______ ________ Describe concerns:	No $_0$ Yes $_1$ ______ ________ Prescription drugs? ______ ________ OTC medicine? ______ ________ Other substances? Describe what and how often:	No $_0$ Yes $_1$ ______ ________ Sleep? ______ ________ Relax? ______ ________ Get more energy? ______ ________ Relieve worries? ______ ________ Relieve physical pain? Describe what and how often:

Do (did) you ever smoke or use tobacco products?

________ Never 0

________ At one time, but no longer 1

________ Currently 2

How much: _______

How often: _______

Is there anything we have not talked about that you would like to discuss?

Assessment Summary

Indicators of Adult Abuse and Neglect: While completing the assessment, if you suspect abuse, neglect or exploitation, you are required by Virginia law, Section 63.1- 55.3, to report this to the Department of Social Services, Adult Protective Services.

Caregiver Assessment

Does the client have an informal caregiver?

________ No $_0$ (Skip to Section on Preferences) Yes $_1$ ________

Where does the caregiver live?

________ With client 0
________ Separate residence, close proximity 1
________ Separate residence, over 1 hour away 2

Is the caregiver's help …

________ Adequate to meet the client's needs? 0
________ Not adequate to meet the client's needs? 1

Has providing care to client become a burden for the caregiver?

________ Not at all 0
________ Somewhat 1
________ Very much 2

Describe any problems with continued caregiving:

Preferences

Client's preference for receiving needed care:

Family/Representative's preference for client's care:

Physician's comments (if applicable):

Client Case Summary

Unmet Needs

No 0	Yes 1	(Check All That Apply)	No 0	Yes 1	(Check All That Apply)
		Finances			Assistive Devices/Medical Equipment
		Home/Physical Environment			Medical Care/Health
		ADLS			Nutrition
		IADLS			Cognitive/Emotional
		Caregiver Support			

Assessment Completed By:

Assessor's Name	Signature	Agency/Provider Name	Provider #	Section(s) Completed

Optional: **Case assigned to: ____________________** **Code #:**

Appendix B: Non-disclosure Agreement between Virginia Department for Aging and Rehabilitative Services and Virginia Commonwealth University

DEPARTMENT FOR AGING AND REHABILITATIVE SERVICES 8004 FRANKLIN FARMS DRIVE
HENRICO, VA 23229

NON-DISCLOSURE AGREEMENT FOR NO WRONG DOOR (NWD)

This **AGREEMENT** is made effective as of the 7th day of April 2020, by and between No Wrong Door (NWD) on behalf of the **Commonwealth of Virginia (the "Commonwealth")** and its contractor Virginia Commonwealth University **("the Contractor")**.

WHEREAS, the Commonwealth is the owner of confidential and proprietary information and other information ("Confidential Information"). "Confidential Information" for purposes of this agreement shall include all data, materials, products, technology, computer programs, specifications, manuals, business plans, software, marketing plans, financial information, statistical information, technical or test data, scientific data, graphic communication, "know-how," drawings, electronic and other information disclosed or submitted, orally, in writing, or by any other media which is in the possession of the Commonwealth or developed by the Commonwealth. All Confidential Information disclosed in tangible form shall be clearly marked or otherwise identified in writing as confidential; Confidential Information disclosed orally or in other non-tangible form shall be identified as confidential at the time of disclosure and summarized in writing within fifteen (15) days thereafter.

WHEREAS, the Commonwealth has entered into an agreement with Virginia Commonwealth University for the Project. The Project is defined as follows: DARS is engaging with VCU to conduct research that is specific to a social isolation risk index, which is a part of our No Wrong Door Business Case Development grant with the Administration for Community Living. The purpose of the agreement is to allow VCU to conduct a multi-factorial analysis of social connectedness among older adults in Virginia by analyzing Uniform Assessment Instrument data collected by Area Agencies on Aging.
The Project will require and encompass the compilation and exchange of confidential and proprietary information among the employees and the Contractor who are assigned to the Project.

WHEREAS, both parties to the Agreement consider the compilation of exchange of such confidential and proprietary information to be necessary and desirable for the purpose of the Project and/or other related activities; and

WHEREAS, this Agreement is being entered into by and between the parties in order to protect the confidentiality and non-disclosure of Confidential Information by all employees and/or contractors assigned to the Project.

NOW, THEREFORE, the parties agree as follows:

The Contractor agrees that the Confidential Information is to be considered confidential and proprietary to the Commonwealth and the Contractor shall hold same in confidence, shall not use the Confidential

Information other than for purposes of the Project, and shall disclose it only to the Project's other employees or contractors with a specific need to know. The Contractor shall not disclose, publish, or otherwise reveal any of the Confidential Information received from the Commonwealth or the Project to any party whatsoever except with the specific prior written authorization of the No Wrong Door Director.

Confidential Information furnished in tangible form shall not be duplicated by the Contractor except for purposes of this Agreement. Upon the request of the Commonwealth, or the No Wrong Door Director, or his or her designee, the Contractor shall return all Confidential Information received in written or tangible form, including copies, or reproductions, or other media containing such Confidential Information, within five (5) days of such request.

The Contractor shall not, without specific prior written authorization of the No Wrong Door Director, or his or her designee or the designated Project Manager, remove any Confidential Information from No Wrong Door.

TERM: The obligations of the Contractor under this Confidentiality Agreement shall be effective from the date of this Agreement or the date the Contractor is assigned to the Project, whichever is earlier, until **two (2)** years from the date first entered herein below.

Any obligation of the Contractor as set forth above shall not apply to any Confidential Information, knowledge, data, and/or know-how which:

Can be demonstrated to have been known to the Contractor prior to the execution of this Agreement and was not acquired, directly or indirectly, from the Commonwealth or from a third party under a continuing obligation of confidentiality;
Is or becomes publicly known without the wrongful act or breach of this Agreement by the Contractor;
Is rightfully received by the Contractor from a third party on a non-confidential basis;
Is subsequently and independently developed by others who had no knowledge of the Confidential Information;
Was approved for release by written authorization of the No Wrong Door Director, or by his or her designee;
Is required to be disclosed by law or judicial action;
Was in the public domain or becomes part of the public domain through no fault of the Contractor.

NO LICENSE: Nothing contained herein shall be construed as granting or conferringany rights by license or otherwise in any Confidential Information.

GOVERNING LAW AND EQUITABLE RELIEF: This Agreement shall be governed and construed in accordance with the laws of the United States and the Commonwealth of Virginia and Contractor consents to the exclusive jurisdiction of Richmond, Virginia for any dispute arising out of this Agreement. Contractor agrees and understands that in the event of any breach or threatened breach of this Agreement, the Commonwealth may seek, in addition to any other legal remedies which may be available, such equitable relief as may be necessary to protect the Commonwealth against any such breach or threatened breach.

BREACH OF AGREEMENT MAY RESULT IN DISMISSAL OR PERSONNEL ACTION: Any Contractor of the Commonwealth who is assigned to the Project and is a party to this Agreement will be immediately dismissed from the Project in the event of any breach of this Agreement by the Contractor.

FINAL AGREEMENT: This Agreement may be modified only by a further writing that is duly executed by both parties.

remain in full force and effect as if such invalid or unenforceable term had never been included.

PUBLICITY: Neither party may use the other party's name or company artwork on a website or in any form of advertising, promotion, or publicity, including press releases, without the prior written consent of the other party. Notwithstanding the foregoing, the parties agree that in order to satisfy its internal, governmental or Conflict of Interest obligations, the Contractor may document this agreement internally as it does other agreements in the normal course of business, and it may identify the Commonwealth, a brief title, and the nature of the Agreement to governmental entities for reporting purposes.

NOTICES: Any notice required by this Agreement or given in connection with it or required by law, shall be in writing and shall be given to the appropriate party by personal delivery or by certified mail, postage prepaid, or recognized overnight delivery services.

If to the Commonwealth: No Wrong Door
Department for Aging and Rehabilitative Services 1610 Forest Avenue, Suite 100
Henrico, VA 23229

If to the Contractor: Virginia Commonwealth University Office of Sponsored Programs
800 E. Leigh Street, Suite 3200
Richmond, VA 23219

IN WITNESS WHEREOF, the parties have executed this Agreement effective as of the date written above.

COMMONWEALTH OF VIRGINIA: CONTRACTOR:

DocuSigned by:
Tina L. Cunningham
30E7A1F4C8DA44E...

Tina L. Cunningham

Sara Link
No Wrong Door Director

AVP for Sponsored Programs

Appendix C: Data Sharing Agreement Between Virginia Commonwealth University and Virginia Department for Aging and Rehabilitative Services

DEPARTMENT FOR AGING AND REHABILITATIVE SERVICES 8004 FRANKLIN FARMS DRIVE
HENRICO, VIRGINIA 23229

DATA SHARING AGREEMENT FOR NO WRONG DOOR (NWD)

This agreement establishes the terms and conditions under which No Wrong Door {NWD) and Virginia Commonwealth University (VCU) can acquire and use data from the other party. Either party may be a provider of data to the ot her, or a recipient of data from the other. Attachment A reflects what data is to be shared and the following agreement will apply to all the data elements reflected in At t achment A.

1. The confidentiality of data pertaining to individuals will be protected as follows:
   a. The data recipient will not release t he names of individuals, or information that could be linked to an individual, nor will the recipient present the results of data analysis (including maps) in any manner that would reveal the identity of individuals.
   b. The data recipient will not release individual addresses, nor will the recipient present the results of data analysis (including maps) in any manner that would reveal individual addresses.
   c. Both parties shall comply with all Federal and State laws and regulations governing the confidentiality of the information that is the subject of thisAgreement .
2. The data recipient will not release data to a third party without prior approval from the dat a provider.

The data recipient will not share, publish, or otherwise release any findings or conclusions derived from analysis of data obtained from the data provider without prior approval from the data provider. However, VCU may use this information for disseminat ion and publication in support of academic dissertations so long as it does not include published Personal Health Information (PHI) or Personal Identifying Information (PII).

Data transferred pursuant to the terms of this Agreement shall be utili zed solely for the purposes set fort h.

All data shared with VCU by NWD shall remain the property of NWD and shall be returned to NWD or destroyed upon termination of this Agreement.

Any third party granted access to data, as permitted under condition #2, above, shall be subject to the terms and conditions of this agreem ent. Acceptance of these terms must be provided in writing by the third party before data will be released.

IN WITNESS WHEREOF, both the Virginia Depart m ent for Aging and Rehabilitative Services, through its duly authorized representative, and VCU, through its duly authorized representative, have here unto executed this Data Sharing Agreement as of the last date below written.

Attachment A

DARS is engaging with VCU, Department of Gerontology, to conduct research that is specific to a social isolation risk index, which is a part of the Department for Aging and Rehabilitative Services' (DARS) No Wrong Door Business Case Development grant with the Administration for Community Living.

Purpose of the agreement

The purpose of the agreement is to allow VCU Gerontology to conduct a multi-factorial analysis of social connectedness among older adults in Virginia by analyzing Uniform Assessment Instrument data collected by Area Agencies on Aging.

Scope

The scope would include first time UAI assessments completed between calendar years 2013 - 2019, where the full part A is completed.

What information is being disclosed and collected and the purpose{s) of each

There are 5 specific research questions that will examine social connectedness from a sod-ecological perspective. Each question will build a model that looks at how 3-5 different variables predict social connectedness. The variables come from the different sections of the UAI - demographics, physical environment, social status, emotional status, financial status, current formal services, benefits, and caregiver assessment. Each research question will control for age, gender, educational level, and race. Additionally, VCU will develop a composite, continuous social connectedness variable comprised of [potentially] many UAI data elements that represent the structural, functional, and quality components of social connectedness

The frequency and duration of information exchanged

A one-time extraction. The data will not be aggregated, but it will not include identifying information [name, birthdate, address, insurance numbers etc.] Age will be requested, however, VCU would ask [per IRB suggest ion) that all records where age is 89 or older be tagged as 89+ rather than actual age in order to de-identify. In a pre-study consult with IRB, the staff reviewer suggested that the IRB
level may be exempt because no identifying information will be exchanged.

Appendix D: Gigi Amateau CV

(This page left intentionally blank for formatting purposes. Gigi Amateau's CV follows on the next page.)

gigi **amateau**

EDUCATION|TRAINING

PhD HEALTH-RELATED SCIENCE
Virginia Commonwealth University
(2021 expected)

MASTER OF SCIENCE / GERONTOLOGY
Virginia Commonwealth University
May, 2018, GPA 4.0

Personal Care Aide Certification
February, 2018

RYT-200 YOGA INSTRUCTOR
Glenmore Yoga/Yoga Alliance
October, 2016

BACHELOR OF SCIENCE / URBAN
PLANNING

RECOGNITION

BEST DATA INSIGHT AWARD
2019, Homeward

PAT ASCH SOCIAL JUSTICE
FELLOWSHIP
2017, YWCA Richmond

A SOUTHERNER OF THE YEAR
2017, *Southern Living*

YAVA Award
2015, Richmond Public Library

PEOPLE'S CHOICE AWARD: FICTION
2013, Library of Virginia

THERESA POLLAK EXCELLENCE IN

EXPERIENCE

VIRGINIA DEPARTMENT FOR AGING AND REHABILITATIVE SERVICES | Policy & Planning Specialist II
11/2018 – present

- Wrote $1.1 million federal grant from ACL to coordinate No Wrong Door's COVID-19 response
- Wrote $1.2 million federal grant from the Administration for Community Living (ACL) to develop business case and return on investment calculators for No Wrong Door Virginia
- Manage technology projects for self-referral, consumer-directed services, and return on investment calculators
- Facilitate data and business case workgroups comprised of local area agencies on aging staff

VCU DEPARTMENT OF GERONTOLOGY Director of Research & Evaluation|Instructor|Research Coordinator|Teaching Assistant
03/2017 - present

- Wrote and coordinated $65,000 Civil Monetary Penalty grant for Person-Centered Trauma-Informed Care:
  - Developed and delivered person-Centered, trauma-informed care training for 388 nursing facility administrators and interdisciplinary staff in Virginia and the northwest region of the U.S.
  - Conducted focus groups with certified nursing assistants working in Virginia nursing facilities
  - Trained 58 certified nursing assistants on trauma and resilience across the lifespan
- Co-instructor, GRTY 606: Aging and Human Values & GRTY 604: Trends in Gerontology
- Co-developed continuing education curricula for navigating loss, trauma-informed care, person-centered care, social connectedness, and narrative gerontology

LONGEVITY PROJECT | Director of Grants & Research
07/2017-present

- Developed and delivered cross-sector, person-centered training for service providers
- Generated $200,000+ in grant funding from regional and national private sector funders
- Co-designed health equity collaborative ($60,000 grant)

EXPERIENCE (continued)

FAMILY LIFELINE| Personal care aide/collaborating artist

02/2018 – 03/2020

- Provided home care and support with activities of daily living for older adults
- Wrote $20,000 Health Equity in the Arts grant to conduct a health and wellness photo-narrative project with direct care providers
- Facilitated a narrative group of nine direct care providers using narrative medicine approach
- Co-designed a photo-narrative exhibit: *Stretching My Hands Out: A celebration of direct care providers*
- Co-developed project website: www.stretchingmyhandsout.com

UNITED WAY | Chief Impact Officer

02/2015-12/2016

Managed 13-person team, $1.6M department budget, $4.2M grantee portfolio, liaison to Board committees

- Co-designed and implemented community impact funding model
- Built system-level partnerships through collaboration
- Led community impact agenda related to adverse childhood experiences (ACEs) across the lifespan and social isolation and social connectedness for older adults

UNITED WAY | Director of Community Impact: Health

02/2014-01/2015

- Managed $935,000 grantee portfolio toward goal of eliminating social isolation for older adults
- Representative to Greater Richmond Age Wave Leadership and No Wrong Door Advisory Council
- Organized *Come Together* a one-day summit related to social isolation and social connectedness
- Provided technical assistance on outcomes, evaluation, and budgeting to 30 non-profit agencies

RTZ Associates | Product Manager: GetCare

Oakland, CA (remote) 06/2008-01/2014

Managed long-term care case management application and provided technical assistance to Aging and Disability Resource Centers (ADRCs) around the U.S. and territories

- Defined product roadmap based on the strategy and vision, managed prioritization and trade-offs among customer experience, site performance, and operational support load
- Led product innovation and development priorities. Gathered and refined all product development business requirements.
- Provided technical assistance, training, and consultation to state, regional, and local ADRC projects in Arizona, Guam, Kansas, Los Angeles County, Maryland, Mississippi, New York, Oregon, San Francisco County, Washington
- Areas of emphasis included inventory and indexing of long-term support services and development of online consumer content related to aging and disability services, health care, wellness, and caregiving

UNITED WAY| Grants Administrator

01/2003-06/2005

- Managed $3M+ in public and private sector grants
- Wrote $1M early literacy grant to U.S. Health and Human Services Department
- Secured $1M+ in privation foundation, corporate, and local government funding for re-engineering of homeless services system

EXPERIENCE (continued)

SENIORNAVIGATOR | Director of Product Development/Consultant
01/2000-5/2008

- Managed 5-person product development team
- Developed statewide database to adhere to AIRS standards
- Recommended product modifications and improvements based on market research, benchmarks, and process analysis
- Analyzed industry trends in health and human services, information and referral, health care, elder care and Internet business models
- Authored federal government and private foundation grants totaling $2.5M to implement Virginia's state-wide ADRC: No Wrong Door

UNITED WAY| Assistant Vice-President, Community Resources
01/1998-12/1999
Managed division with $800,000 budget, 17-person team and 5 programs, including: information and referral center, 2 Retired and Senior Volunteer Programs, volunteer center, and financial aid clearinghouse

UNITED WAY| Director of Community Initiatives
07/1995-06/12/1997
Program officer for basic needs, older adult services, and youth services impact areas

- Managed grant portfolio of $3M and 4 volunteer councils
- Managed project start-up and $250,000 for Homeward, liaison to Board
- Author, *1998 Greater Richmond Continuum of Care: Plan for Homeless Services for City of Richmond and Counties of Chesterfield and Henrico* ($2.4 M) and process facilitator
- Co-author*, 1997 Greater Richmond Continuum of Care: Plan for Homeless Services for City of Richmond and Counties of Chesterfield and Henrico ($1.6M)*

VIRGINIA DEPARTMENT OF SOCIAL SERVICES | Human Services Program Coordinator
Richmond 06/1994-06/1995
Administered $400,000 in federal and state funds through the Dependent Care Planning and Development Grant and the Virginia Day Care Grant for Children of Migrant and Seasonal Workers

RICHMOND AIDS MINISTRY | Development Director
Richmond 05/1992-05/1994
Managed development, marketing, and public relations strategies

CHESTERFIELD COUNTY OFFICE ON YOUTH | Assistant to Director
Chesterfield 04/1991-04/1992
Co-authored county-wide youth needs assessment

VIRGINIA INTERFAITH CENTER FOR PUBLIC POLICY| Associate Director/Program Associate/Research Assistant

RESEARCH INTERESTS

Managed day-to-day agency operations, prepared legislative agenda, and monitored legislation

person-centered trauma-informed care • social connection • narrative practices • resilience across the lifespan • well-being of the direct care workforce