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# Social infrastructure and health among mid-life and older adults in rural America: An environmental scan of existing data

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## Abstract

Growing evidence shows a relationship between social infrastructure (SI) – the physical places where people gather outside of home and work – and health. However, existing data sources for rigorously investigating this relationship are limited, especially for rural areas. Therefore, we conducted an environmental scan of existing data for furthering research on this topic, with a focus on the rural United States (U.S.). A total of 10 datasets met inclusion criteria. Key information was collated from websites and reviewed by data administrators. We summarize key features of these datasets, including available measures of geography/rurality, SI availability and utilization, and physical, mental and social health. We describe analytic strengths and weaknesses of the available data, which is essential for researchers to be able to assess their data options. While the scan



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CRediT authorship contribution statement

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author CRediT statement

All authors contributed to the conceptualization, data curation, writing and editing of the article. Rhubart oversaw project administration for this paper. All authors have reviewed and approve of the final version provided here.

Supplementary materials

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focuses on U.S.-based data, the key points will be applicable more broadly, including a need for more data on availability and use of social infrastructure combined with geographic indicators.

**Keywords**

Social infrastructure; Health; Rural

## 1. Introduction

Growing research demonstrates a link between social infrastructure (SI), or the physical places in a community where people can interact, share information, and build and maintain relationships (e.g. community centers, coffee shops, diners, and libraries) and health among mid-life and older adults. While research on SI and health is growing, it has been limited in two important and related ways. First, data on SI – and particularly SI use – that include or can be linked to health data are limited. Second, much of the research on SI and health among mid-life and older adults focuses on urban settings [1–2], which limits our understanding of whether and how SI matters for physical, mental, and social health among mid-life and older adults in rural settings. Understanding the landscape of data availability, especially with attention to rural contexts, is essential for researchers to assess their data options and to justify further data collection efforts that do not duplicate existing data on this topic.

Therefore, in this paper we conduct an environmental scan of existing public data on SI and health among adult populations in the United States (U.S.). Environmental scans are a tool used for collect information from various sources to assess the options available for studying a particular topic. In this case, we are focused on available data for studying social infrastructure and health. The environmental scan allows us to assess strengths and weaknesses as well as features that allow for rural-urban and within rural analyses. In addition to informing such research efforts in the U.S., this paper also serves as a template for similar data assessments in other countries.

Influenced by foundational pieces like “The Great Good Place” and “Palaces for the People”, SI is linked to outcomes along dimensions of social, mental, and physical health as well as health behaviors [2–8]. Some use ecological approaches focusing on availability or access to SI [1,4], while others examine individual-level use of SI [9–10]. Both are important for understanding mechanisms that might shape the relationship between SI and health among mid-life and older adults.

This research shows that by its very nature, SI facilitates interaction among adults [3]. Those interactions can take a wide variety of forms as strong and weak ties. Fast-food restaurant, parks and coffee shops, for example, can facilitate strong tie formation among older adults [5,11–12]. Libraries, barbershops, and customer-cashier relationships (i.e., commercial friendships) facilitate weak tie formation [10,13–14]. Such ties improve social health and well-being, including among older adults [2,15]. These social interactions also yield mental health benefits [9]. More ecological approaches suggest that availability of social infrastructure is linked to individual emotional support among rural Black and Hispanic older adults and improved cognitive aging among older adults [4–6]. And availability of aging-related social infrastructure is associated with higher rates of COVID-19 vaccination [7]. The literature strongly links social infrastructure to various dimensions of health among older adults and the adult population more broadly. Disentangling the mechanisms that shape these associations is critical for making policy recommendations.

While research on SI and health continues to grow, the majority of this research in the U.S. is conducted in urban settings [1–2]. It is crucial for us to understand these relationships in rural contexts. Rural areas in the U.S. have – on average – higher rates of many chronic conditions and higher suicide and overall mortality rates [16–18]. These rural health penalties are linked to a variety of multilevel factors [19]. Rural residents face specific challenges related to accessing transportation, technological connectivity, health care, and other services [20–21], and differ from urban residents in their social well-being and social activity [22–23]. Understanding the mechanisms that shape rural-urban health inequities, as well as the broader relationship between health and SI across various contexts requires multilevel data, geographic identifiers and/or rural-urban designations, measures of both health and SI, and nationally representative samples that allow for attention to spatial and contextual differences. Such data would inform meaningful national, state, and community-level strategies to better support the health of an aging rural population.

## 2. Methods

### 2.1. Environmental scan design

We conducted an environmental scan to identify existing datasets on social infrastructure and health in the U.S. Environmental scans collect data from both internal (i.e., information already known) and external (i.e., those collected for the purpose) sources to inform a topic. Increasingly, they are used in public health and health care to identify best and emerging practices [24–25]. They are helpful when researchers want to make informed decisions on an emerging topic [26]. Environmental scans allow researchers to refine their search strategy as they identify resources and support decision-making on potential next steps while providing a summary for others to build upon [27–28].

To conduct the environmental scan, we first generated a list of criteria that datasets must meet in order to be included. Inclusion criteria for all individual- and place-level datasets were as followed: data must be public (i.e., publicly available datasets that may or may not have sensitive or restricted data files) and must include information about the availability, access or utilization of in-person SI places and amenities. Inclusion criteria for place-level datasets also required that datasets must cover all places within the United States (e.g. all counties, all census tracts) and that datasets must contain geographic identifiers that can allow for data linking. Inclusion criteria for individual-level datasets required that datasets must have been collected from a nationally representative sample of people within the U.S. in the past decade (i.e., since 2014); data must include variables related to physical, mental, and/or social health; data collected from individuals must be from older adults and mid-life adults;[1] and either geographic identifiers or some measure of rurality and urbanicity is available. Fig. 1 is a visualization of the types of datasets included.

We first compiled a list of datasets that we - as authors - were aware of that met these criteria. Once we had exhausted our knowledge of existing datasets, we conducted a web search for additional datasets using the following key words: ‘social infrastructure’, ‘health’, ‘well-being’, and ‘datasets’. This resulted in 7 individual-level datasets and 3 place-level datasets being selected for inclusion.

### 2.2. Data extraction

We then used the websites and codebooks for these datasets to collect detailed information (described in Table 1). Once online resources were exhausted for documenting the key information for each dataset, the authors contacted the administrators of each dataset and asked them to review and provide edits to the information gathered. All suggested edits were incorporated. Because this review does not meet criteria for human subjects research, institutional review board approval was not required.

## 3. Results

Results are organized in alignment with the categories presented in Fig. 1. Information on original purpose of these datasets, sample sizes, and frequency of data collection, see Appendix A.

### 3.1. Individual-level datasets

Individual-level survey datasets that met our inclusion criteria include: American Time Use Survey (ATUS) [29], Americans’ Changing Lives (ACL) [30], Health and Retirement Study (HRS) [31], Loneliness and Social Connections: A National Survey of Adults 45 and Older (which we will refer to as LSC) [32], National Health and Aging Trends Study (NHATS) [33–34], National Social Life, Health, and Aging Project (NSHAP) [35], and National Study of Caregiving (NSOC) [36].

**3.1.1. Social infrastructure availability—**Of the seven individual-level datasets, only three included measures of perceived SI availability: NSHAP, ACL, and NHATS. Even still, the measures of SI availability in these three datasets were limited. The ACL survey includes measures of parks and walking trails near one’s home and the NSHAP survey has one question that asks interviewers (not participants) if they “saw many amenities (grocery stores, parks)” in the area where the respondent lives. For older adults in “non-nursing home residential care and age-restricted housing,” NHATS collects data on perceived areas for activities like walking, swimming pools or game rooms, or for organized social activities. The other four datasets did not have measures of SI availability.

**3.1.2. Social infrastructure utilization—**All the individual-level datasets included in the assessment had measures of actual SI utilization, but most had narrow foci on specific types of SI. Most surveys included questions related to attending or spending time in places of worship. In nearly all the surveys, SI utilization questions asked about activities that could be assumed to have occurred in a place of SI but were not always explicitly stated as such

[1]The authors chose to select datasets that included data for all adults ages 18 and older given that studies on aging use variable cutoffs for studying mid-life, provided that the study included people age 65 and older.

(e.g. participation in sports teams, social groups, club or committee meetings (ACL, HRS, NHATS, NSHAP, NSOC, and LSC), volunteering (all surveys except for NSOC and ATUS), attending a support group for caregivers (NSOC), or simply “getting together with friends” or “going out for fun” (NSOC, NSHAP, NHATS, and LSC)). The only exception was the ATUS, which explicitly asked for the location of activities (e.g. restaurants or bars, libraries, gyms/health clubs, or the outdoors).

**3.1.3. Individual health measures—**Table 3 presents a summary of each study’s available measures of physical, mental, and social health for the individual-level datasets. These categories are presented for summary purposes – and are not meant to be exhaustive – so that researchers can identify the utility of each dataset for their own work.

**Physical health:** We found several commonalities of physical health measures across the seven individual-level datasets. Each of the datasets includes a measure of self-rated health. All capture at least one measure of disability (e.g., activities of daily living (ADLs), cognition or memory performance, and self-reports of disability, chronic conditions, and/or pain). Several datasets (ACL, HRS, NHATS, NSHAP) have detailed measures of health behaviors (e.g., frequency of doctor visits, substance use, and sleep). Notably, HRS also has in its restricted files biomarker data, which can be used to identify specific health conditions, as well as detailed cognitive assessments, prescription drug use, and related measures.

**Mental health:** Numerous mental health measures are included in the seven individual-level datasets. In general, most have a measure of depression or depressive symptoms, and some also include reports of diagnoses of other mental health conditions. Most datasets (ATUS, ACL, HRS, NHATS, NSOC) have at least one measure related to a subjective assessment of psychological well-being, including resilience, finding meaning in life, and self-rated happiness.

**Social health:** All seven datasets captured some aspect of frequency of social contact and the nature of and/or assessment of the quality of these relationships. The ATUS provides some of the most detailed data on social health. It captures who was with respondents for each of the activities reported but does not capture what role each individual played or how vital that companionship was in carrying out each activity. The ACL and NHATS capture structural aspects of social health (e.g., measures of who survey participants spent their time with (e.g., family, friends, acquaintances)). By contrast, HRS, LSC, NSHAP, and NSOC capture both structural and functional aspects of social health. In addition to reporting who time was spent with, participants reported the importance and/or quality of these relationships and/or how they felt about their level of social contact.

**3.1.4. Opportunities for cross-data linkages and measures of rurality—**Of the seven individual-level datasets, nearly all provide sub-state geographic data that allow for cross-linkages with other data. However, for nearly all, this requires access to sensitive or restricted files. In addition, while ATUS provides core-based statistical area (CBSA) codes and county codes on the ATUS-CPS file, these are suppressed for some rural areas. LSC provides only state-level identifiers. More granular geographic identifiers are available through restricted files for the ACL, HRS, NHATS, NSHAP, and NSOC. Linking these data to other data sources with geographic identifiers requires additional layers of approval to bring external datasets into the restricted data environment.

For measures of rurality, we found considerable variability, although all seven of the datasets use participant geographic location to code them into established classification systems. The only exception to this is the LSC, which also includes a self-report question. Two datasets (ATUS, LSC) reclassify participant residences into metro/non-metro based on the Metropolitan Statistical Areas schema. NHATS and NSOC classify participants into metro/nonmetro using the 2013 Rural-Urban Continuum Codes. One dataset, the HRS, relies on the Beale Urban/Rural Codes. Finally, NSHAP relies on ZIP codes to classify counties as metro, nonmetro, or nonmetro noncore.

## 3.2. Place-level datasets

**3.2.1. Social infrastructure availability—**We also identified three place-level datasets: the U.S. Religion Census, the Public Libraries Survey (PLS), and the National Neighborhood Data Archive (NaNDA)(Table 2) [37–39]. The U.S. Religion Census and the PLS both focus on narrow types of SI. The U.S. Religion Census can be used to create county-level counts of congregations and adherents and a measure of adherents as a percent of the total county population. The PLS provides data on the number and type of programs and services offered by public libraries as well as measures of use of those programs and services. Both datasets can be used to measure the place-level availability of these two types of SI: libraries and congregations. The third database, NaNDA, is more akin to a data repository for various detailed forms of SI. ZIP code and census tract data can be downloaded for counts of religious, civic, and social organizations, social services, parks, various forms of arts, entertainment, recreational places, retail and commercial establishments, among others. NaNDA annual data - drawn from the National Establishment Time Series (NETS) - are available for as early as 2000 through 2015 and 2017 at the time of this publication.

**3.2.2. Health measures—**No health measures were included in the contextual datasets.

**3.2.3. Opportunities for cross-data linkages and measures of rurality—**All three community-level datasets we examined included at least one geographic identifier (e.g., county or tract FIPS codes, ZIP codes) on the public use files, making it possible to link them to other datasets with similar identifiers (Table 3). Only two datasets provide data on rurality (NaNDA and PLS). In both instances, they rely on multiple classification schemes. NaNDA employs multiple measures of rurality, including Urbanicity Scales and RUCA Codes. The PLS relies on the National Center for Education Statistics' local classification system and the Census Urban and Rural Area Criteria. Records are then tagged with metropolitan/micropolitan labels based on these two classification systems. The U.S. Religion Census does not include measures of rurality, but can be linked to rural classifications via geographic identifiers (Table 4).

## 4. Discussion

For research to continue to expand on the role of SI in shaping physical, mental, and social health in the aging process and be attentive to the unique experiences of rural contexts, it is critical to understand the strengths and limitations of existing data in this area. In this paper we provided an environmental scan of data available to study SI and health among mid-life and older adult populations in the United States - identifying the strengths and limitations and assessing if and how these datasets can be used to understand these relationships for rural contexts and rural people. This presentation is limited to just these three categories of measures; however, we recognize that there may be other measures of interest, particularly at the community level. Knowledge of local-level infrastructure, policy, accessibility, and built environment all may be relevant factors. In addition, individual level characteristics related to employment, education, income, and other demographic characteristics may be of interest to researchers. The information presented here does not address these additional categories of measures captured on these studies, but offers a starting point for further screening regarding utility for specific research questions. We now highlight the key strengths and gaps that exist with the current data available.

### 4.1. Key strengths of existing datasets

The data sources identified in this environmental scan each offer utility to researchers of SI and health among adults. Importantly, they all have robust methodologies and generally large sample sizes for external generalizability purposes and for rural-urban and within rural analyses. All datasets, with the exception of ATUS, have cohort designs that allow researchers to use a life course perspective in understanding the relationship between SI and health among mid-life and older adults. Across the three contextual datasets, all offer cross-sectional censuses of SI, allowing them to be linked to individual level data. There are also several advantages about measures of SI, health, and rurality in these datasets.

While SI measures were rather limited in the individual-level datasets, the time diary portion of ATUS provides the most detailed measures of where people go in their communities and with whom [40]. Regarding contextual data sources, prior to the development of the NaNDA data repository, contextual datasets that included measures of SI availability for the entire U.S. were limited in scope (e.g., often focusing just on parks or libraries). However, the wide range of SI types provided by the granular level of data (i.e., ZIP codes and census tracts) for the entire U.S. (including its territories) makes NaNDA an asset to those interested in studying or integrating SI measures into their research.

The detail and types of available health measures vary across individual-level datasets, though there are some forms of physical, mental, and social health variables available in each. This is advantageous as researchers disentangle the mechanisms through which SI shapes the interrelated dimensions of health throughout the aging process (e.g., the role of social health in explaining mental health benefits; how disability may limit use of SI and subsequent benefits) [41]. The datasets described here allow for a focus on these individual aspects of health or the inter-relationship between them. Some (e.g., HRS) offer particular strengths in capturing physical health with a combination of survey and biomarker data collection [42]. Most of the datasets for mental health include measures of psychological well-being and capture depressive symptoms. The social health measures vary the most across datasets, so researchers should consider if and how available measures capture the dimensions of social health (structural/functional, objective/subjective) that reflect the concepts being examined.

### 4.2. Gaps and limitations of existing datasets

There are significant gaps in the available data that limit researchers' ability to better understand the relationship between SI and health. First, among individual datasets that contain health and SI measures, the actual measures of SI availability and utilization are very limited (except for ATUS). The datasets included here are largely unable to answer a wide variety of questions related to how using and engaging with others in specific types of physical places in the community may shape (or is shaped by) physical, mental, and social health.

Second, apart from NaNDA and ATUS, the datasets include very narrow forms of SI. However, in rural contexts where SI is less available, these places may be highly substitutable [43]. For example, in one community it may be a coffee shop that serves as the primary place to gather and connect. In the next community it may be a diner or a pub. And still, the next community may be home to a thriving public library that acts as the gathering space for residents. To focus on just one form of SI may miss the wide array of free and low-cost places in a community and their subsequent benefits for residents. Moreover, people engage in SI in various ways. The type of SI, frequency of use, time spent, activities performed and types and length of interactions with others vary. Capturing all these features cannot currently be done with the existing public datasets.

Third, across measures of health, most rely on self-reports or self-assessments. While these measures are appropriate for population-level analyses and are predictive of premature mortality [44], it is important to note that prior research has identified validity and reliability issues with self-rated health measures [45]. More expansive health measures in surveys with SI content would help improve research opportunities on this topic. In the meantime, depending on the nature of the research, analysts may prefer HRS-sensitive health data products, which include biomarkers and detailed cognitive assessments, among others.

Fourth, a striking finding of this exercise is that in the public use files, not all individual level datasets had rural-urban designations, and none provided sub-state geographic identifiers for the entire U.S. This suggests that rural-urban and within-rural analyses on SI and health may require restricted access to data files. Granted, the sample sizes and robust methodologies behind these surveys may offset the burden of accessing restricted data. Still, the financial, time, and resource constraints associated with accessing restricted data will limit who is able to conduct this research, potentially disenfranchising under-resourced scholars, especially those in rural settings. Finally, all seven datasets rely on standard measures of rurality. While the use of standard measures increases the reliability when examining rural groups in these datasets [46], the use of the self-report measure of rurality and urbanicity in the LSC dataset may prove useful for some research questions, especially if rural identity is important to the research question [47].

Fifth, some of the individual datasets only provide county-level identifiers in restricted files. This unit of analysis is often too large to capture actual community boundaries. This limits our ability to disentangle the relationship between SI availability and individual-level health, especially in large rural counties. Large geographies such as counties may not match the symbolic boundaries of their residents. However, they do represent geographies of jurisdictional power and resource allocation and often have the benefit of having a great deal of demographic and economic data at this level [48–49]. While NaNDA does provide smaller units of analyses (i.e., census tracts and ZIP codes), rural researchers rarely have access to sub-county level identifiers for individual health data – limiting their ability to take full advantage of the contextual data resource. As we try to understand the impact of SI on health, there is a need to balance the precision of geography/community with the availability of SI measures.

## 5. Conclusion

Our understanding of how mid-life and older adult health is shaped by the built environment is constantly expanding. The role of SI holds promise for its potential to influence social, mental, and physical health. Understanding these relationships in rural contexts is particularly important as we continue to understand the causes of rural health penalties as well as the meso-level protective factors. Measurement of SI opens an opportunity to understand mechanisms and inform interventions. Accounting for the strengths and limitations of current datasets on health and SI helps researchers assess their options and provides a foundation for future data collection efforts. This environmental scan also serves as a template for similar data assessments in other countries. The need for such data – and subsequent research – is urgent. While there is growing recognition of the importance of SI for health among mid-life and older adults, policies and programs will lag without clear information on geographic and contextual differences in access to and use of SI.

## Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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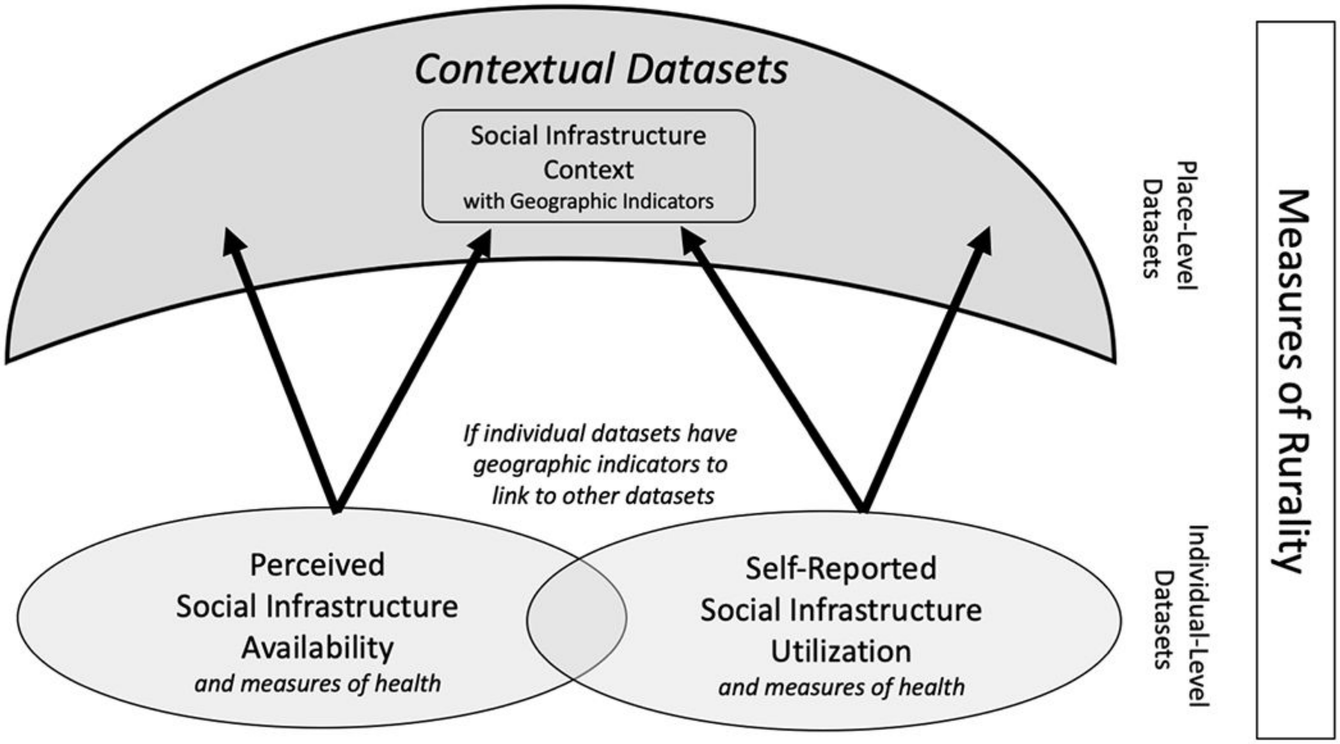


**Fig. 1.**
Visualization of criteria used in the environmental scan.

**Table 1**

Key information collected on datasets.

| Data Description | Measuring Rurality | Social Infrastructure Variables | Health Related Variables |
|---|---|---|---|
| Focus of the study<br>Frequency of data collection<br>Whether data collection is active<br>Participant sampling method<br>Sample size<br>Agency/funder | Whether geographic identifiers are available<br>Rural/Urban identifiers | Social infrastructure availability<br>Social infrastructure utilization | Physical Health<br>Mental Health<br>Social Health |

**Table 2**

Social infrastructure availability and utilization measures across individual- and place-level datasets.

| | | Social infrastructure | |
|---|---|---|---|
| | **Name of Data Source** | **Availability** | **Utilization** |
| Unit of Analysis: Individual | American Time Use Survey (ATUS) | None | In the time diary portion, survey respondents report activities they did, including where and who they were with for these activities. Place options include (but are not limited to) a restaurant or bar, places of worship, a store, a school, a library, a gym/health club, a post office, outdoors, etc. |
| | Americans' Changing Lives (ACL) | Availability of parks or walking trails close to the respondent's home | Frequency of volunteer work, going to church or other religious institution, participation in political groups or labor unions, and senior citizen clubs. |
| | Health and Retirement Study (HRS) | None | Frequency of volunteer work, participation in sports or clubs, attendance at meetings, and time spent on a regular day doing various activities. |
| | Loneliness and Social Connections (LSC): A National Survey of Adults 45 and Older | None | Frequency of going to church or other places of worship, volunteer work, participation in local clubs and social groups, socializing; activities performed when feeling lonely |
| | National Health & Aging Trends Study (NHATS) | For older adults in non-nursing home residential care and age-restricted housing beginning in round 5: areas to walk for pleasure or exercise like an outdoor walking path; other recreational facilities, like swimming pools, game rooms, or tennis courts, for residents; organized social events and activities | Participation and barriers in valued activities, such as social activities, clubs, classes, going out for fun, volunteer work, and religious services. |
| | National Social Life, Health, and Aging Project (NSHAP) | Interviewers' observations of neighborhood amenities | Frequency of volunteer work, attendance at organized group meetings (e.g., choir, committee, sports team, etc.), getting together with friends |
| | National Study of Caregiving (NSOC) | None | Attendance of social support groups with other caregivers. See "Participation" section" for relevant items (e.g., attending religious services, club meetings, group activities, going out for fun) |
| Unit of Analysis: Place | National Neighborhood Data Archive (NaNDA) | Wide variety of measures, including - but not limited to: retail, restaurants, schools, informal gathering places, arts, entertainment, parks, religious, civic and social organizations, arts, entertainment, recreation, and social service organizations. | None |
| | U.S. Religion Census | Number of congregations in each county | Number of adherents and adherents as % of the total county population |
| | Public Libraries Survey | Size of population area served and hours open to the public, number and type of programs and services available to patrons, such as Wi-Fi and Internet computer. | Libraries are asked to report annual visits, registered users, annual circulation, hours open, etc. |

**Table 3**

Individual health measures across individual- and place-level datasets.

| | | Well-Being & Health | | |
|---|---|---|---|---|
| | **Name of Data Source** | **Social Health** | **Mental Health** | **Physical Health** |
| Unit of Analysis: Individual | American Time Use Survey (ATUS) | Time spent alone and with others. For activities other than personal care activities, interviewers also ask who was with them. (Well-being Module) | Measures of happiness, sadness, and stress experienced during three activities randomly selected from the respondent's diary (Well-being Module) | Measure of pain and tiredness felt during three activities selected from the respondent's diary (Well-being Module). Disability is available on the ATUS-CPS file. Self-rated health is available in some modules but not the core ATUS |
| | Americans' Changing Lives (ACL) | Social interaction, interpersonal relationships, frequency of contact | Psychological Wellbeing Scale | Self-rated health, functional health, substance use, doctor visits; ADL measures; chronic conditions |
| | Health and Retirement Study (HRS) | Frequency and type of contact with social ties; social support; family relationships and proximity; who is available to offer help (financial, physical, social); use of technology to stay connected; feeling isolated, lacking companions, feeling left out, and related measures | Mental health conditions and symptoms (including CES-D scale), mental health service utilization, loneliness, life satisfaction and well-being | Self-rated health, sleep, pain, functional health, ADL measures, chronic conditions, frequency of medical appointments, cognitive function, and memory. The restricted file includes biomarker data. |
| | Loneliness and Social Connections (LSC): A National Survey of Adults 45 and Older | Frequency and mode of contact with family and friends; availability of people to offer support, including living parents, relationship status, and who personal matters are discussed with; qualitative questions around social isolation | Mental health conditions including depression, anxiety, mood disorders, loneliness | Self-rated health, chronic conditions, disability, stress, substance use |
| | National Health & Aging Trends Study (NHATS) | Frequency and type of contact about "important things" in life | Positive and negative affect; self-realization, self-efficacy, and resilience; depression; anxiety; items on loneliness (since R11) | Self-rated health, self-reported diseases & chronic conditions, hospital stays and surgeries, falls, pain, physical capacity, memory, cognition/dementia, depression, anxiety, sleep, physical performance tests |
| | National Social Life, Health, and Aging Project (NSHAP) | Frequency of socializing; who is available for support; measures of social networks; quality of relationships | CES-D depression scale; happiness scale; loneliness | Self-rated health, functional health, health behaviors, cognition; ADLs |
| | National Study of Caregiving (NSOC) | Frequency and perceived importance of social contact with friends and family | Brief depression and anxiety screening instruments, positive and negative affect (feeling cheerful, bored, upset, etc.), self-actualization (life purpose and growth), loneliness, and self-efficacy | Self-rated health, fatigue, sleep, COVID-19; certain medical conditions; vision and hearing disability |
| Unit of Analysis: Place | National Neighborhood Data Archive (NaNDA) | None | None | None |
| | U.S. Religion Census | None | None | none |
| | Public Libraries Survey | None | None | None |

## Table 4

Geographic identifiers and measures of rurality.

| | | Geography | |
|---|---|---|---|
| | **Name of Data Source** | **Geographic Identifiers** | **Measure of Rurality** |
| Unit of Analysis: Individual | American Time Use Survey (ATUS) | Metropolitan core based statistical area (CBSA) code and county codes are available on ATUS-CPS files. While the county and CBSA codes are available from the ATUS-CPS files, CPS suppresses geographic identifiers if the defined area has a population <100,000; in some cases, geographic areas with more than 100,000 residents are also suppressed. In January 2022, the Census Bureau announced it would increase the threshold for suppressing geographic areas with populations <250,000. | Metro/ Non-metro variable on ATUS-CPS and Activity Summary files. |
| | Americans' Changing Lives (ACL) | Geographic identifiers available, but in a restricted version of the data. (Specificity unknown, but data collection instrument captures town, state, and ZIP code) | Urban/Suburban/Rural variable. Also, Small Town/ Rural or Other variable |
| | Health and Retirement Study (HRS) | County and ZIP codes available, but in a restricted version of the data. | Beale Urban/Rural codes |
| | Loneliness and Social Connections (LSC): A National Survey of Adults 45 and Older | State of Residence and Region | MSA Status; Self-report of urban/rural with six categories |
| | National Health & Aging Trends Study (NHATS) | Census division is available on public use files. City, state, ZIP code, county, census tract, Hospital Referral Region (HRR) available, but in a restricted version of the data. | Metro/non-metro indicator derived from 2013 Rural-Urban Continuum Codes |
| | National Social Life, Health, and Aging Project (NSHAP) | None on public files, but available in a restricted data enclaved. | "Urban-rural" variable available, but in a restricted version of the data. |
| | National Study of Caregiving (NSOC) | Caregiver's city, state, county, ZIP code, census tract available, but in a restricted version of the data. | Metro/non-metro status based on 2013 Rural-Urban Continuum Codes, but in a restricted version of the data. |
| Unit of Analysis: Place | National Neighborhood Data Archive (NaNDA) | Census tract, ZIP code tabulation area, and county-level data | Multiple - Urbanicity Scales, RUCA Codes |
| | U.S. Religion Census | County/FIPS | None |
| | Public Libraries Survey | Address, census tract, ZIP code, latitude/longitude. | 2020 NCES locale code, CBSA, Metro/ Micropolitan Flags |