



Special Communication

Social Determinants of Health and the Use of Community-Based Rehabilitation Following Stroke: Methodologic Considerations



Elizabeth R. Mormer, MS, CCC-SLP^a,
Sara B. Jones Berkeley, PhD, MPH^b,
Anna M. Johnson, PhD, MSPH^b, Kristin Ressel, MS, ATC^a,
Shuqi Zhang, MS^b, Amy M. Pastva, PT, PhD, MA^c,
Cheryl D. Bushnell, MD, MHS^d, Pamela Duncan, PT, PhD^d,
Janet K. Freburger, PT, PhD^a

^a Department of Physical Therapy, School of Health and Rehabilitation Sciences, University of Pittsburgh, Pittsburgh, PA, USA.

^b Department of Epidemiology, Gillings School of Global Public Health, University of North Carolina at Chapel Hill, Chapel Hill, NC, USA.

^c Department of Orthopaedic Surgery, Center for the Study of Aging and Human Development, Duke University School of Medicine, Durham, NC, USA.

^d Department of Neurology, Wake Forest University School of Medicine, Winston-Salem, NC, USA.

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Abstract Social determinants are nonmedical factors frequently used to study disparities in health outcomes but have not been widely explored in regard to rehabilitation service utilization. In our National Institutes of Child Health and Human Development-funded study, Access to and Effectiveness of Community-Based Rehabilitation After Stroke, we reviewed several conceptual models and frameworks for the study of social determinants to inform our work. The overall objective of this special communication is to describe our approach to identifying, selecting, and using area-level measures of social determinants to explore the relationship between social determinants and rehabilitation use. We present our methods for developing a conceptual model and a methodologic framework for the selection of social determinant measures relevant to rehabilitation use, as well as an overview of publicly available data on social

List of abbreviations: ADI, Area Deprivation Index.

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determinants. We then discuss the methodologic challenges encountered and future directions for this work.

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Introduction

According to the World Health Organization, social determinants of health are nonmedical factors such as access to food security, transportation access, and educational level that influence health outcomes and health inequities, and the wider set of forces and systems shaping the conditions of daily life.^{1,2} In the past 2 decades, a wealth of evidence has accumulated on the significant influence of social determinants on health outcomes, with estimates that 50% of modifiable determinants of health can be attributed to social, economic, and physical environmental factors, whereas 20% are because of clinical care.³ These findings have prompted initiatives, spanning local communities, and health systems to national and international organizations, that aim to consider social, political, and economic contexts in health care delivery and in health care policy development.^{4–6} Increasingly, payors such as the Centers for Medicare and Medicaid Services and private health insurers recognize the importance of social determinants. For example, the first priority of the Centers for Medicare and Medicaid Services Framework for Health Equity is to “Expand the collection, reporting, and analysis of standardized data, including measures of social risk.”⁷ In addition, a recent report found that the top 20 US health insurers spent approximately \$1.87 billion dollars between 2017 and 2021 on activities related to social determinants.⁸

The utilization of health care services is one causal pathway through which social determinants affect health outcomes. Health care utilization is, therefore, one modifiable contributor to health inequity.^{4,9,10} For example, a stroke survivor living in a community with limited public transportation or with a low supply of home health providers may not receive recommended outpatient or home health rehabilitation, which may negatively affect recovery. Indeed, there is robust literature describing the relationship between under-resourced communities and poor health outcomes.^{11–16} Understanding how social determinants influence health care utilization, specifically, can help inform interventions to mitigate health disparities by improving access to and use of health care.^{4,17}

Several published studies have examined factors associated with the use of rehabilitation care. However, few have specifically examined the relationship between social determinants and the use of rehabilitation services.^{18–20} One reason for this, particularly for older studies, may have been the lack of available data on social determinants in clinical and administrative data. Rehabilitation therapists, such as other health care providers, have not systematically collected much information on their patients’ social determinants. Although this is changing as more policies and mandates are in place to collect patient-level social determinants,²¹ much of the health care data currently available to health services researchers lacks this information.²²

Area-level measures of social determinants can serve as an alternative or supplement to individual-level measures of social determinants.²³ Area-level measures of social determinants are population-based measures at select geographic levels (eg, median household income in the census block group where an individual resides). From smallest to largest, these are generally census block groups, census tracts, and county.²⁴ Data are also often collected at the zip code tabulation area level, which maps closely—but not precisely—to census-level geographic boundaries. Area-level measures may also be uniquely informative to supplement individual-level measures and provide opportunities for rehabilitation researchers to understand how social determinants at the community-level impact rehabilitation-related health and health care use outcomes. Because of the growing interest in social determinants in public health, the availability and accessibility of area-level measures of social determinants have increased significantly more than the past decade.^{25–28}

The overall objective of this special communication is to describe our approach to identifying and selecting area-level measures of social determinants and describe the methodologic challenges we encountered exploring the relationship between social determinants and rehabilitation utilization. This work was developed as part of a currently funded National Institutes of Health study examining access to, use, and effectiveness of community-based rehabilitation care following acute stroke (5R01HD101493-03) using data from the Comprehensive Post-Acute Stroke Services study, a Patient-Centered Outcomes Research Institute-funded large, pragmatic clinical trial that evaluated the effectiveness of a transitional care model for stroke survivors discharged home (PCS-1403-14532).^{29,30} One aim of the secondary analysis was to focus on individual, hospital, and community-level factors associated with physical therapy and/or occupational therapy use in the home and outpatient settings. Although the Comprehensive Post-Acute Stroke Services study provided us with robust, individual-level data, information on social determinants at the individual level was limited. We therefore proposed to use area-level measures of social determinants to further our understanding of factors that influence rehabilitation use. In our study, participant data were geocoded at the street level, which allowed for area-level measures at the census block group level (or higher). The specific aims of this special communication are as follows:

- (1) Present a conceptual framework for examining the relationship between social determinants and rehabilitation use.
- (2) Provide information on publicly available, area-level measures of social determinants that may be of use to rehabilitation researchers.

- (3) Discuss some of the key methodologic issues to consider when using area-level measures of social determinants.
- (4) Make recommendations for future work examining the relationship between social determinants and rehabilitation use.

Our motivation for this special communication was due to the limited evidence and guidance on evaluating social determinants from a rehabilitation care perspective, particularly in settings with limited data on individual-level social determinants.

Methods

Conceptual frameworks of social determinants of health

To help guide our work, we reviewed the literature on conceptual frameworks of social determinants of health, which we then considered in the context of available area-level measures of social determinants. Frameworks to conceptualize social determinants can be broadly categorized as mechanistic and domain-specific.³¹

Mechanistic frameworks conceptualize the interactions between social determinants and health outcomes and often account for the multi-level nature of social determinants and their influence over time.³¹ The Commission on Social Determinants of Health Conceptual Framework is a mechanistic framework that divides social determinants of health into structural determinants and intermediary determinants. It depicts how structural determinants at a macro level (socioeconomic and political context) have bidirectional interactions with socioeconomic position (social class, sex, race, ethnicity, education, occupation, and income), which then interact with intermediary determinants (material circumstances such as living and working conditions, behaviors and biologic factors, and psychosocial factors), and the health system. Together, these factors affect equity in health and well-being, which, in turn, influences the structural and social determinants of health inequities.³² Mechanistic frameworks help users understand the complex, multi-level relationships between social determinants and the forces and systems that affect them.

Domain-specific frameworks identify the domains or constructs of social determinants without addressing the relationships among these domains or how the domains are influenced by other factors. Such models can serve as a useful resource for researchers interested in studying the relationship between social determinants and health or health care use. Examples of domain-specific frameworks include the Healthy People 2030 model and the National Institute for Minority Health and Health Disparities framework. The National Institute for Minority Health and Health Disparities model identifies 3 domains of social determinants: physical/built environment, sociocultural environment, and health care system in addition to biologic and behavioral domains that influence health. The National Institute for Minority Health and Health Disparities model also recognizes that social determinants can act at the individual, interpersonal, community, and societal levels.³³ The Healthy

People 2030 Social Determinants of Health model was created as a way to advance the Healthy People 2030 policy goals of eliminating health inequity.³⁴ The model identifies 5 domains of social determinants of health: education access and quality, economic stability, social and community context, neighborhood and built environment, and health care access and quality. This model has been used by government agencies^{35,36} and researchers to explore health and health care disparities and develop interventions to improve health equity.^{37–40}

Our conceptual framework

Although several frameworks aligned with our objectives and data, we selected the Healthy People 2030 framework¹¹ because of its wide use, policy relevance, and because it allows grouping of social determinants within domains. We adapted this framework to represent the social determinants of rehabilitation use. For each of the 5 domains of Healthy People 2030, examples of subconstructs or subdomains are provided. For example, under the economic domain, some subdomains include employment, income, and poverty. To supplement this model and tailor it to best reflect our specific research questions, we explored the literature to identify additional subconstructs or subdomains described or reported by others.^{31,33,41} Figure 1 presents the final conceptual model that guided our work. We identified a total of 48 subdomains across the 5 domains, with 8 to 12 subdomains within each of the domains.

Selection of area-level measures of social determinants

Once the subdomains were identified, we explored publicly available data sets to identify area-level measures that represented the different subdomains or that provided cross-domain or cross-subdomain measures. Our selection of measures was influenced by several factors. First, we focused our search on the subdomain measures we deemed most relevant to rehabilitation use for stroke in our population of adults (eg, we included adult literacy measures but excluded data to represent early childhood development under the Education Domain). Second, we generally prioritized obtaining more granular levels of measurement (ie, census block group data) whenever those data were available. This decision was based on findings that social determinant (eg, socioeconomic status) data from smaller geographic levels provide higher precision when approximating individual-level values.⁴² For example, if census block group-level data were not available, we used the next most granular level of data available (ie, census tract-level). For some subdomains (eg, access to health services), data were only available in larger geographic areas (eg, zip code or county-level). Finally, if multiple measures were identified for the same subdomain and the measures were at the same level, we placed higher priority on measures that had greater acceptance or validation.⁴³ Subdomains outlined in red in figure 1 are those where we identified an appropriate area-level measure from a publicly available data set. Overall, we identified 11 publicly available data sets that contained one or more area-level measures representing the 31 subdomains we identified as relevant. Table 1 describes

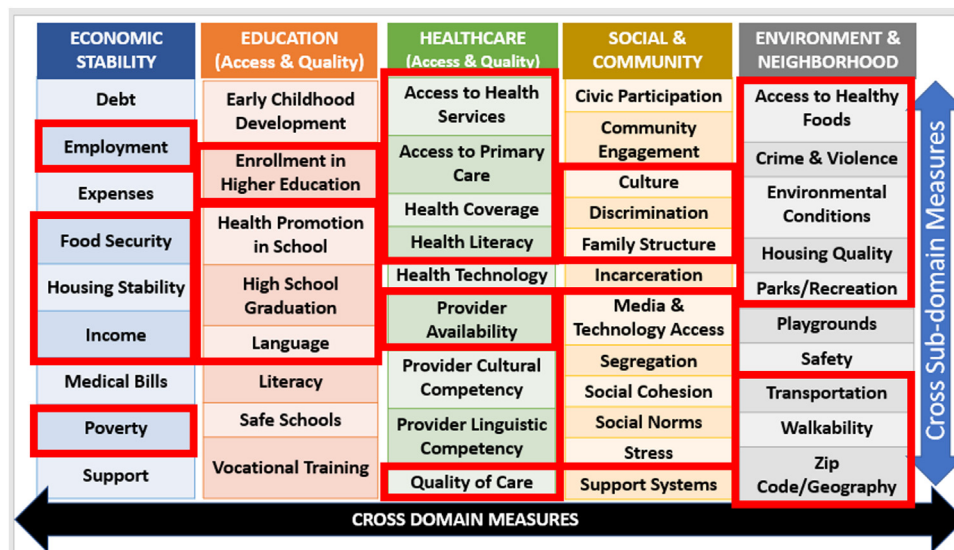


Fig 1 Conceptual model to guide social determinant measure selection. This figure illustrates our version of the Healthy People 2030 model domains with additional subdomains. Subdomains outlined in red are those where we identified an area-level measure in a publicly available database.

these data sets, their source, the domain(s) represented, and the level(s) of data obtained. More detailed information on the measures is provided in [supplemental table S1](#) (available online only at <http://www.archives-pmr.org/>).

In addition to our individual subdomain measures, we included 2 cross-domain measures that provide a composite measure of social determinants, the Area Deprivation Index (ADI)^{26,44} and the Social Vulnerability Index.⁴⁵ The ADI is a composite measurement derived from 17 indicator variables, including census block group (neighborhood) level measures of poverty, housing, and employment from the American Community Survey. The ADI is a comparative measure that ranks socioeconomic disadvantage at both national and state levels.^{25,26} It includes state-only deciles, which rank scores from least to most disadvantaged block groups and then divide them into deciles, allowing for comparisons within a state. National ADI rankings and percentiles are also available.⁴⁶ The Social Vulnerability Index was originally developed to assist the US government with the identification of communities that would require disaster assistance.^{28,45} It is derived from 15 US census tract-level variables and categorized into 4 composite measures: socioeconomic status, household characteristics, racial and ethnic minority status, housing type, and transportation. Each of the 4 composite measures is scored on a scale from 0 to 100 percentile ranking, with higher scores indicating greater vulnerability. An overall Social Vulnerability Index percentile ranking is calculated by averaging the percentile rankings across the 4 categories.

Methodological challenges

Once we identified our subdomain measures, we linked the data to study participant records at the census block group, census tract, zip code tabulation area, or county-level, as appropriate. As we began to consider models to assess the relationship between social determinants and rehabilitation

use, we encountered several methodologic challenges, including measure selection, model specification, and an analytical approach.

Model specification

Model specification requires consideration of model fit, interpretation of resulting estimates, comparability across studies, and practical considerations such as model convergence. Many area-level measures, such as the proportion of the population with a high school degree or higher, will likely not have a linear relationship with the outcome. In such cases, the variable can be modeled as a continuous measure, using higher-order terms (eg, polynomial terms such as quadratic or cubic terms) to account for nonlinearity. The measure can also be categorized according to meaningful cut-points or, when meaningful cut-points are not available, according to the distribution in a given data set (eg, as tertiles or quartiles).⁴⁷ One advantage of using continuous data over categorical data is that more information is retained to understand the relationship being examined.⁴⁸ A disadvantage is the interpretation of results when higher-order terms are used. A continuous variable in a single linear term makes a strong assumption about the consistent effect of every unit change in predictors and limits the model's flexibility. Adding polynomial terms such as quadratic or cubic terms can increase flexibility but make the interpretation of results more difficult. Quantile-based categorization may improve interpretation and mitigate the effects of outliers, but it may not represent meaningful groupings or provide results that cannot be compared across studies that will have their own data distributions.

Another challenge we encountered was difficulty with model fit when several social determinant measures were included in a single model. We initially identified all measures that would be associated with rehabilitation use based on theory and evidence and according to our conceptual framework. We then identified variables with high degrees

Table 1 Publicly available measurements of social determinants

| Name | Source | Domains Represented | Level of Data Aggregation | URL |
|--|---|--|-----------------------------------|---|
| AHRQ Social Determinants of Health Database (AHRQ SDOH) | Agency for Healthcare Research and Quality (AHRQ) | All domains represented | Census tract, zip, count | https://www.ahrq.gov/sdoh/data-analytics/sdoh-data.html#download |
| American Community Survey (ACS) | US Census Bureau | All domains represented | Block group, census tract, county | https://www.census.gov/programs-surveys/acs/data.html |
| Area Deprivation Index | University of Wisconsin | Cross-domain | Block group | https://www.neighborhoodatlas.medicine.wisc.edu/ |
| Area Health Resource Files (AHRF) | Health Resources and Services Administration | Education, health care, environment, and neighborhood | County | https://data.hrsa.gov/topics/health-workforce/ahrf |
| County Health Rankings | Robert Wood Johnson Foundation | Economic, health care, social and community, environment, and neighborhood | County | https://www.countyhealthrankings.org/reports/2023-county-health-rankings-national-findings-report |
| National Assessment of Adult Literacy | National Center for Education Statistics | Education (literacy), health care (health literacy) | Block group | https://nces.ed.gov/naal/datafiles.asp |
| NC Health Professions Data | Cecil G. Sheps Center, University of North Carolina | Health care (provider availability) | County | https://www.shepscenter.unc.edu/data/health-professions-data-system/ |
| NC Uniform Crime Report | NC State Bureau of Investigation | Environment and neighborhood | County | https://www.ncsbi.gov/Services/Crime-Statistics |
| Program for the International Assessment of Adult Competencies | National Center for Education Statistics | Education (literacy, numeracy) | County | https://nces.ed.gov/surveys/piaac/ |
| National Walkability Index | US Environmental Protection Agency | Environment and neighborhood | Block group | https://epa.maps.arcgis.com/home/webmap/viewer.html?webmap=f16f5e2f84884b93b380cfd4be9f0bba |
| Social Vulnerability Index | Centers for Disease Control | Cross-domain | Census tract | https://www.atsdr.cdc.gov/placeandhealth/svi/index.html |

of collinearity using the variance inflation factor and correlation statistics. Where 2 variables were very highly related (eg, R^2 of 0.95) we selected the one most relevant for policy (eg, county-level physical therapy supply was selected over occupational therapy supply because physical therapy is more widely used than occupational therapy). Next, we used a Lasso variable selection procedure to identify a more parsimonious set of variables for our prediction models.⁴⁹ This approach is considered preferable to forward or backward selection because it offers automatic variable selection, handles multicollinearity, balances the bias-variance tradeoff, and is less prone to overfitting.

Another challenge when examining multiple measures of social determinants is the complexity of the relationships across measures and potential interactions. For example, consider the effect of insurance on specific racial groups.⁵⁰ Understanding these relationships may require interrogating myriad interactions and higher-order terms that are not practical using traditional multivariable approaches. The use of machine-learning approaches can help identify these complex relationships and is particularly useful in cases where prediction or discovery of relationships is a primary goal.^{51,52}

Clustering of data

Another methodologic issue with area-level measures is clustering, which may occur at different levels that may or may not be nested within each other. In our case, data were clustered at the census block group, census tract, zip code, and county-level. In addition, patients in our study were enrolled in hospitals, which represents another level of clustering that cannot be considered nested within the other levels. Clustering must be handled analytically to accurately estimate standard errors.⁵³ If clustering is not accounted for, the size of the standard errors may be underestimated, leading to a type I error (eg, the identification of a false-positive association). There are 2 commonly used modeling approaches used when estimating associations with data: clustered random effects models (or mixed models) and population average models with a generalized estimating equation approach. The strengths and limitations of these 2 approaches have been discussed elsewhere.⁵⁴ The choice of approach should be guided by the goals of the study.

Standard software procedures assume, in the case of multiple clusters, that these are nested within each other, such as in the case of census blocks nested within census tracts. When this is not the case, as in our study (eg, patients discharged from enrolling hospitals were not nested within census blocks or tracts), the use of specific statistical procedures is required to obtain correct standard error calculations.⁵⁵ Alternatively, the effects of clustering at one level over another can be explored empirically and decisions made on clustering at the specific level that seems to have the largest effect on the findings, with the limitations of this approach noted.

Temporality

Finally, a limitation of many analyses of social determinants, ours included, is the inability to clearly establish temporality

in measurement. Temporality is a critical requirement for causal inference, and identifying social determinants that, if modified, will impact the outcome of interest is a key objective of much of this work.⁵⁶ For example, social determinants such as income and education vary over the life course of an individual, and typical regression modeling approaches do not account for that. A complete discussion of causal assumptions and how they apply to social determinants research is outside the scope of this paper and has been addressed well in a paper by Kaufman et al.⁵⁶ Multivariable models with variables representing multiple social determinant domains must be interpreted carefully and fit for purpose, whether this is for prediction, estimation of associations to be examined in future studies, or estimating causal effects/causal mediation.

Discussion

We have described our approach to examining the relationship between area-level social determinants and rehabilitation use and discussed some of the methodologic considerations. Our approach, is by no means the only approach nor is it necessarily the right approach. The methodologic issues we highlighted are also not comprehensive, as these issues are often a factor of the specific analytical approach taken. Through this perspective, we hope to stimulate conversation and begin to advance work in this area.

We chose to use the Healthy People 2030 model as the foundation for our conceptual framework because it was simple and offered the opportunity to consider a wide range of measurements of social determinants. We recognize that this model is just one of many and have only briefly reviewed some examples of other models. As awareness of social determinants of health has increased, the number of conceptual models, frameworks, and lists of social determinants has also increased.⁵⁷ Choosing from these models or developing your own can be challenging, but it is a critical step of the process to guide your own research and facilitate advances in the field.

Consideration should also be given to the data sources examined to understand social determinants. Although national data may be more generalizable, local data (eg, at the level of the health system), which is more reflective of the local context, may provide more actionable findings. National data may also obscure smaller area effects.

Although we presented our methods for using area-level measurement as a proxy for individual-level measures out of necessity, there are also instances where the area-level construct may be the target/level of interest (eg, use of residential segregation indices).⁵⁸ There may also be scenarios where both an individual measure and its area-level equivalent are of interest and have independent effects on outcomes (eg, individual income and neighborhood socioeconomic status).

Our methodology organizes variables according to domains and subdomains and provides background on several publicly available measures of social determinants relevant to rehabilitation use. Operationalizing social determinants to study rehabilitation use was not without challenges. The first was balancing comprehensive selection of social determinants with parsimonious model selection. Having a comprehensive database of social determinants requires careful variable selection to avoid collinearity and high-dimensional models.

The selection of measures of social determinants should involve careful consideration of what is most relevant for rehabilitation users and providers. For example, social determinants that are modifiable or actionable may be most relevant. When using multiple social determinants, special consideration and attention must be paid to measurement selection, variable specification, analytical approach, and result interpretation. Future approaches may consider the use of statistical methods that employ artificial intelligence-generated algorithms to predict relationships and outcomes.^{51,59}

Standardization of measures in the field of rehabilitation and/or the creation of a minimum data set may also be important. There are increasing efforts to standardize measurements of social determinants and to provide resources for researchers. For example, the PhenX Toolkit, contains multiple protocols for measuring social determinants of health, including a Core Collection of measurement protocols for race and ethnicity, age, gender identity, annual family income, English proficiency, occupational prestige, and access to health services. The toolkit also includes 2 specialty collections: measurements of individual social determinants (eg, discrimination in health care, internet access) and structural social determinants (eg, minimum wage, neighborhood walking and biking environment).⁶⁰ Additionally, the Centers for Medicare and Medicaid Services have released Z codes, which were created for the purpose of documenting unmet social needs related to education, literacy, employment, and housing that can influence health outcomes.²¹ To date, Z code use has been low, occurring in <2% of samples studied,^{61,62} questioning its utility for health equity researchers and clinicians.

Conclusions

As the field of rehabilitation science advances in its exploration of social determinants, we must ask questions and select methodologies that are meaningful to the populations we serve. In addition to understanding how social determinants relate to rehabilitation use and health outcomes, we also need to understand which of these factors are *modifiable*, and at what level they operate (ie, state or national policy-level, community-level, institution-level, in patient-provider interactions, or on the individual). This can help inform the development and evaluation of interventions to mitigate the inequitable use of health care services, which ultimately promotes improved health outcomes and population health.

Disclosures

P.D. and C.D.B. report ownership interest in Care Directions Inc. P.D. is a research adviser for BQ Technologies. The other authors have nothing to disclose.

Corresponding author

Elizabeth R. Mormer, MS, CCC-SLP, Department of Physical Therapy, School of Health and Rehabilitation Sciences, University of Pittsburgh, Bridgeside Point 1, Suite 210, Pittsburgh, PA. E-mail address: ELM260@pitt.edu.

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Further Reading

1. Social determinants of health literature summaries – healthy people 2030. 2024.