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Identifying Homeless Medicaid Enrollees Using Enrollment Addresses

Katherine D. Vickery, Nathan D. Shippee, Peter Bodurtha, Laura M. Guzman-Corrales ⓘD , Elyse Reamer, Dana Soderlund, Stephanie Abel, Danielle Robertshaw, and Lillian Gelberg

Objective. To design and test the validity of a method to identify homelessness among Medicaid enrollees using mailing address data.

Data Sources/Study Setting. Enrollment and claims data on Medicaid expansion enrollees in Hennepin and Ramsey counties who also provided self-reported information on their current housing situation in a psychosocial needs assessment.

Study Design. Construction of address-based indicators and comparison with self-report data.

Principal Findings. Among 1,677 enrollees, 427 (25 percent) self-reported homelessness, of whom 328 (77 percent) had at least one positive address indicator. Depending on the type of addresses included in the indicator, sensitivity to detect self-reported homelessness ranged from 30 to 76 percent and specificity from 79 to 97 percent.

Conclusions. An address-based indicator can identify a large proportion of Medicaid enrollees who are experiencing homelessness. This approach may be of interest to researchers, states, and health systems attempting to identify homeless populations.

Key Words. Medicaid expansion, homelessness, determinants of health/population health/socioeconomic causes of health

Homelessness is a serious social problem affecting over half a million Americans on any given night (Henry et al. 2015). People who are homeless experience substantial morbidity and premature mortality (Bharel et al. 2013; Hwang and Burns 2014) and increased health care costs (Martell et al. 1992; Duchon, Weitzman, and Shinn 1999). The 2010 Affordable Care Act expanded Medicaid to many previously uninsured homeless adults (Kaiser Family Foundation 2016; Vickery et al. 2016), while also funding cost-reducing interventions to coordinate delivery of subsidized housing with health care (Larimer et al. 2009). Specific attention has focused on strategies to pair Medicaid services for physical and behavioral health conditions with

permanent supportive housing (PSH), including through the Medicaid health home benefit (Doran, Misa, and Shah 2013; Wilkins, Burt, and Locke 2014; Health Affairs 2016).

Effective programs and research to improve the health of homeless Medicaid populations require accurate data to identify homeless individuals. Yet efforts to identify homeless Medicaid populations using secondary health care data in research or clinical care have been limited. Prior research efforts have relied on primary data collection during a health care or social service encounter (Gelberg, Andersen, and Leake 2000; Montgomery et al. 2013; Braciszewski, Toro, and Stout 2016) or on use of secondary databases of homeless service users maintained for administrative purposes (Byrne and Culhane 2015).

Prior work to identify homeless people within health care data has not been generalizable to Medicaid populations. The U.S. Department of Veterans Affairs (VA) has focused on identifying homeless and at-risk veterans as a part of their campaign to end veteran homelessness (U.S. Department of Veterans Affairs). In addition to primary data collection using a screening tool in the electronic health record (Montgomery et al. 2013), VA researchers have examined secondary data indicating use of VA-supported homeless services and/or diagnoses of lack of housing (Edens et al. 2011). They have also used natural language processing to examine free text within VA medical records indicative of homelessness (Gundlapalli et al. 2013). Recent work in New York City has attempted to identify homelessness at the population level using text or addresses that might be proxies for homelessness or unstable housing. Data came from the addresses provided by patients using health care services in a

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regional health information exchange and were not compared to self-report or another source (Zech et al. 2015). While notable, none of these efforts captures a population-level estimate of homelessness, and none was widely adopted.

In this study, we developed and tested a homeless address indicator using Medicaid data. We partnered with local homelessness experts in Minneapolis and St. Paul, Minnesota, who observed consistent patterns of mailing addresses used by homeless people in health care encounters including in Medicaid enrollment. We examined data from a group suspected to include many people experiencing homelessness: Minnesota's urban early Medicaid expansion population of adults without dependent children and income ≤75 percent poverty (Anon 2010; State of Minnesota Executive Department 2011). First, we created indicators to identify adults experiencing homelessness using Medicaid enrollment mailing addresses. Second, we assessed the specificity and sensitivity of the indicators for identifying homeless persons by comparing them to self-reported homelessness on a psychosocial needs assessment.

METHODS

Data Sources and Study Cohort

We obtained Medicaid enrollment and claims data from March 2011 through December 2014 from the Minnesota Department of Human Services (DHS) on adult enrollees without dependents with at least 1 month of eligibility in Hennepin and Ramsey counties for purposes of another study. Medicaid enrollment data included age, race, ethnicity, primary language, education, and up to six historical mailing addresses. We identified a subset of this cohort who completed the Life Style Overview (LSO) in 2011–2014.

The LSO is a verbally administered psychosocial screening tool administered to patients deemed to have multiple needs during visits to Hennepin County Medical Center (HCMC) and affiliate sites. The LSO includes the question, "Where are you living today?" with possible response categories of *homeless, shelter, at a relative or friend's place,* and *your house or apartment* adapted from the Homeless Supplement to the Diagnostic Interview Schedule (North et al. 2004). In this study, following the point-in-time definition of homelessness used by the National Alliance to End Homelessness (National Alliance to End Homelessness 2016), we defined LSO-homelessness as responses of either *homeless* or *shelter.* This definition was preferred to other federal

definitions of homelessness (Anon 2009) as it offered better alignment with the point-in-time LSO question.

Construction of Homeless Address Indicators

The homeless address indicators were based on six sources: (1) a comprehensive directory of shelter and single-site supportive housing programs provided by housing program staff from Hennepin and Ramsey Counties in response to an open-ended inquiry by electronic mail. We added several other address types noted by local homeless experts to this directory, including (2) the General Delivery Address (GDA)— a free service offered by the U.S. Postal Service for an individual's mail to be held at the post office; (3) addresses of local homeless service centers collecting mail for homeless clients; (4) free text responses (e.g., "homeless") recorded in the mailing address section of Medicaid enrollment records synonymous with homelessness; and (5) addresses of institutions commonly used by homeless individuals, including hotels, places of worship, and hospitals (Zech et al. 2015). Finally, (6) within the data, we observed frequent use of the addresses of county administrative offices and added these locations to the directory.

Because individuals residing in permanent supportive housing (PSH) more often report having their own apartment/house and are more stably housed, PSH addresses were excluded from the homeless address indicators.

The homeless address indicators were created to identify the presence of any homeless addresses in Medicaid enrollment records. We matched the indicators to the enrollment address file using *ArcGIS*, version 10.2.1 (ESRI). To understand the reliability of the GDA alone in indicating homelessness, this was analyzed separately from the non-GDA homeless addresses (see Appendix SA2).

This study was approved by the Institutional Review Board of Minnesota Department of Human Services and Minneapolis Medical Research Foundation.

Analysis

We grouped homeless addresses into descriptive categories with input from Hennepin County housing program staff. We counted the number of unique addresses in each category. To determine the accuracy of the homeless address indicators, we matched date ranges for use of Medicaid enrollment addresses with date of response to the LSO housing question.

We described the demographic characteristics of Medicaid enrollees using descriptive statistics and compared the enrollees who were LSO-homeless to nonhomeless groups using t-tests with unequal variance adjustments and chi-square tests.

To assess accuracy of address-based indicators to self-report, we used three simple logistic regression models. We regressed self-reported LSO homelessness first on the indicator for GDA, second on the indicator for non-GDA homeless addresses, and third on an indicator of use of either the GDA or non-GDA homeless address in *Stata*, version 13.1 (StataCorp 2011). We employed robust standard errors to account for correlated observations within persons due to enrollees' multiple LSO responses and multiple addresses over time. Using estimates from each model, we calculated marginal adjusted probabilities of self-reporting homelessness. We calculated sensitivity, specificity, and negative and positive predictive values and used a c-statistic and area under the receiver operator characteristic curve to assess fit of each model.

RESULTS

We grouped the primary homeless address lists provided by county housing program staff into the following address categories: emergency shelters (22 unique addresses), board and lodge facilities (60), and transitional housing sites (30). We included additional institutional addresses that may be used by homeless people, including places of worship (208), hotels (111), hospitals (11), and social service sites and drop-in centers (8) in the seven-county metropolitan region (see Appendix SA2). In total, the homeless address indicator included 450 unique addresses.

We found 1,677 unique enrollees with time-matched enrollment address indicators and answers to the LSO "living today" question. Some participants took the LSO more than once between 2011 and 2014; overall, respondents answered the housing question 1 to 4 times (mean 1.1, median 1, standard deviation 0.31, range 1–4). The cohort was predominantly male, English-speaking, and black (see Table S1).

One-quarter of unique, responding Medicaid enrollees ($n = 427$, 25 percent) reported LSO-homelessness by responding "shelter" or "homeless" one or more times to the LSO instrument's housing question. These individuals were most likely to use the GDA (Table 1) but also used a variety of non-GDA homeless addresses (Table S2). Of these 427 LSO-homeless Medicaid enrollees, over three quarters ($n = 328$, 77 percent unique people or $n = 339$

Table 1: Type of Homeless Addresses Used by Urban Early Medicaid Expansion Enrollees,* 2011–2014

	Homeless, by Self-Report		Not Homeless, by Self-Report		All	
	n	*%*	*n*	*%*	*n*	*%*
No homeless address	107	24	1,076	79	1,183	65
General delivery address (GDA)	207	46	243	18	450	25
Non-GDA homeless address[†]	132	30	46	3	178	10
Either GDA or non-GDA homeless address	339	76	289	21	628	35
Total sample	446	100	1,365	100	1,811	100

*Data reported at the address level. Individuals could use more than one address type over time.
[†]Homeless addresses included emergency shelters, board and lodge facilities, transitional housing, social service sites, drop-in centers, places of worship, hotels, and hospitals. See Table S2 for frequency of use by category.
Source: Authors analyzes of Minnesota Department of Human Services enrollment and claims data and homeless address directory constructed by our research team.

addresses) used one or more addresses included in the homeless address indicators to enroll in Medicaid during the study period.

Enrollees using the GDA had a 46 percent probability of reporting homelessness on the LSO. The GDA indicator had a sensitivity of detecting self-reported homelessness of 46 percent with a specificity of 82 percent (C-statistic = 0.64). Enrollees using the non-GDA homeless address indicator had a 74 percent probability of reporting homelessness on the LSO. The sensitivity of the non-GDA indicator was 30 percent with a specificity of 97 percent (C-statistic = 0.63). When combined, enrollees using either the GDA or a non-GDA homeless address had a 54 percent probability of self-reported homelessness. The combined indicator had a 76 percent sensitivity and 79 percent specificity with a 54 percent positive predictive value and 91 percent negative predictive value (C-statistic = 0.77) (Table 2, Figure 1).

DISCUSSION

Our study offers a new approach to measuring homelessness at the population level using existing, secondary data from Medicaid enrollment records. In contrast to prior efforts to identify homeless populations, enrollment data are collected on all people who register for health insurance and are not limited to the subset who use health care or social services. Our homeless address

Table 2:   Probability of Self-Reported Homelessness with Use of Homeless Addresses on Medicaid Enrollment Forms

|	*Probability of Self-Reported Homelessness on Life Style Overview*	*Sensitivity of Homeless Address on Medicaid Enrollment Forms to Detect Self-Reported Homelessness*	*Specificity of Homeless Address on Medicaid Enrollment Forms to Detect Self-Reported Homelessness*
Use of only general delivery address (GDA)	46%	46%	82%
Use of non-GDA homeless address	74%	30%	97%
Use of *either* GDA or non-GDA homeless address	54%	76%	79%

Source: Authors analyzes of Minnesota Department of Human Services enrollment and claims data; self-reported Life Style Overview data from Hennepin County Medical Center electronic health record.

indicators identified self-report of homelessness with consistently high specificity among early Medicaid expansion enrollees in our sample. This means that enrollees who have the homeless address indicators are likely to self-report homelessness and increases confidence in utilizing this approach to identify homeless Medicaid enrollees in our region. Our findings may have been strengthened by including housing addresses observed by local, frontline homeless service providers. However, the variable sensitivity of our indicators suggests that more work is needed to develop comprehensive measures to accurately identify Medicaid enrollees at risk for homelessness.

Our work builds upon previous research using self-reported address as a marker for unstable housing and health risk but shows that homeless address indicators must be customized to match the local environment. For example, Zech et al. found hospital address to be the most consistently used homeless address type (Zech et al. 2015), while in our study region, the GDA was the most commonly used homeless address. The preponderance of GDA use in our sample suggests regional variation in address patterns indicating homelessness.

Our study has several limitations. First, measurement of homelessness is complex, and there is no single standardized approach (National Coalition for the Homeless 2007). This may be reflected in the low sensitivity of our indicators, which do not reliably capture all people experiencing the spectrum of unstable housing. The point-in-time LSO question does not align with the widely accepted federal definition of people eligible to receive homeless

Figure 1:   Receiver Operating Characteristic (ROC) of Homeless Address Indicator* Compared to Self-Reported Homelessness [Color figure can be viewed at wileyonlinelibrary.com]
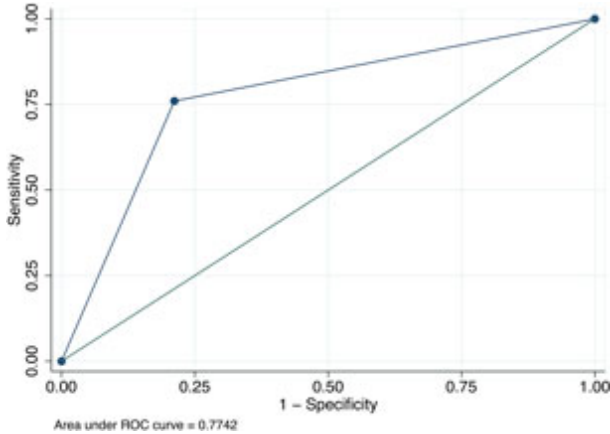
Area under ROC curve = 0.7742

Source: Authors analyzes of Minnesota Department of Human Services enrollment and claims data and self-reported Life Style Overview data from Hennepin County Medical Center electronic health records.
Note: *Indicator of use of either general delivery address (GDA) or non-GDA homeless address.

assistance from the HEARTH Act (Anon 2009; Department of Housing and Urban Development). The LSO question reflects one of many approaches to screening for housing status in health care settings and may underestimate true homelessness in several key ways. First, self-reported homeless screening questions in clinical settings may suffer from response bias due to stigma and other factors (DiPietro and Edgington 2016). Second, the LSO question represents a point-in-time estimate by asking only where respondents were "living today." Similar to national point-in-time homeless estimates (Sumner et al. 2001; National Alliance to End Homelessness 2016), this may miss populations cycling in and out of homelessness. However, prior research suggests that a question about where homeless persons slept last night missed less than 5 percent of those who reported being homeless at some point in the last 30 days (Sumner et al. 2001). Third, we chose not to include people in the LSO sample who responded that they were "staying with relatives or friends." While these "doubled up" respondents represent a significant population at risk for homelessness, our homeless address indicators could not accurately identify this group. Similarly, the homeless address indicators may

underestimate homelessness for several different reasons. First, housing sup-
port sites may close or move over time. Second, variation in spelling of
addresses may limit accuracy of matching. Third, we excluded PSH sites,
which are included in the federal definition of homeless eligibility. Finally, our
nonrandom sample was screened with the LSO based on the assessment of
frontline clinical staff of complex needs and included only adults without
dependents. This limits the generalizability of these findings to other homeless
populations or other regions.

Further work is needed to develop and test ideal homelessness
screening tools for use in clinical settings or during Medicaid enrollment.
Clinical tools could work in conjunction with measures derived from sec-
ondary data available within databases maintained by homeless service
providers. Regular maintenance of address lists would be avoided with use
of shelter and supportive housing records from the national Housing
Inventory Count Reports or the Homeless Management Information Sys-
tem (HMIS) maintained by the U.S. Department of Housing and Urban
Development (HUD). The Housing Inventory Count Reports maintains
an annually updated list of the names and addresses of federally subsi-
dized shelters and other supportive housing sites (HUD 2017). And HMIS
tracks use of such facilities at the individual and family level (HUD 2016).
In spite of significant challenges and some limitations (Gutierrez and Fried-
man 2005), the reports and HMIS represent nationally mandated, locally
administered datasets tracking the homeless population. Linkage to these
housing services databases could allow for more robust identification of
supportive housing locations and add frequency measures of their use by
individuals enrolled in Medicaid, a level of detail not available from our
address indicator. We found no previous work that paired HUD databases
with Medicaid or health care data for research or practice.

Accurately identifying homeless individuals is the first step in delivering
targeted, evidence-based interventions to improve outcomes and control costs
in homeless populations (O'Toole et al. 2010, 2016). While a comprehensive
indicator is ideal, indicators with high specificity using existing secondary data
at the population level may be useful as a transitional step. Increasing evi-
dence supports the value of "housing as health care," with recent policies
encouraging the use of Medicaid dollars to support integration of housing with
medical and behavioral health care (Doran, Misa, and Shah 2013; Wilkins,
Burt, and Locke 2014). Medicaid expansion has increased the insurance cov-
erage of homeless and formerly homeless individuals (Kaiser Family Founda-
tion 2016; Vickery et al. 2016), making improved outcomes and cost control

especially important for participating states. With proposed cuts to federal support for Medicaid (Congressional Budget Office 2017), potential strategies for cost control in homeless Medicaid populations may also be of increasing importance.

CONCLUSION

Existing address data within Medicaid enrollment records identified self-reported homeless populations in one urban region with high specificity. This and other identification strategies may allow for improved research and care delivery to reduce premature morbidity and mortality disproportionately faced by homeless populations.

ACKNOWLEDGMENTS

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SUPPORTING INFORMATION

Additional supporting information may be found online in the supporting information tab for this article:

Appendix SA1: Author Matrix.
Appendix SA2: Technical Appendix.
Table S1: Comparison of Characteristics of Self-Reported Homeless to Non-Homeless Medicaid Expansion Enrollees on Life Style Overview (LSO).
Table S2: Types of Non-General Delivery Homeless Addresses Used by Early Medicaid Expansion Recipients.*