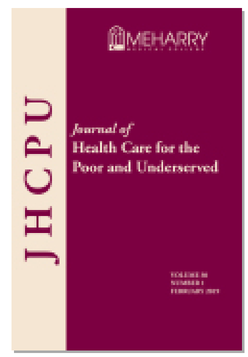
Identifying Patients Experiencing Homelessness in an Electronic Health Record and Assessing Qualification for Medical Respite: A Five-Year Retrospective Review



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ORIGINAL PAPER

Identifying Patients Experiencing Homelessness in an Electronic Health Record and Assessing Qualification for Medical Respite: A Five-Year Retrospective Review

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Abstract: Our team developed a transitional care and medical respite program for people experiencing homelessness and designed a retrospective chart review study to more fully understand the unique needs of this population. Using four independent techniques, we identified individuals (N=1,656) who were experiencing homelessness during at least one hospital encounter (emergency department and/or in-patient admission) in a teaching hospital in the Southeastern United States over a five-year period. Data were manually abstracted from a random sample of patients to determine which patient encounters would or would not have qualified for medical respite if it had been available at the time. This article reports the methods used to identify people experiencing homelessness in the electronic health record, the data abstraction process, the cohort description, and the primary reasons patients would not have qualified for the medical respite program.

Key words: homelessness, transitional care, retrospective studies, medical respite, International Classification of Diseases.

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The ability to readily identify people experiencing homelessness and/or housing-insecure individuals in an electronic health record (EHR) is important for appropriate care delivery. Such identification can assist clinicians in developing interventions that align medical and mental health services, ensure continuity of care, and decrease costly emergency department use and inpatient admissions. However, many health systems do not routinely screen for homelessness or housing instability.[1,2] Our team developed a transitional care and medical respite program* for people experiencing homelessness and designed a five-year retrospective chart review study to understand the needs of this population. This article reports the methods used to identify participants in the EHR and the data abstraction process. We then provide a cohort description and quantify the number of encounters that would have qualified these individuals for medical respite had a program been in place at the time.

Advocates for people experiencing homelessness recommend screening for housing status during clinical encounters.[3,4] Such screening increases the likelihood of identifying housing-insecure and patients experiencing homelessness and referring them to appropriate services.[5] Previous documentation of housing status in the EHR may prompt providers to assess for housing status during subsequent visits. This documentation can also aid clinicians and researchers attempting to locate people experiencing homelessness in the EHR for a myriad of reasons (e.g., understanding the prevalence of homelessness; researching the relationship between housing and disease status; monitoring for disease outbreaks among this vulnerable population). In the absence of screening for and documenting housing status with a specific housing status indicator, researchers have identified patients experiencing homelessness by querying the EHR for shelter and homeless service agency addresses.[6,7] Data mining encounter notes has also shown promise for locating patients experiencing homelessness in EHRs.[8]

Once the patients experiencing homelessness are identified, a retrospective chart review is helpful for assessing the population's needs and health services utilization patterns. This, in turn, aids in designing targeted interventions. Retrospective chart review using EHRs provides relatively easy access to longitudinal information, and data are often readily available.[9] Challenges include poor and highly variable documentation quality, resource availability for data abstraction, and lack of standardized training yielding low data abstractor reliability.[9] Both electronic and manual data abstraction can be helpful to describe high-risk populations at the individual and encounter level. However, manual data abstraction has a high potential for error, and quality assurance of manually abstracted data is rarely mentioned in the literature.[10]

There are several studies that attempt to improve understanding of the needs of patients experiencing homelessness through retrospective chart review. For example, Smith et al. identified 63 patients experiencing homelessness who were admitted to an intensive care unit (ICU) in a large urban academic medical center in Canada, and then established a comparison group of housed patients matched on key diagnoses and

* Medical respite programs provide a safe and clean place for persons experiencing homelessness to recover from illness / injury or for pre-procedure preparation. For more information about medical respite, please see the National Health Care for the Homeless Council at: https://www.nhchc.org/resources/clinical/medical-respite/

demographic characteristics.[11] Patients were located in the EHR through a query of a homelessness indicator variable. Housing status was manually verified, and ICU-related data were manually abstracted using a standard form. A quality assurance process verified data accuracy. Study findings indicated patients experiencing homelessness had higher hospital mortality than their housed counterparts, prompting a call for strategies to improve outcomes for this population. Bauer et al. used retrospective chart review to describe characteristics of clinic patients experiencing homelessness who had died of drug overdoses.[12] Since the EHR was specific to the homeless clinic, patients in the system had a history of homelessness or housing instability. Data were both electronically and manually abstracted, and a random review process served as a quality assurance measure. The study supported the need to educate providers on overdose prevention, prescription of naloxone kits, and augmentation of substance-use services. Retrospective chart review has also been helpful in understanding how specific mental illness diagnoses affect hospital admission and length of stay for patients experiencing homelessness,[13] determining the ongoing visual health needs of patients experiencing homelessness,[14] and establishing exposure to long-acting reversible contraceptives for female veterans experiencing homelessness.[15]

We used multiple methods for locating patients experiencing homelessness in our health system's EHR and both electronic and manual data abstraction to answer the following questions:

1. In the absence of a specific indicator, what is the best way to identify patients experiencing homelessness or housing-insecure individuals in the EHR?
2. In the five-year period from January 2010 through December 2014, how many patients experiencing homelessness or housing-insecure people had at least one emergency department or inpatient encounter in the local academic health care system?
3. Of the patients experiencing homelessness or housing-insecure people who had encounters in the local academic health care system, how many would have qualified for medical respite if a program had been active at the time of encounter?
4. Of the patients experiencing homelessness or housing-insecure people who had encounters in the local academic health care system during the study period, what are the top five reasons they did not qualify for medical respite upon discharge from the emergency department or inpatient hospital stay?

Methods

Design. This is a longitudinal retrospective chart review study that employed both electronic and manual data abstraction processes. Patients who had experienced homelessness and had at least one hospital encounter (emergency department and/or inpatient admission) in the local health care system from Jan. 1, 2010 through Dec. 31, 2014 were included in the sample. The university institutional review board approved all study procedures.

Identifying the sample. Due to the time and staffing burden for querying multiple systems, identification of eligible patients occurred in two rounds. Each round employed two separate methods to identify patients experiencing homelessness in the EHR. In round one, patients experiencing homelessness were identified through matching the patient address with known shelter and homeless service agency addresses through a query of the Duke Enterprise Data Unified Content Explorer (DEDUCE). DEDUCE is an online research tool intended to facilitate exploration of aggregate clinical data in support of operations, quality, and research. We also used a list of known patients experiencing homelessness identified through a partner agency, Project Access of Durham County (PADC). PADC is a nonprofit organization that provides low-income, uninsured Durham NC county residents with specialty care; clinicians who care for persons experiencing homelessness in the community regularly refer patients to PADC. The agency provided a list of all known patients experiencing homelessness during the study time frame, including full name, date of birth, and medical record number for each. These patient records were merged with the patients identified through DEDUCE, and duplicates were removed.

Study data were managed using REDCap electronic data capture tools hosted at Duke University Office of Clinical Research.[16] REDCap (Research Electronic Data Capture) is a secure, web-based application designed to support data capture for research studies, providing 1) an intuitive interface for validated data entry; 2) audit trails for tracking data manipulation and export procedures; 3) automated export procedures for seamless data downloads to common statistical packages; and 4) procedures for importing data from external sources.

In round two, patients experiencing homelessness were identified by querying the electronic documentation system used exclusively by the health care system's care management department. This system had a radio button specific to homelessness that care managers used when a patient experiencing homelessness was identified; the system could be queried on this variable. All patients in this system who were recorded as experiencing homelessness during the study time period were included. We also identified patients experiencing homelessness by querying the EHR for International Statistical Classification of Diseases and Related Health Problems 9th Revision (ICD-9) codes V-60 (lack of housing), V-60.89 (other specified housing or economic circumstance), and V-60.9 (unspecified housing or economic circumstance) using the DEDUCE system. The patient records from these round two queries were merged, and duplicates were removed. Round one and round two patient records were then merged and duplicates removed (see Figure 1)†. The remaining unduplicated patient medical records were exported into a separate REDCap database for manual data abstraction.

Data abstraction. The two REDCap databases (one for each round of identifying patients experiencing homelessness within the EHR) contained data at both the patient and encounter level. Patient demographic characteristics—such as age, sex, race, ethnicity, marital status, number of emergency department and inpatient encounters,

† Due to a miscommunication, people with insurance were initially removed from round one, but added back in round two. This was done after duplicates were removed in each round, thus it did not affect the number of people found by each method nor the total number of unduplicated patients found in each round. It did affect the number of patients allocated to each REDCap database. However, all were randomized prior to abstraction.

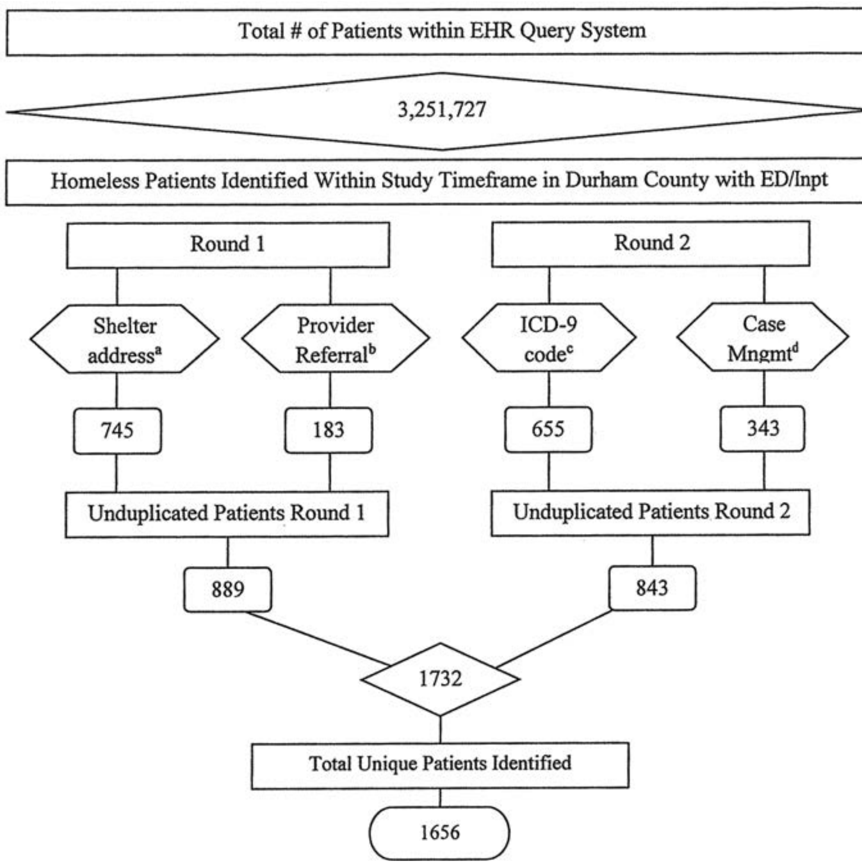

Figure 1. Identifying patients in the EHR.
Notes:
[a]13 shelter/transitional housing addresses were used including frequent misspellings.
[b]Homeless specific providers who made referrals to Project Access of Durham County.
[c]Included: V60—Lack of housing; V60.89—Other specified housing or economic circumstance; V60.9—Unspecified housing or economic circumstance.
[d]Homeless indicator in case management specific data system.
EHR = Electronic Health Record

encounter length of stay, and encounter ICD-9 codes—were captured via a specific electronic patient form. A DEDUCE and corresponding data abstraction form (emergency department or inpatient) was then created for each encounter and linked with the patient form via the use of a unique encounter-level code. For each round of abstraction, records were randomized at the patient level, and then were allocated to each abstractor, with the aim to distribute (more or less equally) routine and more difficult patient cases over the set of abstractors. Once an abstractor selected the patient, they abstracted 100% of that patient's encounters over the five-year period.

The data abstraction team consisted of the primary investigator (PI), co-investigator, and a team of nursing students (the abstractors) in an accelerated Bachelor of Science in Nursing (ABSN) program who participated through a graduate-level directed research course elective. Following institutional human subjects training, the student abstrac-

Box 1.

MEDICAL RESPITE ADMISSION CRITERIA

Single adult
Homeless
Uninsured Durham county resident for at least six months OR veteran who meets VA per diem criteria
Would be discharged to home if one were available
In need of short-term care following hospitalization or for medical stabilization prior to or following outpatient procedure, or while under medical treatment
Able to participate in and maintain safe and harm-free environment including abstinence from drugs, alcohol, and violence
Willing to participate in nurse visits and medical care
Competent in daily living activities (e.g., continent of bowel and bladder, able to prepare simple meals)
Cleared by physical therapy for home discharge and competent in all transfers
Psychiatrically stable

tors were introduced to REDCap. All had previously received training on use of the institution's EHR and had used it extensively during clinical rotations.

The data abstraction process was systematic and guided by a detailed standard operating procedure. Abstractors began with an individual's first encounter within the EHR and followed through in chronological order. Data abstractors documented health behaviors (e.g., smoking, alcohol use), high-risk medication use (i.e., methadone), and ongoing medical needs at discharge (e.g., injectable medications, dressing changes). In addition, they were informed of admission requirements for the local medical respite pilot program. Then, they assessed each of their assigned patients' health care system encounters and determined if the patient would have qualified for medical respite if it had been in place at the time of that encounter (Box 1).

To ensure abstracted data quality, abstractors underwent a rigorous and iterative training process that was developed and led by the PI and co-investigator and included independent abstraction of 15 encounters in a test database and/or on paper forms. Abstractors were then assigned batches of medical records with instructions to stop after their first 10 encounter abstractions for a 100% review and quality check by the PI. If any errors were noted, abstractors were assigned another 10 encounters. After an abstractor completed 10 encounters with no errors, he or she was allowed to proceed with assigned sections of the REDCap database.

Data abstraction quality assurance. The PI performed a 10% random review of all abstraction forms at regular intervals and provided feedback on abstractors' performance. Due to the large number of encounters and clinical decision-making component, a process was established that included an "unverified" indicator for abstractors to use if, after reviewing the entire encounter, they remained unsure regarding abstraction variables or a patient's eligibility for medical respite. Any "unverified" encounters that could not be resolved by the PI or co-investigator were referred to the medical respite clinical director for a final determination.

Data analysis. The REDCap databases were merged into a single SAS® file. Descriptive statistics, including frequencies, percentages, means and standard deviations were calculated. All statistical analyses were performed using the SAS statistical software package, version 9.4 (SAS Institute Inc., Cary, NC, U.S.).

Results

The four separate methods of query yielded 1,656 unique patients (Figure 1). Source frequency analysis revealed shelter addresses and ICD-9 codes captured 77% of patients (Table 1). Patient mean age was 42.3 ± 13.3 years, and 61.3% were male. The sample was 60.9% African American, 32.3% non-Hispanic White, and 2.7% Hispanic or Latino. The remainder did not have race or ethnicity documented.

The cohort of 1,656 patients had 17,017 hospital encounters during the five-year period. Of those, 13,781 (81%) were emergency department visits and 2,824 (17%) were admissions. The remaining 2% of encounters were inpatient psychiatric or labor and delivery. The admissions totaled 17,472 inpatient days for an average length of stay of 6.19 (SD=18.6) hospital days per admission. The median length of stay was 3.5 days.

A total 10,069 (59%) of encounters were manually abstracted, representing 1,296 individuals (81%) of the patient cohort. Of these, 828 (8%) of encounters would have qualified for medical respite were a program in place at time of the encounter. The top three reasons emergency department encounters did not qualify for medical respite were no medical need (63%), hospitalization required (16.3%), and patient left without being seen (6.2%). The top three reasons hospital encounters did not qualify for medical

Table 1.

EHR HOMELESS IDENTIFICATION SOURCE FREQUENCY

Shelter Address	Provider Referral	ICD-9	Case Management	N (%)
X	—	—	—	652 (39.37)
—	—	X	—	472 (28.50)
—	—	—	X	229 (13.83)
—	X	—	—	132 (7.97)
—	—	X	X	66 (3.99)
X	X	—	—	35 (2.11)
X	—	—	X	27 (1.63)
X	—	X	—	24 (1.45)
—	X	—	X	14 (0.85)
X	—	X	X	4 (0.24)
X	X	—	X	1 (0.06)

Note
EHR= Electronic Health Record

Table 2.

TOP 5 REASONS PATIENTS DID NOT QUALIFY FOR MEDICAL RESPITE N (%)

Emergency Department Encounters n=8439			Inpatient Encounters n=1630		
No ongoing medical need	5292	(62.7)	No ongoing medical need	694	(42.6)
Hospitalization necessary	1379	(16.3)	Housed	223	(13.7)
Left without being seen	523	(6.2)	Needed skilled nursing facility	99	(6.1)
Psychiatrically unstable	381	(4.5)	Psychiatrically unstable	89	(5.5)
Less than 18 years of age	300	(3.6)	Left against medical advice	87	(5.3)

respite were no continuing medical need (42.5%), housed (13.6%), and psychiatrically unstable (5.5%) (Table 2).

Discussion

This article describes the process for locating patients experiencing homelessness in an EHR system and methods for assuring high-quality data from both electronic and manual data abstraction. Individual patient encounters are then explored with a determination of whether patients would have qualified for medical respite had it been in place at the time of the encounter, and if not, why.

Screening for and documenting homelessness in EHRs is important in understanding health service utilization patterns and in meeting the specific needs of this particularly vulnerable population. In the current study, a little more than half of the patients were identified through intentional assessment and documentation of homelessness in case management notes (21%) and through ICD-9 codes (34%). Since this study, a 10th revision of the ICD codes has been adopted nationwide. The use of ICD codes to document social determinants of health, including homelessness, are underutilized.[17] The National Health Care for the Homeless Council, United States Interagency Council on Homelessness, and the U.S. Department of Veterans Affairs recommend that health care practitioners screen for and document homelessness using the ICD-10 code specific to homelessness (Z59.0).[3,4,10] Documenting housing status and other social determinants of health offers health care professionals the opportunity to target care and make appropriate referrals for individual patients. This, in turn, has the potential to improve overall population health with interventions, quality improvement initiatives, and the establishment of performance-based metrics.[17,18] Traditionally, providers (e.g., physicians, physician assistants, nurse practitioners) have maintained responsibility for initiating and updating patient problem lists with ICD codes. However, this practice can be shared with other clinicians (e.g., registered nurses, pharmacists, social workers). In 2015, the University of Wisconsin Health System launched a process allowing non-provider clinicians to add specific social conditions to the patient problem list without prior chart documentation by a provider. This improvement is now well-established in the hospital system with expanded preference lists for multiple non-provider clinician groups (G. Klinkner personal communication).

Medical respite programs vary in capacity and design, but minimally provide a safe place for a homeless individual to recover from an injury or illness. In the current study, 828 patient encounters would have qualified for the local medical respite program had it been in place the date of the encounter. Establishing a medical respite program may have multiple benefits for patients experiencing homelessness, clinicians, and the health care system alike. Such programs are associated with decreased emergency department visits,[19,20] decreased inpatient days,[19–21] decreased 90-day readmissions,[22] improved housing status,[19,23,24] and cost savings.[19,20] The National Health Care for the Homeless Council is the preeminent national voice of medical respite in the United States and maintains a registry of medical respite programs. The Council also provides resources and technical assistance for establishing new and developing existing medical respite programs and recently published medical respite program standards.[25] Potential funding sources for medical respite programs include hospitals, private donations, and local/state governments among others.[26]

In the current study, patients who left the ED without being seen (LWBS) or the hospital against medical advice (AMA) were not eligible for the medical respite program. As important quality-of-care indicators, LWBS and AMA may represent increased liability and loss of revenue for hospital systems, and can contribute to poor health outcomes for patients experiencing homelessness. Interventions that may help to decrease LWBS include: increasing communication with waiting patients,[27] having a practitioner in the ED triage area,[28,29] and having protocols for sharing the ED throughput burden with collaborating hospital departments during times of high volume and/or patient acuity.[30] Substance use and addiction are associated with AMA discharges[31–33] and leaving AMA is associated with higher readmission rates[34,35] and increased mortality.[35] Enhancing patient-provider communication[35] and medication-assisted treatment may be effective in preventing patients from leaving AMA.[33,36]

This study contributes to the literature on both EHR retrospective chart reviews regarding patients experiencing homelessness and medical respite, but is not without limitations. Homelessness is a fluid process with individuals flowing between homelessness and various housing arrangements over time.[10] Thus, encounter-level data included both housed and homeless individuals. Lack of encounter-level screening and documentation of housing status prevented identification of the entire population of patients experiencing homelessness and housing instability. The generalizability of these findings is undetermined. The methods described may not be transferrable to other institutions or across other studies. Despite these limitations, the data will support program planning and future studies regarding the health of people experiencing homelessness and housing-insecure people.

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