Title
Cluster Analysis of the Highest Users of Medical, Behavioral Health, and Social Services in San Francisco.

Journal
Journal of general internal medicine, 38(5)

ISSN
0884-8734

Authors
Hewlett, Meghan M
Raven, Maria C
Graham-Squire, Dave
et al.

Publication Date
2023-04-01

DOI
10.1007/s11606-022-07873-y

Peer reviewed

Cluster Analysis of the Highest Users of Medical, Behavioral Health, and Social Services in San Francisco

Meghan M. Hewlett, MD, MPH[1], Maria C. Raven, MD, MPH, MSc[1,2], Dave Graham-Squire, PhD[2], Jennifer L. Evans, MS[2], Caroline Cawley, MPH[1,2], Margot Kushel, MD[2,3], and Hemal K. Kanzaria, MD, MSc[1,2,3]

[1]Department of Emergency Medicine, University of California, San Francisco, San Francisco, CA, USA; [2]Benioff Homelessness and Housing Initiative, University of California, San Francisco, San Francisco, USA; [3]Center for Vulnerable Populations, University of California, San Francisco, USA.

BACKGROUND: In the City and County of San Francisco, frequent users of emergent and urgent services across different settings (i.e., medical, mental health (MH), substance use disorder (SUD) services) are referred to as high users of multiple systems (HUMS). While often grouped together, frequent users of the health care system are likely a heterogenous population composed of subgroups with differential management needs.

OBJECTIVE: To identify subgroups within this HUMS population using a cluster analysis.

DESIGN: Cross-sectional study of HUMS patients for the 2019–2020 fiscal year using the Coordinated Care Management System (CCMS), San Francisco Department of Public Health's integrated data system.

PARTICIPANTS: We calculated use scores based on nine types of urgent and emergent medical, MH, and SUD services and identified the top 5% of HUMS patients. Through *k*-medoids cluster analysis, we identified subgroups of HUMS patients.

MAIN MEASURES: Subgroup-specific demographic, comorbidity, and service use profiles.

KEY RESULTS: The top 5% of HUMS patients in the study period included 2657 individuals; 69.7% identified as men and 66.5% identified as non-White. We detected 5 subgroups: subgroup 1 (N = 298, 11.2%) who were relatively younger with prevalent MH and SUD comorbidities, and MH services use; subgroup 2 (N = 478, 18.0%), who were experiencing homelessness, with multiple comorbidities, and frequent use of medical services; subgroup 3 (N = 449, 16.9%), who disproportionately self-identified as Black, with prolonged homelessness, multiple comorbidities, and persistent HUMS status; subgroup 4 (N = 690, 26.0%), who were relatively older, disproportionately self-identified as Black, with prior homelessness, multiple comorbidities, and frequent use of medical services; and subgroup 5 (N=742, 27.9%), who disproportionately self-identified as Latinx, were housed, with medical comorbidities and frequent medical service use.

CONCLUSIONS: Our study highlights the heterogeneity of HUMS patients. Interventions must be tailored to meet the needs of these diverse patient subgroups.

KEY WORDS: cluster analysis; health systems; services use.

J Gen Intern Med 38(5):1143–51

DOI: 10.1007/s11606-022-07873-y

Prior Presentation: *Results from this manuscript have not been previously presented to the public or at any conference.*

Received March 28, 2022

Accepted October 24, 2022

Published online November 29, 2022

INTRODUCTION

Five percent of the US population accounts for 50% of annual health care spending and 1% accounts for almost 25% of expenditures.[1] Frequent users of the health care system are defined as patients with ≥ 4 emergency department (ED) visits or ≥ 3 hospitalizations annually.[2, 3] This patient population commonly experiences comorbid mental health (MH) and substance use disorders (SUD), homelessness, incarceration, and unemployment.[4–6] To decrease costs and address patient needs, policymakers have focused on reducing ED use and hospitalizations, although most efforts have been unsuccessful.[7–9]

Frequent users of medical services have high use of MH and SUD crisis services (e.g., inpatient psychiatric centers, alcohol sobering centers etc.), as well as homelessness services.[4, 6, 10–15] Given the lack of care coordination between services, individuals engaging with multiple systems often experience fragmented care. The City and County of San Francisco developed the High Users of Multiple Systems (HUMS) score to identify individuals experiencing fragmented care who would benefit from improved coordination.[14, 15] Analysis of frequent health care systems users, including HUMS patients, suggests a range of medical, behavioral health and social needs that require tailored interventions.[14–16]

Interventions for such patients, including case management and permanent supportive housing (PSH), vary by care model (e.g., medical, behavioral health, or social needs focus), intensity (e.g., staff/client ratio, staff training), and services offered (e.g., direct service delivery vs. coordination). Interventions may be applied in a uniform manner without accounting for varied needs across heterogeneous frequent user subgroups.[16, 17] Prior frequent user studies focus on patterns of medical health comorbidities and medical service use to characterize subgroups.[18, 19] No study has accounted for MH, SUD, or social service use.

Integrated data that includes such information may facilitate understanding and addressing the needs of frequent users. [20]

In 2007, the San Francisco Department of Public Health (SFDPH) implemented the Coordinated Care Management System (CCMS) which integrates patient-level medical, MH, SUD, and social data from multiple county-level services.[14, 15] Leveraging this data, we sought to identify distinct subgroups within the HUMS population to inform tailored intervention strategies.

METHODS

Data Source and Patient Population

We used the CCMS, which compiles information about complex, high-needs patients across multiple service domains by integrating data from several county agencies and the San Francisco Health Plan (SFHP), San Francisco County's primary Medicaid managed care plan. The CCMS includes medical and behavioral electronic health care records, homelessness services, and jail encounters. The CCMS creates a record for any patient (a) reported as unhoused by a San Francisco County agency, or (b) with county jail contact, or (c) who uses urgent or emergent county medical, MH, or SUD services. The database integrates and matches data at the patient level. We previously detailed the CCMS dataset and the HUMS methodology and explain them succinctly below.[14, 15]

We obtained patients' use of county urgent and emergent medical, MH, SUD, and social services from the CCMS for fiscal years 2017 through 2020. Our primary analysis year was the 2019–2020 fiscal year (July 1, 2019–June 30, 2020). Notably, San Francisco County issued a stay-at-home order on March 17, 2020, for the COVID-19 pandemic. The University of California San Francisco Institutional Review Board provided research approval on partially deidentified human subjects, and we conducted the analysis according to protected health information and Code of Federal Regulations (Confidentiality of Substance Use Disorder Patient Records, 42 C.F.R. Part 2 [2017]) protocols.

We identified the top 5% of HUMS patients for the 2019–2020 fiscal year by calculating a use score for each patient, hereafter known as a HUMS score, by summing all specified encounters from nine urgent and emergent medical, MH, and SUD services during the fiscal year (Table 1). We restricted the study population to patients within the top 5% of HUMS scores for the fiscal year. For the cluster analysis, we obtained variables from the CCMS that characterized patient demographics, social risk factors, comorbidities, and service use.

Demographics and Social Risk Factors. We examined sociodemographic variables, including patient insurance and housing status. Among frequent health care users, prior studies report distinct patterns of service use and inequities related to age, gender, race, ethnicity, and disability status.[15, 17, 21, 22] We included such variables as markers of differential experience of the health care system and to identify structural inequities for future interventions targeting ageist, sexist, racist, and ableist policies. For example, we chose to include race in our analysis, not to suggest any causal relation to frequent user subgroups, but rather to serve as a proxy for differential experiences of interpersonal and structural racism. Patient gender, race, and ethnicity were self-reported. We ascertained past and current homelessness through observed use of homelessness services and self-reported homelessness during service encounters.[14] We defined prolonged homelessness as having a history of homelessness for ≥5 years. We stratified insurance status into four groups: receipt of Medicaid alone; Medicaid with Supplemental Security Income and/or Social Security Disability Insurance (SSI/SSDI) with or without Medicare; Medicare alone; or Other. We included SSI/SSDI as a separate category to identify individuals who were either ≥65, blind, or disabled. As all individuals entering county jail have a jail health screening, we included this as a proxy for a jail stay.

Table 1 Catalog of Services Used to Calculate High Users of Multiple Systems (HUMS) Score in San Francisco County

System	Urgent/emergent service	Unit
Medical health system	Emergency department	Visit
	Hospital medical inpatient	Stay
	Urgent care clinic	Visit
Mental health system	Psychiatric emergency services	Visit
	Hospital psychiatric inpatient	Stay
	Psychiatric urgent care clinic	Visit
Substance use disorder system	Medical detoxification	Stay
	Social detoxification	Stay
	Emergency department	Visit

Medical, Mental Health, and Substance Use Disorder Comorbidities. We obtained International Classification of Diseases, Ninth and Tenth Revision, Clinical Modification (ICD-9-CM, ICD-10-CM), codes for principal diagnoses associated with service use and defined the presence of an Elixhauser medical, MH, or SUD comorbidity as having ≥2 diagnosis codes during service encounters for the respective comorbidity in the 2019–2020 fiscal year and the prior two fiscal years.[23] Appendix 1 lists these Elixhauser comorbidities. We separately included reports of an involuntary psychiatric hold during the 2019–2020 fiscal year.

Service Use. We assessed use of urgent and emergent services across three domains (i.e., medical, MH, and SUD) during the 2019–2020 fiscal year for all patients — using the same services to calculate HUMS score (Table 1). This included out-of-network medical services use for SFHP beneficiaries.

Persistent HUMS. To assess prior service use among the study population, we calculated HUMS scores for patients with available data for the prior two fiscal years. From these scores, we created a dichotomous variable that defined a patient as a "persistent HUMS" if they also ranked within the top 5% of HUMS scores in any of the two prior fiscal years.

Clustering and Statistical Analysis

To identify subgroups within the study population, we employed a cluster analysis. We considered initial candidate variables for clustering based on clinical insight, identifying variables most informative for potential intervention efforts. We removed variables with a high degree of association to minimize redundancy and maximize parsimony. We selected 17 variables for inclusion and chose the *k*-medoids approach given the mixed composition of continuous, categorical, and ordinal variables (Table 2). As the algorithm requires a predetermined number of clusters (k), we ran multiple analyses with various values of k ($k = 2$ to $k = 15$) to identify distinct clusters with adequate group sample size to detect between-group differences.[24] We calculated an optimal number of clusters using a silhouette width measure which is described in detail in Appendix 2. However, we based our final number of clusters on clinical judgment and utility to inform intervention strategies.[25]. We employed the *k*-medoids algorithm to identify subgroups based on correlations around a central point for each cluster, known as a medoid, represented by an individual HUMS patient. HUMS patients are assigned to the cluster with the closest medoid. More specifically, the algorithm deems data points as "similar" or "dissimilar" according to a well-defined distance metric between the points using the Partitioning Around Medoids (PAM) algorithm and Gower distance which accommodates continuous, categorical, and ordinal variables.[24] To further examine subgroup robustness, we repeated our analysis using two other methods: *k*-means and latent class analysis (LCA). As *k*-means requires all variables to be numerical, we transformed non-numerical variables to a series of indicator variables with numerical values. We used the R Statistical Package to employ the *k*-means and *k*-medoids algorithms, and the Proc LCA package in SAS, version 9.4, to perform the LCA.[26, 27]

Table 2 Demographic, Comorbidity, and Service Use Variables Included for Cluster Analysis of the Top 5% of High Users of Multiple Systems (HUMS) Patients for the 2019–2020 Fiscal Year

Variable description	Variable category
Age	Numerical
Race and ethnicity	Categorical — 7 groups
Gender	Categorical — 4 groups
Years of homelessness	Ordinal — 5 levels
Last known housing status	Categorical — 4 groups
Insurance status	Categorical — 4 groups
Jail stay	Binary
Shelter stay	Binary
Persistent HUMS patient	Binary
Elixhauser medical comorbidity	Binary
Elixhauser mental health comorbidity	Binary
Elixhauser substance use disorder comorbidity	Binary
Medical services use ranking*	Ordinal — 4 levels
Mental health services use	Binary
Substance use disorder services use	Binary
Number of service domains used†	Ordinal — 3 levels
Involuntary psychiatric hold	Binary

**We defined medical services use ranking as the relative ranking of a patient's urgent and emergent medical service use compared to all users of urgent and emergency medical services captured by the Coordinated Care Management System during the 2019–2020 fiscal year.*
†Service domains are defined as medical, mental health, and substance use disorder

RESULTS

We identified 2657 patients in the top 5% of HUMS patients for the 2019–2020 fiscal year (Table 3). The mean age (SD) was 48.2 (14.1) years, 69.7% self-identified as men, and 66.5% self-identified as non-White. Compared to the general population of San Francisco County, the study population had a higher proportion of patients who were unhoused; self-identifying as men, Black, Latinx, and Native American; and a lower proportion self-identifying as Asian/Pacific Islander.[28–30] Overall, 82.4% reported a history of homelessness, 47.5% were housed, 22.2% had a jail stay, and 42.0% received SSI/SSDI. Additionally, 64.5% and 74.5% had a MH and SUD comorbidity, respectively; 39.7% and 16.3% used MH and SUD services, respectively; and 47.2% used multiple service domains. We identified five subgroups (Table 4). Most clustering occurred along housing characteristics, presence of a MH comorbidity, medical and MH service use, and receipt of SSI/SSDI.

Subgroup 1 — High MH, SUD, and Incarceration

Subgroup 1 ($N = 298$, 11.2%) was the youngest group (mean age (SD) 37.7 (10.7) years), with the highest proportion self-identifying as men. Most patients self-identified as White. This subgroup had prevalent prior and current homelessness; MH and SUD comorbidities; MH service use; and the least medical services use. The subgroup had the highest percentage of patients with jail stays (63.1%) and involuntary psychiatric holds (72.8%). Almost all patients used ≥ 2 service domains.

Subgroup 2 — Trimorbidity, High Shelter Use

Subgroup 2 ($N = 478$, 18.0%) had racial, ethnic, and gender demographics similar to subgroup 1. The subgroup had the lowest percentage of patients who were housed (13.4%) and the highest use of shelter services (78.9%); all but one patient had a history of homelessness. Most patients had a medical, MH, and SUD comorbidity; and 81.6% of patients were in the top 5% of medical services users.

Subgroup 3 — Unhoused, High Multiple Services Use

Subgroup 3 (N=449, 16.9%) patients largely self-identified as men and Black. The majority of patients were unhoused as of their last service encounter. Most patients had a medical, MH,

Table 3 Characteristics of the Top 5% of High Users of Multiple Systems (HUMS) Patients for the 2019–2020 Fiscal Year

Characteristic	No. (%) (*N* = 2657)
Age, mean (SD), years	48.2 (14.1)
Race and ethnicity	
Black	943 (35.5%)
Asian/Pacific Islander	212 (8.0%)
Latinx	464 (17.5%)
Multiracial	85 (3.2%)
Native American	41 (1.5%)
White	889 (33.5%)
Not reported	23 (0.9%)
Gender	
Women	772 (29.1%)
Men	1852 (69.7%)
Transgender	27 (1.0%)
Not reported	6 (0.2%)
Years of homelessness	
Never	467 (17.6%)
< 1 year	291 (11.0%)
1–4 years	548 (20.6%)
5–9 years	384 (14.5%)
≥ 10 years	967 (36.4%)
Last known housing status*	
Outdoors	431 (16.2%)
Shelter	713 (26.8%)
Housed	1262 (47.5%)
Other	251 (9.4%)
Insurance status†	
Medicaid only	1373 (51.7%)
Medicaid and SSI/SSDI with or without Medicare	1116 (42.0%)
Medicare only	81 (3.0%)
Other/uninsured	87 (3.3%)
Jail stay	589 (22.2%)
Shelter stay	742 (27.9%)
Persistent HUMS patient	1102 (41.5%)
Elixhauser medical comorbidity	2025 (76.2%)
Elixhauser mental health comorbidity	1715 (64.5%)
Elixhauser substance use disorder comorbidity	1980 (74.5%)
Medical services use ranking‡	
Top 1%	535 (20.1%)
2–5%	1790 (67.4%)
6–10%	173 (6.5%)
11–100%	159 (6.0%)
MH services use	1054 (39.7%)
SUD services use	432 (16.3%)
Involuntary psychiatric hold	660 (24.8%)
Number of service domains used‡	
1	1404 (52.8%)
2	1027 (38.7%)
3	226 (8.5%)

Abbreviations: SSI, Supplemental Security Income; SSDI, Social Security Disability Insurance; percentages may not sum to 100% due to rounding.

**Last known housing status is stratified into four categories: Outdoors status includes individuals living outdoors or another unhoused status not otherwise specified by other categories; shelter status includes those residing in a shelter, shelter-in-place hotel, isolation and quarantine hotel, or receiving housing and/or shelter services from the San Francisco Department of Homelessness and Supportive Housing; housed status includes those who are housed or living in permanent supportive housing; other status includes those residing in the following: temporary housing, treatment facility, institution, skilled nursing facility, Veterans Affairs hospital, inpatient psychiatric hospital, jail, prison, or have no reported housing status.*

†California residents receiving SSI and/or SSDI are automatically enrolled to receive Medicaid benefits. Only patients who have received 24 months of payments via SSDI qualify for Medicare outside of the standard Medicare eligibility requirements. Other/uninsured status includes those who are self-pay, receive private insurance benefits, or are uninsured.

‡Table 2 footnotes explain medical services use ranking and number of service domains used

and SUD comorbidity; all patients used MH services; and there was a higher prevalence of jail stays and involuntary psychiatric holds relative to most subgroups. The subgroup had the largest proportion of patients with prolonged homelessness (78.6%), receiving SSI/SSDI (71.5%), meeting criteria for persistent HUMS (73.5%), comprising the top 1% of medical services use (31.0%), and using services across all three service domains (21.4%).

Subgroup 4 — Trimorbidity, High Medical Services Use

Subgroup 4 (*N*= 690, 26.0%) patients were older (mean age (SD) 52.7 (12.0) years), and disproportionately self-identified as men and Black. Most patients had a history of prolonged homelessness; however, most were housed as of their last service encounter. The majority of patients received SSI/SSDI. The subgroup had the highest proportion of patients with a medical comorbidity and who were in the top 5% of medical services users (90.9% and 99%, respectively), with most meeting criteria for persistent HUMS. While most patients had a MH comorbidity, none used MH services.

Subgroup 5 — Housed, New High Medical Services Use

Subgroup 5 (*N* = 742, 27.9%) patients disproportionately self-identified as men and Latinx; however, the subgroup had the highest percentage of patients self-identifying as women (34%) and Asian/Pacific Islander (15.8%). The subgroup also had the highest percentage of patients who were housed (70.2%). Many patients had a medical comorbidity; and while almost all patients were in the top 5% of medical services users, only 11.9% met criteria for persistent HUMS. The subgroup had the lowest prevalence of MH and SUD comorbidities and minimal MH and SUD service use.

Repeating our analysis using a *k*-means cluster algorithm and LCA, we found subgroup characteristics retained similarity between all three methodologic approaches (Appendix 3 & 4).

DISCUSSION

This study contributes to the growing literature acknowledging the vulnerability and heterogeneity of frequent health care users and provides guidance for targeted interventions. Expanding prior work, we found that HUMS patients commonly self-identified as Black, experienced homelessness, disability, and significant comorbidity.[15]

Our study is the first to incorporate cross-sector medical and social data in a cluster analysis to identify distinct subgroups, highlighting the heterogeneity of the HUMS population. Despite high medical services use overall, the subgroup-specific profiles suggest the need for tailored interventions to address differing medical, behavioral health, and social needs (Table 5).

Table 4 ***k*****-Medoids Analysis of Subgroup Characteristics of the Top 5% of High Users of Medical Systems (HUMS) Patients for the 2019–2020 Fiscal Year**

Characteristic	Subgroup 1 High MH, SUD, and Incarceration No. (%) (*N* = 298, 11.2%)	Subgroup 2 Trimorbidity, High Shelter Use No. (%) (*N* = 478, 18.0%)	Subgroup 3 Unhoused, High Multiple Services Use No. (%) (*N* = 449, 16.9%)	Subgroup 4 Trimorbidity, High Medical Services Use No. (%) (*N* = 690, 26.0%)	Subgroup 5 Housed, New High Medical Services Use No. (%) (*N* = 742, 27.9%)
Age, mean (SD), years	37.7 (10.7)	47.2 (12.2)	46.9 (12.7)	52.7 (12.0)	49.8 (16.4)
Race and ethnicity					
Black	77 (25.8%)	102 (21.3%)	216 (48.1%)	378 (54.8%)	170 (22.9%)
Asian/Pacific Islander	24 (8.1%)	20 (4.2%)	27 (6.0%)	24 (3.5%)	117 (15.8%)
Latinx	28 (9.4%)	66 (13.8%)	54 (12.0%)	70 (10.1%)	246 (33.2%)
Multiracial	14 (4.7%)	16 (3.3%)	13 (2.9%)	18 (2.6%)	24 (3.2%)
Native American	1 (0.3%)	11 (2.3%)	11 (2.4%)	10 (1.4%)	8 (1.1%)
White	152 (51.0%)	258 (54.0%)	126 (28.1%)	190 (27.5%)	163 (22.0%)
Not reported	2 (0.7%)	5 (1.0%)	2 (0.4%)	0 (0.0%)	14 (1.9%)
Gender					
Women	56 (18.8%)	119 (24.9%)	132 (29.4%)	213 (30.9%)	252 (34.0%)
Men	239 (80.2%)	354 (74.1%)	305 (67.9%)	471 (68.3%)	483 (65.1%)
Transgender	3 (1.0%)	5 (1.0%)	12 (2.7%)	6 (0.9%)	1 (0.1%)
Not reported	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	6 (0.8%)
Years of homelessness					
Never	20 (6.7%)	1 (0.2%)	30 (6.7%)	83 (12.0%)	333 (44.9%)
< 1 year	60 (20.1%)	40 (8.4%)	19 (4.2%)	58 (8.4%)	114 (15.4%)
1–4 years	106 (35.6%)	161 (33.7%)	47 (10.5%)	97 (14.1%)	137 (18.5%)
5–9 years	49 (16.4%)	99 (20.7%)	84 (18.7%)	99 (14.3%)	53 (7.1%)
≥ 10 years	63 (21.1%)	177 (37.0%)	269 (59.9%)	353 (51.2%)	105 (14.2%)
Last known housing status*					
Outdoors	149 (50.0%)	82 (17.2%)	74 (16.5%)	64 (9.3%)	62 (8.4%)
Shelter	52 (17.4%)	295 (61.7%)	98 (21.8%)	161 (23.3%)	107 (14.4%)
Housed	67 (22.5%)	64 (13.4%)	217 (48.3%)	393 (57.0%)	521 (70.2%)
Other	30 (10.1%)	37 (7.7%)	60 (13.4%)	72 (10.4%)	52 (7.0%)
Insurance status*					
Medicaid Only	234 (78.5%)	329 (68.8%)	107 (23.8%)	173 (25.1%)	530 (71.4%)
Medicaid and SSI/SSDI with or without Medicare	37 (12.4%)	119 (24.9%)	321 (71.5%)	490 (71.0%)	149 (20.1%)
Medicare only	15 (5.0%)	21 (4.4%)	13 (2.9%)	10 (1.4%)	22 (3.0%)
Other/uninsured	12 (4.0%)	9 (1.9%)	8 (1.8%)	17 (2.5%)	41 (5.5%)
Jail stay	188 (63.1%)	106 (22.2%)	115 (25.6%)	105 (15.2%)	75 (10.1%)
Shelter stay	53 (17.8%)	377 (78.9%)	117 (26.1%)	124 (18.0%)	71 (9.6%)
Persistent HUMS patient	65 (21.8%)	174 (36.4%)	330 (73.5%)	445 (64.5%)	88 (11.9%)
Elixhauser medical comorbidity	83(27.9%)	372 (77.8%)	383 (85.3%)	627 (90.9%)	560 (75.5%)
Elixhauser mental health comorbidity	280 (94.0%)	397 (83.1%)	441 (98.2%)	463 (67.1%)	134 (18.1%)
Elixhauser substance use disorder comorbidity	271 (90.9%)	440 (92.1%)	409 (91.1%)	601 (87.1%)	259 (34.9%)
Medical services use ranking†					
Top 1%	36 (12.1%)	124 (25.9%)	139 (31.0%)	163 (23.6%)	73 (9.8%)
2–5%	142 (47.7%)	266 (55.6%)	204 (45.4%)	520 (75.4%)	658 (88.7%)
6–10%	53 (17.8%)	58 (12.1%)	53 (11.8%)	4 (0.6%)	5 (0.7%)
11–100%	67 (22.5%)	30 (6.3%)	53 (11.8%)	3 (0.4%)	6 (0.8%)
Mental health services use	273 (91.6%)	319 (66.7%)	449 (100.0%)	0 (0.0%)	13 (1.8%)
Substance use disorder services use	58 (19.5%)	163 (34.1%)	96 (21.4%)	79 (11.4%)	36 (4.9%)
Involuntary psychiatric hold	217 (72.8%)	115 (24.1%)	325 (72.4%)	0 (0.0%)	3 (0.4%)
Number of service domains used†					
1	16 (5.4%)	80 (16.7%)	1 (0.2%)	611 (88.6%)	696 (93.8%)
2	236 (79.2%)	314 (65.7%)	352 (78.4%)	79 (11.4%)	46 (6.2%)
3	46 (15.4%)	84 (17.6%)	96 (21.4%)	0 (0.0%)	0 (0.0%)

Abbreviations: MH, mental health; SSI, Supplemental Security Income; SSDI, Social Security Disability Insurance; SUD, substance use disorder; percentages may not sum to 100% due to rounding.
**Table 3 footnotes explain last known housing and insurance status stratifications.*
†Table 2 footnotes explain medical services use ranking and number of service domains used

Such interventions vary in focus and have differing potential to serve subgroups. For example, PSH offers housing alongside customizable services ranging in intensity and scope (e.g., MH and SUD care, physical rehabilitation, employment services, and connection to legal services).[31, 32] Case management programs also vary in focus, staff composition, and service intensity.[33] A brokerage model provides service referral and coordination whereas a clinical model offers medically, behaviorally, or socially focused therapeutic services.[34, 35] Intensive models include assertive community treatment (ACT) for clients with MH needs in which a multidisciplinary team with a small client-to-staff ratio delivers personalized 24-

Table 5 Summary of Subgroup Characteristics and Proposed Interventions

	Subgroup 1 High MH, SUD, and Incarceration No. (%) (N = 298, 11.2%)	Subgroup 2 Trimorbidity, High Shelter Use No. (%) (N = 478, 18.0%)	Subgroup 3 Unhoused, High Multiple Services Use No. (%) (N = 449, 16.9%)	Subgroup 4 Trimorbidity, High Medical Services Use No. (%) (N = 690, 26.0%)	Subgroup 5 Housed, New High Medical Services Use No. (%) (N = 742, 27.9%)
Demographics	Younger age, predominantly White Largely unhoused, prevalent jail stays, and involuntary psychiatric holds	Predominantly White Largely unhoused and high shelter use	Predominantly Black Largely unhoused, historical prolonged homelessness, receiving SSI/SSDI, frequent psychiatric holds, persistent HUMS	Older age, predominantly Black Largely housed, historical prolonged homelessness, receiving SSI/SSDI	Predominantly Latinx, more women Largely housed, new HUMS
Comorbidities	MH and SUD comorbidities	Medical, MH, and SUD comorbidities	Medical, MH, and SUD comorbidities	Medical, MH, and SUD comorbidities	Medical comorbidities
Service use	High MH services use	High medical services use	High medical, MH, and SUD services use	High medical services use	High medical services use
Proposed Interventions	PSH with ACT	PSH, addiction treatment with medical services, CM with a clinical/rehabilitation model	PSH with ACT	Medical and behavioral health-focused supplemental CM	Identify and address racial and ethnic inequities in primary care

Abbreviations: ACT, assertive community treatment; HUMS, high users of multiple services; MH, mental health; PSH, permanent supportive housing; SSI, Supplemental Security Income; SSDI, Social Security Disability Insurance; SUD, substance use disorder

h, daily services to clients in their environment (e.g., MH treatment, integrated dual-disorder treatment, vocational rehabilitation, medication support, counseling). Intensive Case Management is less intensive than ACT, without shared caseloads.[36, 37] Effective program tailoring for patients with diverse needs requires understanding the specific capabilities of such programs and their differences.

Homelessness characterized subgroups 1–4, though each demonstrated differential needs. We observed co-existing MH and SUD comorbidities as well as a higher prevalence of jail stays in subgroups 1 and 3. Co-existing MH and SUD are associated with increased psychiatric hospitalization, and individuals with MH system contact prior to or after incarceration have higher shelter use and odds of re-incarceration.[38, 39] The criminalization of homelessness and mental illness may contribute to the "institutional circuit" between incarceration, hospitals, psychiatric institutions, and shelters.[40–42] Integrating PSH (shown to reduce the average number of shelter, psychiatric hospitalization, and incarceration days) with ACT (shown to reduce hospitalizations, improve housing stability and symptom management, and increase quality of life) may address housing needs while providing high-intensity supportive services.[36, 43, 44] Our results reflect the well-known need for more MH and SUD services in San Francisco, resulting in recent reform efforts.[45, 46]

Subgroup 2 had low SUD service use compared to the prevalence of SUD comorbidities; however, most patients exclusively used medical services. In addition to PSH, these patients could benefit from integration of addiction treatment into medical care delivery and a clinical/rehabilitation model of case management for clients with SUD.[47, 48] Despite a high prevalence of prior prolonged homelessness in subgroup 4, many patients were housed as of their last service encounter, often through PSH. However, we also observed no MH services use relative to the prevalence of MH comorbidities and high medical services use. PSH programs may therefore need supplemental case management services with a medical and behavioral health focus (e.g., a Masters-trained behavioral health specialist with physician oversight).

Our results highlight inequities related to structural ableism and racism in the health care system.[49] Individuals in subgroups characterized by SSI/SSDI receipt (a proxy we used for disability) had prevalent medical comorbidities and medical service use. Our results may be the result of downstream effects of interpersonal discrimination from health care providers, access limitations to preventative care and medications, and care dissatisfaction experienced by individuals with disabilities.[50–54] With respect to race and ethnicity, the majority of patients in subgroups 3 and 4 self-identified as Black; and both subgroups had high burdens of patients with all three comorbidity domains, significant medical service use, and minimal SUD service use. Socioeconomic disinvestment in predominantly Black and Latinx neighborhoods contributes to the paucity of primary and MH care, as well as the poor health outcomes experienced by Black and Latinx individuals.[55–57] Structural racism also exists in policies that limit the accessibility of SUD treatment and perpetuate the criminalization of SUD.[58] Our findings may reflect the downstream effects of such social determinants of health. Additionally, subgroup 5 comprised mostly of members of racial and ethnic minority groups and almost all patients used medical services exclusively. The high percentage of patients with a medical comorbidity coupled with the lowest percentage of persistent HUMS patients may indicate temporary frequent use; however, this also may reflect racial and ethnic inequities in primary care which include lower quality care, poorer patient-physician communication, and lower likelihood of receiving indicated interventions.[59–65]

The strengths of our study included using an integrated, cross-sector dataset to identify frequent users across multiple systems. The HUMS score is a proxy for fragmented care, helping identify individuals that could benefit from improved care coordination.

Our study had several limitations. The index year of study included the first 3.5 months of the COVID-19 pandemic in San Francisco County; therefore, our results may not reflect typical service use previously given changes in service availability during the pandemic. However, the County quickly implemented alternative services with non-congregate shelters to limit COVID-19 exposure among unhoused individuals and to offset service closures.[66, 67] Also, while we obtained data across multiple non-medical service domains, we primarily accounted for service use within San Francisco County. However, we included Medicaid encounters (in- and out-of-network), which allowed for comprehensive capture of acute medical services use for SFHP beneficiaries. Our results may not be generalizable to non-safety net systems or those with marked differences in public health infrastructure. Additionally, we included more variables in our *k*-medoids cluster algorithm with the intent of producing clinically and practically informative clusters at the expense of a parsimonious model. Clusters may be less distinct from one another using silhouette width measures; however, we found consistency in subgroup characteristics across the three cluster algorithms, demonstrating the robustness of our findings.

Cross-sector, integrated data informed our understanding of HUMS patients, and underscores the heterogeneity of this patient population both in characteristics and interventional needs. Our study emphasizes the benefit of subgroup identification and the need to match service provision to the underlying needs of patients.

Supplementary Information: *The online version contains supplementary material available at https://doi.org/10.1007/s11606-022-07873-y.*

Acknowledgements: *The authors thank Dr. Hali Hammer and the members of the Whole Person Care team at the San Francisco Department of Public Health for their partnership.*

Corresponding Author: *Meghan M. Hewlett, MD, MPH; Department of Emergency Medicine, University of California, San Francisco, San Francisco, CA, USA (e-mail: Meghan.hewlett@ucsf.edu).*

Funding *The analysis of the work described was supported by the Benioff Homeless and Housing Initiative at the University of California, San Francisco. The funding source had no role in the design and conduct of the study; collection, management, analysis, and interpretation of the data; preparation, review, or approval of the manuscript; and decision to submit the manuscript for publication.*

REFERENCES

1. **Cohen SB**. The Concentration of Health Care Expenditures and Related Expenses for Costly Medical Conditions, 2012. In: *Statistical Brief (Medical Expenditure Panel Survey (US))*. Agency for Healthcare Research and Quality (US); 2012. http://www.ncbi.nlm.nih.gov/books/NBK470837/
2. **Jiang HJ, Weiss AJ, Barrett ML, Sheng M**. Characteristics of Hospital Stays for Super-Utilizers by Payer, 2012: Statistical Brief #190. In: *Healthcare Cost and Utilization Project (HCUP) Statistical Briefs*. Agency for Healthcare Research and Quality (US); 2015. http://www.ncbi.nlm.nih.gov/books/NBK310271/
3. **Jiang HJ, Weiss AJ, Barrett ML**. Characteristics of Emergency Department Visits for Super-Utilizers by Payer, 2014: Statistical Brief #221. In: *Healthcare Cost and Utilization Project (HCUP) Statistical Briefs*. Agency for Healthcare Research and Quality (US); 2017. http://www.ncbi.nlm.nih.gov/books/NBK442038/
4. **Hunt KA, Weber EJ, Showstack JA, Colby DC, Callaham ML**. Characteristics of frequent users of emergency departments. *Ann Emerg Med*. 2006;48(1):1-8. https://doi.org/10.1016/j.annemergmed.2005.12.030
5. **Sandoval E, Smith S, Walter J, et al.** A comparison of frequent and infrequent visitors to an urban emergency department. *J Emerg Med*. 2010;38(2):115-121. https://doi.org/10.1016/j.jemermed.2007.09.042
6. **Raven MC**. What we don't know may hurt us: interventions for frequent emergency department users. *Ann Emerg Med*. 2011;58(1):53-55. https://doi.org/10.1016/j.annemergmed.2011.04.009
7. **Williams BC**. Limited effects of care management for high utilizers on total healthcare costs. *Am J Manag Care*. 2015;21(4):e244-246.
8. **Peikes D, Chen A, Schore J, Brown R**. Effects of care coordination on hospitalization, quality of care, and health care expenditures among Medicare beneficiaries: 15 randomized trials. *JAMA*. 2009;301(6):603-618. https://doi.org/10.1001/jama.2009.126
9. **Finkelstein A, Zhou A, Taubman S, Doyle J**. Health care hotspotting - a randomized, controlled trial. *N Engl J Med*. 2020;382(2):152-162. https://doi.org/10.1056/NEJMsa1906848
10. **Gawande A.** Finding Medicine's Hot Spots | The New Yorker. https://www.newyorker.com/magazine/2011/01/24/the-hot-spotters
11. **Hasselman D.** Super-Utilizer Summit Common Themes from Innovative Complex Care Management Programs. Published online 2013:32.
12. **Emeche U.** Is a strategy focused on super-utilizers equal to the task of health care system transformation? Yes. *Ann Fam Med*. 2015;13(1):6-7. https://doi.org/10.1370/afm.1746
13. **Kushel MB, Perry S, Bangsberg D, Clark R, Moss AR**. Emergency department use among the homeless and marginally housed: results from a community-based study. *Am J Public Health*. 2002;92(5):778-784. https://doi.org/10.2105/ajph.92.5.778
14. **Kanzaria HK, Niedzwiecki M, Cawley CL, et al.** Frequent emergency department users: focusing solely on medical utilization misses the whole person. *Health Aff (Millwood)*. 2019;38(11):1866-1875. https://doi.org/10.1377/hlthaff.2019.00082
15. **Cawley C, Raven MC, Martinez MX, Niedzwiecki M, Kushel MB, Kanzaria HK**. Understanding the 100 highest users of health and social services in San Francisco. *Acad Emerg Med*. n/a(n/a). https://doi.org/10.1111/acem.14299
16. **Hong CS, Siegel AL, Ferris TG**. Caring for high-need, high-cost patients: what makes for a successful care management program? *Issue Brief Commonw Fund*. 2014;19:1-19.
17. **Johnson TL, Rinehart DJ, Durfee J, et al.** For many patients who use large amounts of health care services, the need is intense yet temporary. *Health Aff Proj Hope*. 2015;34(8):1312-1319. https://doi.org/10.1377/hlthaff.2014.1186
18. **Lee NS, Whitman N, Vakharia N, PhD GBT, Rothberg MB**. High-cost patients: hot-spotters don't explain the half of it. *J Gen Intern Med*. 2017;32(1):28-34. https://doi.org/10.1007/s11606-016-3790-3
19. **Grant RW, McCloskey J, Hatfield M, et al.** Use of latent class analysis and k-means clustering to identify complex patient profiles. *JAMA Netw Open*. 2020;3(12):e2029068. https://doi.org/10.1001/jamanetworkopen.2020.29068
20. **Kanzaria HK**. Leveraging cross-sector data to address social needs in the emergency department. *Ann Emerg Med*. 2020;76(4):468-469. https://doi.org/10.1016/j.annemergmed.2020.04.016
21. **Billings J, Raven MC**. Dispelling an urban legend: frequent emergency department users have substantial burden of disease. *Health Aff Proj Hope*. 2013;32(12):2099-2108. https://doi.org/10.1377/hlthaff.2012.1276
22. **Kanzaria HK, Niedzwiecki MJ, Montoy JC, Raven MC, Hsia RY**. Persistent frequent emergency department use: core group exhibits extreme levels of use for more than a decade. *Health Aff (Millwood)*. 2017;36(10):1720-1728. https://doi.org/10.1377/hlthaff.2017.0658

23. **Elixhauser A, Steiner C, Harris DR, Coffey RM**. Comorbidity measures for use with administrative data. *Med Care*. 1998;36(1):8-27. https://doi.org/10.1097/00005650-199801000-00004
24. **Kaufman L, Rousseeuw PJ**. *Finding Groups in Data: An Introduction to Cluster Analysis*. Vol 344. John Wiley & Sons; 2009.
25. **Rousseeuw PJ**. Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. *J Comput Appl Math*. 1987;20:53-65. https://doi.org/10.1016/0377-0427(87)90125-7
26. R Core Team. R: a language and environment for statistical computing. Published online 2014. http://www.R-project.org/
27. SAS Institute Inc. SAS Software. Published online Copyright 2013. sas.com
28. U.S. Census Bureau QuickFacts: San Francisco County, California. https://www.census.gov/quickfacts/sanfranciscocountycalifornia
29. Census 2020 California Hard-to-Count Fact Sheet - San Francisco County. https://census.ca.gov/wp-content/uploads/sites/4/2019/06/San-Francisco.pdf
30. Applied Survey Research, Housing Instability Research Department. *San Francisco Homeless Count and Survey Comprehensive Report*. San Francisco Department of Homelessness and Supportive Housing; 2019:77.
31. **Raven MC, Niedzwiecki MJ, Kushel M**. A randomized trial of permanent supportive housing for chronically homeless persons with high use of publicly funded services. *Health Serv Res*. 2020;55 Suppl 2:797-806. https://doi.org/10.1111/1475-6773.13553
32. **Resnikoff N.** Housing First is Not Housing Only. Benioff Homelessness and Housing Initiative. Published October 21, 2021. https://homelessness.ucsf.edu/blog/housing-first-not-housing-only
33. **Raven MC, Kushel M, Ko MJ, Penko J, Bindman AB**. The effectiveness of emergency department visit reduction programs: a systematic review. *Ann Emerg Med*. 2016;68(4):467-483.e15. https://doi.org/10.1016/j.annemergmed.2016.04.015
34. Guarino K. Step-by Step: A Comprehensive Approach to Case Management. https://www.homelesshub.ca/resource/step-step-comprehensive-approach-case-management
35. **Raven M.** Emergency Department Visit Reduction Programs. Presented at: Medicaid and CHIP Payment and Access Commission; February 2014; California Medicaid Research Institute. https://www.macpac.gov/wp-content/uploads/2014/02/Emergency-Department-Visit-Reduction-Programs.pdf
36. **Bond GR, Drake RE**. The critical ingredients of assertive community treatment. *World Psychiatry*. 2015;14(2):240-242. https://doi.org/10.1002/wps.20234
37. **Stein LI, Test MA**. Alternative to mental hospital treatment. I. Conceptual model, treatment program, and clinical evaluation. *Arch Gen Psychiatry*. 1980;37(4):392-397. https://doi.org/10.1001/archpsyc.1980.01780170034003
38. **Antai-Otong D, Theis K, Patrick DD**. Dual diagnosis: coexisting substance use disorders and psychiatric disorders. *Nurs Clin North Am*. 2016;51(2):237-247. https://doi.org/10.1016/j.cnur.2016.01.007
39. **Metraux S, Culhane DP**. Homeless shelter use and reincarceration following prison release. *Criminol Public Policy*. 2004;3(2):139-160. https://doi.org/10.1111/j.1745-9133.2004.tb00031.x
40. **Greenberg GA, Rosenheck RA**. Jail incarceration, homelessness, and mental health: a national study. *Psychiatr Serv Wash DC*. 2008;59(2):170-177. https://doi.org/10.1176/ps.2008.59.2.170
41. **Hopper K, Jost J, Hay T, Welber S, Haugland G**. Homelessness, severe mental illness, and the institutional circuit. *Psychiatr Serv Wash DC*. 1997;48(5):659-665. https://doi.org/10.1176/ps.48.5.659
42. **Reid KW, Vittinghoff E, Kushel MB**. Association between the level of housing instability, economic standing and health care access: a meta-regression. *J Health Care Poor Underserved*. 2008;19(4):1212-1228. https://doi.org/10.1353/hpu.0.0068
43. **Culhane DP, Metraux S, Hadley T**. Public service reductions associated with placement of homeless persons with severe mental illness in supportive housing. *Hous Policy Debate*. 2002;13(1):107-163.
44. **Latimer EA, Rabouin D, Cao Z, et al.** Cost-effectiveness of housing first with assertive community treatment: results from the Canadian at home/Chez Soi trial. *Psychiatr Serv*. 2020;71(10):1020-1030. https://doi.org/10.1176/appi.ps.202000029
45. Mental Health SF Legislation Approved Unanimously by Board of Supervisors | Office of the Mayor. Published December 10, 2019. Accessed September 5, 2022. https://sfmayor.org/article/mental-health-sf-legislation-approved-unanimously-board-supervisors
46. Mental Health SF | San Francisco. Published May 19, 2022. Accessed September 5, 2022. https://sf.gov/information/mental-health-sf
47. Center for Substance Abuse Treatment. *Comprehensive Case Management for Substance Abuse Treatment*. Substance Abuse and Mental Health Services Administration (US); 1998. http://www.ncbi.nlm.nih.gov/books/NBK64863/
48. **Martin M, Snyder HR, Coffa D, et al.** Time to ACT: launching an Addiction Care Team (ACT) in an urban safety-net health system. *BMJ Open Qual*. 2021;10(1):e001111. https://doi.org/10.1136/bmjoq-2020-001111
49. **Feagin J, Bennefield Z**. Systemic racism and U.S. health care. *Soc Sci Med*. 2014;103:7-14. https://doi.org/10.1016/j.socscimed.2013.09.006
50. **Rasch EK, Gulley SP, Chan L**. Use of emergency departments among working age adults with disabilities: a problem of access and service needs. *Health Serv Res*. 2013;48(4):1334-1358. https://doi.org/10.1111/1475-6773.12025
51. **Coughlin TA, Long SK, Kendall S**. Health care access, use, and satisfaction among disabled Medicaid beneficiaries. *Health Care Financ Rev*. 2002;24(2):115-136.
52. **Long SK, Coughlin TA, Kendall SJ**. Access to care among disabled adults on Medicaid. *Health Care Financ Rev*. 2002;23(4):159-173.
53. **Lagu T, Iezzoni LI, Lindenauer PK.** The Axes of Access — Improving Care for Patients with Disabilities. https://doi.org/10.1056/NEJMsb1315940.
54. **Kirschner KL, Breslin ML, Iezzoni LI.** Structural impairments that limit access to health care for patients with disabilities. *JAMA*. 2007;297(10):1121-1125. https://doi.org/10.1001/jama.297.10.1121
55. Institute of Medicine (US) Committee on Understanding and Eliminating Racial and Ethnic Disparities in Health Care. *Unequal Treatment: Confronting Racial and Ethnic Disparities in Health Care*. (Smedley BD, Stith AY, Nelson AR, eds.). National Academies Press (US); 2003. Accessed September 23, 2020. http://www.ncbi.nlm.nih.gov/books/NBK220358/
56. **Bailey ZD, Krieger N, Agénor M, Graves J, Linos N, Bassett MT**. Structural racism and health inequities in the USA: evidence and interventions. *Lancet Lond Engl*. 2017;389(10077):1453-1463. https://doi.org/10.1016/S0140-6736(17)30569-X
57. **Cummings JR, Allen L, Clennon J, Ji X, Druss BG**. Geographic access to specialty mental health care across high- and low-income US communities. *JAMA Psychiatry*. 2017;74(5):476-484. https://doi.org/10.1001/jamapsychiatry.2017.0303
58. **Shim RS**. Dismantling structural racism in psychiatry: a path to mental health equity. *Am J Psychiatry*. 2021;178(7):592-598. https://doi.org/10.1176/appi.ajp.2021.21060558
59. **Mauvais-Jarvis F, Bairey Merz N, Barnes PJ, et al.** Sex and gender: modifiers of health, disease, and medicine. *Lancet Lond Engl*. 2020;396(10250):565-582. https://doi.org/10.1016/S0140-6736(20)31561-0
60. **Brar A, Markell M**. Impact of gender and gender disparities in patients with kidney disease. *Curr Opin Nephrol Hypertens*. 2019;28(2):178-182. https://doi.org/10.1097/MNH.0000000000000482
61. **Li Shanshan, Fonarow Gregg C., Mukamal Kenneth J., et al.** Sex and race/ethnicity–related disparities in care and outcomes after hospitalization for coronary artery disease among older adults. *Circ Cardiovasc Qual Outcomes*. 2016;9(2_suppl_1):S36-S44. https://doi.org/10.1161/CIRCOUTCOMES.115.002621
62. **Cook Nakela L., Ayanian John Z., Orav E.** John, Hicks LeRoi S. Differences in specialist consultations for cardiovascular disease by race, ethnicity, gender, insurance status, and site of primary care. *Circulation*. 2009;119(18):2463-2470. https://doi.org/10.1161/CIRCULATIONAHA.108.825133
63. **Epstein AM, Weissman JS, Schneider EC, Gatsonis C, Leape LL, Piana RN**. Race and gender disparities in rates of cardiac revascularization: do they reflect appropriate use of procedures or problems in quality of care? *Med Care*. 2003;41(11):1240-1255. https://doi.org/10.1097/01.MLR.0000093423.38746.8C
64. **Blendon RJ, Buhr T, Cassidy EF, et al.** Disparities in physician care: experiences and perceptions of a multi-ethnic America. *Health Aff (Millwood)*. 2008;27(2):507-517. https://doi.org/10.1377/hlthaff.27.2.507
65. **Blendon RJ, Buhr T, Cassidy EF, et al.** Disparities in health: perspectives of a multi-ethnic, multi-racial America. *Health Aff*

(Millwood). 2007;26(5):1437-1447. https://doi.org/10.1377/hlthaff.26.5.1437

66. **Fuchs JD, Carter HC, Evans J, et al.** Assessment of a hotel-based COVID-19 isolation and quarantine strategy for persons experiencing homelessness. *JAMA Netw Open.* 2021;4(3):e210490. https://doi.org/10.1001/jamanetworkopen.2021.0490
67. **Fleming MD, Evans JL, Graham-Squire D, et al**. Association of shelter-in-place hotels with health services use among people experiencing homelessness during the COVID-19 pandemic. *JAMA Netw Open.* 2022;5(7):e2223891. https://doi.org/10.1001/jamanetworkopen.2022.23891