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

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**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 heterogeneous 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.

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**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.\(^2\) This patient population commonly experiences comorbid mental health (MH) and substance use disorders (SUD), homelessness, incarceration, and unemployment.\(^4\) To decrease costs and address patient needs, policymakers have focused on reducing ED use and hospitalizations, although most efforts have been unsuccessful.\(^5\)–\(^9\)

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.  

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.

#### 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

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**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         |

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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.\(^{26, 27}\)

**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†                           |                     |
| Medicare only                               | 1373 (51.7%)        |
| Medicare and SSI/SSDI with or without       | 1116 (42.0%)        |
| Medicaid                                    | 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         | 1713 (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                | 606 (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.

†Californi 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.

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. 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).
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). Case management programs also vary in focus, staff composition, and service intensity. A brokerage model provides service referral and coordination whereas a clinical model offers medically, behaviorally, or socially focused therapeutic services. 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 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%) |
| Native American | 1 (0.3%) | 11 (2.3%) | 11 (2.4%) | 10 (1.4%) | 8 (1.1%) |
| White | 152 (51.0%) | 238 (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%) | 155 (35.6%) | 105 (15.2%) | 75 (10.1%) |
| Shelter stay | 53 (17.4%) | 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 | 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.
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 care 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.56, 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.

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