

Intersection of Complexity and High Utilization Among Health Center Patients Aged 18 to 64 Years

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A small proportion of individuals incur the majority of health care spending in the United States.¹ The quest to reduce and contain the escalating costs of care in the United States has generated extensive research on identifying high-cost patients, the reasons for their high costs, and what can be done to reduce those costs. A significant number of studies have focused on high utilization of services, categorizing patients based on frequent emergency department (ED) visits and hospitalizations.²⁻⁶ Research aimed at distinguishing characteristics of high utilizers (HUs) is dominated by assessing complicating factors such as mental health (MH) conditions, substance use disorders (SUDs), and homelessness.^{2-4,7} This has led to using labels such as “high-need high-cost” and calls for effectively managing these patients’ needs to reduce costs and improve their health.^{2,8} Most research on these patients is focused on populations with specific forms of coverage and patients of specific health care providers that grapple with identifying ways to address their patients’ needs and reduce utilization and costs. For example, some studies have focused on specific populations of payers, such as Medicaid, private insurance, or Medicare, or patients of integrated delivery systems or specific hospitals.^{4,5,7,9-11}

Information that characterizes complex HUs is limited for nearly 30 million low-income and uninsured patients served by Health Resources and Services Administration (HRSA)–funded health centers (HCs), also called community or federally qualified HCs.^{4,9,10,12} HCs may be funded under Community HC, Migrant HC, Health Care for the Homeless, or Public Housing Primary Care programs.

HCs are the cornerstone of the safety-net system of care in the United States and provide comprehensive and culturally competent primary care and social services regardless of the ability to pay at more than 13,000 delivery sites.¹² Evidence shows that HC patients have lower rates of ED visits and hospitalizations compared with patients served at other primary care providers.^{13,14} Yet, HCs serve patients with a high burden of disease, including diabetes (15%), hypertension (28%), asthma (6%), overweight/obesity (23%), depression (50%), generalized anxiety (35%), and panic disorders (19%).^{12,15} Additionally, these conditions are complicated by high rates of high-risk behaviors such as smoking and SUDs.^{16,17} This high

ABSTRACT

OBJECTIVES: Existing literature indicates that multimorbidity, mental health (MH) conditions, substance use disorders (SUDs), and social determinants of health are hallmarks of high-need, high-cost patients. Health Resources and Services Administration–funded health centers (HCs) provide care to nearly 30 million patients, but data on their patients’ complexity and utilization patterns are limited. We identified subgroups of HC patients based on latent concepts of complexity and utilization.

STUDY DESIGN: We used cross-sectional national data from the 2014 Health Center Patient Survey and latent class analyses to identify distinct and homogenous groups of complex high-utilizing patients aged 18 to 64 years.

METHODS: We included indicators of chronic conditions (CCs), MH, SUD risk, and health behavior to measure complexity. We used number of outpatient and emergency department visits in the past year to measure utilization.

RESULTS: HC patients were separated in 9 distinct groups based on 3 complexity latent classes (MH, multiple CCs, and low risk) and 3 utilization classes (low, high, and superutilizers). Conditions associated with each subgroup differed. The highest prevalence of bipolar disorder (45%) and high SUD risk (6%) was observed among MH superutilizers, whereas the highest prevalence of cardiovascular disease (48%) and obesity (96%) was seen among CC superutilizers. Most MH superutilizer patients concurrently had MH conditions and obesity and were smokers, but most CC superutilizer patients concurrently had hypertension, obesity, and cardiovascular disease.

CONCLUSIONS: Our examination of complexity and utilization indicated distinct HC patient populations. Managing the care of each group may require different targeted intervention approaches such as multidisciplinary care teams that include MH providers or specialists.

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burden of disease is further complicated by the disadvantages of being low income and uninsured and is likely a barrier to improving outcomes of care.^{18,19} Thus, successful provision of effective primary care in HCs has a crucial role in the overall success of efforts to improve population health and reduce costs.

There is wide variability in defining complexity in the literature, making it difficult to identify and treat such patients.^{8,20} Complex patients are frequently distinguished by presence of multiple chronic conditions (CCs), complicating MH diagnosis and SUDs, risky behaviors, social determinants of health (SDOH) such as unstable housing and employment, and environmental factors.^{8,21-23} Conceptualization of complexity has varied by health care discipline, and various conceptual frameworks have been developed to identify and describe complexity and quantify the extent of the relationship among complexity aspects.^{4,21,23-27}

Joint identification of complex patients and HUs can be instrumental in effective treatment of these patients, which includes delivery of a coordinated combination of medical, MH, and social interventions.^{2,28-30} This moves away from focusing on a specific condition or disease or treating complex patients as homogenous groups.^{28,29} A deeper understanding is needed of the confluence of factors that lead to complexity and of the subsequent relationship of complexity with high utilization of services.³¹

In this context, we aimed to simultaneously characterize complexity and high utilization among HC patients aged 18 to 64 years by identifying distinct subgroups. We described each population by examining the prevalence of specific conditions within each group. We also identified co-occurrence of various indicators of complexity and HUs for patients within each group. This information would allow for a better understanding of which subgroups of HC patients need targeted and focused interventions.

METHODS

Data and Sample

We used the 2014 Health Center Patient Survey, a nationally representative cross-sectional survey of HC patients that included information on patient demographics, health care utilization, health conditions, and behaviors. The 3-stage sampling design included the selection of 169 HC organizations, 520 HC sites within those organizations, and a random sample of HC patients who were eligible if they had visited the HC once in the past 12 months and were interviewed during their second appointment. A total of 7002 patient interviews were surveyed, representing 59.1% of all patients screened. Patients were excluded if they refused, discontinued the screening interview, or did not have a prior visit. The survey completion rate was 91.4%. We restricted our sample to patients aged 18 to 64 years to reduce significant variations in health conditions, utilization patterns,

TAKEAWAY POINTS

We identified 9 latent subgroups that represented the health status and utilization profiles of complex patients who use Health Resources and Services Administration–funded health centers. The findings demonstrate the importance of understanding health behaviors, physical and mental health conditions, and utilization patterns to develop effective interventions for complex, high-utilizing patients.

- ▶ Three complexity classes (mental health, multiple chronic conditions, low risk) and 3 utilization classes (low, high, and super-utilizers) were identified.
- ▶ The intersection of these categories provided insight on the highest prevalence of characteristics and co-occurring conditions among latent subgroups.
- ▶ Interventions and treatments must consider these patients holistically and incorporate care coordination among providers for the provision of patient-centered care.

and insurance coverage between these adults and children or older adults.³² Our final analytic sample size totaled 5040.

Main Measures

We included 2 sets of variables to measure the latent concepts of complexity and high utilization. To measure complexity, we included health indicators, MH, SUD, and health behaviors guided by the literature.^{4,22} We used direct, objective health indicators including having hypertension, diabetes, asthma, cancer, stroke, chronic obstructive pulmonary disease (COPD), liver disease, weak/failing kidneys, and cardiovascular disease (CVD). We also included indicators of overweight/obesity status. Indicators of MH included depression, generalized anxiety, panic disorder, schizophrenia, and bipolar disorder. We also included an indicator of high risk of SUD based on the World Health Organization Alcohol, Smoking, and Substance Involvement Screening Test algorithm. We used current or former smoking (vs never) as a health behavior indicator.

To measure HUs, we used self-reported number of ED and outpatient visits in the past year. To help understand unique characteristics of latent classes, we examined demographics such as age, gender, race/ethnicity, education, and employment. We also examined health insurance and poverty. In addition, we examined subjective or less direct health indicators including self-assessed health status, any functional limitations (any instrumental activities of daily living), homelessness, and veteran status. Further detail on the constructions of these measures can be found in **eAppendix Table 1** (available at ajmc.com).

Analytic Methods

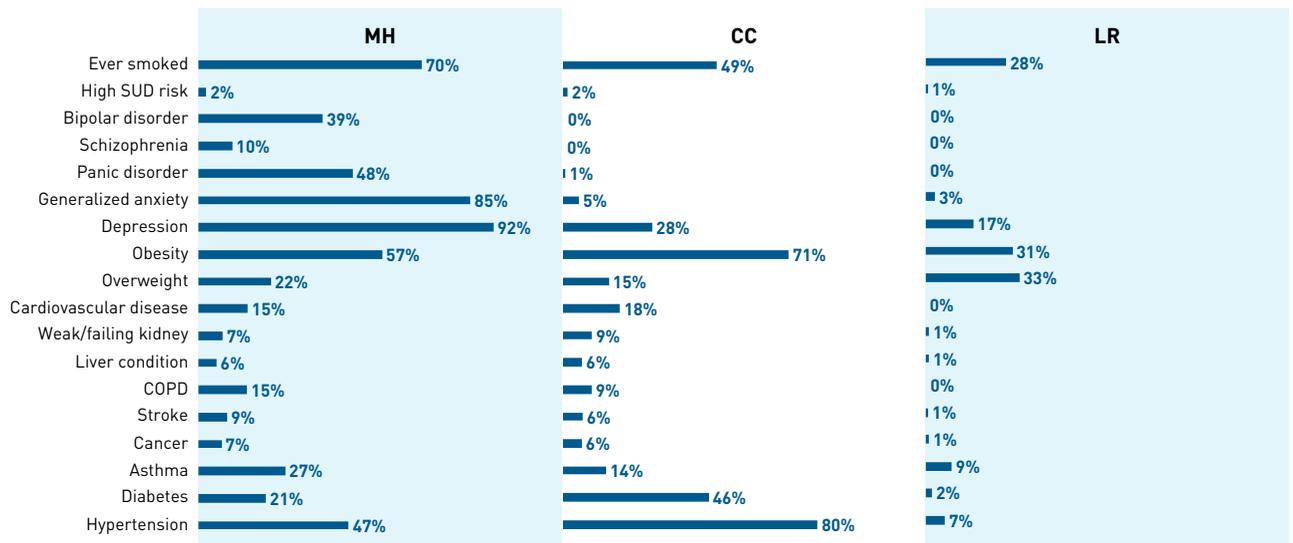
We used latent class analysis (LCA) to simultaneously identify latent concepts of complexity and high utilization.³³ LCA is an established methodology used to define subgroups of a population based on an investigator-selected list of observed characteristics and relates them to an unobserved latent variable indicated by class membership using structural equation modeling techniques (see LCA section of the **eAppendix**). The results identify mutually exclusive and parsimonious and interpretable classes of individuals who share some similarities but focus on the most notable attributes of each class. The model-generated highest posterior probabilities are used

TABLE 1. Class Fit Statistics From 1 to 4 Class Models

Number of class*class	Likelihood	AIC	BIC	Entropy	Class description
2*2	-60,315.37	120,727	121,040	0.891	2 classes of complexity and 2 classes of utilization
2*3	-57,645.34	115,399	115,751	0.876	2 classes of complexity and 3 classes of utilization
3*2	-59,111.86	118,364	118,820	0.860	3 classes of complexity and 2 classes of utilization
3*3	-56,441.19	113,036	113,539	0.855	3 classes of complexity and 3 classes of utilization

AIC, Akaike information criterion; BIC, Bayesian information criterion.

FIGURE 1. Prevalence of Complex Conditions Within Complexity Latent Class^a



CC, chronic conditions; COPD, chronic obstructive pulmonary disease; LR, low-risk; MH, mental health conditions; SUD, substance use disorder.

^aThe sample size for the MH class is 1643 (32%); CC class, 1534 (27%); and LR class, 1863 (41%).

to attribute each individual to a class. This approach is preferred to conventional regression approaches.^{4,9,11}

We conducted the LCA using Mplus 7 (Muthén & Muthén) and used weights to account for the survey sampling design. We identified the classes for each concept by fitting models with 2 to 4 classes and determined the best fit by assessing likelihood ratio (lower values indicate better fit), Akaike and Bayesian information criteria (lower values indicate better distinction between classes), and entropy statistic (higher values indicate accurate class identification given the number of classes).⁴ We took into account the sample size of each class and did not retain those with less than 3% of the sample. We included age and gender as primary confounders of complexity and health insurance status as the primary confounder of high utilization.

We described the resulting classes in Stata 15 (StataCorp) using demographics, health status, and utilization variables. We also used Gephi version 0.9.2 (Association Gephi) to visualize the inter-relationships among various indicators within a class. **Appendix Figure 1** shows the prevalence of conditions (bubbles) and the co-occurrence of conditions (lines) where bigger bubbles show higher

prevalence and thicker lines show a higher rate of co-occurrence. The visualization of the line thickness indicates the independent co-occurrence between conditions. We calculated the thickness of the lines by summing the sampling weights of dyads of conditions among all patients with these conditions and rescaling them from 0 to 1 to visually present the relationship between dyads.

RESULTS

Sample characteristics showed high rates of hypertension (39%), diabetes (20%), obesity (50%), depression (44%), anxiety (30%), and current or past smoking (47%) (**eAppendix Table 2**). Additional health status indicators showed many with fair/poor health (42%) and functional limitations (38%). The majority were Medicaid beneficiaries (54%), and many were not in the labor force (42%) or were employed (40%). Patients had a mean of 8.3 outpatient and 1.6 ED visits last year.

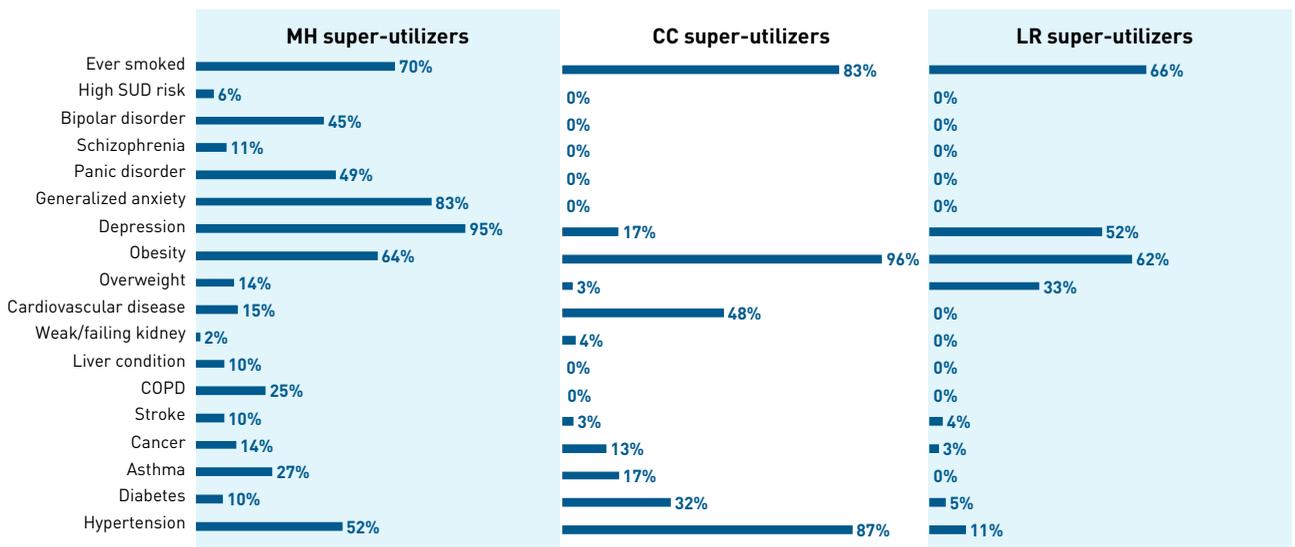
The LCA led to the identification of 3-class complexity and 3-class high utilization latent variables based on best fit and parsimony

TABLE 2. Utilization Latent Class

	Low utilizers	High utilizers	Super-utilizers
Total	3755 (73%)	1136 (24%)	149 (3%)
Outpatient visits			
Mean	3.8	15.3	56.7
Median	4.0	12.0	50.0
Mode	4.0	10.0	50.0
Minimum	0	6	34
Maximum	10	34	99
ED visits			
Mean	1.2	2.3	6.0
Median	0.0	1.0	2.0
Mode	0.0	0.0	0.0
Minimum	0	0	0
Maximum	35	50	151

ED, emergency department.

FIGURE 2. Prevalence of Complex Conditions Among Super-Utilizers by MH, CC, and LR Classes^a



CC, chronic conditions; COPD, chronic obstructive pulmonary disease; LR, low-risk; MH, mental health conditions; SUD, substance use disorder.

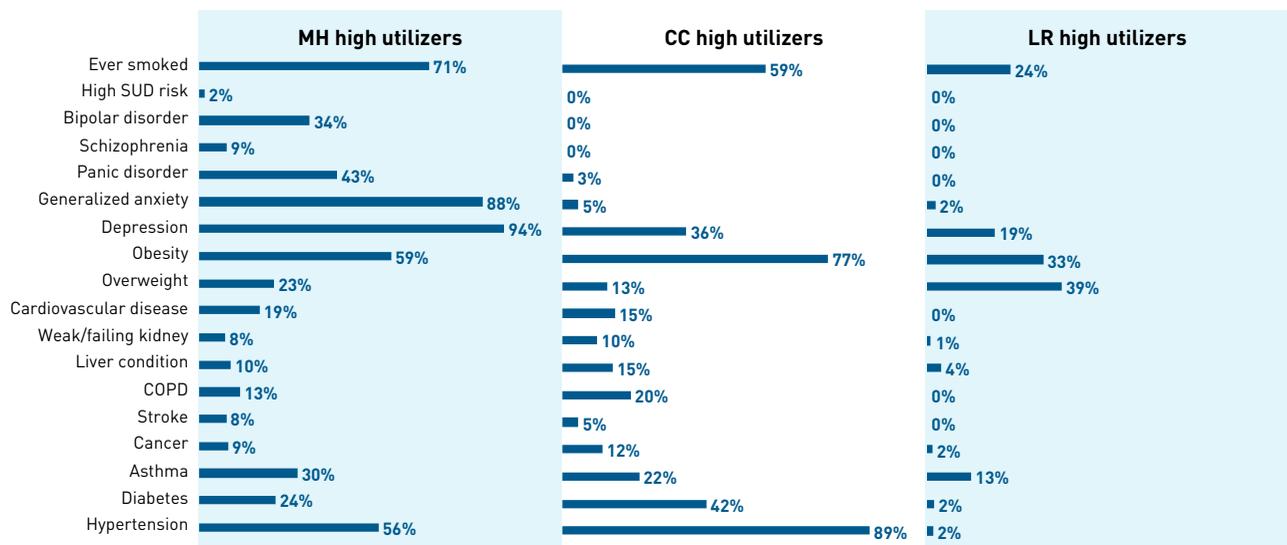
^aThe sample size for the MH super-utilizer class is 119 (3%); CC super-utilizer class, 15 (0.03%); and LR super-utilizer class, 15 (0.5%).

(Table 1). Figure 1 shows an MH conditions class (32%) dominated by highest prevalence of conditions such as depression (92%), general anxiety (85%), panic disorder (48%), bipolar disorder (39%), and schizophrenia (10%). This class also had the highest prevalence of smoking (70%). A second multiple CC class (27%) was dominated by highest prevalence of hypertension (80%), obesity (71%), diabetes (46%), and asthma (14%). The third class was the largest (41%) and dominated by lowest prevalence of all the examined conditions and was classified as low risk (LR). These individuals may still be at risk for developing more severe and complex conditions

due to dominance of risk factors such as smoking, obesity, CVD, and depression.

The prevalence of indicators for the 3 classes of high utilization indicated low utilizers (LUs; 73%), HUs (24%), and superutilizers (SUs; 3%) (Table 2). Among LUs, the mean numbers of outpatient and ED visits last year were 3.8 and 1.2, respectively. HUs represented 24% of the sample and had a mean of 15.3 outpatient and 2.3 ED visits last year. SUs (3%) had a mean of 56.7 outpatient and 6.0 ED visits.

Comparing the SUs across the complexity classes shows that those in the MH class had the highest prevalence of depression

FIGURE 3. Prevalence of Complex Conditions Among High Utilizers by MH, CC, and LR Latent Classes*

CC, chronic conditions; COPD, chronic obstructive pulmonary disease; LR, low-risk; MH, mental health conditions; SUD, substance use disorder.

*The sample size for the MH high utilizers class is 548 (11%); CC high utilizers class, 338 (6%); and LR high utilizers class, 250 (7%).

(95%), bipolar disorder (45%), COPD (25%), cancer (14%), stroke (10%), and high SUD risk (6%) (Figure 2). Among the CC class, SUs had the highest rates of obesity (96%), being current or past smokers (83%), and CVD (48%). Among the LR class, SUs had high rates of being current or past smokers (66%), obesity (62%), depression (52%), and overweight (33%).

Comparing HUs, the MH class had the highest rates of general anxiety (88%) and asthma (30%); the CC class had the highest prevalence of hypertension (89%), liver conditions (15%), and weak/failing kidneys (10%); the LR class had the highest rate of overweight but was not distinguishable by high prevalence of specific chronic or MH conditions (Figure 3). Additional data on LU characteristics in each complexity class are available in eAppendix Figure 2.

Using the underlying LCA data, we displayed the co-occurrence of combinations of most prevalent conditions for individual patients in each group (eAppendix Figure 1). Within the MH SUs, most patients had MH conditions along with hypertension, were obese or overweight, and were current or past smokers. In contrast, within the small CC SU group, most patients had hypertension and CVD, were current or past smokers, and were overweight or obese. Within the small group of LR SUs, most patients were overweight or obese, but few had CCs. Complete prevalence of complex conditions, sociodemographic, financial, and health status indicators among the 9 latent classes are available in eAppendix Table 3.

DISCUSSION

Using a nationally representative sample of patients who obtain care services at HRSA-funded HCs, we identified 3 complexity

and 3 high utilization latent classes among patients aged 18 to 64 years. The complexity classes indicated distinct populations of patients with a high prevalence of MH conditions, multiple CCs, or conditions and behaviors that might increase the risk of more complex conditions. The high utilization classes also identified distinct populations separated by gradation in use of outpatient and ED visits from low to high to super-HUs. The confluence of 3 latent classes identified 9 distinct classes with different profiles of health and utilization and common co-occurrence of specific chronic or MH conditions.

Our classification of complex patients in this study is consistent with other studies that highlight the high rate of co-occurrence of MH conditions, but we also show a distinct separation between those who are primarily defined by high prevalence of MH conditions with some CCs vs those primarily defined by CCs complicated with depression.^{4,25,34,35} Our findings indicating co-occurrence of MH conditions with smoking status or of hypertension and diabetes with obesity have been shown in the literature, but other relationships such as high prevalence of MH conditions with obesity or hypertension are more emergent.³⁶⁻³⁹ Our utilization classes found that only 3% are SUs, supporting the existing literature that only a small proportion of the population are SUs.¹ Of those characterized as SUs, our findings support previous contributions that the majority are driven by MH conditions, followed by CCs such as cancer or social risk factors.^{4,7} Our classification of patients with high utilization is also consistent with studies that distinguish SUs as those with many ED visits, but we examined the combined use of outpatient and ED visits and separated SUs from other HUs.^{4,7,40} Our joint classification of patients by complexity and high utilization

is aligned with the concept of high-need, high-cost patients and provides insights into 9 homogenous and distinct groups of HC patients who require targeted interventions designed to address their unique health care needs.²

Our findings have implications based on complexity alone, as well as for complex patients who are HUs or SUs. The MH class is characterized clinically by a high prevalence of MH conditions along with other CVD risk factors including smoking, obesity, and hypertension. These findings suggest that these risk factors cannot be treated effectively without addressing MH issues, and, therefore, collaboration between primary care providers and psychiatrists and other MH specialists is most appropriate to treat this patient population.⁴¹ The CC class is also characterized by CVD risk factors including hypertension, obesity, and diabetes, and it has lower prevalence of most MH conditions. These risk factors differ somewhat from those of the MH class. This patient population would likely benefit from appropriate interventions to reduce cardiovascular events, including lifestyle modification and medications to control blood pressure and blood glucose level. The LR class is not dominated by chronic health or MH conditions but likely reflects those with risk of developing more severe and complex health conditions, such as diabetes or hypertension, based on their risk factors including obesity, smoking behavior, and depression. These patients would probably benefit most from intensive patient-centered primary and preventive care to arrest development of more serious conditions.

By focusing on complexity classes and SUs, more refined sets of interventions to avoid excessive service use emerge. SUs with MH complexity may require the presence of MH providers to manage patients' depression and bipolar disorder; SUD staff in the care team to address high SUD risk; and significant coordination with oncologists, pulmonary specialists, and neurologists.^{7,42,43} In contrast, reducing excessive use among SUs with CCs may require a greater focus on smoking cessation efforts in the primary care setting, including nutritionists in care teams and coordination with cardiologists.^{27,28,30,44} Similarly, care of HU patients with CCs may require a greater focus on managing patients with hypertension and coordination with hepatologists and nephrologists to reduce avoidable use. Additionally, care of HU patients with MH complexity may require better management of general anxiety and asthma to reduce avoidable care use. Further research is required to better assess factors associated with high use of care by LR patients.

Our findings highlight the importance of providing effective care to HC patients and the potential complexity of this task, which is complicated by SDOH such as low income, lack of transportation, inability to take time off from jobs that do not offer paid time for medical care, and lack of insurance. The profile of these patients indicates the need for multidimensional approaches including multidisciplinary teams of providers and care coordination with specialists and other providers outside the HC. In addition, treatment of these patients requires multiple care steps and visits. These issues have led to HRSA initiatives to help maximize patients' access to integrated care and promoting the patient-centered medical

home model of care. HRSA has also made significant investments in behavioral health and primary care integration, including establishing a supplemental funding opportunity in 2019 to help increase behavioral health staffing and access in HCs.⁴¹ Our data indicate the importance of escalating these and other efforts to improve the health of these patients.

Limitations

We used survey data for this study, which may be susceptible to measurement error and recall bias. In particular, utilization indicators are likely to be estimates at the higher ranges. The sample sizes of SUs among LR and CC classes were small. We lacked other important indicators of high utilization such as hospitalizations and expenditures. The sample was not large enough to test the fit of additional complexity and high-utilization classes and did not allow us to include other indicators of complexity such as severity. The number of conditions identified in the data were also not exhaustive of all diagnoses for each patient. In addition, our measure of complexity lacked the provider perspective, which would include as assessment of the severity of conditions and other observations of patients' problems.^{22,25} We also lacked a more direct measure of actual SUD and relied on risk status. We lacked data on SDOH, receipt of social support services, and ability of patients to manage their condition, which are important indicators for utilization and health status.⁴⁵ We lacked data on future utilization patterns to assess regression to the mean.

Our findings are primarily generalizable to patients of HCs, who may differ from low-income and uninsured patients receiving their care in other settings such as private providers or hospital-based outpatient care. Our study is applicable to adult patients aged 18 to 64 years and may not be generalizable to older adults, whose condition profiles are frequently dominated by low functional status and frailty, multiple CCs, and cognitive impairment. Older adults also are primarily covered by Medicare, and these differences lead to different patterns of care utilization and access.^{32,46}

CONCLUSIONS

Our data provide a deeper understanding of the combined latent concepts of complexity and high utilization for nearly 30 million low-income and uninsured patients receiving care from HRSA-funded HCs.¹² Our findings provide insights into factors associated with complexity and high utilization and how the care of these patients may be adequately or effectively managed. Improvement in health of these patients could reduce unnecessary outpatient and ED visits and garner savings at the federal level. ■

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Supplemental eAppendix

eAppendix Table 1. Supplemental Information on Measures and Methods

Construct	Measure and/or Question
Main Measures	
Health Indicators	<p>Questions on health indicators are prefaced with: The next questions are about other health conditions. Please tell me yes or no for the following conditions. Has a doctor or other health professional ever told you that {you/he/she} had...)</p> <ul style="list-style-type: none"> • Hypertension • Diabetes • Asthma • Cancer • Stroke • Chronic obstructive pulmonary disease • Liver disease • Weak or failing kidneys • Cardiovascular disease (indicated ever having been told having congestive heart failure, coronary heart disease, angina, or myocardial infarction)
Mental Health Indicators	<p>Questions on health indicators are prefaced with: Has a doctor or other health professional ever told you that you had...?</p> <ul style="list-style-type: none"> • Depression • Generalized anxiety • Panic disorder • Schizophrenia • Bipolar disorder
Health Behavior Indicators	
Smoking Status	<p>Respondents aged 13 and older were first asked "Have you smoked at least 100 cigarettes in your entire life?" Respondents answering "yes" were then asked "Do you now smoke cigarettes every day, some days, or not at all?"</p> <ul style="list-style-type: none"> • Never Smoked was defined as those that have never smoked or have smoked less than 100 cigarettes in their lifetime. • Past Smoker was defined as responding "yes" to having smoked at least 100 cigarettes in their lifetime but had quit smoking at the time of interview. • Current Smoker was defined as those who have smoked at least 100 cigarettes in their lifetime and still currently smoke every day or on some days. <p>Past and current smoker were combined to ever smoked (vs. never smoked)</p>

Substance Use Disorder Risk	<p>Risk of substance use disorder was determined based on the World Health Organization's Alcohol, Smoking, and Substance Involvement Screening Test.</p> <ul style="list-style-type: none"> • High SUD risk was defined as having a score of 13 or higher. • Low and moderate SUD risk was defined as having a score of less than 5, and 5 to 12, respectively.
Utilization Measures	
Number of Emergency Department visits last year	<p>Respondents were asked: “During the past 12 months, that is since {12 MONTH REFERENCE DATE}, how many times {have you/has NAME} gone to a hospital emergency room about {your own/his/her} health? This includes emergency room visits that resulted in a hospital admission.”</p>
Number of outpatient visits last year	<p>Respondents were asked: “During the past 12 months, that is since {12 MONTH REFERENCE DATE}, how many times have you seen a doctor or other health care professional about {your own/NAME’s} health at a doctor’s office, a clinic, or some other place?”</p>
Sample Characteristics	
Sociodemographic indicators	
Age	<p>Age was categorized into 4 categories:</p> <ul style="list-style-type: none"> • 18-35 years • 36-54 years • 55-64 years
Gender	<p>Gender was categorized into 2 categories:</p> <ul style="list-style-type: none"> • Male • Female
Race/Ethnicity	<p>Race/ethnicity was categorized into 6 categories:</p> <ul style="list-style-type: none"> • Non-Hispanic White • Non-Hispanic African American • Hispanic/Latino • Non-Hispanic Asian • Non-Hispanic American Indian/Alaska Native • Non-Hispanic other
Education	<p>Education was categorized into 3 categories:</p> <ul style="list-style-type: none"> • Less than high school • High school graduate • Any college
Employment	<p>Employment was categorized into 3 categories:</p> <ul style="list-style-type: none"> • Employed • Unemployed • Not in labor force
Financial indicators	
Health Insurance	<p>Health insurance coverage was categorized into 3 categories:</p> <ul style="list-style-type: none"> • Uninsured

	<ul style="list-style-type: none"> • Medicaid • Other
Federal Poverty Guideline	<p>Poverty was classified into 3 categories:</p> <ul style="list-style-type: none"> • Less than 100% of the federal poverty guideline • 100-199% of the federal poverty guideline • 200% or more of the federal poverty guideline
Subjective measures of health status	
Self-assessed health status	<p>Self-assessed health status was classified into 2 categories:</p> <ul style="list-style-type: none"> • Fair or poor • Good, very good, or excellent
Any functional limitations	<p>Functional limitations were indicated if the respondent reported any limitations to instrumental activities of daily living:</p> <ul style="list-style-type: none"> • Dressing or bathing • Eating • Getting in or out of bed or chairs • Need help using the toilet, including getting to the toilet • Walking or climbing stairs • Have difficulty doing errands alone such as visiting a doctor’s office or shopping • Have difficulty concentrating, remembering, or making decisions
Homelessness	<p>Respondents were asked: “Over the past 7 days, where did {you/NAME} usually sleep at night?”</p> <p>Respondents were categorized as homeless if they responded:</p> <ul style="list-style-type: none"> • Room other than at a hotel or motel; emergency shelter; a transitional shelter including transitional housing; a church or chapel; an abandoned building; a place or business; a car or other vehicle; anywhere outside; or some other place <p>Those were categorized as not homeless if they responded:</p> <ul style="list-style-type: none"> • A house, townhouse, or mobile home; an apartment or condo; or a hotel or motel
Veteran status	<p>Respondents were asked: “Have you ever served on active duty in the U.S. Armed Forces, military Reserves, or the National Guard?”</p> <ul style="list-style-type: none"> • Yes • No

Latent Class Analysis Methodology Additional Description

We used latent class analysis methodology to simultaneously identify latent concepts of complexity and high utilization. This approach is preferred to conventional regression approaches that examine associations between known characteristics and outcomes and require parsimony in variables included. Latent class analysis is also preferred to the conceptually similar factor analysis that focuses on correlations between variables among the entire sample rather than examining patterns within individuals.

We identified classes for each concept by fitting models to determine best fit. A four-class complexity and three class high utilization model had better indicators of model fit, but the four-class complexity latent variable had sparsely populated categories. In addition, the entropy for the three by three class was not as high as the two by two model, but the latter model had the poorest model fit statistics. Therefore, we decided on the three-class complexity and three-class high utilization models.

Additional Information on Characteristics of Low Utilization in Each Complexity Class

Among low utilizers, the mental health (MH) class had highest rates of general anxiety (83%), depression (90%), and were current or past smokers (68%). Among the chronic condition (CC) class, low utilizers had highest rates of obesity (69%) and hypertension (78%). Among the low risk (LR) class, low utilizers had emerging rates of obesity (30%) and overweight (32%).

eAppendix Table 2. Sample Characteristics

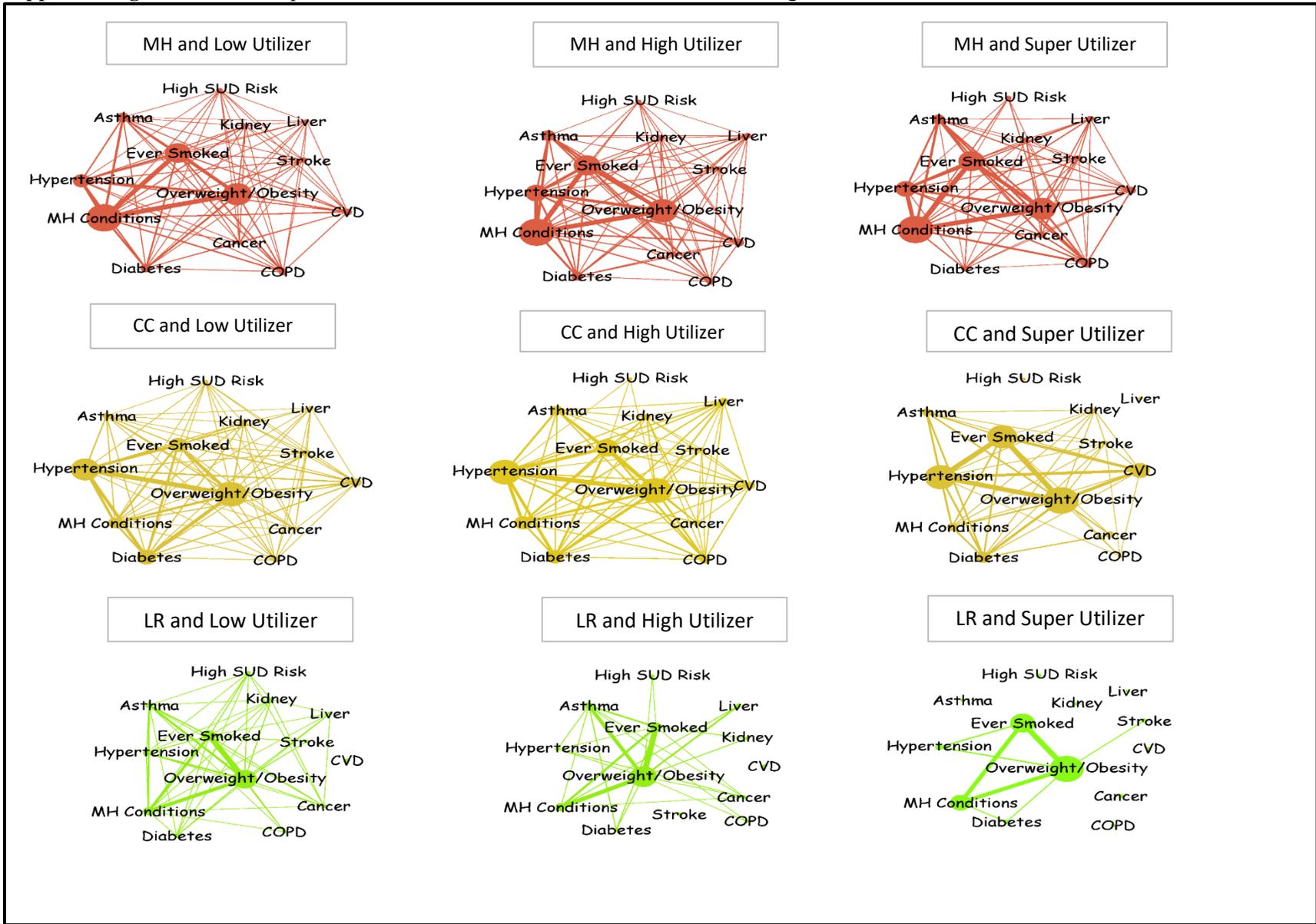
	Total (mean or %)
N	5,040
<i>Chronic Health Conditions</i>	
Hypertension	39%
Diabetes	20%
Asthma	16%
Cancer	4%
Stroke	5%
COPD	7%
Liver Condition	4%
Weak/Failing Kidney	5%
Cardiovascular Disease	10%
Overweight	25%
Obesity	50%
<i>Mental Health Conditions, Substance Use Disorder (SUD) Risk, and Behavior</i>	
Depression	44%
Generalized Anxiety	30%
Panic Disorder	16%
Schizophrenia	3%

Bipolar	13%
High SUD Risk	2%
Ever Smoked	47%
Utilization	
Outpatient Visits	8.3
ED Visits	1.6
Sociodemographic Indicators	
Age	
18-35 Years	41%
36-54 Years	41%
55-64 Years	18%
Female	65%
Race/Ethnicity	
Non-Hispanic White	49%
Non-Hispanic Black	20%
Hispanic	25%
Non-Hispanic Asian	3%
Non-Hispanic American Indian/Alaskan	
Native	1%
Non-Hispanic Other	2%
Education	
Less than High School	34%
High School	29%
More than High School	37%
Employment Status	
Employed	40%
Unemployed	17%
Not in Labor Force	42%
Financial Indicators	
Insurance	
Medicaid	54%
Uninsured	30%
Other	17%
Federal poverty guideline	
Less than 100%	57%
101% - 199%	29%
200% or More	14%
Additional Health Status Indicators	
Fair/Poor Health Status (vs. good/very good/excellent)	42%
Functional Limitations	38%
Homeless	5%
Veteran	3%

Notes: Functional limitations are based on any activities of daily living or instrumental activities of daily living.

Acronyms: ED, emergency department; COPD, chronic obstructive pulmonary disease; SUD, substance use disorder

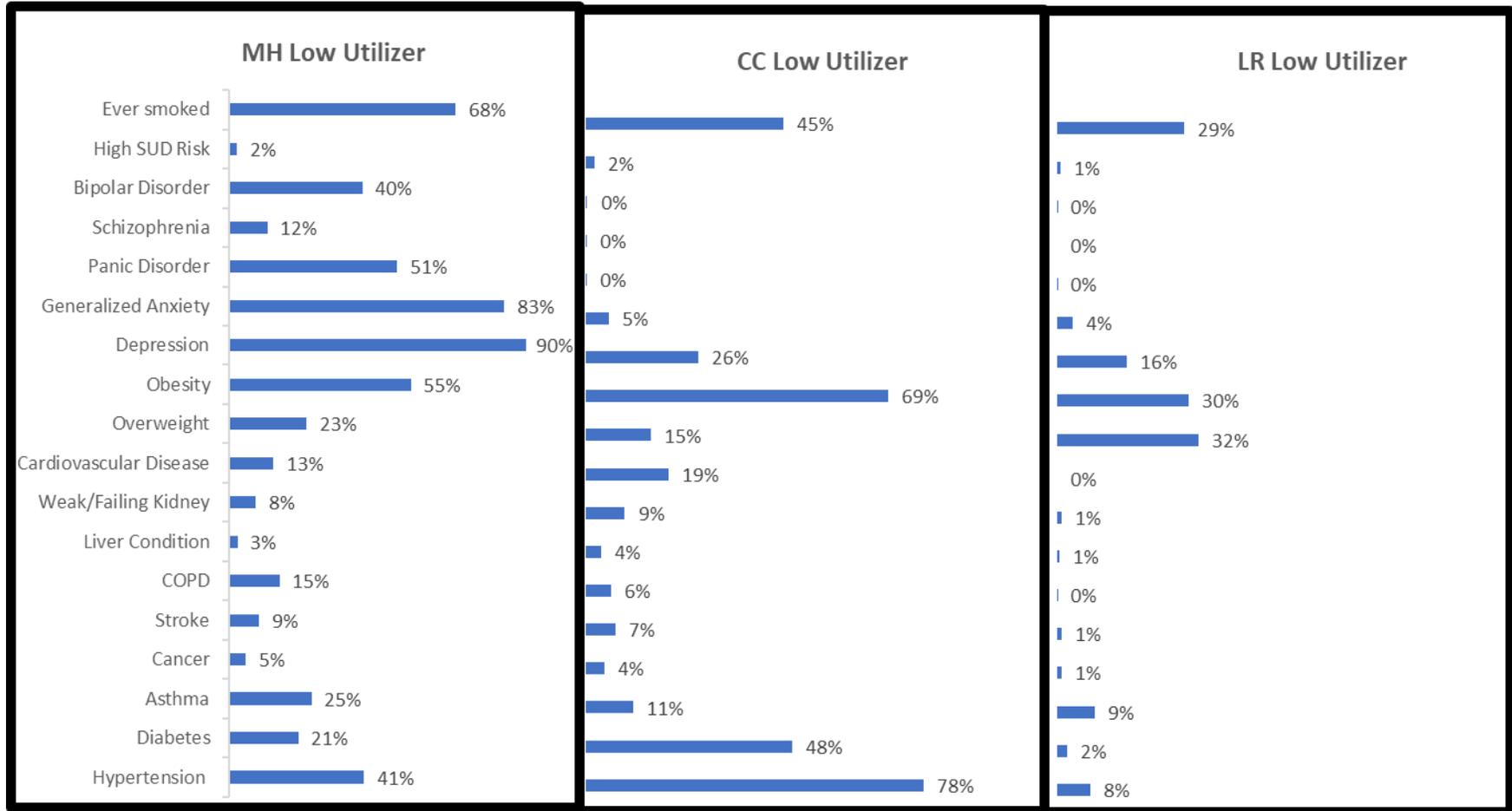
1 **eAppendix Figure 1.** Visual Depiction of Common Co-occurrence of Conditions among Health Center Patients in Latent Classes
 2



Note: Bubbles display the prevalence of conditions while lines display the co-occurrence of conditions. Larger bubbles show higher prevalence and lines show higher rate of co-occurrence.

Acronyms: MH, mental health conditions; CC, chronic conditions; LR, low risk; COPD, chronic obstructive pulmonary disease; CVD, cardiovascular disease; SUD, substance use disorder.

eAppendix Figure 2. Prevalence of Complex Conditions among Low Utilizers by Mental Health (MH), Chronic Conditions, and Low Risk (LR) Latent Classes



Notes: The sample size for the MH low utilizer class is 976 (18%); CC low utilizer class is 1,181 (20%); and LR low utilizer class is 1,598 (34%).

Acronym: SUD, substance use disorder; COPD, chronic obstructive pulmonary disease; MH, mental health conditions; CC, chronic conditions; LR, low risk.

eAppendix Table 3. Prevalence of complex conditions, sociodemographic, financial, and health status indicators among confluence and utilization latent classes

	Total	MH Low Utilizer	MH High Utilizer	MH Super Utilizer	CC Low Utilizer	CC High Utilizer	CC Super Utilizer	LR Low Utilizer	LR High Utilizer	LR Super Utilizer
N	5,040	976 (18%)	548 (11%)	119 (3%)	1,181 (20%)	338 (6%)	15 (0.03%)	1,598 (34%)	250 (7%)	15 (0.5%)
Hypertension	39%	41%	56%	52%	78%	89%	87%	8%	2%	11%
Diabetes	20%	21%	24%	10%	48%	42%	32%	2%	2%	5%
Asthma	16%	25%	30%	27%	11%	22%	17%	9%	13%	0%
Cancer	4%	5%	9%	14%	4%	12%	13%	1%	2%	3%
Stroke	5%	9%	8%	10%	7%	5%	3%	1%	0%	4%
COPD	7%	15%	13%	25%	6%	20%	0%	0%	0%	0%
Liver Condition	4%	3%	10%	10%	4%	15%	0%	1%	4%	0%
Weak/Failing Kidney	5%	8%	8%	2%	9%	10%	4%	1%	1%	0%
Cardiovascular Disease	10%	13%	19%	15%	19%	15%	48%	0%	0%	0%
Overweight	25%	23%	23%	14%	15%	13%	3%	32%	39%	33%
Obesity	50%	55%	59%	64%	69%	77%	96%	30%	33%	62%
Depression	44%	90%	94%	95%	26%	36%	17%	16%	19%	52%
Generalized Anxiety	30%	83%	88%	83%	5%	5%	0%	4%	2%	0%
Panic Disorder	16%	51%	43%	49%	0%	3%	0%	0%	0%	0%
Schizophrenia	3%	12%	9%	11%	0%	0%	0%	0%	0%	0%
Bipolar Disorder	13%	40%	34%	45%	0%	0%	0%	0%	0%	0%
High SUD Risk	2%	2%	2%	6%	2%	0%	0%	1%	0%	0%
Ever smoked	47%	68%	71%	70%	45%	59%	83%	29%	24%	66%
<i>Sociodemographic Indicators</i>										
Age										
18-35 years	32%	28%	29%	10%	12%	0%	66%	84%	88%	41%
36-54 years	51%	56%	54%	49%	38%	46%	30%	15%	12%	41%
55-64 years	18%	16%	17%	41%	50%	54%	4%	2%	0%	18%

Female	65%	72%	70%	66%	43%	47%	32%	74%	79%	96%
Race/Ethnicity										
Non-Hispanic White	49%	65%	72%	66%	53%	55%	1%	30%	40%	62%
Non-Hispanic Black	20%	17%	12%	21%	24%	24%	70%	23%	20%	5%
Hispanic	25%	15%	11%	5%	19%	17%	13%	40%	31%	25%
Non-Hispanic Asian	3%	1%	1%	4%	2%	1%	0%	5%	8%	3%
Non-Hispanic American Indian/Alaskan Native	1%	1%	1%	1%	1%	2%	2%	1%	2%	0%
Non-Hispanic Other	2%	2%	3%	4%	1%	1%	14%	2%	1%	5%
Education										
Less than high school	34%	34%	33%	15%	40%	38%	32%	33%	32%	27%
High school	29%	30%	21%	33%	24%	27%	10%	36%	26%	2%
More than high school	37%	35%	46%	52%	36%	35%	59%	32%	42%	71%
Employment Status										
Employed	40%	29%	26%	30%	45%	17%	46%	54%	37%	66%
Unemployed	17%	22%	14%	7%	14%	16%	2%	19%	16%	0%
Not in labor force	42%	49%	60%	64%	41%	67%	53%	27%	47%	34%
<i>Financial Indicators</i>										
Insurance										
Medicaid	54%	60%	63%	71%	36%	59%	40%	50%	76%	96%
Uninsured	30%	26%	25%	13%	41%	14%	46%	34%	12%	4%
Other	17%	14%	13%	16%	23%	27%	15%	15%	13%	0%
Federal poverty guideline										
Less than 100%	57%	65%	63%	59%	52%	51%	40%	55%	57%	40%
101% - 199%	29%	23%	28%	39%	30%	31%	60%	30%	26%	59%
200% or more	14%	12%	9%	2%	18%	18%	1%	16%	17%	0%
<i>Additional Health Status Indicators</i>										

Fair/Poor Health Status (vs. good/very good/excellent)	42%	50%	55%	64%	56%	56%	41%	25%	19%	23%
Functional limitations	38%	62%	67%	86%	35%	49%	85%	13%	29%	16%
Homeless	5%	8%	8%	8%	4%	5%	15%	3%	1%	0%
Veteran	3%	4%	1%	4%	4%	6%	0%	2%	0%	1%

Notes: Functional limitations are based on any activities of daily living or instrumental activities of daily living.

Acronyms: MH, mental health conditions; CC, chronic conditions; LR, low risk; COPD, chronic obstructive pulmonary disease; SUD, substance use disorder