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RESOURCE ALLOCATION, ACCESS, & PATTERNS OF HEALTHCARE SERVICE UTILIZATION AMONG PATIENTS WITH ALCOHOL-USE DISORDERS

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ABSTRACT

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Healthcare service utilization (HSU) describes how individuals engage with healthcare systems. Studies examining differences in rates of HSU among acute care-seeking patients have identified disparities in access to appropriate treatments. Alcohol-use disorders (AUDS) are increasingly prevalent among patients presenting for treatment in acute care settings. AUDS are emblematic of a broader trend in acute care; disproportionate rates of acute care encounters by patients with heavy socioeconomic (e.g., socioeconomic status, homelessness) burden, primary psychiatric/behavioral disorders (e.g. schizophrenia, AUDs), and reliance on emergency rooms for seeking treatment. Numerous studies have linked these risk factors with both AUDs and with high HSU. Despite this, few studies have examined HSU specifically within this patient population.

Given these findings in the literature, we expected to find that factors related to patients' sociodemographic characteristics and emergency room use would better predict future HSU than patients' primary diagnosis, levels of disease burden, or comorbidities. A binary classification algorithm was used to model the impact of access and need on future HSU. A widely-used metric for efficacy of HSU, 30 Day readmissions, was treated as the outcome.

The classification model indicated that the strongest predictor of a patient's future HSU was their past HSU. Patients with 3 or more past year ED visits had over 9 times greater higher odds of readmission within 30 days (point estimate=2.285; 95% CI: 1.99, 2.42; $p<.0001$) compared with patients with no past year ED use. This effect was linear; e.g. Patients with 2 past year ED admissions were also significantly more likely to return within 30 days compared to patients with no past year ED visits (point estimate=0.915, 95% CI: 0.645, 1.19; OR: 2.5, $p<.00001$). Other risk factors, such as smoking history, also conferred significantly higher odds of 30 day readmission. Patients with documented smoking histories were over 2 times more likely to return within 30 days (point estimate=0.716; 95% CI: 0.51, 0.92; $p<.00001$) compared with nonsmokers.

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INTRODUCTION

Structure shaping use.

Health care utilization (HSU) describes the kind and quality of individuals' engagement with services to prevent or cure health problems, maintain health status, or to gain information about their health status and prognosis (Carrasquillo, 2013). HSU encompasses a myriad of service types, such as inpatient treatment, pharmacological treatment and prescriptions, and acute care services, including those delivered in the emergency room or within inpatient settings. HSU is often studied in terms of the rate and frequency with which individuals seek these health care services.

Existing literature on patterns in HSU underscores the extent to which this behavior is shaped by both the structure of a healthcare system, shifts in policy, and constraints on access to treatment. In the early parts of the 20th century, individuals in the highest-income groups had the highest rates of hospitalizations. Eventually a rising standard of living, systemic improvements in therapeutics and healthcare delivery, and an expansion of coverage for private and public insurance plans allowed a greater number of individuals to access inpatient treatment (Anderson, Davidson, & Baumeister, 2014). As a result, the average rate of admissions per year per 100 persons more than doubled between 1930 to 1975 – increasing from 6 to 14.

Along with these increases in population-level rates of HSU came changes in the rates of services utilized, and the compositions of patients seeking these services. For example, by 2011 the rate of hospitalizations for those with incomes less than 100 percent of the poverty level was twice that of those with incomes 400% above the poverty level (Anderson, Davidson, & Baumeister, 2014). Contrasting this with the HSU patterns in the early 20th century, this inversion reflects an increase in access to services for those living in poverty and a decrease in the need for those services by those living furthest above poverty level. In other words, if hospitalizations are used as a metric of levels of need, then those patients with the greatest need are those living at, or below, the poverty level. As a steady influx of individuals gained access to acute care, so did the costs of sustaining healthcare networks. In the mid 1970's, admission rates became the target of cost-reduction policies. Research began examining predictors of HSU. The most impactful of these studies is perhaps the RAND Health Insurance study (Brooke, et al., 1984), which used a nationally representative sample to examine individual's predicted rates of HSU based on differences in levels of financial obligation by individuals to pay for their needed medical services. In this study, participants were randomized into groups defined by the proportion of medical services covered by insurance (e.g. 100% covered, 75% covered, etc.). The results of the study showed that individuals who had to pay more for healthcare services were less likely to use services. The authors concluded that rates of HSU were inversely related to the direct cost shouldered by the individual, and this study provided insights into the thresholds of coverage at which reductions in HSU would not negatively impact patients' health (Brooke, et al., 1984).

Recent criticisms have called the conclusions of the RAND study into question and cast shadows on the study methodology, among other concerns (e.g., Aron-Dine, Einav, & Finkelstein, 2013). Nevertheless, at the time the RAND study contributed to an industry-wide effort by public and private interests to curb healthcare costs, with rates of readmission serving as a key metric (Anderson, Davidson, & Baumeister, 2014). The RAND study remains the only study of its kind and scale ever attempted and is an empirical bulwark for arguments supporting the current, market-driven approach to healthcare service allocation.

The RAND study was only part of a broader shift in policy towards reshaping patients' patterns of HSU; also included were efforts to shift treatment away from the more costly acute care services to managed care, primary care, and preventative medicine. Beginning in the 1970s and 1980s, deinstitutionalizing mental health treatment further shifted the burden of care from nationally run programs utilizing intensive, inpatient care to community agencies and other outpatient services (Anderson, Davidson, & Baumeister, 2014). Systems such as diagnosis-related group (DRG) billing schemes attempted to taxonomize patient needs in order to more effectively allocate hospital resources and determine government disbursement rates. Other systemic changes, such as the movement from a fee-for-service model to a system driven by prospective payments from Medicare/Medicaid and coinsurance systems further incentivized reducing both the frequency and duration of inpatient care (Anderson, Davidson, & Baumeister, 2014). The coverage afforded to types of services varies widely across insurance plans and these changes clearly affect the ways patients seek services. For example, patients report the greatest barrier to utilization of services outside of acute care, such as mental health treatments, is access, i.e. the costs of treatment (Network, 2018).

Prioritizing reductions in repeated readmissions continues to influence national healthcare policies. For example, the Hospital Readmissions Reductions program is a Medicare value-based purchasing program that applies financial penalties for excess readmissions of Medicare patients (Alper, O'Malley, Greenwald, Aronson, & Park, 2017). The success of these policies in reducing acute care use is evident; in 1982, there were more total hospital admissions in the US than in 2017 (n=39,095 vs. n=36,510, respectively), despite the differences in population between these two years. These changes in policy are reflected in large part through these changes in patient's patterns of HSU.

Since the early 20th century, healthcare policy in the U.S. has attempted to integrate two potentially conflicting goals; to reduce costs associated with HSU on the one hand, while increasing access to healthcare services on the other. It is worth noting then, that healthcare costs in the United States have risen disproportionately since market-driven attempts at reducing costs were more willingly adopted into U.S. healthcare policy beginning in the 1970s and 1980s (Tikkanen & Abrams, 2019). A study conducted by the Organization for Economic Cooperation and Development (OECD) compared costs of healthcare (defined as proportion of GDP) between the U.S. and other high-income countries from 1980 to 2018. In 1980 healthcare constituted 8.2% of national GDP in the U.S, conversely the country with the lowest healthcare expenditures, the U.K., spent around 5%. By 2018 the U.S. was spending over 16% of its GDP on healthcare, while the lowest spending country, New Zealand, spent roughly 9% of its GDP on healthcare costs (Tikkanen & Abrams, 2019).

As numerous studies have suggested, these increased costs have not resulted in greater overall health for the U.S., as evinced by infant mortality rates or quality-of-life estimates, among other metrics (Ridic, Gleason, & Ridic, 2012; Tikkanen & Abrams, 2019). Furthermore, the U.S.'s healthcare spending is not positively related to how the healthcare system is perceived by its users; the United States healthcare system fares worse in terms of patient satisfaction than other nations with similar income levels (Ridic, Gleason, & Ridic, 2012) and in terms of patients' perceptions of access to services beyond acute care, especially psychiatric and behavioral health services (Network, 2018).

While efforts to curb healthcare spending have failed, so too have attempts at providing access to effective and appropriate treatment. The most recent major attempt at expansion of access, the Affordable Care Act (ACA), successfully significantly reduced the proportion of uninsured individuals in the U.S.; an estimated 20 million individuals have received health insurance since its implementation in 2014 (McConville, Raven, Sabbagh, & Hsia, 2018). However, a recent study examined characteristics of patients presenting in the emergency room before and after implementation of the ACA (McConville, Raven, Sabbagh, & Hsia, 2018). The proportion of uninsured patients among those with the highest HSU decreased from 29% before the ACA to 8% afterwards, although the total number of visits by these patients actually increased from 3,578,207 to 4,057,165 during this same period. Furthermore, the clinical profiles of these patients appears not to have been altered by the ACA; in this study, rates of mental health conditions in this group actually increased from 61% to 65% and rates of substance use disorders increased from 23% to 30%. For these patients, it appears that there remains a mismatch between the clinical factors causing them to seek treatment, their level of access to treatment, and the efficacy of those treatments in reducing levels of need, and with it, levels of HSU.

The effects of policies determining the means with which healthcare services & resources are allocated is evident in the changes in the patterns through which individuals seek these services. If all HSU is driven by some need (e.g. medical, psychiatric), either real or perceived, then reductions in HSU would indicate a reduction in this need by some appropriate healthcare service. Conversely, we would expect that patients without access to appropriate treatments would fail to have needs met, thus failing to reduce their HSU.

In this configuration, the needs of the patients with the highest levels of HSU would indicate the needs most likely to be left unmet. Along with this, the characteristics of these patients would form a profile of the types of patients most likely to have chronically unmet needs. Below, disparities in HSU and risk factors associated with high HSU are discussed to illustrate relations between levels of access and needs of patients in acute care settings.

Relative Disparities in HSU.

Rates of ED and inpatient treatments often reflect patients' levels of access (Anderson, 1995; Anderson, Davidson, & Baumeister, 2014). Emergency room encounters are disproportionately higher for individuals who are underinsured or who have public insurance; 50% of the total costs incurred by these patients are due to repeated utilizations of acute care services (Moe, Bailey, Oland, Levesque, & Murray, 2013). The patients with the highest HSU account for roughly 5% of all patients, yet they are responsible for roughly 30% of all costs (Reinhart, et al., 2018). A plurality of high HSU patients have some measure of public insurance, e.g. Medicaid or Medicare, suggesting their patterns of HSU are shaped by their level of access.

Disparities in access also can reflect disparities in health and quality of life (Anderson, Davidson, & Baumeister, 2014; Small, 2010). High HSU patients typically present with more severe comorbidities, substance use, mental illness, and diseases of greater chronicity and mortality at rates higher than those with lower HSU (Reinhart, et al., 2018). Patients with high rates of ED use are frequently seen for acute presentations of chronic conditions, such as hypertension or diabetes, that may otherwise have been managed in outpatient settings and reduced the likelihood of needing acute care.

Disparities in need are not limited to medical conditions. One study estimated that need for treatment, defined by self-reported health status, activity limitation, dental carry, and psychological distress, was 2-to-7 times greater for those living below the poverty line compared with those above it (Anderson, Davidson, & Baumeister, 2014). Interviews with patients experiencing homelessness and high HSU use detail how these patients reported seeking out treatment in acute care settings in the wake of personal and psychological crises (Gelberg, Andersen, & Leake, 2000; Moore, Conrick, Reddy, Allen, & Jaffe, 2019).

A review of interventions to reduce readmissions found that the overall results of their effectiveness were mixed (Barata, et al., 2017). Although some studies resulted in decreased HSU, these effects were mild-to-moderate. The most successful increased access directly to services outside of acute care settings. For example, interventions which involve intensive care management, community support, or expanded medical coverage such as home treatment teams and care planning demonstrated the greatest reductions in readmissions.

The results from interventions in the ED suggest increased access is often tied to frequency of acute care services. However, the authors of this review noted the high heterogeneity of studies included in their sample, specifically in the variations in how HSU was defined. They suggest that this lack of consensus makes generalizing any results difficult (Barata, et al., 2017). Nevertheless, across studies certain risk factors appeared to consistently predict high HSU, specifically socioeconomic status, and psychiatric & substance use disorders (Barata, et al., 2017). The latter two constructs are highlighted below as an increasingly prevalent need among patients presenting for treatment in acute care settings.

Substance use and HSU.

Patients with primary or comorbid psychiatric and substance use disorders are frequently observed among those presenting to acute care settings (Fleury, Grenier, Bamvita, & Ferland, 2020). Often these patients have limited access to healthcare services and tend to rely heavily on acute care for treatment (Fleury, Grenier, Bamvita, & Ferland, 2020). This trend appears to only be increasing; in the past ten years, there has been a 50% increase in non-psychiatric HSU for patients presenting with primary psychiatric and substance use disorders. According to some estimates, now nearly half of all ED encounters are related to substance use disorders (K Hawk, G D'Onofrio, 2018; White, et al., 2018).

Alcohol-use in particular is among the most frequently identified factors associated with high HSU of acute care services. Between 2006-2014, there was a 61% increase in ED encounters by patients with alcohol-use disorders as their primary need, translating into a 272% increase in costs during that time (White, et al., 2018). Primary care and hospitalized patients are reported to meet criteria for alcohol dependence at rates as high as 20-42% (Awissi, Lebrun, Coursin, Riker, & Skrobik, 2012; Smothers, Yahr, & Ruhl, 2004). These patients are often seen with co-occurring medical comorbidities and sociodemographic risk factors that add to the complexity of addressing their primary need for seeking treatment (Huynh,, Ferland,, Blanchette-Martin, N. *et al.*, 2016). The presence of these risk factors within the high HSU population as a whole suggest their impact on patterns of HSU.

The presenting needs of patients with alcohol-use disorders (AUDS) can be heterogenous; AUD patients can present with differences in the symptoms and severity of their AUD (Awissi, Lebrun, Coursin, Riker, & Skrobik, 2012). In some cases, AWD symptoms are relatively mild, such as tremors and agitation, but AWD can also lead to severe psychological and physiological consequences if left untreated (Awissi, Lebrun, Coursin, Riker, & Skrobik, 2012). More severely intoxicated patients may display symptoms of delirium, agitation or aggressive behavior, and in severe cases seizures or death. Chronic users may develop alcohol-dependence, and around 40% of these individuals are at-risk for alcohol-withdrawal disorder (AWD) following cessation of drinking. The most severe type of AWD, delirium tremens, is a potentially fatal condition characterized by hallucinations, severe fluid and electrolyte imbalance, vomiting, and seizures. The heterogeneity of AUDs suggests that different resources & services may be more appropriate than others for different patients.

Treating alcohol-use in acute care settings.

Appropriate treatments in acute care settings for patients with alcohol-use disorders vary by levels of illness severity. Although treatments are available to address the physiological consequences of alcohol-use, fewer options in acute care are available for managing the behavioral and psychological correlates of chronic dependence. Hospitals are also ill-suited to address the socioeconomic risk-factors affecting many of these patients, a gap frequently noted in qualitative interviews with clinicians and healthcare providers (e.g. Indig, Copeland, Conigrave, & Rotenko, 2009)

In acute care settings, patients presenting with acute intoxication can be provided with targeted treatment in outpatient, emergency room, or inpatient settings (Elliott, 20219). For those to whom treatment can be provided, determining the appropriate treatment requires an assessment of AUD symptomatology. Most acute intoxicated patients require minimal care, although more severe cases of intoxication may require careful monitoring and intravenous fluids to combat dehydration (Elliott, 2019). For patients with more severe symptoms, such as AWD, pharmacological treatments are considered the gold-standard (Elliott, 2019). This treatment entails an assessment of the patient's drinking history along with a measure of AWS symptomatology, most often by using the Clinician-Administered Withdrawal Scale (CIWA), a 10-item screener which measures the severity of a patient's alcohol-withdrawal symptoms (Morgan, et al., 2015; Stephens, Liles, Dancel, Gilchrist, Kirsch, & DeWalt, 2014; Sullivan, Sykora, Schneiderman, Naranjo, & Sellers, 1989). CIWA is considered a symptom-triggered therapy (STT), in that patients' symptoms are continuously reassessed and determine benzodiazepine dosage. STT has been shown to outperform other medication regimens such as fixed-schedule dosing, where medication dosage is tapered based on intervals of time.

Treatments for acute intoxication and AWD are effective and are generally highly accessible, as they are often available within acute care settings (Elliott, 2019; Stephens, Liles, Dancel, Gilchrist, Kirsch, & DeWalt, 2014). However, treatments for other risk factors associated with AUDs are often less available or efficacious in these settings

(Barata, et al., 2017). For example, brief psychological interventions, such as motivational interviewing, have been implemented for patients with risky drinking or chronic dependence presenting for acute care (Barata, et al., 2017). These interventions are administered in EDs and attempt to alter patients' patterns of drinking and encourage them to enter into treatment. (D'Onofrio, McCormack, & Hawk, 2018). Results of these studies have been mixed, with some reporting mild-to-moderate reductions in HSU. As with interventions for reducing readmissions across all high HSU patients, the most effective non-pharmacological interventions for alcohol-use were those which increased patients' access outside of acute care. In one study, patients who received direct referral or who were directly transferred to specialized facilities were 30 times more likely to enroll in treatment (Borg, Douglas, Hull, Keniston, Moss, & Clark, 2018).

Treatments for AUDs in acute care settings are often limited to symptom reduction, either for acute intoxication or withdrawal (Elliott, 2019). However, the AUD patient population presents with needs beyond those directly impacted by medical interventions. It appears as if the presence of AUDs among high HSU reflects a mismatch between their most pressing needs, and the types of treatments available.

Anderson's Behavioral Model of Healthcare Service Utilization

Model Overview.

The Behavioral Model of Health Service Use (BM), proposed by Anderson and Aday, is one framework to study patterns of HSU (Anderson, 1995; Anderson & Aday, 1978; Anderson, Davidson, & Baumeister, 2014). The Anderson Model provides a potential framework to explain the trends in HSU within acute care settings.

Anderson's model describes HSU as driven by sets of predisposing, needs-based, and enabling factors (Anderson, 1995; Anderson & Aday, 1978; Anderson, Davidson, & Baumeister, 2014). Predisposing factors include socioeconomic risk factors (e.g. age and race) and socioeconomic deprivation (e.g., homelessness, low SES). Levels of need reflect the clinical factors present at admission (e.g., patient diagnoses, illness severity, and comorbid conditions). Enabling factors reflect the type and frequency of health services patients are able to access (e.g. services covered by insurance plans). Different versions of the Anderson Model have been proposed, often which also include factors related to process of care (i.e., treatment in the ED vs. on inpatient service units, and the type of treatment offered) and negative health behaviors (e.g. drinking and smoking histories; Smith, Stocks, & Santora, 2015). Health behaviors can exacerbate levels of need and increase HSU, while processes of care affect treatment outcomes and the likelihood of HSU (Anderson, 1995).

The effects of these dimensions in the Anderson model have been examined in a variety of types of HSU, including rates of readmission (e.g., Walley, et al., 2018). Readmission rates refer to the frequencies at which individuals return to a healthcare service for treatment within a set interval of time. Thirty-day readmission rates are an indicator of quality of care for many hospitals.

Risk for readmission has been studied in many different ways; using retrospective analysis of medical records or medical claims data, qualitative interviews, in prospective cohort studies, and using supervised learning algorithms (e.g. Kansagara, et al., 2011). Despite numerous studies on the topic, accurately modeling the risk of readmission has proven difficult; findings have failed to replicate or generalize, and models have often performed poorly (Kansagara, et al., 2011). Models also suffered from a limited range of predictors, with many excluding sociodemographic, psychiatric, and substance use factors (e.g., Kansagara et al., 2011; Moore, White, Washington, Coenen, & Elixhauser, 2017; Sirotich, Durbin, & Durbin, 2016). This may be especially detrimental to model performance, as each has been associated with high HSU.

The risk factors for readmission will now be reviewed within the context of Anderson's model. The literature on readmissions for patients with alcohol-use will also be reviewed, along with the strengths and limitations of previous models of readmission.

Predisposing risk factors.

Predisposing factors for readmission include both sociodemographic factors such as age, gender, income, as well as health behaviors, such as smoking or poor eating habits (Anderson, Davidson, & Baumeister, 2014). Rates of readmission have been shown to be higher among men and those who are older(Anderson, 1995). Differences in race are mixed; some studies reported higher HSU by white participants, others have not replicated this finding (McCormick, Rao, Kressin, Balaban, & Zallman, 2019; Radford, 2020). Homelessness also predicts an increased likelihood of frequent ED admissions, with findings from several studies converging on the importance of this factor (McCormick, Rao, Kressin, Balaban, & Zallman, 2019; Reinhart et al., 2018; Walley et al., 2018;).

Health behaviors include drinking and smoking histories. These behaviors drive HSU by reducing the efficacy of treatment outcomes and increase the risk of both psychiatric and medical problems (Hiscock, Bauld, Amos, Fidler, & Munafò, 2012). The associations between smoking and lower SES are also thought to drive HSU (Hiscock, Bauld, Amos, Fidler, & Munafò, 2012).

Needs based risk factors.

Needs-based factors comprise the medical and/or psychiatric diagnoses driving an individual to seek treatment. Need is impacted by predisposing factors, e.g. increasing age adds risk for a variety of conditions, while enabling factors define the type and number of options patients have for treatment.

Unsurprisingly, patients with greater disease burden are often among those with the highest levels of HSU. Medical comorbidities and conditions with risk of mortality are drivers of readmission. Diseases with greater chronicity are also tied to readmissions. Co-occurring physical illnesses are higher among patients with substance use, and these physical illnesses are often drivers of HSU; increased burden of illness due to medical comorbidities has also been shown to impact rates of HSU (van Walraven, Austin, Jennings, Quan, & Forster, 2009).

However, repeated readmissions also can be driven by psychiatric and substance use, independent of medical comorbidities. Psychiatric disorders, such as schizophrenia or Bipolar disorder, have been linked to increased likelihood of readmission in numerous studies (Brennan, Chan, Hsia, Wilson, & Castillo, 2014). Studies have found that depression and smoking each uniquely predict increased readmission rates (e.g. Wally, et al., 2018). Alcohol use has consistently been implicated in high HSU in numerous studies (e.g., White, 2018), although studies of HSU restricted to patients with alcohol-use diagnoses specifically are limited.

Enabling Factors.

One of the major goals of the behavioral model is to explain the concept of access to healthcare services (Anderson, 1995). Enabling factors are the umbrella term used to describe patients' levels of access within healthcare systems. Access itself refers to the level of availability of services to patients, and their ability to utilize different types of healthcare services (e.g. acute care, primary care).

In the Anderson model, enabling factors can be broken down into potential and realized access (Anderson, 1995; Anderson & Aday, 1978). A direct metric of potential access is a patient's insurance status (e.g. private or public insurance) as variations exist in coverage for different types of services based on the insurance plan an individual has. Potential access can also describe the presence or absence of factors which could allow for appropriate and available treatments, e.g. the presence of facilities, adequate physician-to-bed ratios at local hospitals. Potential access also extends to the availability of social and community support a patient has, such as having reliable transportation to visits or utilizing child care. It is assumed that potential access thus increases the likelihood than an individual could, if they so needed, seek out and attain appropriate services (Anderson, 1995).

Realized access, on the other hand, is a measure of patients' actual patterns of HSU. This is commonly represented by the rate and frequency of services used by a patient in the past. Counts of previous ED visits have been used as indicators of HSU rates (e.g. Fleury, et al., 2019). Other studies have incorporated a wider range of healthcare services to include the number of primary care visits or use of community health services. An individual's past HSU is often considered indicative of their future patterns of HSU. Realized access provides an objective measure of the types and frequencies of services an individual has used, and therefore, serves as a potential barometer for their future HSU (Sun, Burstin, & Brennan, 2003) Patterns of realized access have been shown to be among the best predictors of future HSU (e.g. Penzenstadler, Gentil, Huỳnh, Grenier, & Fleury, 2020).

Both potential and realized access impact patients' patterns of current and future HSU. For example, studies have shown that among some subgroups of high utilizers, there are associations between high ED use and high use of other types of services (Rinehart, et al., 2018). These patients could be considered to have relatively higher levels of both potential and realized access; not only are there services available for them, but they are also able to, and do, utilize them. Conversely, patients with limited potential access, such as those on insurance plans with limited coverage or who live in areas with few outpatient or primary care treatment facilities, have been shown to utilize the ED at disproportionate rates compared with other types of healthcare services (e.g., Schmidt, 2018; Fuda & Immekus, 2006; Ledoux & Minner, 2006). Each type of access is therefore an important component of a patient's patterns of HSU. Consequently, the interpretation of ED visit level depends on the potential and actual use of other services.

Process of care.

Process of care describes the level and quality of treatment an individual receives when seeking healthcare services (Anderson, 1995). It is the operationalization of healthcare resource distribution,(i.e. which patients receive what type of treatment). Length of visit, inpatient admissions, transfer between and within hospitals are each examples of processes of care and are associated with future HSU (Alper, O'Malley, &

Greenwald, 2020). In the BM model, equitable or inequitable distribution of healthcare resources are the result of how well patients' needs are able to be addressed. HSU in an equitable system is determined primarily by predisposition and need, while inequitable systems are driven by levels of access (Anderson, 1995; Andersen, McCutcheon, Aday, Chiu, & Bell, 1983).

The process of care is also impacted by both how the patient perceives their level of need, and how healthcare providers perceive the severity of the patient's need. For example, in determining whether patients with AWD require inpatient care, protocols such as the CIWA incorporate both physiological data and patient's own subjective appraisals of withdrawal symptoms (Sullivan, et al., 1989). These symptoms drive service delivery, including the use of benzodiazepines and other supportive measures.

Modeling the risk of readmission.

Although risk factors for readmission have been identified in numerous studies, reliable models predicting high HSU have been difficult to develop (Kanasaga, et al., 2011). The majority of models have included factors relating to demographic and needs-based factors (e.g. patient age, illness severity, number and type of comorbidities) as well as process of care variables (e.g., length of stay, whether visit occurring in the ED or inpatient settings). Models which have incorporated sociodemographic and enabling factors, such as income or insurance status, have tended to perform better (Alper, O'Malley, & Greenwald, 2017; Kanasaga, et al., 2011). However, these models have been comparatively under-studied.

A 2011 review examining the performance of 26 unique models of readmission found that most performed poorly (Kanasaga, et al., 2011). In this review, models were compared using the C-statistic, or the ratio of true-negatives correctly classified by the model against the rate of true positives correctly classified. Most models had C-statistics of 0.7 or below, generally considered to indicate poor-to-adequate performance. Only a few incorporated sociodemographic or contextual factors – those that did tended to perform better by comparison.

Screening tools for future HSU.

Two of the more commonly used screening tools for predicting future HSU are the LACE index (van Walraven, et al., 2010) & the HOSPITAL score (Donze, et al., 2016). The LACE index was derived from a sample of medical and surgical patients (van Walraven, et al., 2010). A stepwise logistic regression was used to identify significant predictors among a host of patient-level and admissions-level variables. Four predictors were included in the final model; length of stay, whether the visit was acute/inpatient, comorbidities, and the number of ED visits in the 6 months prior to the index admission. However, the results of this study (van Walraven, et al., 2010) showed that the LACE performed poorly in predicting 30-day readmission (C statistic = 0.684).

The HOSPITAL score emphasizes easily collectable predictors, such as hemoglobin A1c and sodium levels or length of hospital stay, variables that are often included in patient records (Donze, et al., 2016). The HOSPITAL was designed so that all the necessary data to predict risk of readmission is available during the patient's visit, in order to potentially intervene prior to their discharge. Initial validation studies showed the tool had adequate discrimination (C-statistic=0.72) in general patient samples in both the US and Canada.

In a study comparing the LACE and HOSPITAL, the HOSPITAL outperformed the LACE index at predicting 30 Day readmissions (C-statistics of 0.75 and .58, respectively; Robinson & Hudali, 2017). The authors suggested this may have been due to the study sample, which had a more complex and severe burden of disease and higher ED use than the sample on which the LACE was trained. They concluded that the LACE alone may be inadequate for identifying risk within complex patient populations.

Both the HOSPITAL and LACE focus on clinical factors and patterns of HSU (Donze, et al., 2016; val Walraven, 2010). For example, the LACE tool uses the number of ED visits by a patient over the previous 6 months as a predictor of future readmission. The subtext of both the HOSPITAL and LACE is that readmission is driven by levels of need. This needs more elaboration and an explanation of what you mean by the subtext - are most of the variables related to need?

Models of readmission have failed to incorporate a broader range of sociodemographic factors, even though many of these are readily available in patients' records (Kanasaga, et al., 2011). The limitations and inconsistencies of needs-based models for readmission highlights the importance of including predisposing and enabling factors, along with measures of need. Although a number of studies have identified characteristics of those at-risk for readmission, there are gaps in knowledge regarding their generalizability and specificity.

Equitable vs. Inequitable allocation of resources.

The Anderson Model defines equitable allocation of healthcare resources as occurring when service utilization is driven by need. In this conceptualization, reduced HSU is the result of reduced need, high HSU implies higher need (Anderson, 1995;

Anderson, McCutcheon, Aday, Chiu, & Bell, 1983). Conversely, systems with inequitable resource allocation are those in which HSU is primarily a function of enabling factors.

In an inequitable system, patients with lower access to appropriate treatment may be, paradoxically, more likely to have higher overall HSU. Relative to others with similar conditions but lower access, those with better access to more appropriate treatment would be more likely to have their needs reduced and with it, their rates of HSU. Enabling risk factors have been clearly delineated within general patient populations(Kroner, Hoffman, & Brousseau, 2010) The relative effects of access within distinct patient populations are not as well known (Fleury, et al., 2019).

Accounting for Heterogeneity of Need & Access

Gaps exist in the literature on how high HSU is conceptualized and on the variations in HSU within specific subgroups. This especially true for patients with substance use and psychiatric disorders, where fewer studies have been conducted. Models used to predict future HSU may suffer from the variations in defining high HSU, as it may be more difficult to summarize findings to identify the best risk factors to include as predictors.

Heterogeneity in defining HSU.

A review of the literature on high HSU patients found significant variations in how this construct is defined (LaCalle & Rabin, 2010). For example, across studies reviewed for the current study (e.g., Belcher & Alexy, 1999; Blank, et al., 2003; LaCalle & Rabin, 2010; LeDuc, et al., 2006; Milbrett & Halm, 2009), the cut-off to be considered high HSU ranged from 2-12 visits per year (Blank, et al., 2003; LeDuc, et al., 2006). . Although the most common threshold for defining high HSU is 3-4 visits per year (LaCalle & Rabin, 2010), this is disputed (Kanasaga, et al., 2011). Differences in the type of encounter used to calculate HSU frequencies also vary, with some hospitals only including inpatient admissions in counts of HSU and others' focusing on ED admissions. These criteria vary between hospitals as well, adding to the difficulty of identifying and addressing high HSU (LaCalle & Rabin, 2010).

Heterogeneity within high HSU populations.

Patients with high HSU, especially in the ED, have often been negatively portrayed as "unscrupulous and uninsured". High utilizers are seen as responsible for ED overcrowding by presenting with problems better treated elsewhere (LaCalle & Rabin, 2010). Racist and classist subtext aside, this belies a longstanding perception of this group as homogenous.

Recent studies examining this population suggest this is unlikely. A retrospective analysis of hospital data applied a latent class analysis to a sample of "super utilizers"taken from a general patient population (Rinehart, et al., 2018). In the study, five distinct clusters of patients were identified based on socioeconomic (e.g. income, housing insecurity), clinical factors, and access to treatment (e.g. insurance status). The group with the highest rates of emergency room use were characterized by alcohol use and homelessness. The group with higher inpatient use included patients with more severe medical comorbidities and fewer sociodemographic or psychiatric risk factors. Patterns of HSU over the preceding six months indicate that patients with alcohol use and homelessness had the highest average number of ED visits and the lowest number of primary care visits (LaCalle & Rabin, 2018). This study suggests that high HSU is driven by potentially different pathways of need, predisposition, and access; as those with more predisposing factors (e.g. homelessness) were more likely to rely on the ED for treatment.

Furthermore, in the literature there have been calls for better understanding of the factors which differentiate patients within specific diagnostic groups (e.g. Fleury, et al., 2019; LaCalle & Rabin, 2018; Rinehart, et al., 2018). The logic of such studies is based on notions of access and predisposing factors having equal, if not stronger, relations to HSU than need. Studying factors related to high HSU across all patients provides absolute estimates of the impact of specific predictors across patient populations. However, studying the differences in factors within specific diagnostic groups allows for the evaluation of the relative risks associated with factors related to access and predisposition, controlling for levels and type of need.

Although some of high HSU patients' needs (e.g. socioeconomic conditions such as homelessness) may not be able to be addressed in acute care settings , identifying the unique patterns of HSU for these patients could potentially help to target interventions to increase access to appropriate services elsewhere. Therefore, more basic research which focuses on specific subgroups of high HSU patients may be needed.

Heterogeneity within patients with alcohol-use disorders.

Alcohol-use is frequently implicated as a risk-factor for readmission and high HSU overall, yet this patient subgroup remains understudied (White, et al., 2018). Given the high prevalence of alcohol-use among patients seeking acute care, and the variations in the type and severity of alcohol-related disorders, research on the differences in HSU and associated risk factors specific to this group is needed.

Studies of HSU patterns among patients with alcohol-use disorders have often been restricted to patients at-risk for AWD (e.g., Salottolo, McGuire, Mains, van Doorn, & Bar-Or, 2017; Yedlapati, & Stewart, 2018). In these studies, HSU is typically examined as readmission rates within detoxification units. In the AWD literature, their documented history of AWD severity among hospitalized patients is considered an important predictor of future AWD severity (Kim, Kim, Bae, Park, & Kim, 2015). The Prediction of Alcohol Withdrawal Severity Scale (PAWSS) was developed based on documented risk factors for AWD (Maldonando, 2014). AWD history (e.g. has the patient had withdrawal-related seizures in the past) is included along with physiological (e.g. autonomic arousal and blood-alcohol level), psychiatric (e.g. levels of alcohol-dependence) and demographic factors (e.g. age and gender). The PAWSS was used within a national readmissions database and found the two strongest predictors of future readmissions for AWD were leaving against medical advice and comorbid psychosis.

Focusing on AWD is important, given the risk of mortality, yet limiting samples in this way may limit the ability to detect broader trends in HSU in the alcohol-use population. For example, patients may have multiple visits related to alcohol-use which did not result in AWD, and thus would potentially be excluded from these analyses.

Similarly, there is a need for a better understanding of patterns in HSU specifically within the AUD patient population (LaCalle & Rabin, 2010; Penzenstadler, Gentil, Huỳnh, Grenier, & Fleury, 2020; Reinhart, et al., 2018). Most studies of HSU and AUDs have focused on the characteristics of ED visits due to psychiatric and substance use within a general patient population (Smith, Stocks, & Santora, 2015) or examined the prevalence rates of these conditions among all patients seen in the ED (Barratt, Rojas-García, Clarke, Moore, Whittington, Stockton, et al. 2016)

Fewer studies have examined all-cause HSU for patients with AUDs (Fleury, et al., 2019). Given the links between patients with psychiatric and substance use disorders and low access to treatment, research is needed which examines broader patterns of use within this population. Research outside of patients at-risk for AWD has examined the characteristics associated with all visits involving substance use or mental health disorders.

To date, relatively few studies has compared differences in all-cause HSU within a subgroup of patients with substance use or psychiatric disorders (Fleury, et al., 2019). In this study, conducted on a sample of patterns of ED use in patients with alcohol-use disorders, the authors grouped patients based on their level of HSU; low (1 visit/year), moderate (2+ visits/year) and high (3+ visits/year). The results showed that individuals with mental health issues, especially substance use, were more likely to be in the high ED use group. Contextual factors, such as neighborhood deprivation, and clinical factors, such as chronic disease severity, were also predictive of future use. Interestingly, levels of need were found to negatively correlate with high HSU; patients with lower acuity of illness were more likely to have high ED use compared to those with more severe illness.

Perhaps most relevant to the current study, factors related to levels of access were closely related to ED use (Fleury, et al., 2019). For example, prior ED use was positively associated with higher ED use. In contrast, hospitalization following a patient's second ED visit was negatively associated with future ED use. In the context of Anderson's model these results suggest that patients who were hospitalized were better able to have their needs met and thus were less likely to be seen multiple times in the ED.

Lastly, it is worth noting that the most of these studies of HSU within AUD populations have occurred outside of the U.S. (Böckmann, Lay, Seifritz, Roser, Kawohl, & Habermeyer, 2019; Fleury, et al., 2019; Huynh, Ferland, Blanchette-Martin, et al., 2016; Verelst, Moonen, Desruelles, & Gillet ,2012). In countries such as Switzerland and Canada, where a number of these studies have been conducted, there is generally broader health insurance coverage than in the U.S. Studies conducted in the U.S. have shown that insurance status is linked to the risk of readmission (Smith, Stocks & Santora, 2014). Therefore, the results from research outside of the U.S. may underestimate the impact of both access as well as need and predisposing factors in the patterns of HSU among patients with AUDs.

The variations in the persistence and severity of AUD, along with the drastic increases in acute care visits by patients with AUD underscore the need for additional studies of HSU across severity of alcohol-related disorders. The findings from the recent study of variations in HSU within a group of patients with alcohol-use highlight the potential differences in access and need which occur in this group. These variations in access and need may affect their overall HSU for reasons only indirectly related to their alcohol-use.

Understanding this overall trend is important. In order to provide externally valid findings that identify overall trends among patients with alcohol-use disorders, rather than trends in visits associated with alcohol-use only, studies may need to focus on all-cause HSU within this population specifically.

Incorporating patterns of HSU into models of readmission.

In the BM model, future HSU is determined by past HSU (Anderson, 1995; Anderson, Davidson, & Baumeister, 2014). For example, patients unable to receive appropriate treatment are thought to be at-risk for higher HSU due to the increasing chronicity of their unmet needs. Studies of risk factors for AWD often cite the importance of past severity of withdrawal symptoms in predicting the severity of future symptoms (Yedlapati & Stewart, 2018).

Chronicity may be measured by examining the specific patterns of need. High HSU patients tend to fall into two subgroups, based on their clinical history (LaCalle & Rabin, 2009). One of these groups is defined as “serial users,” or those who present to the ED with a variety of primary diagnoses. The other can be defined as “single-complaint users”, who present to the ED multiple times with the same primary problem. For serial users, there are often co-occurring medical and psychiatric conditions which drive HSU. These patients are also seen in other settings, suggesting relatively higher access to treatment, or at least access to treatments appropriate for ameliorating the effects of medical conditions. In this context, a serial user may be an individual who presents at multiple sites for a variety of different treatments; e.g., seeking outpatient care for dialysis while also frequenting acute care settings for psychiatric or substance use disorders (LaCalle & Rabin, 2009).

Single-complaint users, on the other hand, may represent patients with chronic conditions and needs that have been unmet (LaCalle & Rabin, 2009). For example, a patient who presented repeatedly to the ED for alcohol abuse and/or intoxication may be a single-complaint user. Persistence of patient needs regarding a specific condition is possibly reflected by the rate at which they have sought treatment to address it. Thus, identifying "single-cause" subgroups among patients for alcohol dependence may represent a target for interventions aimed at increasing access outside of acute care because these patients' HSU patterns may reflect both a desire for treatment but an inability to access appropriate care.

Research on high HSU patients emphasizes the importance of considering how past HSU predicts future HSU. However, variations in thresholds for defining high HSU suggest counts of prior use may not be sufficient. Studies of AWD show that patients' AUD history can be useful in predicting future AUD severity. Numerous studies of patients with alcohol-use disorder suggest a sizeable proportion have chronic alcohol-dependence and high rates of ED use. Identifying those with "single-cause" vs. the "serial users" and high ED use is a potentially useful strategy for developing profiles of patterns of HSU in patients with alcohol-use disorders.

Along with the persistence of single-cause admissions, greater specificity in the types and rate of service use may provide useful information for predicting future use. This is evidenced in studies which have used Emergency Department Reliance (EDR), or the proportion of a patient's total visits occurring in the ED (Kroner, Hoffman, & Brousseau, 2010). EDR has been used as a proxy for access in prior studies (e.g., Kroner, Hoffman, & Brousseau, 2010; Singh, Yan, Brandow, & Panepinto, 2019). Low EDR is thought to indicate greater access, especially for patients with high overall HSU. This suggests that those in the high HSU/low EDR group have high levels of need, often medical, which is most often treated in inpatient or ambulatory settings. For these patients, their clinical needs are being effectively addressed in non-emergency settings, reducing use of emergency services. In contrast, high EDR and high overall HSU by patients is thought to reflect limited access. In a study of children and adolescents, those with high HSU but low EDR tended to be younger and have a special health need, whereas those with high HSU and high EDR were primarily low income, Black, and on public insurance (Kroner, Hoffman, & Brousseau, 2010). Those in the high HSU/high EDR group display ED use driven by a bottleneck of access (Kroner, Hoffman, & Brousseau, 2010).

Taken together, the literature on HSU is well-established among general patient populations. However, more work is needed to understand the ways in which patterns of HSU develop among patients with alcohol-use disorders. Below, the current study is introduced. Following a brief summary of this literature review, the overarching research questions and specific hypotheses will be introduced.

The Current Study

The overall aim of this study is to apply the Anderson Model of Healthcare Service Utilization (HSU) as a framework for understanding risk factors for high HSU within a sample of patients with alcohol-use disorders. AUD patients represent an ever-larger plurality of the seeking acute care population, yet this group remains understudied.

The Anderson Model has been used extensively in previous research on HSU, with much attention paid to patients with the highest rates of utilization. Studies have found that patients with the highest HSU comprise around 5% of the general patient population while accounting for 30% of all service use. These patients often present with non-medical risk factors and limited access to psychiatric or substance treatment. However, most studies have modeled rates of HSU within general patient populations; gaps in knowledge exist regarding differences in HSU within specific diagnostic subgroups.

Nevertheless, studies in general patient populations provide strong evidence of the link between high HSU and sociodemographic factors, psychiatric & substance use disorders, and limited access to services or support outside of acute care. Recent epidemiological trends have shown significant increases in the number of patients presenting to acute care services with primarily alcohol-related disorders. Alcohol-use has been linked to higher HSU in numerous studies, and AUDs have been frequently associated with other risk factors for increased service use (e.g. psychiatric disorders, homelessness) and low access (e.g. under/uninsured, use of outpatient/rehabilitation services). Acute intoxication, chronic alcohol dependence, and alcohol withdrawal are each distinct yet prevalent forms of alcohol-use disorder among patients, associated with distinct interventions, cost, and outcomes. Nevertheless, to date only one study has examined differences in the factors associated with HSU specifically within a sample of patients with alcohol-use disorders.

We aim to extend the findings of Fleury, et al., (2019) to identify potentially unique risk factors of HSU among patients with alcohol-use disorders. Our predictions are derived from axioms of the Anderson Model and types of healthcare systems; the Anderson Model predicts access drives HSU in inequitable systems and several studies have found that the best predictors of future HSU are patterns of past HSU. Given additional findings from the literature (e.g., patients with AUDs are often among the highest HSU patients, these patients are often treated at disproportionately lower rates than they present), we believe that in the case of AUDs, the current healthcare system is unable to appropriately address the psychiatric, socioeconomic, and access-related risk factors of these patients. Therefore, resources are inequitably distributed for these patients.

To test this hypothesis, we will partially replicate the design of Fleury, et al. (2019), in which realized access was operationalized based on the number of ED encounters during one year. Broadly, we expect to find that among patients with alcohol-use disorders, rates of HSU are driven more by enabling factors rather than need, thus reflecting an inequitable allocation of resources to these patients within the healthcare system. Therefore, our overarching hypothesis is:

1. Enabling factors will better predict patterns of HSU compared with patient need, supporting the hypothesis of inequitable resources allocation for AUDS.

Additionally, we predict that:

1. The highest HSU subgroup will have relatively higher rates of socioeconomic risk factors (e.g. homelessness) and negative health behaviors (e.g. smoking) compared with subgroups with lower HSU.

2. Patients with the highest rates of HSU will present as single-cause patients, (i.e. with the greatest proportion of visits due to a single condition).

3. Patients with the highest rates of HSU will have relatively lower levels of need, compared with patients with lower HSU.

4. Patients with the highest levels of HSU will be less likely to receive treatment for AWD, such as the CIWA protocol or administration of benzodiazepines.

   Patients with the highest rates of HSU will be more likely to present in the emergency room vs. being admitted as inpatients.

METHOD

The current study is a retrospective analysis consisting of all encounters by patients with either a current or past alcohol-related diagnosis. The sample consisted of patients seen at an urban safety-net hospital. Data spanned just over three years (from 12/15/2015 to 12/31/2018) and was obtained from the electronic medical record (EMR).

The inclusionary criteria for the study were any documented alcohol-related diagnosis in a patient's EMR, whether as a primary diagnosis or secondary diagnosis, or included as part of the patient's medical history. Alcohol-related diagnoses were indicated in the patient record by the presence of an ICD-10 code between F10.00 to F10.99 (e.g., acute alcohol intoxication, alcohol dependence, alcohol withdrawal with complications). Admissions occurring in both the emergency room (ED) and inpatient settings were included.

Both encounter-level and patient-level variables were used in the current study. The former comprise characteristics specific to a single encounter, such as aspects of treatment or a patient's presenting complaint. Patient-level variables used in the current study differ between patients, such as demographic characteristics or past-year HSU. Patient level variables are derived using samples of unique patients, while observation level variables are derived using samples of encounters.

In the current study the full dataset was subset by year, with patient encounters occurring between 1/1/2017 and 12/31/2017 serving as the training & testing dataset of index admissions. Due to multiple patients appearing multiple times in this period, only the first encounter by each patient seen in 2017 was used. Observation level variables were taken from the values present at these encounters. Unless indicated otherwise, descriptive and bivariate analyses were conducted using this sample.

All encounters occurring from 12/15/2015 to 12/31/2016 were used to calculate patient-level variables of interest that would serve as measures of past year HSU (e.g. past year ED use) and predisposing characteristics (e.g. homelessness in the past year). Patients with encounters in both 2016 & 2017 were linked and the values based on their 2016 encounters were used in modeling the likelihood of readmission.

Overall Sample.

The total sample used in the current study comprised 24600 admissions and 12252 unique patients. In the EMR, patients are identified with a unique MRN number. Prior to analyses, these were deidentified using a coding scheme to assign de-identifiable subject ids. Duplicate entries (n=300) were identified in the dataset. These were removed prior to analyses.

The EMR record also contained consecutive admissions by patients which detailed an ED visit immediately followed by inpatient admission. These ED-to-inpatient admissions were treated as single encounters, with redundant/duplicate data removed (dbl_ED). If ED admissions extended past midnight, a second row in the EMR was assigned. Of these, the row which contained data for a larger proportion of the encounter was retained and the other was eliminated prior to analyses (enc_N). Following this pre-processing, the resulting dataset included 22,896 of the original 24,600 observations.

Readmission events and rates of readmission.

The outcome of interest, future HSU, was operationalized in the dataset using variables to indicate whether any one encounter was followed by a second encounter within 30 days (index30ADM_2017).

Methods of predicting 30 day readmissions were adopted from previous studies (e.g., Mahajan & Ghani, 2019; van Walraven, et al., 2010). Typically, studies model this risk by first selecting a sample of encounters by a set of unique patients. These encounters are termed index admissions. The likelihood of any one patient returning following an index admission is modeled based on the characteristics present at the index admission.

Index admissions preceding a 30 day readmission were identified by an algorithm which calculated the difference in days between any two consecutive admissions by the same patient (DaysBTW). An indicator variable was used to mark if the difference was <= 30 days (index30ADM), with 0=”not followed by 30 day remission” and 1=”followed by 30 day readmission”. It should also be noted that the index30ADM=0 group encompassed both patients with only one encounter across the study period and those patients whose next visits occurred after 30 days.

Thirty day readmission was modeled based on index admissions occurring in 2017 and 2018. In order to maintain independence of observations, the datasets used to model likelihood of readmission only comprised the first encounter by each patient for that year; i.e. the training/test sample included the first encounter by all patients between 1/1/2017 to 12/31/2017 (n=4,766 unique encounters) and the validation sample included the first encounter by all patients between 1/1/2018 & 12/31/2018 (n=4845).

For both the 2017 and 2018 samples, predisposing (e.g. past year smoking status) and enabling factors (e.g. past year ED use) were derived using data from the previous year. For example, past year homelessneses for patients presenting in 2018 was determined based on all encounters by that patient between 1/1/2017 and 12/31/2017. Statistics based on total HSU (e.g., total visits, average number of visits) were calculated using all visits between 12/15/2015 & 12/31/2018 (n=22,986).

Predisposing factors.

In the Anderson model, predisposing factors can include both demographic variables, socioeconomic factors, and health behaviors. Some studies differ in these constructions, but this taxonomy is derived from the most recent revisions of the Anderson Model (Anderson, 1995). Sociodemographic characteristics and health behaviors in the study consisted of patient age, gender, race, homelessness and smoking history.

Twelve instances of gender were coded as "unknown." These observations were removed and gender was treated as a binary variable with 0=male & 1=female. Race was coded as a five level categorical variable, with levels for Latinos (race.num=1), Black (race.num=2), West Indian (race.num=3), White (race.num=4), Asian (race.num=5) and Other (race.num=6). The "Other" category included all self-reported racial and ethnic identifications present in less than 1% of all encounters; e.g. Native American, Pacific Islander, Alaskan Native.

Homelessness and smoking were operationalized at both the level of the encounter and at the patient level. Overall homelessness and overall smoking status referred to the presence of either in the EMR during at least one encounter by a patient between 12/15/2015 and 12/31/2018 where they had been identified as homeless or a smoker.

At the encounter-level, binary variables were used to indicate if a patient was identified during any one encounter as either homeless (Homeless) or a smoker (smoke01). At the patient-level, past year homelessness and/or smoking status was calculated from any encounters by the patient in the dataset which occurred between 12/15/2015 and 12/31/2016. These variables then indicated whether any patient appearing between 1/1/2017 and 12/31/2017 had a history of homelessness (Homeless01_2016) or smoking (Smoking01_2016) at the time of their 2017 index admission.

Needs factors.

Clinical characteristics included primary alcohol-related diagnosis, rate at which an alcohol-related diagnosis was the primary diagnosis in the patient's medical history? , primary psychiatric diagnosis, and comorbidity burden.

Primary alcohol-related diagnosis (prF10dx) was a binary observation-level variable which indicated whether an encounter resulted in a primary diagnosis related to alcohol-use (prF10dx=1) or if another primary diagnosis was given (prF10dx=0).

An encounter-level categorical variable was created for primary psychiatric diagnoses, also based on ICD-10 codes (AxisI_pr); 0= no primary Axis I disorder, 1= primary Bipolar diagnosis (F31.XX), 2= primary major depression diagnosis (F32.XX - F33.XX) , 3=primary schizophrenia/psychosis diagnosis(F20.XX - F29.XX).

The Elixhauser comorbidity index was used as an encounter-level measure of the presence and severity of co-occurring medical and psychiatric conditions. The Elixhauser

Index comprises a set of 31 binary variables representing the presence of one or more diagnostic codes within pre-specified diagnostic groupings. Conditions include both chronic and acute medical conditions, along with psychiatric and substance use categories. Groupings are based on the ICD-10 codes listed in the EMR, with the presence of any identified comorbid condition resulting in an indication of 1 for that diagnostic group. Elixhauser groupings were calculated using the comorbidity package in R (Gasparini, 2018).

A system of weighting each comorbidity was developed by Van Walraven & others (2010) that assigns weights to each Elixhauser category based on disease severity. This weighting system provides a measure of relative risk across Elixhauser categories. Weights are derived by first using logistic regression to model the risk of in-hospital mortality as a function of all Elixhauser categories, and then by dividing the resulting coefficients for each category by the coefficient for the category with the smallest estimate. The resulting scores indicate the cumulative relative risk of mortality conferred by a patient's presenting comorbidities.

Enabling factors.

Levels of access were operationalized by past year using past year ED use (total_EDvisits2016). Based on previous studies (Fleury, et al., 2019), past-year ED use was defined using the total number of ED visits between 12/15/2015 and 12/31/2016 (EDvisits_2016.cat), These groups were; No past year ED use (0 ED encounters), Low Use (1 ED encounter), Moderate Use (2 ED encounters), High Use (3+ ED encounters).

MAX patient status (MAX01) was a binary, patient-level variable based on the internal flagging system used by the hospital where the current study took place. In the hospital EMR, a MAX patient is one who has been admitted as an inpatient 3 or more times in one year. Once identified, flagged patients are linked to community and psychiatric resources, thus MAX patient status served as a proxy for levels of potential access. The variable was set to 1 only if a patient had been identified as a MAX patient, and set to 0 otherwise.

Realized access was also operationalized by the type of service utilized. In the dataset, nearly all encounters occurred in either the ED or on inpatient units. Therefore, an observation-level binary indicator (inpYN) was used to identify whether patients were seen as inpatients (inpYN=1) or in the ED (inpYN=0) during any one encounter.

Process-of-care factors.

Process related factors included in the current study included length of stay for the index admission, if restraints were used, the outcome of an encounter, if alcohol-related treatments were used, and the disposition flag of the encounter.

Length of stay (LOS) was a continuous variable measuring the length of time an encounter lasted, with 1 hour=1/24=~0.4167 and values greater than 1 indicating the encounter lasted longer than 1 day. Physical restraint use was indicated with an observation-level, binary indicator set to 1 if a patient was restrained (restraint01) during a particular encounter and set to 0 otherwise.

Alcohol-related treatment was operationalized by whether patients received treatment for alcohol withdrawal symptoms. An observation-level, binary variable was used to indicate if the CIWA protocol was recorded in the EMR as having been administered (CIWA_Adm=1, otherwise CIWA_Adm=0). An observation-level, binary variable was used to indicate if benzodiazepines were administered during an encounter

(MEDS01). Benzodiazepines are a central component in the CIWA protocol, and interventions for alcohol-withdrawal generally. In the EMR, the medications administered included Ativan, Librium, Valium, Oxazepam, and Xanax. However, the majority (89%, n=4766) of patients receiving medication were given Ativan, therefore this was treated as a binary variable to indicate whether any benzodiazepine was administered (MEDS01=1, otherwise MEDS01=0).

The outcome of each encounter was recorded in the EMR as the "Disposition Flag." The vast majority (n=19,673 , 88%) of all encounters resulted in a disposition flag of "Discharged to Home," while the remaining 12% (n=2,559) included a myriad of other outcomes. Outcome of encounter was transformed into a categorical variable (Dispo01) with levels for whether the patient was discharged to home (Dispo01=0), left against medical advice (Dispo01=1), if the patient was transferred within the hospital (Dispo01=2), or transferred outside of the hospital (Dispo01=3).

ANALYTIC PLAN

Comparisons across levels of HSU.

Univariate and bivariate statistics were calculated to compare the sample across levels of HSU. Following the methods outlined in Penzenstadler, et al. (2020), the sample was split based on past-year ED use (0 ED visits, 1 ED visits, 2 ED visits, 3+ ED visits). ED use groups were then compared across predisposing, need, enabling, and process of care factors. Two way frequency tables were used for comparing proportions of categorical factors (e.g. gender) across groups and ANOVAs were used to compare differences in continuous factors (e.g. age) across levels of ED use.

30 Day Readmission.

The likelihood of readmission based on characteristics present at index admissions was modeled using logistic regression. Predisposing, need, and enabling factors at both the patient and encounter levels were used as predictors of the likelihood of readmission. All models were trained using a 80/20 train-test split of the data. In order to account for imbalance between classes of the outcome variable, different sampling methods (up vs. down sampling) were compared.

Model performance was evaluated based on the following indices; accuracy, area under the curve (AUC), Cohen's Kappa, precision, recall, and the F1 statistic. These metrics are considered to accurately assess a model's classification abilities (Koyejo, Natarajan, Ravikumar, & Dhillon, 2014), although studies of readmission have typically failed to include all relevant metrics (e.g., Donze, et al., 2016).

Accuracy is the proportion of correct predictions across all predictions, i.e. (True Positives + True Negatives)/(True Positives + True Negatives + False Positives + False Negatives). Accuracy provides an estimate of the ability for the model's ability to both correctly classify true positives (returned in 30 days) and true negatives (no return in 30 days).

Cohen's Kappa will be used as a measure of the agreement between predicted classifications and observed classifications. The area under the curve (AUC), or the ratio of true positives to true negatives correctly classified by the model, will assess the rate at which the model correctly classified patients as those with and without 30-day readmissions. Accuracy, Cohen's Kappa, and AUC are all frequently reported in studies using classification algorithms.

However precision, recall, and F1 are often preferred over accuracy alone when modeling unbalanced outcomes, i.e. with unequal class sizes between the positive and negative class, as these metrics do not include the rate of True Negatives. Precision is a measure of the rate of correct positive classifications (true positives) out of the total number of predicted positive classifications (true positives + false positives). Precision is a function of the model's Type I error. Recall is a metric providing the rate of correct positive classifications (true positives) out of all positive classifications actually present in the sample (True Positives + False Negatives). Recall is a function of the model's Type II error. These two metrics are linked statistically, and thus the F1 statistic, or the ratio of Precision:Recall, provides a metric of a model's ability to balance both the rate and amount of correct predictions.

RESULTS

Below, the results of these analyses are reported. These can be divided into three sections. The first section reports the characteristics of patients grouped by past year ED use, as in Fleury, et al. (2019). This includes descriptive statistics of the sample, along with bivariate relations between variables of interest.

The second section describes the construction of a model of readmission across four stages of development. First, models of enabling vs. need based factors are compared using 2017 data. Likelihood ratio tests will be used to compare which better predicts readmission, along with the metrics described above. Next, the significant predictors will be used to build the final model of readmission. The final section of results is the validation of the readmission model using only 2018 data. The predictors used in the final model derived in section 2 will be applied.

Descriptive & Bivariate Statistics (2017)

After grouping the 2017 sample based on past year ED use, the largest group, those with no past-year ED use, comprised 86% of the sample (n=4,132). Of the remaining groups, those with 1 past-year ED visit comprised 6% of the sample (n=305), 2 past year ED visits (n=132) comprised 3% of the sample, and those with 3 or more visits comprised 4% of the total sample (n=197).

Predisposing factors.

Patients in the 3+ ED visits group were significantly older (mean age=49.26) than other groups, the largest differences present in comparison to those in the no ED visit group (mean age= 44.08; F(3, 4762)=8.832, *p*<.001). Significant differences were found across ED groups in the proportions of Latino patients (z-score=4.68, *p*<.0001) and West Indian patients (z-score=3.61, p<.005). Twelve percent of patients (n=501) in the no past year ED use group self-identified as West Indian, compared with 23% of patients in the 3+ past year ED use group (n=45).

Significant differences were found between ED groups in proportions of patients with any period of identified homelessness across the three years of data (n=22896, z-score=17.25, *p*<.0001) and of patients identified with experiencing homelessness in the past year (n= 4,766, z-score=21.44, *p*<.00001); 37% of patients in the highest ED use group (n=72) were identified as homeless during at least one encounter between 12/15/2015 & 12/31/2018, while 17% (n=34) were identified as homeless within one year of their first encounter in 2017. These differences were not significant across groups for homeless status at the time of index admission (n=4,766, z-score=1.85, *p*=0.33).

Similar patterns were observed for smoking status. Significant differences were found between groups based on overall smoking history (n=22896, z-score=14.96, *p*<.00001) and past year smoking status (n=4766, z-score=33.18, *p*<.000001), with the highest ED use group having the highest proportions of patients with any positive smoking status (69%, n=136) and past year smoking status (52%. n=103). These differences were not significant for smoking status identified at index admission (4766, z-score=1.84, *p*=0.33).

See Table 1 for a complete list of comparisons between predisposing factors across groups.

Need and illness severity.

Z-tests of proportions identified differences across ED groups based on the type and rate of alcohol-related diagnoses seen at index admission. Groups significantly differed in the proportions of patients with non-F10 diagnoses (z-score=7.93, p<.0001), alcohol abuse (z-score=5.67, p<.0001), and alcohol dependence (z-score=4.98, p<.0001).

The proportion of non-alcohol diagnoses declined across ED groups (49% of patients in no past year ED use vs. 24% of patients in 3+ past year ED encounters), while proportions rose with number of past year ED visits (44% in no ED group vs. 60% of 3+ ED group) and alcohol dependence (7% in no ED group vs. 15% in 3+ ED group). The proportion of index admissions in 2017 directly related to alcohol use were also significantly different across groups (z-score=7.93, p<.00001), with 76% of index admissions due to alcohol-use by the 3+ past year ED group (n=150) resulting in a primary F10 diagnosis compared with 51% of the no past year ED group (n=2,215).

Differences were found between groups based on illness severity, risk of mortality, and type and prevalence of comorbidities. Patients with more past ED use tended to be considered at lower risk for illness due to medical comorbidities; 84% of the 3+ past year ED group (n=166) were considered in the Low Risk category of the Elixhauser index compared with 71% of the no past year ED group (n=2877, z-score=5.17, p<.0001). Conversely, 12% of the no past year ED group (n=11) were in the highest risk category of the Elixhauser index compared with 6% of the 3+ past year ED group (n=495); these differences were significant (z-score=3.82, p=.002).

Among comorbidities, rates were low for most conditions. Only conditions occurring in more than 10% of the total sample (n=22893) were included in the analyses.

Nevertheless, counts of conditions across ED groups were still often low. The comorbidities used were hypertension (z-score=3.53, p=0.006), liver disease (z-score=3.5, p=0.007), fluid & electrolyte disorders (z-score=4.45, p=0.0002), drug use (z-score=4.12, p=0.0007), and psychosis (z-score=6.08, p<.00001); these were each significantly different between ED groups. Patients with no past year ED use tended to have more medical comorbidities; patients in the no past year ED group had the highest rates of liver disease (n=172, 4%), fluid & electrolyte disorders (n=376, 9%) and drug use (n=540, 13%). Those in the highest past year ED group had the greatest proportions of hypertension (n=52, 26%) and psychosis (n=16, 8%).

See Table 2 for a complete list of comparisons between needs-related factors across groups.

Enabling factors.

Significant differences were found in terms of overall visits ($F(3, 4762)=1121$, p<.0001). Past year ED use displayed strong relations with future HSU. Across the three years of the sample those in the no past year ED group averaged 1.71 visits per patient (7049 visits total), those with 1 ED visit averaged 4.63 visits per patient (1412 visits total), those with 2 past year ED visits averaged 8.54 visits per patient (1127 visits total), and patients with 3 or more ED visits in 2016 averaged 26.58 visits per patient (5236 visits total) between 12/15/2015 and 12/31/2018.

Few patients in any group were considered “MAX” patients in the hospital record. Across all index admissions in the 2017 sample, only 109 patients (2.29%) were flagged as at-risk for high HSU and given access to internal and external resources. This included only 2% (n=4) of patients in the 3+ ED encounter group.

See Table 3 for a complete list of comparisons between enabling factors across groups.

Process of care.

Higher ED use was associated with the setting of service utilization. Patients in the no past year ED use group were the most often seen as inpatients at index admission (26.11%) compared with other groups, while those in the 3+ past year ED use group were least often seen as inpatients at index admission (12.18%).

Significant differences were also found between groups based on length of stay of index admissions ($F(3, 4762)=4.29$, $p<.005$). Patients with no past year ED use stayed significantly longer than each of the past year ED groups, with the greatest differences seen between the no past year ED group and those with 3+ past year ED encounters (mean LOS=1.97 days vs. 0.89 days, respectively). The total number of hours across all index admissions for patients in the 3+ ED group equaled 175.34, while the no past year ED use group's total time spent during index admissions equaled 8159.

Differences were also seen in the proportion of patients given medication for alcohol withdrawal (z-score=3.22, p=0.02), with higher rates seen in patients with 1 past year ED encounter (n= 30%) and 2 past year ED encounters (n= 31%) compared with those in the 3+ past year ED use group (n= 22%).

Although significant differences were found between proportions of patients discharged to home following index admissions (z-score=3.28, p=0.01), 88% of all index admissions in the 2017 sample resulted in a discharge to home.

Modeling likelihood of 30-Day readmission (2016-2017)

To test the hypothesis that healthcare resources are inequitably distributed for patients with alcohol-use disorders, models of readmission were structured that compared the performance of a model based on predisposing & enabling factors and a model based on predisposing & need factors. The first model in essence controlled for predisposing factors without accounting for patients' current levels of need or illness severity at the time of the index admission, i.e. "without encounter-level data". The second model estimated readmission controlling for predisposing factors and levels of need, "i.e. without patient-level HSU data."

Predisposing factors included age, gender, race, past year Homelessness & past year smoking. Needs based factors included presence of primary alcohol related diagnosis, Elixhauser severity Index score, and comorbidities. The most frequently occurring comorbid conditions were included (hypertension, chronic pulmonary disease, liver disease, diabetes, fluid & electrolyte disorders, drug use, psychosis, and mood disorders).

Enabling factors were past year ED use and inpatient vs. ED encounter at index admission. CIWA administration and use of benzodiazepines at index admission were included in both models to account for treatment effects.

Model 1: Predisposing & Enabling factors.

A binary logistic regression was conducted to model the likelihood of 30 Day readmission as predicted by predisposing and enabling factors. Individual predictors used in this first model included age, gender, race, past-year smoking status, past year homeless status, and number of past year ED encounters.

Overall, the results indicate a significant association between the linear combination of predictors and 30 Day readmission (X^2 (13)=1180, p<.0001) compared with an intercept-only model. In terms of predisposing factors, older age conferred a significantly higher likelihood of readmission (point estimate=0.011, 95% CI:(0.01, 0.01) , Odds Ratio(OR)=1.011, p<.0001). Gender was also significantly associated with 30 day readmission, with female patients less likely to return within 30 Days (point estimate=-0.327, 95% CI:(-0.47, -0.19) , OR:0.72, p<.0001) than male patients. Significant differences were also seen across racial and ethnic groups; compared to individuals self-reporting as Latino, individuals self-reporting as Asian were significantly more likely to return within 30 days (point estimate=0.213, 95% CI:(0.01, 0.42) , OR: 1.237, p=0.038).

Predisposing factors related to health behaviors and sociodemographic characteristics each conferred higher likelihood of readmission, although only individuals identified as smokers in the past year were significantly more likely to return within 30 days (point estimate=0.747, 95% CI:(0.55, 0.95), OR: 2.112, p<.0001). Differences in the likelihood between patients identified as homeless within the past year were not significantly more likely to return in 30 days from the index admission.

Patients with 1 or more ED encounters within the past year were more likely to return within 30 days of the index admission, compared with those in the no past year ED use group. This effect increased linearly with number of ED encounters; compared with individuals without a past-year ED readmission, those with 1 ED encounter (point estimate=-0.249, 95% CI:(0.05, 0.45) , OR: 1.282, p=0.015), 2 ED encounters (point estimate=0.95, 95% CI:(0.68, 1.22), OR: 2.589, p<.0001), and 3 or more ED encounters (point estimate=2.29, 95% CI:(2.04, 2.55) , p<.0001) were all significantly more likely to have a 30 day readmission following an index admission. Patients with 3 or more ED visits within a year of the index admission had nearly 10 times greater odds of readmission compared with patients with no past year ED visits.

Model 2: Predisposing & Needs factors.

A binary logistic regression was conducted to examine the relations between 30 day readmission and predisposing & need based characteristics. Predisposing factors included age, gender, race, past year homelessness, and past year smoking status. Needs related predictors included primary alcohol-related diagnosis and Elixhauser comorbidity index score, hypertension, chronic pulmonary disease, liver disease, diabetes, fluid & electrolyte disorders, drug use, psychosis, and bipolar disorder/major depression.

Multicollinearity was assessed using the Variance Inflation Factor (VIF) and identified a high degree of multicollinearity (i.e., VIF > 3) between Elixhauser Index groupings (VIF>4). This variable was removed from modeling.

Overall, the results indicated the linear combination of predictors better fit the data compared with an intercept-only model (X^2 (22)=969, $p<.0001$). Among predisposing factors, age and gender remained significantly related to 30 day readmissions, as seen in model 1. Estimates of racial and ethnic differences replicated across models, with patients self-identifying as West Indian and Asian being significantly more likely to return in 30 Days compared to patients identifying as Latino, the comparison group.

Sociodemographic and health behaviors showed stronger relations with the outcome of interest without accounting for enabling factors. Past year homelessness was significant in this model, conferring 2.27 higher odds of 30 day readmission compared with patients not identified as homeless in the past year (point estimate=0.818, 95% CI:(0.413, 1.241) , $p<.0001$). Past year smoking status conferred 4.15 higher odds compared with patients without such histories (point estimate=1.423, 95% CI:(1.249, 1.604) , $p<.0001$).

Patients presenting with a primary alcohol-related diagnosis were significantly more likely to return within 30 days (point estimate=0.541, 95% CI:(0.427, 0.655), OR: 1.73, $p<.0001$) than those with a non-alcohol related primary diagnosis. Presence of comorbid psychosis conferred over 4 times higher odds of 30 Day readmission (point estimate=1.437, 95% CI:(1.157, 1.763) , $p<.0001$). Other individual comorbidities associated with an increased likelihood of 30 day readmission included liver disease (point estimate=0.437, 95% CI:(0.147, 0.713) , OR: 1.55, $p=0.003$), and bipolar disorder/major depression (point estimate= 0.581, 95% CI:(0.353, 0.840), OR: 1.788, $p<.0001$).

Model Comparison & Final Model Selection.

Model 1 and model 2 were compared using the likelihood test of variance. Significant differences were found (X^2 (13, 19)=215, $p<.00001$). This suggests that Model 1, which used predisposing and enabling factors, significantly outperformed Model 2, which relied on predisposing and needs factors.

The significant predictors of models I & II were used in a binary logistic regression predicting 30 Day readmission with index admissions occurring in 2017. The final model included predisposing (age, gender, race, past year Homelessness & Smoking status), need (primary alcohol-related diagnosis, comorbid liver disease, comorbid psychosis, comorbid mood disorder), and enabling (past year ED use) factors. CIWA administration was not significant when controlling for needs past factors, and thus was removed.

Parameter estimation demonstrated significant improvement over an intercept-only model (X^2 (18)=1335, p<.0001), with 13% of variance explained as indicated by McFadden's Adjusted Pseudo-R^2. The Final Model AIC (8419) was also lower than either model 1 or model 2. The strongest predictors remained past year ED use, with odds increasing linearly by number of encounters and those with 3+ past year ED visits having nearly 9 times greater odds of 30 day readmission than those without any past year ED encounters (point estimate=2.16, 95% CI: (1.90, 2.42), p<.0001). Past year smoking status (point estimate=0.69, 95% CI:(0.49, 0.90) , OR: 2.00, p<.0001), primary alcohol-related diagnosis at index admission (point estimate=0.39, 95% CI:(0.27, 0.51), OR:1.48, p<.0001), and comorbid psychosis (point estimate=1.15, 95% CI:(0.85, 1.46), OR: 3.15, p<.0001) were also significantly related to readmission.

The final model was tested on the remaining 20% of training data. The model's accuracy was found to be 0.80, indicating that 80% of observations in the test dataset were correctly classified. The value of cohen's kappa (0.24) is considered to indicate a "fair" agreement between the predictions and actual cases. The area under the curve (0.76) is considered in the acceptable-to-good range. Model precision (0.23), model recall (0.58) and model F1 score (0.33) indicate the model had a higher False Positive than False Negative rate. These metrics indicate that although the model correctly predicted only 23% of all the positive predictions the model made, this represented 60% of all possible positive cases in the test sample.

Modeling Likelihood of 30-Day readmission (2017-2018)

In order to further assess the generalizability and account for potential model overfitting, the model parameters derived using 2017 data were then validated on 2018 data. As with the 2017 data, only the first encounter by a patient occurring between 1/1/2018 & 12/31/2018 were used in estimations, with predisposing (Homelessness) and enabling (ED visits) calculated using all visits between 1/1/2017 to 12/31/2017.

Model 4: Predisposing, Need, and Enabling factors.

Overall metrics of this model indicated significant differences between the fitted model compared with the intercept-only model (X^2 (20)=1796, p<.0001). McFadden's Pseudo-R indicated the model explained 17% of the variance in the sample. The strongest individual predictors remained enabling factors; patients with 3+ ED visits between 1/1/2017 & 12/31/2017 had over 10 times higher odds of returning within 30 days of their 2018 index admission (point estimate=2.34, 95% CI:(2.08, 2.6) , p<.0001). The 2018 model identified past year Homelessness as a significant predictor (point estimate=1.357, 95% CI:(0.99, 1.73) , OR: 3.88, p<.0001) conferring nearly 4 times greater odds of readmission.

As with the 2017 data, this model was then tested on the remaining 20% of training data. The model's accuracy was 0.76, indicating that 76% of all observations in the test dataset were correctly classified. The area under the curve (0.79) falls just beneath the good-to-excellent range. The value of cohen's kappa (0.21) is considered to indicate a "fair" agreement between the predictions and actual cases. Model precision (0.20), model recall (0.66) and model F1 score (0.31) indicate the model had a higher False Positive than False Negative rate. This indicates that the model had a high false positive rate relative to its false negative rate; although only 20% of all predicted positive cases (i.e. when 30 Day readmissions followed index admissions) were correctly classified by the model, this represented 66% of all actual positive cases in the dataset.

DISCUSSION

The primary goal of the current study was to examine patterns of HSU within a sample of patients with alcohol-use disorders (AUDs). Despite converging evidence showing increases in the rates of patients presenting with AUDs in acute care settings and replicable associations with other risk factors for high HSU, significant gaps exist in the literature on HSU within this patient population. Our aim was to contribute to a small, but burgeoning, literature on the HUS of patients with AUD.

Our examination was formulated within the Anderson Model, which posits HSU is a function of resource allocation rather than medical need. The equitability of resource allocation shapes patterns of HSU, which in turn best predict future patterns of HSU. From these premises, it was predicted that factors associated with limited access, i.e. homelessness & high ED use, would be most prevalent among the highest HSU patients. Furthermore, we predicted these factors would better predict readmission within 30 days than the severity of the patients' presenting needs. In keeping with the recent findings in the literature, rate of ED use was used as a proxy for access and patterns of HSU.

As predicted, higher HSU was found to be best predicted by access, defined as past year ED use, and was linked with the highest rates of homelessness and the greatest proportion of smokers. Also in line with the study hypotheses, these high HSU patients accounted for disproportionate rates of HSU. This group also tended to have the most persistent presenting problems; this group had the highest proportion of past year encounters due to AUDs, while also presenting with AUDs in 76% of all 2017 index admissions by these patients. This suggests a possible “single-cause” driving HSU rather than a myriad of different primary needs.

Also in line with study hypotheses, those with the highest rates of HSU tended to present with the lowest severity of medical need, as measured by the Elixhauser Comorbidity Index. Overall, this group had both the highest proportions of alcohol dependence (15%), but the highest proportion of low risk Elixhauser index scores (90%) compared with other past year ED groups. These patients tended to present with chronic (e.g. hypertension) and psychiatric (e.g. psychosis) comorbid conditions. Patients with low HSU, on the other hand, had a comparatively higher likelihood of presenting with acute medical comorbidities, e.g. liver disease, fluid & electrolyte disorders, and were more likely to be considered high-risk. This suggests that these patients are not exhibiting high HSU due to a severe medical burden or risk for mortality, instead they present with chronic conditions (e.g. dependence without AWD, hypertension) which reduce overall quality of life without necessarily rising to the level of acute need.

Equitability of resource allocation.

According to the Anderson Model, the equitability of healthcare resource allocation can be assessed by examining drivers of HSU. In equitable systems, patients’ rates of HSU are determined by predisposing factors, such as age, and their levels of need. Inequitable allocation of resources is found within systems where HSU is primarily the result of access, often operationalized as patterns of HSU.

This study is the first to test this assumption of the Anderson Model directly. We expected to find evidence in support of inequitable resource allocation, given the socioeconomic burden and limited access often observed in patients with AUDs with high HSU. In line with our hypotheses and previous studies of HSU among general patient populations, a small group of patients accounted for a disproportionate level of encounters; the highest past year ED group comprised just under 200 patients. However, this group of patients accounted for over 5500 encounters across three years (over 25% of all visits by 12,252 patients), with an average of 26 encounters per patient.

Higher HSU was associated with fewer allocated healthcare resources, while greater presenting needs predicted greater allocation of resources for treatment, and thus lower likelihood of readmission. Eighty-six percent of encounters by the 3+ past year ED group occurred in the ED. These patients were less likely to receive treatment for alcohol withdrawal or medication. On average, the 3+ ED group was seen for less time than lower HSU patients (6 hours, on average).

Modeling risk factors for readmission within 30 days identified strong, positive links between access and future HSU. The likelihood of readmission increased exponentially based on the number of past year ED encounters (1.2, 2.6, & 10 times higher odds for patients with 1, 2, or 3+ past year ED visits, respectively). A comparison of models of predisposition & access with models of predisposition & need provided strong evidence for the superior predictive power of a patient's history over a patient's present, i.e. of access over need. An access-based model explained 13% of variance, compared to the 4% of variance explained by a needs-based model. This suggests that levels of access and predisposing risk factors better predict future HSU than any characteristics associated with patients' presenting needs.

While the results of this study demonstrate that HSU among patients with AUDs is in large part a function of limited access to appropriate treatments, there is a counterclaim against drawing the conclusion that resources are inequitably distributed: It could also be argued that these findings illustrate that the hospital appears to be responding appropriately, given the types of AUD patients presenting for treatment. Patients with greater medical burden, e.g. liver disease or fluid & electrolyte disorders, were more likely to receive CIWA, be admitted as inpatients, receive medication, and have longer visits. This is the medically appropriate response and an appropriate allocation of resources. For the highest HSU patients, these interventions may not have been appropriate, given their overall lower illness burden.

There may also be perverse incentives for hospitals to maintain the status quo. The highest past year ED group appeared in the ED for 173 of 197 index admissions in 2017. Using the average cost of an emergency room encounter as a multiplier ($1,389) the total costs to the hospital for these 173 encounters would cost $240,297. As of 2017, the average inpatient admission in the U.S. cost up to $22,543; by this measure the remaining 14% (n=24) inpatient counters would then potentially cost $541,032 to the hospital, or nearly double the cost of all ED encounters. In this view, allocating additional resources to these patients may not be efficient economically.

It is then perhaps reasonable to assume that patients with AUDs suffer equally from lack of available and appropriate treatments in general, as much as they suffer from inequitable allocation of available services. This distinction between access vs. availability vs. appropriateness is exemplified by attempts to expand access, such as the ACA's medicaid expansion, which often do not provide access to mental health or community services, important resources often needed by these patients. Patients with AUDs are inequitably treated within healthcare systems due to a lack of alternatives for

AUD treatments in acute care outside of medical interventions, and because legitimate economic constraints inhibit hospitals' ability to allocate additional resources towards patients' non-medical needs. However, several studies have noted the sharp increase of patients with AUDs, psychiatric & behavioral disorders among the acute care seeking patient population. Given these trends & policies, it seems likely that acute care settings will continue to see increasing numbers of these patients. Therefore, hospitals might begin to consider effective methods of tracking and intervention before the issue becomes unmanageable.

Limitations

Although the results of the study are supported by the methods and findings of previous research, several limitations should be noted.

Generalizability of findings.

One primary limitation of the study is its potential lack of generalizability. In order to model both the impact of past year HSU and other variables of interest (e.g. Homelessness) while also accounting for the non-independence introduced by patients appearing multiple times in the dataset, the subsamples used in the readmission models represented only about 20% of all encounters in the full dataset (n=22,300). Furthermore, the data used in the current study was taken from a single hospital. This likely limits the generalizability of findings. In previous studies on readmission, samples have typically pulled from larger datasets across multiple hospitals/providers/systems (e.g., van Walraven, et al., 2010).

Steps were taken to avoid model overfitting and improve generalizability. First, models for both the 2017 and 2018 datasets were run using a test/train split. This technique is commonly used in classification algorithms to examine how well estimated model parameters perform with new data. The results of the model on the test dataset lend support to the validity of results; metrics such as accuracy and ROC curve analysis are in line with the best performing readmission models in the literature. Furthermore, many of the variables used as predictors (e.g. comorbid psychosis, past year ED use) have been found to be associated with AUDs in previous research.

Although definitive limitations on the generalizability of findings, such as data taken from a single site, care was taken to appropriately tune the classification model to address. This was accounted for splitting the sample into test and training data, then by upsampling in order to account for imbalance between outcome classes, i.e., 30 day readmission vs. not. Furthermore, the replication of findings from the literature lends additional support to the usefulness of these findings.

Overlapping cases.

Related to the issues of over-fitting and generalizability is the potential overlap between the 2017 and 2018 subsamples used in validating readmission models. Although model results replicated across samples, this does not necessarily provide evidence for the generalizability of findings to other populations. This is due to the likelihood that patients appeared in both the 2017 & 2018 test/train datasets. This should not be taken as a refutation of the findings, but a direction in which future research should attempt to replicate using a distinct sample of patients.

Directions for Future Research

The current study both builds from and expands on previous research, yet the issue of relative risk factors for high HSU within patients with alcohol use disorders remains understudied. Based on these findings, the methods outlined in HSU10 and used in the current study appear to be a useful means for identifying patients with AUDs at-risk for high HSU . Furthermore, the current study illustrates how these distinctions can be useful and relevant predictors. Future studies should seek to replicate this methodology using a larger sample, ideally with data taken from multiple sites.

Another point of emphasis to derive from this study is the importance of tracking non-clinical predisposing factors, such as homelessness or smoking status. Homelessness has been shown to be strongly associated with HSU, especially among patients with alcohol-use disorders. Smokers are also considered at higher risk for increased HSU. In the current study, these variables showed strong relations with 30 day readmissions, and significant differences were found on these factors across levels of HSU. However, descriptive analyses identified potential issues with documenting smoking status and homelessness in the EMR. For example, the proportion of patients identified as homeless or a smoker at the time of the index admission was less than half the number of patients identified as such within the past year.

Hospitals use ICD-10 Z-codes to identify social determinants of health, like smoking and homeless, which are then entered into the EMR. However, they are often inconsistently recorded (Truong, Luke, Hammond, Wadhera, Reidhead, & Maddox, 2020). Examining the current dataset indicates that many patients with a smoking and/or homelessness history did not have this documented in the EMR at the time of their encounter. Future research should focus on how this potentially important data can be more reliably tracked and entered.

Finally, the impact of smoking on readmission should be further studied. Previous research has linked smoking with higher HSU, alcohol-use, and importantly, low SES. The current study found smoking status significantly and independently predicted readmission. It is possible this is partially because smoking acted as a proxy for low SES. This cannot be determined from the current data, but may be an important avenue for future research.

CONCLUSION

The current study aimed to provide a rigorous application of the Anderson Model to understanding HSU among patients with AUDs. A dearth of studies focusing on patterns of HSU among these patients warranted further investigation. We extended the methods and findings from the handful of recent studies on AUDs and HSU, along with research using a general patient population.

We proposed that structural changes in healthcare systems over the past century shape patterns of HSU at the patient-level. The structure of this system, along with the prescribed means of allocating healthcare resources within it, appears to be ill-suited to addressing the types of needs often present among AUD patients. This mismatch between available resources, levels of access, and levels of need was believed to underlie the disproportionate rates of AUDs among acute care patients.

The value of the results of our study are tempered by limitations in the generalizability of parameters and the potential redundancy between training and test datasets. However, these findings nevertheless provide strong evidence for the utility of tracking past HSU within AUD patients. The performance of readmission models was significantly better when limiting predictors to predisposition and realized access than models of patient's presenting needs. This is potentially useful for improving tracking of high HSU patients, along with more efficacious referrals to community and mental health services.

Appendices

Table 1: Predisposing Characteristics Across Low, Moderate, and High ED users

	Overall Sample (n=4,766)	Past-Year ED:0 (n=4,132)	Past-Year ED:1 (n=305)	Past-Year ED:2 (n=132)	Past-Year ED:3+ (n=197)	Test Statistics	p values
Age (sd)	44.40 (14.30)	44.08 (14.59)	45.06 (12.28)	45.62 (13.19)	49.26 (10.43)	8.83	0***
Male (%)	3,822 (80)	3,280 (79)	255 (84)	118 (89)	169 (86)	3.786	0.002**
Race							
Asian (%)	330 (7)	255 (6)	27 (9)	21 (16)	27 (14)	1.994	0.264
Black (%)	1,253 (26)	1,097 (27)	74 (24)	37 (28)	45 (23)	1.485	0.531
Latinos (%)	1,289 (27)	1,105 (27)	95 (31)	40 (30)	49 (25)	4.685	0***
West Indian (%)	613 (13)	501 (12)	46 (15)	21 (16)	45 (23)	3.605	0.005**
White (%)	708 (15)	629 (15)	49 (16)	6 (5)	24 (12)	6.344	0***
Primary Language							
English (%)	4,083 (86)	3,517 (85)	267 (88)	120 (91)	179 (91)	3.03	0.027*
Spanish (%)	467 (10)	414 (10)	31 (10)	10 (8)	12 (6)	2.019	0.253
Other (%)	216 (5)	201 (5)	7 (2)	2 (2)	6 (3)	2.892	0.039*
Homelessness							
Homeless History, 2016-2018 (%)	355 (7)	223 (5)	36 (12)	24 (18)	72 (37)	17.253	0***
Past Year Homelessness (2016)	61 (1)	10 (0)	10 (3)	7 (5)	34 (17)	21.445	0***
Homeless at Index Admission	144 (3)	122 (3)	11 (4)	7 (5)	4 (2)	1.852	0.33
Smoking Status							
Smoking History, 2016-2018 (%)	1,530 (32)	1,172 (28)	146 (48)	76 (58)	136 (69)	14.962	0***
Past Year Smoking (2016)	322 (7)	98 (2)	73 (24)	48 (36)	103 (52)	33.179	0***
Smoking Status at Index Admission	1,045 (22)	899 (22)	79 (26)	26 (20)	41 (21)	1.847	0.333

Table 2: Needs-Related Characteristics Across Low, Moderate, and High ED users

	Overall Sample (n=4,766)	Past-Year ED:0 (n=4,132)	Past-Year ED:1 (n=305)	Past-Year ED:2 (n=132)	Past-Year ED:3+ (n=197)	Test Statistics	p values
F10 diagnosis							
no f10 dx (%)	2,231 (47)	2,007 (49)	138 (45)	39 (30)	47 (24)	7.933	0***
ETOH abuse (%)	2,142 (45)	1,807 (44)	138 (45)	78 (59)	119 (60)	5.672	0***
ETOH dependence(%)	341 (7)	271 (7)	26 (9)	14 (11)	30 (15)	4.977	0***
ETOH w/ comp(%)	52 (1)	47 (1)	3 (1)	1 (1)	1 (1)	0.934	0.832
Rate of past year ETOH-related admissions	0.10 (0.28)	0.01 (0.08)	0.66 (0.45)	0.66 (0.34)	0.71 (0.28)	3262	0***
Proportion of primary ETOH dx at Index Adm	2,535 (53)	2,125 (51)	167 (55)	93 (70)	150 (76)	7.933	0***
Primary Psychiatric Diagnosis							
Bipolar (%)	158 (3)	138 (3)	16 (5)	4 (3)	0 (0)	3.219	0.016*
Major Depression (%)	141 (3)	127 (3)	9 (3)	3 (2)	2 (1)	3.216	0.016*
Schizophrenia/Psychosis(%)	158 (3)	140 (3)	10 (3)	3 (2)	5 (3)	1.732	0.392
Mean # of Comorbidities (sd)	1.36 (1.68)	1.40 (1.73)	1.18 (1.32)	1.02 (1.43)	0.92 (1.17)	0.943	0.828
Elixhauser Severity Index							
Low risk: <0	648 (14)	588 (14)	33 (11)	15 (11)	12 (6)	3.663	0.004**
Low risk: 0	3,377 (71)	2,877 (70)	234 (77)	100 (76)	166 (84)	5.176	0***
Moderate risk: 1-4 (%)	202 (4)	172 (4)	16 (5)	6 (5)	8 (4)	0.931	0.833
High risk: >=5 (%)	539 (11)	495 (12)	22 (7)	11 (8)	11 (6)	3.815	0.002**
Comorbidities							
hypertension, uncomplicated (%)	892 (19)	746 (18)	68 (22)	26 (20)	52 (26)	3.537	0.006*
Chronic Pulmonary Disease (%)	254 (5)	219 (5)	16 (5)	7 (5)	12 (6)	0.488	0.971
Liver Disease (%)	182 (4)	172 (4)	6 (2)	4 (3)	0 (0)	3.496	0.007*
Diabetes, uncomplicated (%)	372 (8)	317 (8)	25 (8)	13 (10)	17 (9)	1.058	0.773
Fluid & Electrolytes (%)	404 (8)	376 (9)	18 (6)	8 (6)	2 (1)	4.45	0***
Drug Use (%)	591 (12)	540 (13)	30 (10)	13 (10)	8 (4)	4.117	0.001**
Psychosis (%)	102 (2)	75 (2)	9 (3)	2 (2)	16 (8)	6.078	0***
Bipolar/Depression (%)	207 (4)	185 (4)	11 (4)	4 (3)	7 (4)	1.192	0.701

Table 3: Enabling Factors Across Low, Moderate, and High ED users

	Overall Sample (n=4,766)	Past-Year ED:0 (n=4,132)	Past-Year ED:1 (n=305)	Past-Year ED:2 (n=132)	Past-Year ED:3+ (n=197)	Test Statistics	p values
AUD Treatment							
CIWA administered during Index Admission	319 (6.69\%)	288 (6.97\%)	20 (6.56\%)	6 (4.55\%)	5 (2.54\%)	2.634	0.074
Pharmacological tx given during Index Admission (%)	1,152 (24.17\%)	974 (23.57\%)	92 (30.16\%)	41 (31.06\%)	45 (22.84\%)	3.224	0.016
Site & Duration of Treatment							
LOS mean, Index Admissions (sd)	1.88 (4.86)	1.97 (4.96)	1.52 (3.77)	1.37 (4.20)	0.89 (4.70)	4.29	0.005
Index Admission admitted as Inpatient (%)	1,193 (25.03\%)	1,079 (26.11\%)	59 (19.34\%)	31 (23.48\%)	24 (12.18\%)	5.033	0***
Index Admissions by MAX patients (%)	109 (2.29\%)	92 (2.23\%)	7 (2.30\%)	6 (4.55\%)	4 (2.03\%)	1.772	0.371
Restrained during index admission (%)	267 (5.60\%)	242 (5.86\%)	17 (5.57\%)	5 (3.79\%)	3 (1.52\%)	2.744	0.057
Disposition							
Discharged to home (%)	4,209 (88.31\%)	3,625 (87.73\%)	279 (91.48\%)	124 (93.94\%)	181 (91.88\%)	3.285	0.013
Admit to Psych Fac (%)	119 (2.50\%)	102 (2.47\%)	9 (2.95\%)	0 (0.00\%)	8 (4.06\%)	2.373	0.131
Left Against Medical Advice (%)	108 (2.27\%)	98 (2.37\%)	6 (1.97\%)	3 (2.27\%)	1 (0.51\%)	1.756	0.379
Other Inpatient Transfer (%)	330 (6.92\%)	307 (7.43\%)	11 (3.61\%)	5 (3.79\%)	7 (3.55\%)	3.512	0.006
HSU patterns							
Average Visits, 2016-2018 (sd)	3.11 ± 7.84	1.71 ± 2.06	4.63 ± 4.72	8.54 ± 6.95	26.58 ± 26.83	1121	0***
Total Visits 2016-2018	14824	7049	1412	1127	5236	NA	
Total Hours of Index Admissions	8979	8159	464	181	175	NA	

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