National Policing Institute

Examining the Utility of Sobering Centers: Analyses of Police and Sobering Centers Across Five Jurisdictions

Final Report

April 2023

Nicholas Corsaro, Ph.D.
Ryan Motz, M.S.
Gabrielle T. Isaza, Ph.D.
Jennifer Calnon Cherkauskas, Ph.D.
Robin S. Engel, Ph.D.

National Policing Institute
PURSUING EXCELLENCE THROUGH SCIENCE AND INNOVATION

This research was supported by funding from Arnold Ventures to the University of Cincinnati, with research components and report writing subcontracted to the National Policing Institute. The findings and recommendations presented within this report are from the authors and do not necessarily reflect the official positions or opinions of Arnold Ventures, the National Policing Institute, or the University of Cincinnati. We would like to thank all of the police and sobering center officials across our five partner sites for their assistance and insights throughout the duration of this study. Please direct all correspondence regarding this report to Robin S. Engel, Ph.D., Senior Vice President, National Policing Institute, 2550 S. Clark Street, Suite 1130, Arlington, VA 22202; 202-833-1254; rengel@policinginstitute.org

TABLE OF CONTENTS

EXECUTIVE SUMMARY

This report documents the findings from the second and third phases of a broader research study designed to examine the utility of sobering centers as an alternative to arrest.[1] Despite the decades-long conversation and investment of public funds in sobering centers, few studies examine the effectiveness of these emergency response facilities for individuals suffering from acute alcohol or drug intoxication. Using five jurisdictions as case study sites, we conducted comprehensive examinations of sobering center operations and police use of this arrest alternative in Oklahoma City, OK; Tulsa, OK; Wichita, KS; Austin, TX; and Houston, TX.

The primary purpose of Phase II of the research study was to address the following research questions using sobering center admission data and official police agency records:

1. What are the general trends in sobering center admissions, and what are the characteristics of the clientele?
2. What patterns among the information provided by the sobering centers emerged that delineated one-admission from repeat clients, and what client characteristics are associated with the length and stay and receiving a referral for service?
3. What impact did the sobering center have on official arrests?
4. What types of arrests were reduced the most if diversion to the sobering center was used as an alternative to arrest?
5. Were the potential changes in alternatives to arrest consistent across different demographic groups in different settings?

Across each site, we examined admission and client data from sobering centers and arrest data from police departments. We conducted focus groups with police officers in four of the five jurisdictions. The data structures (e.g., data availability, time frame, and variables collected) for the police and sobering center sources varied by setting. These descriptions are detailed in each site-specific chapter. While we attempted to replicate the same analyses across jurisdictions, this was not always possible.

[1] All three reports for this research study may be found at https://www.policinginstitute.org/publications/.

Five Jurisdictions

Oklahoma City, OK

- Sobering services are provided to Oklahoma City through The Public Inebriate Alternative (PIA), which is defined as a program of the Oklahoma City Police Department (OKCPD), but is managed by OKC Metro Alliance, Inc.
- The PIA opened in 1973, making it one of the longest-operating sobering centers in the US. The PIA requires a mandatory 10-hour hold as the person is technically in protective custody by the peace officer or emergency service patrol.

Tulsa, OK

- Sobering services are provided to the city of Tulsa through the Tulsa Sobering Center (TSC).
- The TSC is located in downtown Tulsa and opened in May 2018; it is modeled after the PIA in Oklahoma City.
- The TSC only accepts clients from the Tulsa Police Department (TPD) and requires a mandatory 10-hour stay.

Wichita, KS

- Sobering services in Wichita are provided by the Sedgewick County Coordinating Crisis Center (CCC), which is co-operated by COMCARE (mental health services provider) and the Substance Abuse Center of Kansas (SACK; substance abuse services provider).
- Within the CCC is a sobering unit, among other crisis service units. CCC staff determine which unit or service is most appropriate given each individual's needs.
- The SACK sobering unit (SACKSU) opened in downtown Wichita in February 2015. Staying in the SACKSU is voluntary, and clients can remain in the unit for up to 23 hours, although the average stay is about 10 hours.
- Unlike other sites, the SACKSU is not typically used agency-wide in Wichita, but is primarily used by the Wichita Police Department Unhoused Outreach Team.

Austin, TX

- The Sobering Center of Austin (SCA) serves as the primary sobering facility in Austin. Opened in September 2018, the SCA was modeled after the Houston (TX) Recovery Center.

- Located downtown, the SCA allows referrals from law enforcement, emergency services, and other referral partners. The stay within the SCA is voluntary; clients can leave whenever they want.

Houston, TX

- The sobering services in Houston are provided by the Houston Recovery Center (HRC), located in the same building in Downtown Houston as the Houston Police Department Mental Health Division.
- The HRC opened in April 2013 and was modeled after the San Antonio (TX) Sobering Center.
- While all client holds are voluntary, the average stay at the HRC is about four to six hours.

Trends in Sobering Center Admissions and Client Characteristics

- Descriptive, bivariate, and multivariate analyses were used to understand better the use of sobering centers and their clientele, who otherwise would have likely been transported to jail if the sobering center was not an option.
- All case study sites operate a sobering center available 24 hours a day, seven days a week. Most clients across all five case study sites were admitted to the sobering center during nighttime hours.
- The impact of COVID-19 varied by site, with admissions in Austin, Houston, and Wichita significantly reduced during parts of the pandemic, while admissions in Tulsa and Oklahoma City remained relatively stable.
- Findings suggest that there are geographic patterns in sobering center admissions. Individuals admitted to the sobering center tended to be detained or picked up at locations relatively close to the sobering center.
- Across sobering center facilities, the clientele was primarily male, White, with an average age between 35 and 43.
- For Oklahoma City and Tulsa, most clients admitted were unhoused, while about one-third in Austin and two-fifths in Houston and Wichita were unhoused.
- In examining the factors which predict repeat admissions, we found the probability of a client being a repeat is greatest when an individual is unhoused, older, male, and admitted for using a single substance.
- In exploring the association between admission characteristics and length of stay, we found that in all sites but Wichita, unhoused clients had a longer average stay at the sobering center than clients who were housed. In Austin and Houston, older clients had a longer stay, on average, than younger clients. In all sites but Houston, the average stay in the sobering center was longer for clients admitted during the day.

- The factors that predict whether a client receives treatment or referral for service upon discharge included clients who were older, admitted during the daytime, and admitted during the weekend. Clients in Tulsa and Wichita were more likely to receive referrals or treatment if admitted in winter than in the summer.
- While client race and ethnicity were sometimes associated with sobering center outcomes within a site, no consistent pattern across sites was observed.
- Generally speaking, the findings from the sobering center analyses underscore the importance of housing status driving the likelihood of being a repeat client, the number of sobering center admissions, the amount of time to re-admission, and the length of stay at sobering centers. This finding is made even more critical when considering the large proportion of sobering center clients that were unhoused across the five sites.
- These results demonstrate sobering centers play an important role in diverting unhoused members of the public away from the criminal justice system for minor offenses.
- Based on our estimates, these five sobering center sites combine to save approximately 3,894 days spent in jail per year if sobering center admissions are actual diversions from jail.

Officer Decision-Making and the Impact of Sobering Centers on Police Arrest Rates

- We examined arrest data from each police agency within our case study sites, with timeframes ranging from a minimum of six years in Houston to a maximum of 23 years in Oklahoma City.
- Descriptive, bivariate, and multivariate analyses assessed how the availability of a sobering center impacted arrests, although specific analyses within each site varied based on available data.
- We also conducted focus groups with officers in four of the five case study sites to understand their experiences with using the sobering center as an alternative to arrest for publicly intoxicated individuals.
- We found that all five police departments guide officer decision-making regarding diversion to sobering centers for a public intoxication arrest through departmental policy. This was alsosupported during focus groups with officers.
- To understand why individuals contacted for public intoxication are still taken into police custody and arrested, we examined supplemental Tulsa Police Department records documenting these reasons.
    - These data show that the most cited reason was for aggressive or violent behavior.

    - This is consistent with the findings from the focus groups, where officers indicated that if an inebriated individual is violent or belligerent, they will be taken to jail.
- We examined the direct impact of sobering center openings (pre/post analysis) in Tulsa, Wichita, and Austin. Overall, the bivariate and multivariate time series analyses indicated a pattern of findings supporting the hypothesis that opening a sobering center would significantlyreduce specific arrests. There was, however, some variation across sites.
- In Tulsa and Austin, public intoxication arrests declined by 20% and 24%, respectively, above and beyond any changes in total arrests and net of time-varying controls.
- By contrast, once other factors were controlled in Wichita, overall arrests did not change at the time of the sobering center opening, nor did arrests for public intoxication. We attribute this to several unique factors of the WPD-SACKSU relationship, including that WPD's use of the SACKSU is primarily limited to specialized unhoused outreach team officers rather than patrol officers.
- While our case study analyses showed that sobering centers have the potential to reduce arrests related to public intoxication, the establishment of a sobering center will not eliminate arrests for public intoxication violations. Indeed, across the five case study sites, the percentage of arrests for intoxicate-related charges varied between 15% to 30%, with most sites ranging between 20% to 25% post-implementation of a sobering center.
- Given that the time series analyses indicated statistically significant declines in specific intoxication-related arrests, we also examined whether these changes varied by arrestee race/ethnicity. In the two sites where this analysis was possible, Tulsa and Austin, we found that public intoxication arrests significantly declined for all racial and ethnic groups.
- In Houston, we examined the beat-level comparisons of where arrests versus sobering center intakes occurred. These structural analyses indicated that neighborhood disadvantage measures were heavily associated with crime and arrests but not necessarily public intoxication diversions for all racial groups. For instance, the same predictors of arrests for Blacks and Whites predict sobering center intakes for Hispanics (but do not predict sobering center intakes for Blacks and Whites). This suggests that contextual conditions that correspond to intake variation by race might exist.

Feasibility Assessment

- Our analysis of data collection efforts across sobering center sites found considerable variability in the type and quality of data collected.
- Phase III of our study included a feasibility assessment to provide recommendations on how to define and collect uniform, consistent measures that will assist in comparing sobering centers across jurisdictions and enhance future research.
- This information can be used to assist sobering centers in measuring trends in admissions, client characteristics and needs, as well as promote more rigorous examinations of the factors that predict repeat clients and the circumstances under which clients are most likely to accept referral services.

Study Limitations

Although this study provides critical insights, the limitations of this research must be acknowledged.

- The five case study jurisdictions that serve as the focus of this report may not accurately represent all cities and counties with sobering centers, thereby potentially reducing the generalizability of these findings.
- Due to data limitations, we could not address an original research question: whether diverting individuals to sobering centers instead of arrest alters their relative risk of recidivism or future contact with police. Data available to our team did not include any specific identifiers (i.e., name of the person arrested), nor did any sobering center provide us any unique identifying information based on privacy protection requirements. Future research would need matched identifiers across the data sources to measure individual-level trajectories.
- The ability to compare outcomes across the case study sites was limited by the variation in data availability, definitions, and quality sent to our research team, particularly for sobering center data. While there was more consistency across police departments, some did not include all requested variables.

Study Conclusions

Our research team traveled to each site – Oklahoma City, OK; Tulsa, OK; Wichita, KS; Austin, TX; and Houston, TX – to gain first-hand insight into sobering center operations and partnerships across the US. We found similarities and differences across the sites, filling crucial gaps in knowledge. This study builds on previous literature that has almost exclusively focused on sobering centers' operations by incorporating the police perspective through analyses of official police data and focus groups with officers who divert publicly intoxicated individuals to sobering centers. Analyses of sobering center data underscore the importance of dealing with housing status, highlighting how sobering centers play an important role in diverting unhoused members of the public away from the criminal justice system for minor offenses and placing them in facilities where they can be connected to recovery and social services.

Across all sites, officers voiced positive perceptions of the utility and benefits of sobering centers as an arrest alternative to save officer time. They also agreed that it is the best option for most individuals because it provides protective care, the opportunity for additional resources and treatment, and avoids the costs and consequences of being arrested.

Analyses of police arrest data across sites also demonstrated the positive impact of sobering centers on public intoxication arrests. It should be noted, however, that diverting individuals from jails and placing them in a sobering center does not necessarily reduce overall costs. Instead, sobering centers simply shift the costs and resources from one entity (jails) to another (sobering centers). However, sobering centers are likely better situated to alleviate the recurring problems of persons with substance abuse issues and connect this clientele to additional resources and treatment options.

Our third and final report in this series, *Examining the Utility of Sobering Centers: Project Summary and Recommendations for the Future,* includes a summary of each phase of this research project. In this summary, we also lay out recommendations for police agencies, sobering centers, policymakers, and researchers based on knowledge gained throughout this study.

CHAPTER 1: INTRODUCTION

As part of a national movement to reduce the use of arrest for vulnerable populations, some police departments divert inebriated individuals into sobering centers rather than handling these minor offenses through the criminal justice system. Yet, despite the decades-long conversation and investment of public funds in sobering centers, little systematic knowledge exists about the use and effectiveness of these emergency response facilities for individuals suffering from acute alcohol or drug intoxication. To date, only a handful of studies have examined the impact of sobering centers on criminal justice system outcome measures, such as arrests, jail admissions, and incarceration rates, and these studies typically focus on a single site (Jarvis et al., 2019; Turner, 2015).

In this report, we refer to "sobering centers" as those facilities that provide short-term recovery, detoxification, and recuperation from the effects of acute alcohol or drug intoxication, providing an alternative to jail (for public intoxication arrest) or emergency departments. In some jurisdictions, these facilities may be referred to as detoxification centers or public inebriate alternatives. In the US, sobering centers were introduced in the 1960s as law enforcement executives recognized the sheer volume of arrests for public intoxication – nearly 40% of all arrests reported to the FBI Uniform Crime Reports in the 1960s – diverted officers' time away from more serious crimes, and placed individuals in overcrowded jails (Nimmer, 1970; Thacher, 2018; President's Commission on Law Enforcement and Administration of Justice, 1967). Additionally, the negative impacts of alcohol and the handling of intoxicated persons are demonstrated in overburdening both the healthcare system (Cornwall et al., 2012; Flower et al., 2011) and the criminal justice system, where there were still nearly 250,000 arrests made for public drunkenness in the United States in 2019 (FBI, 2021). Sobering centers present a unique opportunity to reduce the use of arrest for more beneficial alternatives for publicly inebriated persons.

To build the evidence base on the efficacy of sobering centers, Arnold Ventures funded our three-phase research study assessing the utility of these facilities as an alternative to arrest. This research employs multi-site, multi-methodological approaches to understand the current state of sobering center practices. It also fields difficult and unanswered questions regarding officer discretion as it relates to the decision to use sobering centers, identifies barriers in practice and policy, highlights strategies to overcome such obstacles, and assesses the utility of sobering centers to ultimately reduce re-contact with the criminal justice system.

This three-phase research study was launched in January 2020. In this research, we examine four primary research questions:

1. *What are the patterns of policies and practices for police use of sobering centers as an alternative to arrest? What guides this decision-making?*
2. *What are the situational factors police use in practice to determine whether or not to use sobering centers as an alternative to arrest?*
3. *How do police balance and overcome policy and legal inconsistencies guiding the transport to and use of sobering centers?*
4. *When individuals are sent to sobering centers in lieu of arrest, does it alter their relative risk of recidivism or future contact with police?*

Phase I included a scan of the field to identify operational sobering centers and used interviews and surveys to understand patterns of policies and practices for police and sobering centers across the United States. Phase I addressed research questions 1 and 3 from the list above. The results of Phase I are discussed in the *Examining the Utility of Sobering Centers: National Survey of Police Departments and Sobering Centers Final Report.*[2]

Phase II includes site-specific analyses of five case study jurisdictions—Oklahoma City, OK; Tulsa, OK; Wichita, KS; Austin, TX; and Houston, TX—based on police and sobering center data as well as qualitative data in each site. The goal of Phase II is to assess the direct impacts of sobering centers on criminal justice and sobering center outcomes. Finally, Phase III includes a feasibility assessment to promote the further use of sobering centers and enhance research on the effectiveness of sobering centers. Phase II and Phase III are the focus of this report. A third and final summary ties together the entirety of this research project and highlight directions for research and policymakers, the *Examining the Utility of Sobering Centers: Project Summary and Recommendations for the Future*.[3]

This report discusses the research findings of the five distinct case studies, assessing the impact of sobering centers within these jurisdictions. We quantify their impact on police use of arrest, including examining trends across arrests for different intoxication-related charges and civilian demographics. Relying on sobering center data, we investigate patterns of sobering center admissions, including bivariate and multivariate analyses of several outcome measures. We employ focus groups in jurisdictions to understand officer decision-making regarding diversion to sobering centers; assess perceptions of supervisory, command, and peer support of sobering centers; and gauge officer views on the benefits and obstacles of using sobering centers. Collectively, these findings shed light on the distinct impact of sobering centers on intoxication-related arrests within these five

[2] Available at https://www.policinginstitute.org/publications/.

[3] Available at https://www.policinginstitute.org/publications/.

cities. This is the first study to compare these effects across jurisdictions and the first to contextualize officer decision-making in diverting intoxicated persons.

This report is organized in nine chapters. Following the introduction, Chapter 2 details the methodology and data sources used in this research study, including additional research questions tailored to the outcomes measured in Phase II. Each site-specific chapter (Chapters 3-7) introduces the jurisdiction, the police department, and details the sobering center's general operations. Analyses of sobering center data are presented next, followed by the results of police data analyses and focus group discussions with sworn police officers. Chapter 8 provides the findings and recommendations from the feasibility assessment. Finally, Chapter 9 of this report compares and contrasts the study results across the five case study sites regarding the impact of sobering centers on police arrest behavior, officer decision making regarding this alternative to arrest, and the trends in sobering center admissions.

CHAPTER 2: RESEARCH METHODOLOGY AND ANALYTICAL TECHNIQUES

This report provides findings from Phase II and Phase III of our research project examining the utility of sobering centers as an alternative to arrest. The data from this study were culled from three primary sources 1) sobering center records, 2) official police records, and 3) focus group interviews with police personnel.[4]

The data structures (e.g., data availability, time frame, and variables collected) for the police and sobering center sources varied by setting. These descriptions are detailed explicitly in each site-specific chapter where measures were distinct.[5] The data from the sites were digitally transferred to secure data portals from the agency (i.e., police departments or sobering centers) to the University of Cincinnati research team following Institutional Review Board-approved protocols. The data were cleaned (e.g., removal of duplicate records) and verified to ensure the highest possible data quality. The arrest data did not contain any specific identifiers (i.e., name of the person arrested), nor did the sobering center data collect unique identifying information (i.e., the name of the clients to be consistent with sobering center concerns regarding Health Insurance Portability and Accountability (or HIPPA) requirements for treatment). Some sobering center databases include a unique identifier that ties an admission to a specific individual. When available, these identifiers were used to link cases (e.g., the same person admitted to the sobering center on more than one occasion) for specific analyses.

The primary purpose of these data and analyses were to address the following research questions:

1. *What are the general trends in sobering center admissions and what are the characteristics of the clientele?*

[4] For data that included address or police beat information, we also (where applicable, e.g., Houston) included census and criminal offense measures, culled to the same geographic units of analysis.

[5] For example, the official arrest data in Austin ranged from 1/2010 to 6/2022. Comparatively, the Tulsa official arrest data ranged from 1/2009 to 12/2021. The fluctuations depended upon a variety of factors including changes to data systems and turnover among records management personnel. The same variations occurred in each of the sobering centers, where some measures were collected 'as time progressed' and thus not all measures are available for all time periods in each setting. These nuances are described in greater detail in each site-specific chapter.

2. *What patterns among the information provided by the sobering centers emerged that delineated one-admission from repeat clients, and what client characteristics are associated with the length and stay and receiving a referral for service?*
3. *What impact did the sobering center have on official arrests?*
4. *What types of arrests were reduced the most if diversion to the sobering center was used as an alternative to arrest?*
5. *Were the potential changes in alternatives to arrest consistent across different demographic groups in different settings?*

Accordingly, each data source and analytical technique was selected to address these questions, which are described in further detail below.

Source 1: Sobering Center Data

Official data from each of the five sobering centers were gathered to inform the analysis of sobering center trends. We collected all available data for each sobering center between February 2021 and February 2022. The exact date of data transfer varies by site, which impacts the data end date for all variables. This data typically included intake, processing, demographics, and release information. These data were used to provide insights to our fourth research question (RQ#4): What patterns among the information provided by the sobering centers emerged that delineated individuals involved in single-intakes versus multiple-intakes?

Description of Data Sources

Sobering centers obtained information on the individual client who received services (the vast majority of whom were individuals who received treatment in lieu of arrest). All sites collected personal demographic information for each client (i.e., sex/gender, race/ethnicity, age/birthdate) and housing status at the time of admission. The majority of sites also measured the blood alcohol level of individual clients as well as the suspected substance they were suspected to be under the influence at admission. Finally, some sites provided our research team with blinded (e.g., numeric) identifiers (which could be used to link the same individual in the event they were admitted more than once to identify single versus multiple admission clients.

Beyond standard demographic measures, several sites collected information on prior medical, arrest, and discharge history, as well as the different types of housing and services the client agreed to participate in post-release. A comprehensive comparative list of measures across sites is shown in Table 2.1 below.

Table 2.1. Sobering Center Data Outline by Site

	Ok City	**Tulsa**	**Wichita**	**Austin**	**Houston**
Time Frame	1/19-10/21	5/18-10/21	2/15-2/21	10/18-9/21	4/13-3/21
Unique Identifier	No	Yes	Yes	Yes	Yes
Demographics					
Age	Yes	Yes	Yes	Yes	Yes
Gender	Yes	Yes	No	Yes	Yes
Race/Ethnicity	Yes	Yes	Yes	Yes	Yes
Social Indicators					
Unhoused	Yes	Yes	Yes	Yes	Yes
Military Veteran	No	Yes	No	Yes	Yes
Student	No	No	No	Yes	No
Currently Employed	No	No	No	No	Yes
Income Status	No	No	No	Yes	Yes
Health Insurance	No	No	Yes	Yes	Yes
Mental Health	No	No	No	Yes	Yes
Intoxicant					
Substance	No	Yes	Yes	Yes	Yes
Multiple Substances	No	No	Yes	Yes	Yes
BAC	Yes	Yes	No	Yes	Yes
Transportation Info					
Unit and Officer	Yes	Yes	No	Yes	No
Beat/Division	No	Yes	No	Yes	Yes
Location	Yes	Yes	No	No	No
Discharge Info					
Discharge Date	No	Yes	Yes	Yes	Yes
Discharge Transport	No	Yes	No	Yes	Yes
Discharge Plan	No	Yes	Yes	Yes	Yes
History					
Info on Non-Admit	No	No	No	Yes	Yes
House/Family Info	No	No	No	Yes	No
Previous Treatment	No	No	No	Yes	Yes
Addiction Tests	No	No	No	Yes	No
Follow-Up	No	No	Yes	Yes	No
Arrest History	No	No	No	No	Yes
Trauma History	No	No	No	No	Yes
Treatment Ready	No	No	No	No	Yes
Education History	No	No	No	No	Yes
Safe Housing	No	No	No	No	No

Analytic Techniques

In terms of analyses, the statistical methods used to assess the information obtained by the sobering centers in this report include basic descriptive statistics, bivariate analyses, and multivariate analyses.

Descriptive statistics (e.g., frequencies, percentages, means) are used to summarize the sobering center data for the population of clients who received services. Bivariate analyses assess the relationship between two variables but do not consider any other factors that might influence the relationship. Bivariate analyses only take into consideration the effect of a single predictor on the outcome of interest. As a point of origin, they provide a reasonable baseline estimation of a single measure. These bivariate approaches—corresponding to the levels of measurement of the variables of interest—include: (1) the chi-square test for independence for categorical comparisons (to assess whether bivariate correlations between non-linear measures have significantly different values than expected), (2) the independent *t* test (an inferential statistic used to determine if there is a statistically significant difference between the means of two variables) to compare means (e.g., BAC levels) of two groups, (3) the one-way analysis of variance (ANOVA) to compare means (an inferential statistic used to determine if there is a statistically significant difference between the means of three or more variables) among three or more groups, and (4) the product-moment correlation coefficient (an inferential statistic where the value ranges between -1 and 1 tells you the strength and direction of a relationship between metric variables) to measure the association between two continuous variables.

Conversely, multivariate analyses are capable of simultaneously assessing the effects of several predictor variables while taking into consideration the effects of those additional predictors. Multivariate statistical models include multiple independent variables (i.e., covariates) and simultaneously measure the individual and independent impact on the outcome for all variables. Importantly, in a multivariate framework, the associations between specific covariates can be observed while holding constant the influence of all other covariate variables on the outcome of interest. The ability to simultaneously adjust for the influence of all predictor variables on the outcome is what makes multivariate analysis a stronger analytical strategy than bivariate analysis.

The appropriate statistical modeling technique for a multivariate regression analysis depends on the different types of measurement (i.e., categories or numbers) of the outcome variable(s). The subsequent analyses include outcomes that are continuous (e.g., length of stay in the sobering center), dichotomous (e.g., whether the client was a repeat visitor or not), and time-based measurement (e.g., the number of days until repeat admission). Based on these different regression analyses, we rely on a variety of multivariate techniques to assess the association between the covariates of interest and the various outcomes at the individual level.

When examining the association of continuously measured outcomes, ordinary least squares (OLS) regression is the statistical technique that was used (Fox, 2019). OLS regression is a statistical analysis that estimates the relationship between one or more independent variables and a dependent variable that is continuously and normally distributed. The method estimates the relationship by minimizing the sum of the squares in the difference between the observed and predicted values of the dependent variable.

Binary logistic regression is the statistical technique used to examine the association of covariates on dichotomously measured outcomes (Long and Freese, 2014). Logistic regression is a natural extension of the OLS model. Where the dependent variable is dichotomous or binary in nature, we cannot use simple linear regression due to the violation of the assumption that the residuals in the model are constant (which cannot happen on a two-category outcome). Logistic regression is the statistical technique used to predict the relationship between predictors (our independent variables) and a predicted variable (the dependent variable) where the dependent variable is binary in nature.

Cox proportional hazard methods are a type of survival analysis that include methods that can also be extended to simultaneously assess several risk factors. Survival methods are similar to multiple linear and multiple logistic regression analyses (i.e., include multiple predictors on the outcome of interest). In a Cox proportional hazards regression model, the measure of effect is the hazard rate, which is the risk of failure (i.e., the risk or probability of suffering the event of interest) given that the participant has survived up to a specific time. In short, the estimation method is used to predict 'time until failure' (e.g., time until readmission into a sobering center or time until re-arrest).

Regardless of the multivariate technique used, the control variables included in each regression were site contingent (depending on whether the measures were collected or not) and holding constant the demographic characteristics of the clients (which were measured and made available to the research team across all sites). Each regression output and its corresponding results are described within the site-specific chapter(s).

Source 2: Police Data

Our research team gathered official police agency data from all five police agencies participating in this study between September 2021 and September 2022. The exact date of data transfer varies by site, which impacts the data end date for all measures included in the various analyses. The data requested from each agency usually included arrests, charges, suspect/arrestee demographics, and patrol shapefiles.[6]

---

[6] We also requested and received additional information from sites such as calls for service, citations, and criminal offenses. We did not include them in the assessment of the impact for the sobering centers for

Description of Data Sources

The primary police data used was police arrests, charges of interest (among arrests), and arrestee demographics (where available). As noted previously, additional measures were available in specific sites, Table 2.2 below highlights the measures analyzed in this report to address the outlined research questions.

Table 2.2. Police Data Outline Available by Site

	OK City	**Tulsa**	**Wichita**	**Austin**	**Houston**
Arrest Data	Yes	Yes	Yes	Yes	Yes
Time Frame	1/00–6/22	1/09-12/21	1/10-7/21	1/10 – 6/22	1/16-6/21
Pre/Post	No	Yes	Yes	Yes	No
Multiple Charges	Yes	Yes	Yes	Yes	Yes
Suspect Demographics	No	Yes	No	Yes	Yes
Criminal Offenses	No	No	No	No	Yes
Calls for Service	No	No	No	No	Yes

For three of the five sobering center locations included in this study, the arrest data provided by the city police department preceded the opening of the affiliated sobering centers, which allowed for a pre/post-arrest (and charges within arrests) analysis in these locations. In one setting, Houston, the sobering center opened relatively recently (April 2013), but the Houston Police Department had since experienced a records management change that did not allow for a pre/post analysis.[7] Finally, in Oklahoma City, the sobering center has existed for nearly 50 years (opening in 1973), making a pre/post analysis impossible. However, official police data analyses on Houston and Oklahoma City provide crucial contextual information beyond what was found in the interrupted time series analyses conducted in the other three sites.

Given that sobering centers are designed to provide a safe recovery location as an alternative to arrest for individuals who are: 1) publicly intoxicated (on alcohol or known drugs) and 2) non-violent and not in the commission of another crime during the event,

---

several reasons. First, calls for service include no identifying information. Second, citations included substances retrieved from the stops; however, for public intoxication, these would be more consistent with a DUI or possession charge. Third, we analyzed monthly criminal offense data for possession, DUI, and/or public intoxication. The results were virtually identical to the arrest analyses. This is due to the fact that for some criminal offenses (e.g., robbery, assault, or burglary) a civilian reports an offense to police whether or not an arrest occurs. However, for possession and intoxication offenses, are only likely to be recorded if the police make an arrest for the offense. Thus, the arrest/offense overlap is highly dependent on the arrest (unlike, for example, burglary where a person can report the theft and no arrest is made).

[7] It is important to note that for the Houston site, we were able to examine where HPD officers transported individuals into sobering centers from the HPD police beats. This data source was unique to the Houston sobering center, which allowed for a structural analysis of the locations of sobering center diversions.

only certain types of arrests are likely to be directly impacted by their usage. Specifically, for each site, we focused on arrest patterns across four general arrest types related to intoxication: (1) public intoxication, (2) possession of drugs, (3) driving while under the influence,[8] and (4) disorderly conduct. These arrest charges are not mutually exclusive; thus, for each outcome, the analysis was charge-specific.[9] The arrest count is person-event specific and not charge specific (e.g., a person arrested for disorderly conduct, public intoxication, and driving under the influence has three charges but only a single custodial arrest, which in these data would equate to a single arrest event).

Analytic Techniques

The primary analytic techniques used in the police data analyses were (1) bi-variate trend analyses; (2) time series analyses, and (3) count regression analyses. These techniques were used to provide insights into our first three research questions.

Bivariate trend analyses were used to assess general pre/post shifts. While the bivariate trends alone do not provide accurate insight into the potential impact of the sobering center on specific arrest types, they do provide a general perspective of broader shifts and trends as a point of onset in the analysis. However, more context is needed because bivariate (simple pre/post changes) trends are limited in that they do not account for trends, drifts, and/or stationarity in the time-varying count of events. Additionally, the impact of the global COVID-19 pandemic (and its associated 'lockdown' on businesses) that occurred post-April 2020 could potentially overestimate changes in arrest patterns when examining simple pre/post analyses.

The time-series analyses relied upon Generalized Linear Modeling count regression methods (Long, 1997) to estimate the site-specific impact of criminal incident counts. Traditional linear (least squares) regression models are inappropriate for analyzing count outcomes because count data do not follow or approximate a normal distribution, and thus analysis from these models would lead to biased and inconsistent estimates (King, 1988). Each outcome examined across the different locales was estimated using a log-

---

[8] We never anticipated that DUI arrests would be directly influenced by the opening of a sobering center. However, we included them in the analyses for two reasons. First, they are a proxy of substance usage per month (substance + operating a vehicle). Second, by impacting intoxication arrests with an alternative to arrest (i.e., treatment) we believed it was important to examine the potential indirect influence on DUI arrests (i.e., a potential reduction in arrests by reducing inebriation or drug usage through treatment) that could have happened via the opening/usage of sobering centers.

[9] For example, if a person was arrested for public intoxication only, the 'event' would only appear in the public intoxication trend analyses. However, if a person was arrested and charged with public intoxication as well as possession of a controlled substance, the event would appear in both the public intoxication trends as well as the possession trends. The alternative would be to conduct analyses on the 'highest level' charges, but this selection would limit our ability to determine the impact of the sobering center on specific arrest charges. Thus, we examine charge-specific arrests for this study.

linear Poisson distribution. The only exception was for analyses where the sample variance was significantly greater than the sample mean (i.e., an overdispersed distribution). In this case, negative binomial regression was used, given its additional parameter to account for the variance distribution independent from the mean (Long, 1997; Long and Freese, 2006).[10]

For each count regression analysis, we included seasonal (i.e., monthly dummy variables) shifts in the time series to control for seasonal fluctuations. We also included a control variable for the COVID-19 pandemic (April 2020 onward) to estimate the effects of the pandemic shutdown. We also included, where applicable, linear trend estimates to control for underlying drifts in the time series. These control variables allowed us to better estimate the unique impact on arrests that corresponded with the opening of the sobering center in each location.

Source 3: Focus Group Interviews with Law Enforcement Officials

Members of the research team conducted focus groups at four of the five sites in August 2022. In general, the specific details for the focus groups, such as the number and type of participants in each setting, are described in the site-specific chapters. However, more broadly, focus groups have several noteworthy benefits that center on interviewed individuals providing subjective thoughts and experiences about participating in the phenomenon under inquiry (Merton and Kendall, 1949).

Additionally, focus groups unravel in-depth data about an organization's culture and worldviews (see Lee, 1999). The police cultural perspective of sobering centers and diversion alternatives is particularly salient given that the vast number of sobering center intakes occurred as a result of a citizen-generated call for police services to respond to individuals who were under some form of intoxication. The focus group interviews are viewed as data triangulation to the official data sources described previously.

The fifth site, Wichita, did not include focus groups because the sobering center is not typically used agency-wide. Rather, our research team engaged in a one-on-one interview with a WPD officer who frequently collaborated with the sobering unit in Wichita. We also met with the director of the detox center in Wichita to understand how the various treatment providers (sobering centers, detox, and multiple outreach centers) were coordinated and how they worked to establish optimal treatment plans.

[10] We examined the goodness-of-fit statistics for each full regression and chose, where appropriate, negative binomial regression models in place of Poisson models when the Chi-Square p-value statistics were statistically significant ($p < .05$), which indicates statistically significant evidence of overdispersion (Long and Freese, 2006).

Focus Group Process and Instrument

Each conversation began with a short statement from the lead researcher about the purpose of the focus group, the scope of the conversation, and the officers' guarantees of anonymity. Approximately nine open-ended questions were used to guide the conversation. The development of these questions was informed by quantitative findings of sobering center and police data analyses as well as by knowledge gaps and follow-up questions based on findings from the National Survey[11] during the first phase of this research study. The questions used to guide the conversation are listed below.

1. What are the benefits of using the sobering center in your city?
2. What do you view as any challenges or obstacles to using the sobering center?
    a. Is this an issue due to your agency's policies or the policies of the sobering center?
3. Can you describe any negative experiences you or a fellow officer have faced when using the sobering center?
    a. Is this an issue due to your agency's policies or the policies of the sobering center?
4. What might prompt your decision to pick up an inebriated person and take them to a sobering center rather than arrest? Any situational factors?
5. What might prompt your decision to pick up a chronic intoxicant (i.e., an individual you know has frequented the sobering center) on a particular day? What are some of the situational factors?
6. Can you describe some of the supervisory expectations for using sobering centers? Do you think your supervisor pays attention to when you use or do not use the sobering center for a non-violent intoxicated citizen? In your experience, has this varied by supervisor?
7. Does this match any expectations from command staff regarding using sobering centers?
8. How does where the intoxicated citizen is located impact your decision on whether to take them to a sobering center or to jail?
    a. Follow up: Are there any other areas with a high concentration of inebriated individuals? If so, are they less likely to be dropped off at the sobering center because it is less convenient?
9. If you had to provide any advice to a police officer who has never dropped off at a sobering center, what would you tell him or her?
    a. Follow up: If you could provide advice to cities that are considering implementing sobering centers, what would you suggest?

---

[11] This report can be found at https://www.policinginstitute.org/publication/examining-the-utility-of-sobering-centers-national-survey-of-police-departments-and-sobering-centers/

During each focus group, notes were taken by the research team. These notes were used to guide the content analyses from each focus group. No recordings or transcriptions were taken during the conversations to encourage candor. The conversation goals are to understand officer decision-making in using sobering centers in lieu of arrest and the barriers and benefits of this alternative to arrest strategy. A similar methodology was employed by Hanafi et al. (2008), which helped unravel police empathy, patience, and stereotyping/stigmatizing for crisis intervention teams.

CHAPTER 3: OKLAHOMA CITY, OKLAHOMA

Oklahoma City is the capital and largest city in the State of Oklahoma, with a population of 687,725 residents in 2021 (US Census, 2022). Located in the West South Central sub-region of the South, Oklahoma City is the 20th largest city in the US. The population has the largest majority of White residents (49.5%), followed by Hispanic (21.3%), Black (13.8%), Mixed (7.6%), Asian (4.6%), and Native American (3.4%). The median income for a household in the city is $56,456.

Policing services are provided to Oklahoma City by the Oklahoma City Police Department (OKCPD). The OKCPD is comprised of 1,169 sworn officers and 300 civilian employees. The OKCPD has over 2,500 police reporting districts, and covers calls for almost 700 square miles. In addition to the Patrol Bureau, the OKCPD includes an Investigations Bureau, a Bike Patrol Unit, an Airport Police Unit, a Helicopter Unit, a Motorcycle Unit, a Canine Unit, and a Lake Patrol Section. Additionally, the department operates the City's Emergency Management and 9-1-1 program. According to the 2016 LEMAS data, the OKCPD has an annual operating budget of $186,695,241, receives about 1,512,000 calls each year, and dispatches officers to about 868,000 of those calls.

An intoxicated person in a public place, as defined in Section 8 of Title 37 of the Oklahoma Mental Health Law (Title 43A O.S. § 1-110) , can be taken into protective custody/detention by peace officers for transport. Per Oklahoma State Statute, transporting intoxicated persons to their homes or an alternative approved treatment facility is preferred to proceeding with an arrest under the statutory or municipal requirements of prosecution and imprisonment for handling intoxicated persons. Thus, OKCPD policy requires that police use the sobering center upon the voluntary approval of the intoxicated person and the sobering center in Oklahoma City. Additionally, there is a mandatory 10-hour hold as the person is technically in protective custody by the peace officer or emergency service patrol. However, the state statute also indicates that no record shall be made, meaning the person has not been arrested or charged with a crime.

The Public Inebriate Alternative (PIA) is a program of the OKCPD, managed by OKC Metro Alliance, Inc., and serves as the sobering facility in Oklahoma City. The PIA provides an alternative to jail and court systems for adults detained for public intoxication. Notably, the PIA reports that approximately $37,730 of taxpayer money is saved each month, estimating the costs avoided for jail, court services, and officer time (OKC Metro Alliance, n.d.). The PIA accepts referrals from various law enforcement and emergency service organizations but does not allow self-referrals (walk-ins). The PIA is usually operated by one full-time staff member with a director on-call, and is open around-the-clock.

The PIA's standard capacity is 30 males and 15 females, with an additional isolation room for each gender. Dorm rooms are locked at all times and controlled by the staff at the observation desk. Once a client enters the facility, the intake procedure includes a breathalyzer (limit of 0.350) conducted on-site by non-medical staff. Officers search individuals in the presence of the staff, and personal items are removed and inventoried. Staff document a handful of details regarding the individual, such as name, date of birth, location of detention, and arresting officer's name and unit number. Once admitted to the PIA, clients must stay for ten hours before being released. While in the sobering center, clients receive meals, access to showers, and a safe place to sleep. Services provided to clients upon release from the sobering center include referral to alcohol/substance use programs or mental health treatment, transportation via cab within a three-mile radius, and the provision of clothing, shoes, and food baskets.

Analyses of Oklahoma City Sobering Center

This report section relies on data collected by the Public Inebriate Alternative ("PIA") in Oklahoma City. The primary unit of analysis is an individual admitted to the sobering center, referred to as a "client." In operation since 1973, the PIA only recently began collecting information electronically. Previous paper files are not available in digital format and, unfortunately, are unavailable for analysis. The analyses in this report are based on data collected from January 1, 2019, through October 31, 2021. Data collection efforts by the PIA are limited compared to other case study sites. The available data sent by the PIA includes date and time of admission, client demographic characteristics (i.e., race/ethnicity, gender, age), BAC, whether the individual was transferred from a hospital, client address, and the last name and unit number of the transporting officer. Table 1 included in Appendix A presents a detailed description of all PIA variables used in the following analyses, including the variable definition, date range of availability, and how the variable was coded and used in analyses.

Missing from this data collection protocol is a unique identifier for repeat individuals. As such, our ability to perform analyses related to one-admission clients versus repeat clients and the timing between admissions was not possible. Furthermore, PIA does not currently collect information on the duration of stay or information regarding what, if anything, the client did upon discharge (e.g., go to treatment, receive a treatment referral, or go to detox). Due to these limitations, the analyses presented herein are focused on the exploration of just two research questions:

1. *What are the trends in PIA admissions?*
2. *What are the characteristics of the PIA clientele?*

Descriptive and bivariate analyses are used to glean a clearer understanding of the use of the PIA and its clientele, who would otherwise be transported to jail if the PIA was not an available alternative.

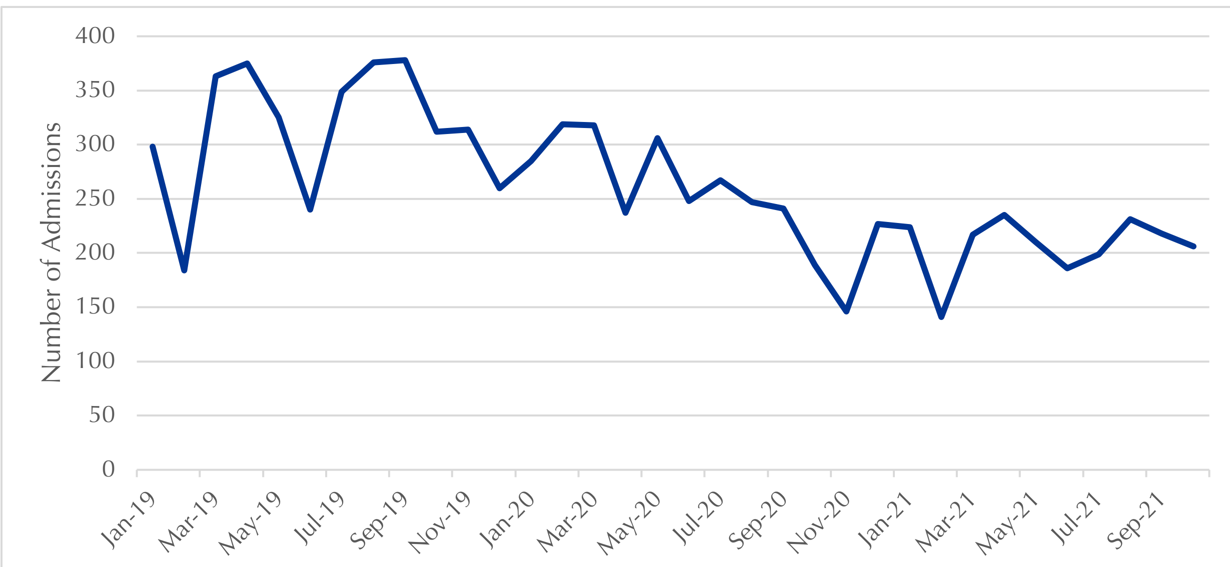
Trends in Sobering Center Client Admissions

This section provides a descriptive account of the trends in PIA admissions. Specifically, charts and descriptive statistics are used to demonstrate the trends in admissions counts, admission characteristics and the use of PIA, and client characteristics.

Trends in Admissions

From January 1, 2019, to October 31, 2021, the PIA had 8,871 admissions, an average of 3,131 per year or 261 per month. Figure 3.1 displays the admission counts by month for this period. When comparing admission counts to other months, the number of admissions does not appear to be significantly affected by the COVID-19 pandemic.

Figure 3.1 PIA Admissions Counts by Month from 1/1/2019 to 10/31/2021 (*N* = 8,871)[12]



Estimate of Jail Days Saved

Based on the PIA admission counts, we calculated an estimated number of "jail days" saved if each sobering center admission was a true diversion from an arrest and jail admission. The number of "jail days" saved was estimated by multiplying the number of yearly admissions by the average number of hours spent in the sobering center per

[12] Note that our data shows 8,184 admissions for the full time period but there appear to be incomplete data for July and August of 2019. The missing count of cases (n=687) were gathered from PIA for use in this figure but are unavailable for analysis in this section of the report.

admission per year. This number was then divided by 24 to estimate the number of "days" saved. The average number of hours spent in the sobering center used for this analysis was 10 hours, given that PIA has a 10-hour mandatory hold. Table 3.1 shows the number of jail days saved per year. By our estimates, 8,871 clients admitted over the course of 34 months stayed an estimated total of 88,710 hours in the PIA. This translates to approximately 3,696 days. When considering the two full calendar years in the available data, we see that an average estimate of 1,418 jail days per year are saved by diverting individuals from jail to the PIA.

Table 3.1. Estimated Jail Days Saved by Diversion to Sobering Center by Year (*N* = 2,911 admissions)

	Jail Days Saved
2019	1,573
2020	1,263
2021*	861

Note: * indicates when data does not cover the full calendar year.

Admissions Characteristics

Table 3.2 displays PIA admission characteristics by time of day, day of the week, and season. Two-thirds (66.8%) of admissions occurred at night (7:00 PM to 6:59 AM). Admissions across days of the week were fairly consistent, with the lowest proportion occurring on Mondays (10.3%) and the largest proportion occurring on Saturdays (17.4%). The admissions split between days of the work week and weekends was approximately even, with 51.7% occurring during the work week (Monday, Tuesday, Wednesday, and Thursday) and 48.3% occurring over the weekend (Friday, Saturday, and Sunday). Admissions were relatively consistent across seasons, with 20.9% occurring in summer, 21.7% in fall, 26.5% in winter, and 31.0% in spring. It should be noted, however, that the distribution of counts by season is skewed due to data availability. For example, the PIA data collection for this project ended on October 31, 2021. Therefore, data for late fall and early winter 2021 are not available.

A significant association existed between the time of day and whether the admission occurred during the work week or the weekend ($\chi^2 = 54.952$; $df = 1$; $p < 0.001$). As expected, a larger proportion of weekend admissions occurred during nighttime than during the work week (70.8% vs. 63.1%). A significant association was also observed between the time of day and season ($\chi^2 = 8.215$; $df = 3$; $p = 0.042$). Nighttime admissions made up 66.8% of admissions. While the proportion of nighttime admissions did not vary from what was expected in the winter or summer (66.5% and 68.1%, respectively), they made up a slightly greater proportion of admissions in the fall (68.6%) and a smaller proportion in the spring (64.9%).

Table 3.2. PIA Admission Characteristics (*N* = 8,184)

	%
Daytime Admission	33.2
Day of the Week	
Sunday	15.6
Monday	10.3
Tuesday	13.6
Wednesday	14.5
Thursday	13.2
Friday	15.4
Saturday	17.4
Weekend Admission	48.3
Season of Year	
Winter	26.5
Spring	31.0
Summer	20.9
Fall	21.7

PIA collected residence zip codes for all PIA clients in a database. Nearly 14% of clients were from the same zip code as the sobering center (73106). In total, 80 unique zip codes were included in the PIA's database. Of note, however, is that 75% of clients resided within only 13 unique zip codes, and approximately 90% of clients were from the same 22 zip codes.

Client Characteristics

Table 3.3 contains descriptive information about clients admitted to the PIA. Individual admissions during the data timeframe were overwhelmingly male (81.4%). Among racial/ethnic groups, 42.8% of clients were White, 23.1% were African American, 22.1% were Native American, and Hispanics made up 11.2% of admissions (0.9% were identified as Asian or "unknown"). Data regarding housing status was only available for the last two months of data provided from PIA (September and October 2021; *n* = 337). While these two months may not fully represent the admissions, a slight majority (51.9%) of clients admitted during these two months were identified as unhoused. Looking at the distribution of age at intake across admissions from our timeframe, the average age (and median age) was 43 years (13-point standard deviation). The youngest at intake was 17 years, and the oldest was 77.

During the PIA admissions process, all clients receive a blood alcohol test. In our data, the average BAC (and median) at intake was nearly twice the legal limit (0.154 and 0.155). Approximately 16% of clients had a BAC below the legal limit, with 2.7% recording a BAC of 0.000. OKC police officers were responsible for transporting individuals to the PIA. Some admissions, however, were direct transports from hospitals. Of the 8,184 PIA admissions, approximately one-quarter (24.1%) were clients transported from a hospital.

Table 3.3. PIA Client Characteristics

	Mean (SD) / %
Male (N=8,184)	81.4
Race/Ethnicity (N=8,169)	
White	42.8
African American	23.1
Hispanic/Latino	11.2
Native American	22.1
Asian	0.6
Unknown	0.3
Transport from Hospital (N=8,184)	24.1
Unhoused (N=337)	51.9
Age (years) (N=8,146)	43.2 (13.1)
BAC at Intake (N=7,236)	0.154 (0.074)

Admissions Trends by Client Characteristics

Next, we analyzed the PIA data to test for potential bivariate associations between trends in admissions—including time of day, day of the week, and season of the year—and characteristics of the individuals admitted to the PIA. The client characteristics explored include gender, race/ethnicity, age, BAC at intake, whether the client was a transported from the hospital, and housing status. The appropriate bivariate statistical test (i.e., chi-square test for independence, independent *t*-tests) is used depending on the level of measurement of the two variables.

Day vs. Night

Table 3.4 shows the observed associations between characteristics of the individual admitted to the PIA and whether the admission occurred during the day (between 7:00 AM and 6:59 PM) or at night (7:00 PM to 6:59 AM). Aside from housing status (which is limited because of the limited timeframe for which the data was collected), all associations were statistically significant: **age** (t = 11.10; p < 0.001), **gender** (χ^2 = 5.961; df = 1; p = 0.015), **race/ethnicity** (χ^2 = 71.543; df = 3; p < 0.001), **transport from hospital** (χ^2 = 53.464; df = 1; p < 0.001), and **BAC** (t = 12.25; p < 0.001).

The average age of daytime admissions was 45.5 years, significantly greater than those admitted during nighttime hours (42.1 years). Although males represent a large majority of PIA client admissions regardless of time, a larger proportion of clients admitted during the day were male (82.9%) compared to clients admitted at night (80.7%). Some differences in admissions were observed by race and ethnicity. For example, more Native American clients were admitted during the day (26.3%) compared to nighttime (20.2%). Conversely, a larger than expected proportion of nighttime admissions were Hispanic/Latino (13.0%)

compared to daytime admissions (7.9%). The proportion of daytime and nighttime admissions did not meaningfully differ for White or African American clients. Next, a greater proportion of nighttime clients were transported to the PIA from a hospital compared to those admitted during the day (26.6% vs. 19.2%). Lastly, the average BAC at intake was 16% higher for clients admitted during the daytime than those admitted during the night (0.169 vs. 0.146).

Table 3.4. Differences in Characteristics of Daytime and Nighttime Admissions

	Day	Night
Age (n = 8,146)	45.5	42.1
Male (n = 8,184)	82.9%	80.7%
Hispanic/Latino (n = 8,096)	7.9%	13.0%
Native American (n = 8,096)	26.3%	20.2%
Transport from Hospital (n = 8,184)	19.2%	26.6%
BAC (n = 7,236)	0.169	0.146

Work Week vs. Weekend

Associations were observed between client characteristics and whether admission occurred during the work week or over the weekend. Significant associations were observed for **age** (t = 8.99; p < 0.001), **race/ethnicity** (χ^2 = 53.318; df = 3; p < 0.001), **BAC** (t = 4.83; p < 0.001), **transport from hospital** (χ^2 = 25.014; df = 1; p < 0.001), and **housing status** (χ^2 = 12.218; df = 1; p < 0.001). Gender was not associated with work week or weekend PIA admissions.

On average, clients admitted to the PIA during the work week were 2.6 years older than those admitted to PIA on the weekend. A greater proportion of Native American clients were admitted during the work week (24.2%) compared to the weekend (20.2%), while a greater proportion of Hispanic/Latino clients were admitted on the weekend (13.7%) compared to the work week (9.0%). Work week clients also had an average BAC that was 5% higher at intake compared to weekend clients (0.158 vs. 0.150). A greater proportion of hospital transports were observed during the work week compared to the weekend. Specifically, 26.4% of PIA clients were transported from a hospital during the work week compared to 21.7% during the weekend. Finally, while limited to just two months of data, a greater proportion of unhoused clients were found to be admitted to PIA during the work week than during the weekend (60.7% vs. 41.6%).

Table 3.5. Differences in Clients Admitted during the Work Week Compared to Weekend

	Work Week	Weekend
Age (n = 8,146)	44.5	41.9
Hispanic/Latino (n = 8,096)	9.0%	13.7%
Native American (n = 8,096)	24.2%	20.2%
Transport from Hospital (n = 8,184)	26.4%	21.7%
Unhoused (n = 337)	60.7%	41.6%

BAC (n = 7,236)	0.158	0.150

Season of the Year

Trends regarding characteristics of PIA clients were also observed across seasons of the year.[13] Although age, gender, race/ethnicity, and transport from the hospital were not statistically significantly associated with the season of the year, a significant association was observed for **BAC** ($F = 47.73$; $p < 0.001$). The average BAC was highest in the summer (0.163), followed by the spring (0.162), fall (0.155), and winter (0.138). When considering pairwise comparisons, the average BACs in the spring, summer, and fall were all significantly higher than the winter average. Furthermore, the average BAC in the fall was significantly lower than the average in the spring and summer. No significant difference in average BAC level was observed between spring and summer.

Table 3.6. Differences in Clients Admitted by Season of the Year

	Winter	Spring	Summer	Fall
BAC (n = 7,236)	0.138	0.162	0.163	0.155

Summary of Findings from PIA Data

Unfortunately, data limitations regarding the PIA database limited the analyses that could be conducted to better understand the individuals in Oklahoma City who are diverted from jail and referred to the PIA. The lack of comprehensive data collection made it impossible to conduct analyses on the differences between one-admission clients and repeat clients, characteristics related to the time between admissions for repeat clients, the length of client stays, and the characteristics associated with what, if anything, the client did upon discharge.

Nonetheless, we were able to explore how clients varied depending on when the admission occurred. Our findings demonstrate that the clientele brought to the PIA varies depending on when they were admitted. For example, the clients brought to the PIA during the day and work week tended to be older and have a higher BAC. Additionally, a greater proportion of daytime and work week admissions were Native American.

Housing status was only captured in the PIA database for the last two months of the data made available for this report. As such, we are unable to fully speak to the role of housing across admissions characteristics; the limited data available indicates unhoused individuals comprised a larger proportion of individuals admitted to the PIA during the work week as compared to the weekend. Furthermore, in the focus groups, officers discussed the role of housing and PIA admissions. The officers believed that individuals would seek out the opportunity to be admitted to the PIA during the winter months to get

[13] Housing status was not included in the analyses for differences by season of the year because the available data were limited to only Fall of 2021.

a warm meal and have a place to sleep for the night. It appears that there is some evidence in favor of this hypothesis. Specifically, when considering differences in the characteristics of PIA clientele across seasons, we observed that the average BAC at intake is lowest during the winter. While more data are needed to fully understand clients' behavior, this could point to clients purposely seeking admission to PIA in the winter since they tend to be admitted with a lower BAC compared to other months.

Analyses of Oklahoma City Police Data

The Oklahoma City study setting provides opportunities and challenges when examining official police data. The Public Inebriate Alternative (PIA) has existed since 1973, making it one of the longest-operating sobering centers in the US. Unfortunately, because the records management system at Oklahoma City Police Department changed in 2000, our research team was not able to determine the short-term and immediate impact of the sobering center's opening on changes in specific types of arrests (which was a major focus in several of the other newer onset sites). Additionally, while 2000-2001 data were available for analyses, the number of missing variables in those years was considerably higher than from 2002 onward (and thus, our data range was 1/2002-6/2022). This time frame does not allow for a pre/post analysis of the changes in arrests. OKCPD also did not provide the race of arrestees, which precluded an analysis of arrest patterns by arrest type over time for different racial/ethnic groups.

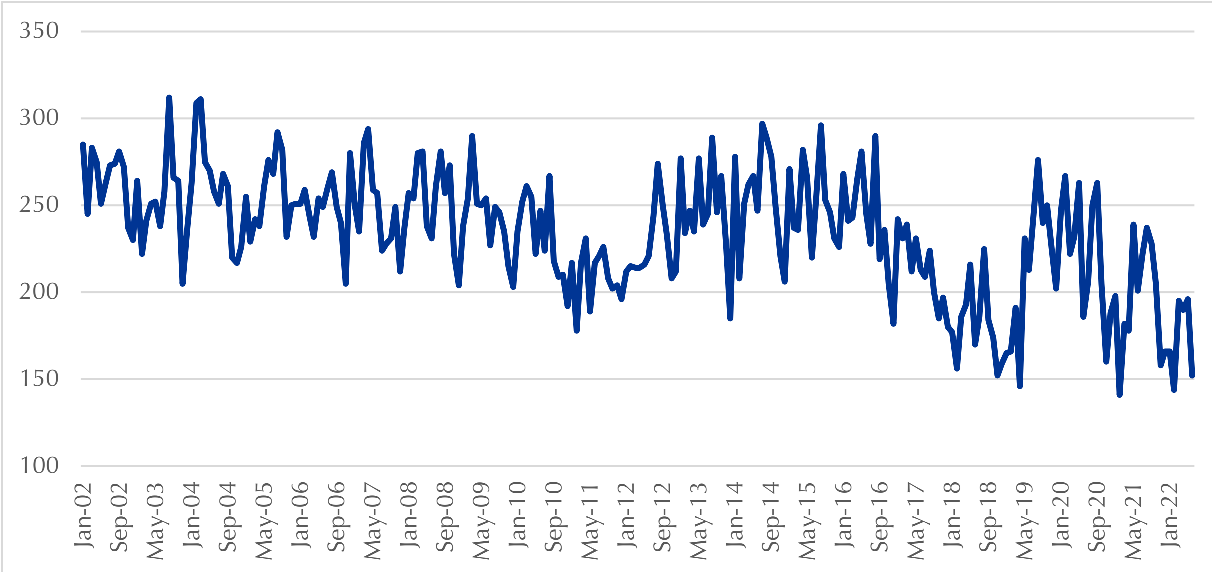
Nevertheless, given the duration of the sobering center's existence and the frequency by which the OKCPD relies on its usage, the Oklahoma City setting made it possible to explore the following question:

1. *Over an extended period of time, what proportion of total arrests in Oklahoma City do sobering center-related events comprise, including public intoxication, driving a motor vehicle under the influence, drugs and/or drug possession, and disorderly conduct?*

This research question is particularly important because the Oklahoma City PIA is well-established as an alternative to arrest, and the OKCPD has relied on it extensively for over three decades. This is the only study setting that can be used to assess whether a permanent alternative to arrest for public intoxication and related offenses can permanently impact arrests for these targeted arrest outcomes.

We examine a total of 57,622 arrests that occurred in Oklahoma City over a period from January 2002 to June 2022. The total monthly arrests ranged from 147 to 310, averaging 245 per month (seen in Figure 3.2 below).

Figure 3.2: Trends in Total Arrests in Oklahoma City (1/2002 – 6/2022), n=57,622



Over the twenty-year period, approximately 32% of all arrests (n=18,517/57,622) included at least one charge for public intoxication (PI), driving a motor vehicle while under the influence (DUI), possession (PO), and/or disorderly conduct (DC). Figure 3.3 below shows the percentage of total arrests over time that were intoxication-related. From 2002 to 2018, the proportion of intoxication-related arrests averaged approximately 40%; from 2019 to 2022, however, the average percentage of total arrests that were intoxication-related dropped to approximately 25%. One possible reason for this reduction in the proportion of intoxication-related arrests was the legalization of medicinal marijuana in November 2018 which went into effect in 2019.

Figure 3.3: OKCPD Intoxication-Related Arrests Percent of Total Arrests (2002-2022), n=57,622

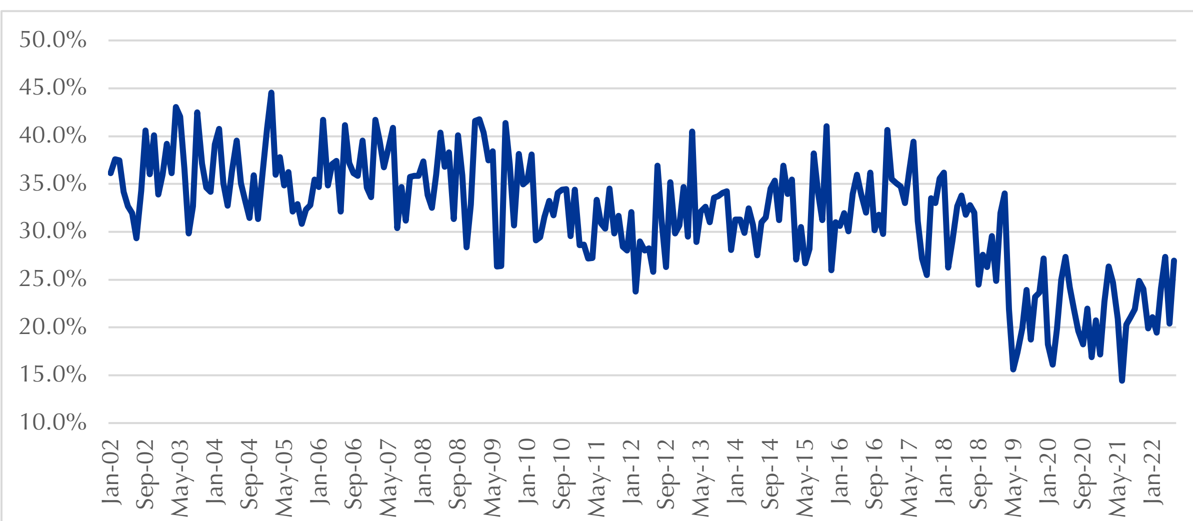


Figure 3.4 shows the count of intoxication-related arrests between 2002 and 2022. Intoxication-related arrest counts averaged roughly 85 per month between 2002 and 2017 and 50 per month from 2018 to 2022.

Figure 3.4: OKCPD Intoxication-Related Arrest Count (2002-2022), n=18,517

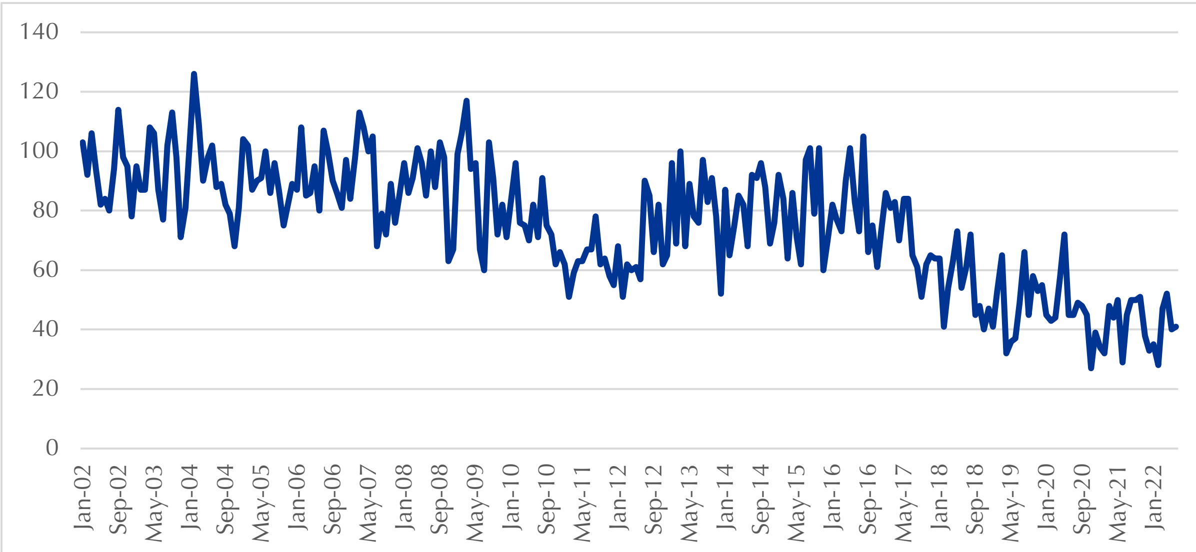


Table 3.7 displays the four specific charges of interest and their proportion of intoxication arrests and total arrests. Among intoxication-related arrests, the most common charges were related to drug, alcohol, or paraphernalia possession (55.2% of intoxication-related arrests and 17.7% of total arrests during this period). The second most common charge type was public intoxication (30.2% of intoxication-related arrests and 9.7% of total arrests), while DUI arrests comprised 25% of all intoxication arrests and 8.1% of total arrests. Disorderly conduct arrests were far less frequent, representing 4.2% of intoxication arrests and 1.4% of total arrests.

Table 3.7: Intoxication Specific Charges Among Arrests of Interest in Oklahoma City (1/2002-6/2022, Total N = 57,622)

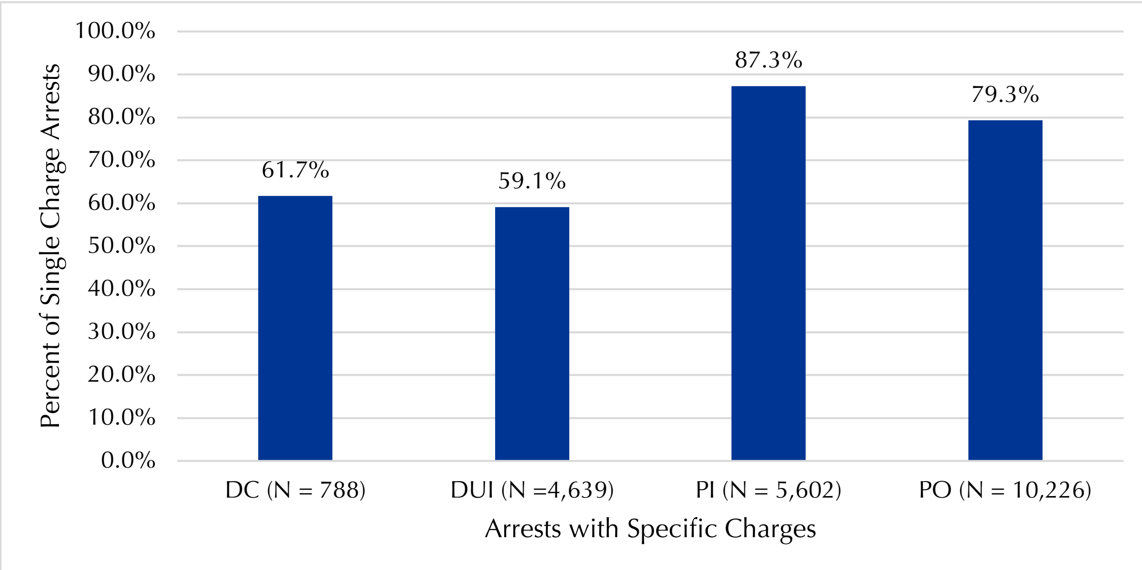
Arrests Charges	N	% Intoxication Arrests (N = 18,517)	% Total Arrests (N = 57,622)
Public Intoxication	5,602	30.2%	9.7%
Possession	10,226	55.2%	17.7%
Disorderly Conduct	788	4.2%	1.4%
DUI	4,639	25.0%	8.1%

Figure 3.5 below shows the percent of arrests by charge type that involved only a single charge.[14] As shown, 87.3% of public intoxication arrestees were arrested only for public

[14] Note that some individuals who are arrested may be charged with multiple crimes while some individuals are only charged with one crime.

intoxication (and not any of the other three intoxication-related charges). Similarly, possession arrests were highly likely to be single charges within these four intoxication-related arrest charge categories (79.3%). In contrast, arrestees of disorderly conduct were charged only for disorderly conduct 61.7% of the time, and DUI arrestees were only charged for a DUI 59.1% of the time.

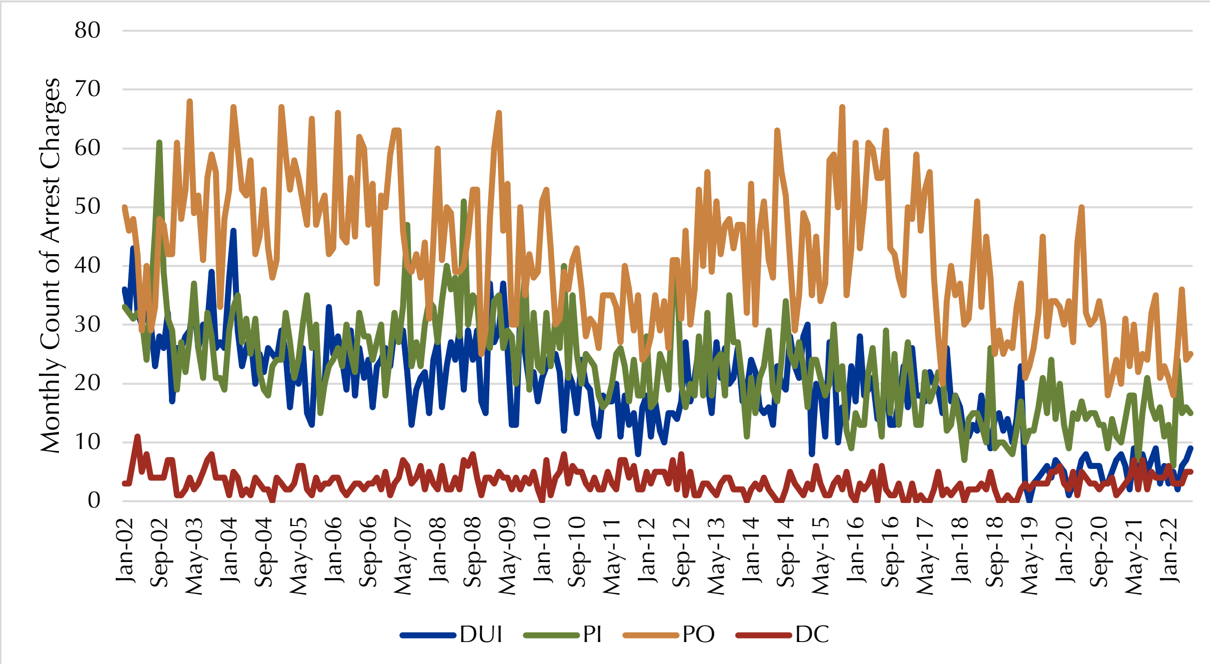
Figure 3.5: Percent of Arrests with a Single Charge by Charge Type, Oklahoma City



We also examine the changes in these four intoxication-related arrest charge patterns over time. We found consistent ebbs and flows between 2002 and 2022 in the monthly count of intoxication-related arrests. Disorderly conduct arrests were not common at any point in time between 2002 and 2022 (averaging under ten events per month during the entire period). Comparatively, possession arrests had much higher degrees of variability in their monthly event count ranging from as few as 25 per month to as many as 70 per month. Aside from a peak of arrests from 2007-2009 (which averaged roughly 45 arrests per month), public intoxication arrests averaged between 17 to 30 events per month in Oklahoma City between 2002 and 2022, which was similar on average to the monthly number of arrests for DUI during this period.[15]

[15] It is noteworthy that DUI arrests experienced several precipitous drops beginning in May 2019, which were sustained through the period where there was a state legislative change on recreational marijuana (in 2019) and the impact of COVID-19 (in April 2020 onward).

Figure 3.6: Trends in Intoxication-Related Arrests in Oklahoma City (1/2002 to 6/2022)



The proportion of total arrests for intoxication-related charges over the 20 years of examination was 32.1%. The total number of arrests between 2002 and 2022 averaged roughly 245 per month, with a proportional range of intoxication-related arrests from 17% to 40%. In short, there were peaks and valleys in the overall distribution of intoxication-related arrests and the proportional makeup of all arrests. Intoxication-related arrest counts in Oklahoma City were stable for most of the twenty years examined here (from 2002 to 2017, with a linear decline from 2018 onward), as noted by the trend graphs. However, it is worth noting that there were periods of variation across the arrest categories (in particular, clear shifts in the average monthly counts of possession and DUI arrests were observed over time). This is important because the sobering center was operational and used by OKCPD throughout this period; in contrast to the other case study sites, the post-sobering center period was ten years longer in Oklahoma City. During this extended period, many unmeasured factors could have impacted total and intoxication-related arrests. Within this long post-sobering center period, we found that among intoxication-related arrests, the most common charge was possession (55.2%). Intoxication-related charges were relatively stable across charge types (possession, public intoxication, DUI, and disorderly conduct) over the period examined here. Finally, individuals arrested for intoxication and/or possession were somewhat unlikely to be charged with multiple intoxication-related charges.

Results of Focus Group with Oklahoma City Police

In August 2022, researchers traveled to the Springlake Division of the Oklahoma City Police Department to engage in two focus group sessions with OKCPD officers on the use of the Oklahoma City sobering facility (the PIA). The first session occurred on the evening of August 22 and included four patrol officers (three males and one female). The second session occurred on the morning of August 23 and included six patrol officers (five males and one female). The Springlake Division was identified by OKCPD executives as the best location to talk with officers who were high-utilizers of the sobering center. As such, these officers represented those who used the sobering center most frequently. The focus groups lasted about 30 minutes each. The conversation began with a short statement from the lead researcher about the purpose of the focus group, the scope of the discussion, and the officers' anonymity guarantees. Approximately nine open-ended questions were used to guide the conversation. The primary goal of this focus group was to understand OKCPD officer decision-making in using sobering centers instead of arrest.

Benefits and Obstacles

The focus group discussion began by asking officers to describe the benefits of using the sobering center in their city. Officers described the sobering center as fast, easy, and relatively convenient, which makes time management one of its biggest benefits. Officers perceived the sobering center intake process to be much more efficient than taking someone to jail, saving an officer valuable time. Officers highlighted that trips to the jail could take up to an hour, while a drop-off at the PIA may only take five minutes. When taking an individual to jail, much of the time is spent waiting while jail staff conducts their intake process. When taking an individual to the sobering center, officers ensure the client is safe and return to patrol duties. In other words, the officers felt that the PIA was very well run, especially in comparison to the jail, and thought it best suited the officers' needs.

In addition to the time-saving benefits, officers who used the sobering center held positive opinions about the PIA practice of often holding inebriates longer than the jail does. Often, the charges for inebriated individuals will require a jail hold of ten hours or less. As such, these individuals are often quickly released, which means they can soon become a burden to the officer again.

Next, the researchers asked officers to describe the challenges or obstacles to using the sobering center. The focus group participants felt no major challenges or obstacles related to using the sobering center existed. Some slight inconveniences, however, were described. For instance, in a recent policy update, PIA clients must have a BAC under 0.350 to be admitted. Previously, officers and sobering center staff could determine whether the client was intoxicated based on visual cues. According to officers, this policy becomes an issue when the client refuses to take a breathalyzer test. In these situations, the client is denied admission, and officers must transport them to jail or the hospital. Many officers perceived this as wasted time.

Another infrequent inconvenience relates to transporting admitted clients to jail due to violations of sobering center rules. Some officers noted that they felt some staff were too quick to decide to remove a client, particularly in situations where the client was verbally, but not physically, aggressive. Like clients who refuse to take the breathalyzer, these situations are often viewed as a time burden for officers. On a similar note, the officers interviewed were all from the OKCPD division home to the PIA. As such, officers voiced frustration over the situations where officers from other divisions drop individuals off at the sobering center that probably should have been taken to jail. When these individuals become aggressive or noncompliant once admitted to the sobering center, some officers within the Springlake division expressed that they are the ones who have to respond and take the client to jail. Thus, officers viewed that some of time saved by diversion to the sobering center is reduced by time spent by officers who must return to the center to remove the client and transport them to jail.

In describing negative experiences when using the sobering center, their main concern was that some clients were abusing the system by purposefully trying to get admitted to the sobering center. The PIA provides clients with a meal, a bed, and a shower, and they will wash the client's clothes. As such, officers detailed situations where individuals have called 911 on themselves or have purposely engaged in activities to get others to report them to the police to get shelter and a meal.

Another concern of the officers was the safety and security of the sobering center. Specifically, the officers felt the sobering center needed more isolation rooms to help prevent property damage and interpersonal violence. The officers explained that the sobering center is often not a very happy environment and that clients often get into conflicts. More isolation rooms would provide a better opportunity to remove problematic clients from the bunk room, allowing them to cool down instead of relying on the police to intervene and transfer them to jail.

Officer Decision-Making

During the focus group discussions, officers were asked to describe their decision-making when faced with a publicly inebriated person. Officers described the driving factor of the decision to intervene with an inebriated person in public was that they had received a call for service about the individual. Unless calls are extremely slow, which is rarely the case in the Springlake division, officers are not patrolling the streets seeking out intoxicated individuals. Officers do not intentionally go to unhoused camps to look for people eligible to go to the sobering center. When civilian contact is not the result of a call for service, it is often a situation where an officer has observed a situation that would likely become a call for service. Such examples include groups of vagrants congregating at bus stops, parks, gas stations, or business fronts.

The decision of where to take an intoxicated individual is typically made in the field based on an individual's behavior and state of well-being. While the sobering center is the preferred destination, sometimes it is inappropriate. For example, if the inebriated individual is non-ambulatory, cannot stand, or is unresponsive, the officer will take the individual to the hospital or call emergency medical services to act upon the individual. Similarly, inebriated individuals will likely be jailed if they act belligerently. Officers suggested that when an individual is being aggressive with police officers, it is best to expect they will act aggressively—and possibly be violent—with the sobering center staff. Therefore, these individuals will be taken to jail rather than be diverted to the sobering center. The only situation in which belligerent individuals are not taken to jail is when it is clearly a mental health crisis. In such cases, the individuals are taken to the hospital.

The focus group participants also discussed how they typically handle situations where the officer deals with an individual with outstanding warrants. Whether an individual is taken to jail often depends on what the warrants are for and what the individual is doing to get a police response. Often, these interactions are with members of the transient population who have several city warrants (officers estimated that ten city warrants might be the average for this population). City warrants, however, are only for lower-level crimes that violate a city ordinance. For the transient population, the city will drop many of these charges if the individual appears in court. If they fail to appear, the warrant will not be dropped, and the individual will accrue more and more city warrants. Therefore, if the intoxicated individual only has city warrants and acts in a manner that does not require a trip to the jail, officers will likely take them to the sobering center. More serious warrants (i.e., felonies) always result in the individual being jailed.

Finally, officers were asked what might prompt their decision to pick up a chronic intoxicant on a particular day versus other times. Officers spoke about times when they chose not to pick up these individuals. In particular, when the individual is not causing problems for other people or businesses, the officers will often let them be. Officers felt there was no need to fill up the sobering center with individuals who were drunk and kept to themselves. The people who should go to the sobering center and need to be removed from the streets are those who are drunk and causing problems.

Supervision

Officers were asked to describe supervisory expectations regarding sobering center use. Overall, the officers did not have much to say regarding these expectations. They stated that, for the most part, supervisors are hands-off when it comes to using the sobering center, except for reporting. Supervisors will look at reports and want to know why the officer did not take an individual to the sobering center and why they had a public intoxication arrest. The reason for this, however, is not necessarily to encourage sobering center use. Instead, it is for documenting why the sobering center was not used.

Impact of Geography

Officers were asked whether the location of the intoxicated citizen had any impact on the decision to take them to the sobering center or jail—the jail and sobering center are about

1.5 miles apart in downtown Oklahoma City. Overall, the officers did not feel the intoxicant's location played a role in deciding how to handle these individuals. However, they noted that the sobering center had been strategically located. The PIA is placed within the Springlake division, which has the largest number of publicly intoxicated individuals. Therefore, while officers in this division deal with more inebriates, the sobering center is nearby. Officers did note that this may not be true for other districts. For example, officers in the Hefner division may have to travel 20 to 30 minutes to drop individuals off at the PIA. Yet, the convenience factor of the sobering center compared to jail means officers from other divisions will still choose to use the PIA.

Officer Recommendations

At the conclusion of the focus group, participants were asked if they had any advice to provide to a police officer who had never dropped off at a sobering center. Officers emphasized how the sobering center is a fantastic resource for law enforcement officers. They explained that dropping off at the sobering center is faster than taking someone to jail and ultimately more rewarding to divert people in need to somewhere other than jail. As a result, officers highlighted they would encourage new officers to take publicly intoxicated individuals and chronic inebriates to the sobering center rather than jail at any opportunity.

Concluding Remarks

The primary goal of the focus groups was to understand OKCPD officer decision-making in using sobering centers rather than making an arrest. Officers find that the sobering center is much more efficient than taking publicly intoxicated individuals to jail and provides a better overall experience. Officers considered the jail unorganized and poorly ran. Regarding obstacles or negative experiences related to using the sobering center, officers expressed frustration about PIA admission restrictions and returning to the sobering center to remove a client. Officers did not feel pressure from supervisors or the command staff to use the sobering center. The sobering center remains the preferred location to transport intoxicated citizens regardless of supervisory and command staff guidance or expectations.

CHAPTER 4: TULSA, OKLAHOMA

Tulsa is the second largest city in Oklahoma, with 411,401 residents in 2021 (US Census, 2022). Located in the South Western region of the US, Tulsa is the 47th largest city in the US. The population has the largest majority of White residents (53.4%), followed by Hispanic (17.1%), Black (15.0%), Mixed (8.9%), Asian (3.5%), and Native American (4.5%) (US Census, 2022). The median income for a household in the city is $49,474.

Policing services are provided to the City of Tulsa by the Tulsa Police Department (TPD). The TPD is comprised of approximately 807 sworn officers and 180 civilian employees. Divided across three Bureaus: Operations, Investigations, and Administration, the TPD is responsible for 197 square miles of jurisdiction. According to the 2021 TPD Annual Report, the TPD receives about 520 thousand calls each year, resulting the in the dispatch of officers to about 277 thousand of those calls. In the fiscal year 2021, the reported annual operating budget for the TPD was 123 million dollars (Sullivan and Baranauckas, 2020). The TPD has a specific policy to guide officer decision-making in handling publicly intoxicated persons.

An intoxicated person in a public place, as defined in Section 8 of Title 37 of Oklahoma's Mental Health Law (Title 43A O.S. § 1-110) , is allowed to be taken into protective custody/detention by peace officers for transport. According to Oklahoma law, transportation of intoxicated persons to their home or an alternative approved treatment facility is preferred to proceeding with an arrest under the statutory or municipal requirements of prosecution and imprisonment for handling intoxicated persons. Thus, TPD policy requires that police use the sobering center upon the voluntary approval of both the intoxicated person and the sobering center in Tulsa. Additionally, there is a mandatory 10-hour hold as the person is technically in protective custody by the peace officer or emergency service patrol. However, the state statute also indicates that no record shall be made, meaning that the person has not been arrested or charged with a crime.

The Tulsa Sobering Center (TSC), located in downtown Tulsa, Oklahoma, has two sobering rooms with a maximum capacity of 30 beds for males and 15 beds for females (pre-pandemic; during the pandemic, this number was reduced to 15 men and seven women). The TSC is operated by 12&12, a comprehensive addiction recovery center, with funding from the City of Tulsa but is considered a program of the TPD. Opening its doors in May 2018, the TSC is modeled after the Public Inebriate Alternative in Oklahoma City. Notably, the TSC only accepts clients from the TPD—no other police agencies or referrals are accepted, though referral sources may be widened in the future. Most days, the TSC is run by one non-medical staff, but staffing is often doubled on Fridays. Upon intake, TSC staff collect demographic information and provide a breathalyzer to assess BAC (clients must be below 0.35 BAC). During their stay, clients are provided with food, a safe place to sleep, and a connection to services for counseling, rehabilitation, or other programs.

Analyses of Tulsa Sobering Center

This report section relies on data collected by the Tulsa Sobering Center (TSC). The primary unit of analysis is an individual admitted to the sobering center, referred to as a "client." The TSC began data collection on May 30, 2018, when the facility opened. Variables such as race and ethnicity, gender, age, BAC, the primary substance used, detaining officer, detaining location, and duration of stay in the sobering center have been collected since the facility's opening. Over time, additional variables have been incorporated into data collection efforts as the staff realized the importance of capturing housing status, veteran status, police division of detaining officer, and referral information. The analyses in this report are based on TSC data collected through October 14, 2021. Table 1 in Appendix B presents a detailed description of all TSC variables used in the following analyses, including the variable definition, date range of availability, and how the variable was coded and used in analyses.

The purpose of analyzing these sobering center data is to understand TSC use and its clientele overall. As such, in this section, we explore five broad research questions:

1. *What are the trends in TSC admissions?*
2. *What are the characteristics of the TSC clientele?*
3. *Are there differences in the characteristics of one-admission and repeat-admission clients (those who have been admitted to the TSC on multiple occasions)?*
4. *What client characteristics are associated with differences in the length of stay per admission at the TSC?*
5. *What client characteristics are associated with a client receiving a referral to a community organization or center upon discharge from the TSC?*

Several analyses provide insight into these research questions. Descriptive, bivariate, and multivariate analyses are all used to glean a clearer understanding of the use of the TSC and its clientele, who otherwise would likely be transported to jail if the TSC was not an available alternative.

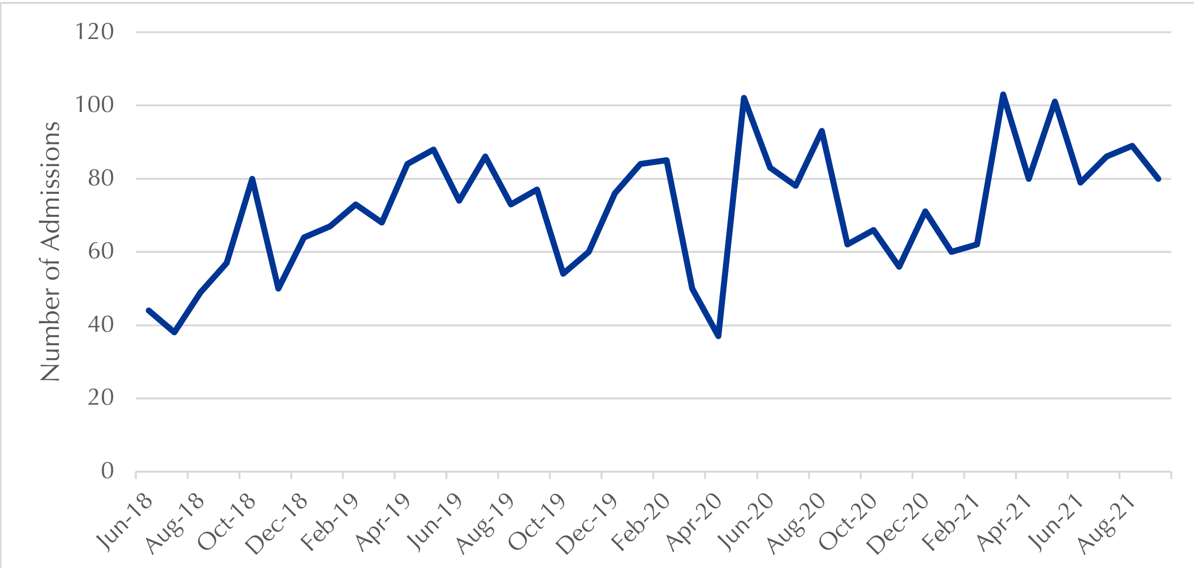
Trends in Sobering Center Client Admissions

This section provides a descriptive exploration of the trends in the TSC's admissions. Specifically, charts and descriptive statistics are used to demonstrate the trends in admissions counts, admission characteristics and the use of TSC, and client characteristics.

Trends in Admissions

From May 30, 2018, to October 14, 2021, the TSC had 2,911 admissions. This corresponds to approximately 861 admissions per year or 72 admissions per month. Figure 4.1 displays the admissions counts by month for all months with complete data. Compared to admissions counts in 2019, the number of admissions does not appear to be majorly affected by the COVID-19 pandemic outside of April 2020 (the first full month of lockdown).

Figure 4.1. TSC Admissions Counts by Month from 6/1/2018 to 9/30/2021 (N = 2,869)[16]



Estimate of Jail Days Saved

Based on the TSC admission counts, we calculated an estimated number of "jail days" saved if each sobering center admission was a true diversion from an arrest and jail admission. The number of jail days saved was estimated by multiplying the number of yearly admissions by the average number of hours spent in the sobering center per admission per year. This number was then divided by 24 to estimate the number of days saved. Table 4.1 shows the number of jail days saved per year. By our estimates, 2,911 clients admitted over 40 months stayed 32,866 hours (or 1,369 days) in the TSC since its opening. When considering the two full calendar years in the available data, we see that an average estimate of 411 jail days per year are saved by diverting individuals from jail to the TSC.

Table 4.1. Estimated Jail Days Saved by Diversion to Sobering Center by Year (N = 2,911 admissions)

Jail Days Saved

[16] Includes all months with full data; data is incomplete for the months of May 2018 and October 2021.

2018*	180
2019	414
2020	408
2021*	364

Note: * indicates when data does not cover the full calendar year

Admissions Characteristics

The TSC is available 24 hours a day, seven days a week. Table 4.2 displays the descriptive statistics for TSC admissions characteristics. There were slightly more admissions occurring at night (from 7:00 PM to 6:59 AM). Admissions across days of the week were fairly consistent, with the lowest admissions occurring on Mondays (12.9%) and the largest on Saturdays (16.8%). Admissions between work days and weekends is a split, with approximately 54% of admissions occurring during the work week (Monday through Thursday) and 46% occurring over the weekend (Friday through Sunday).

Admissions are also relatively consistent across seasons, with 21.6% of admissions occurring in the fall, 22.5% in the winter, 26.2% in the spring, and 29.8% in the summer. It should be noted, however, the distribution of counts by season is skewed due to data availability. For example, the TSC data collection began in May 2018. Therefore, data for late winter and early spring 2018 are not available. Similarly, the data analyzed in this report end in October 2021. As such, no admissions for winter 2021 are captured here. Nonetheless, a significant association exists between the time of day for admission and whether the admission occurred during the work week or the weekend ($\chi^2 = 22.145$; $df = 1$; $p < .001$). As expected, a larger proportion of weekend admissions occur during the nighttime than TSC admissions during the work week.

Nearly all referrals for admission to the TSC come from police officers with the Tulsa Police Department (TPD). Specifically, 2,847 of the 2,911 admissions in the available data—or 97.8% of admissions—were referred to the TSC by TPD officers. The remaining 2.2% of admissions were referred by probation officers (2.0%; $n = 57$) or other law enforcement agencies (0.2%; $n = 7$).

The TSC began collecting information regarding the TPD division from which the referring officer was assigned on March 1, 2020. Given the later onset of data collection, division information is missing for nearly half (49.4%; $n = 1,439$) of admissions in the available timeframe (unavailable for May 2018 to Feb 2020). When observing the available 1,440 TSC admissions referred by TPD officers with available division information, the largest share of referrals come from Riverside (40.9%), followed by Mingo Valley (31.7%) and Gilcrease (26.2%), with just over 1% of TPD admissions coming from "Other" divisions.[17]

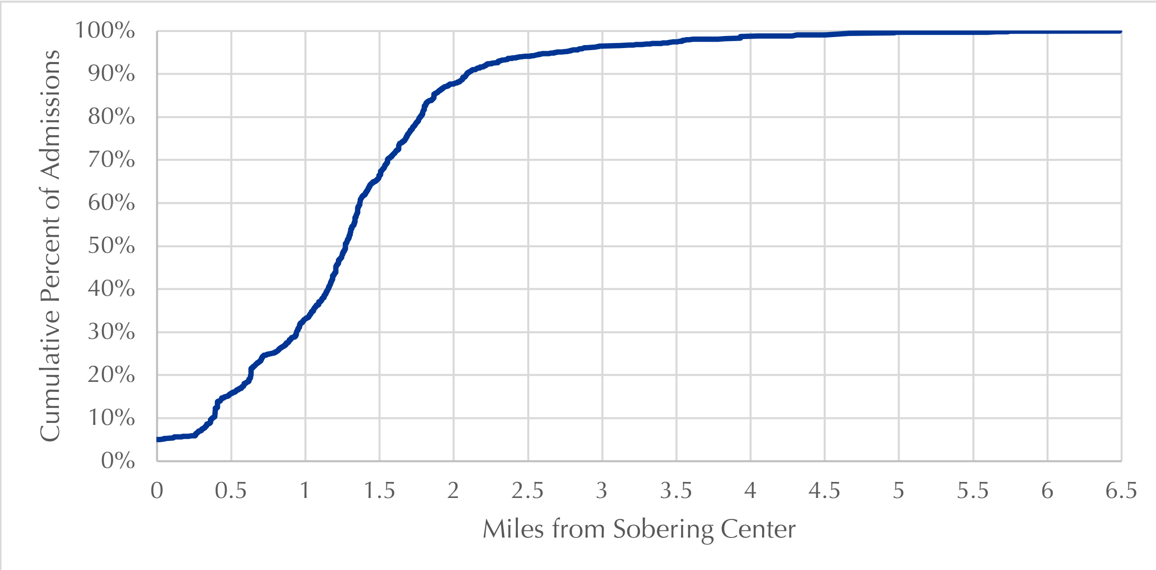
Table 4.2. Tulsa Sobering Center Admission Characteristics

	Mean (SD) / %
Daytime Admission (N=2,911)	43.1
Day of the Week (N=2,911)	
Sunday	13.9
Monday	12.9
Tuesday	13.8
Wednesday	13.3
Thursday	13.7
Friday	15.7
Saturday	16.8
Weekend Admission (N=2,911)	46.3
Season of Year (N=2,911)	
Winter	22.5
Spring	26.2
Summer	29.8
Fall	21.6
TPD Division (N=1,440)	
Riverside	40.9
Mingo Valley	31.7
Gilcrease	26.2
Other	1.3
Distance from TSC (N=2,770)	1.300 (0.813)

The TSC also instructs the referring party to provide the client's detention location by the TPD. Our research team geocoded these locations and measured the distance between the location of detention and the TSC. We successfully geocoded 2,770 of the 2,911 (95.2%) admissions. The location distance from the TSC ranged from 0 miles to 6.5 miles and an average of 1.3 miles. As demonstrated in Figure 4.2, one-third of admissions (33%) have a detention location less than 1 mile from the TSC, and 88% have a location less than 2 miles away.

[17] A total of *n* = 1,472 TSC admissions contain data on TPD division. Yet, *n* = 32 cases were identified as referrals to the TSC by an agency other than TPD. Of these cases, *n* = 2 identified Riverside as their division, while *n* = 30 identified with an "other" division. These cases have been removed in the numbers presented in the text.

Figure 4.2. Detaining Location's Distance from the Tulsa Sobering Center from 5/30/2018 to 10/14/2021 (*N* = 2,770 admissions)



As demonstrated above, admissions to the TSC are not uniformly distributed across TPD divisions. The same can be said about the TPD officers who bring individuals to the TSC. Specifically, the TSC database collects data on the referring officer, including their name and badge number. An examination of admissions counts by TPD officers shows that 504 TPD officers are responsible for 2,832 TSC admission referrals. The officer with the most referrals was responsible for 57 TSC admissions. The average number of referrals across all officers was 5.6 admissions, yet this number is slightly skewed as the median is four admissions. The data demonstrates that 10% of all TPD admission referrals come from only eight officers, and approximately 50% of all admission referrals come from 93 TPD officers.

Client Characteristics

Table 4.3 contains descriptive information about clients admitted to the TSC. Individuals admitted into the TSC during the data timeframe were overwhelmingly male (78.6%) and White (63.5%). Among other racial/ethnicity groups, 15.1% of admissions were African American, 12.3% were Native American, and Hispanics made up 7.6% (1.7% were identified as either Asian or "other"). A slight majority (54.1%) were individuals who were identified as unhoused at admission to the TSC. Individuals admitted to the TSC are primarily non-veterans of the United States military (89.1%).

Looking at the distribution of age at intake across all admissions, the average age was 41.03 years (12.73-point standard deviation) with a median of 40 years. The youngest age at intake was 18 years, and the oldest was 79 years. The TSC collects information on the primary substance being used by the client at admission. Alcohol (77.2%) was overwhelmingly the most common substance used that led to a TSC admission.

Methamphetamine (14.1%) was the next most common substance, followed by "unknown substance" (3.5%). The remaining 5.4% of admissions involved substances such as heroin (1.2%), marijuana (1.1%), pharmaceuticals (1.1%), benzodiazepines (0.7%), cocaine (0.5%), opioids (0.4%), and inhalants (0.4%).

Table 4.3. Tulsa Sobering Center Client Characteristics

	Mean (SD) / %
Male (N=2,911)	78.6
Female (N=2,911)	21.4
Race/Ethnicity (N=2,911)	
White	63.5
African American	15.1
Hispanic/Latino	7.6
Native American	12.3
Asian	0.9
Other	0.8
Unhoused (N=2,141)	54.1
Veteran (N=2,141)	10.9
Age (N=2,911)	41.03 (12.73)
Substance (N=2,911)	
Alcohol	77.2
Methamphetamine	14.1
Heroin	1.2
Pharmaceuticals	1.1
Benzodiazepines	0.7
Opioids	0.4
Marijuana	1.1
Cocaine	0.5
Inhalants	0.4
Unknown	3.5
BAC at Intake (N=2,892)	0.140 (0.106)
Repeat Visit (N=2,911)	29.2
Admissions Count (N=2,061)	1.41 (1.88)
Stay Duration (hours) (N=2,903)	11.28 (3.67)

During the TSC admissions process, all clients receive a blood alcohol concentration (BAC) test. For all admissions (including the individuals who were not using alcohol), the average BAC at intake was nearly twice the legal limit (0.140). This average, however, is slightly skewed by the non-alcohol users who are inflating BACs equal to 0.000. Specifically, 95.2% of the clients who had an identified primary substance other than alcohol (n = 661) had a BAC equal to 0.000. When considering only the clients with alcohol identified as their primary substance, the average BAC increases to 0.181, with a minimum BAC of 0.000 and maximum of 0.400. For all clients who had a BAC test at intake that was positive for alcohol (i.e., not equal to 0.000) regardless of primary substance used, the average BAC was 0.185.

The TSC data collection efforts attempt to track individual clients. As such, a unique identifier is collected that corresponds to a specific individual to track repeat visits. Of all admissions, 70.8% were the first TSC admissions, and 29.2% were repeat visits. When looking at TSC admissions at the individual level, we see 2,061 unique individuals (clients) make up the 2,991 total TSC admissions. The average number of admissions per individual equaled 1.41 with a standard deviation of 1.88. The median and modal frequency of admissions were equal to one (84% had only one admission), and the highest number for a single individual was 44 admissions during the 42-month time period.

Finally, despite the TSC policy requiring a ten-hour mandatory hold, variation existed for how long clients stayed at the TSC. The average stay at the TSC per admission was 11.28 hours (standard deviation = 3.67). The distribution of data on the length of stay for admissions ranged from 0 hours to just shy of 24 hours, with a median and modal duration of 10 hours (46.4% of the total admissions). The majority (65.5%) of clients stayed at the TSC between 9 and 12 hours before being released.

Admission Trends by Client Characteristics

Next, we analyzed the TSC data to test for potential associations between trends in admission—including time of day, day of the week, and season of the year—and characteristics of the individuals admitted to the TSC. Due to the length of this section, it has been moved to Appendix B in this document.

Analysis of One-Admission vs. Repeat Clients

Of particular interest for trends in admissions is whether differences exist between clients who are admitted to the TSC only once (one-admission client) compared to those who are admitted to the TSC two or more times (repeat client). As detailed above, 2,061 unique individuals were responsible for the 2,991 total admissions into the TSC during the timeframe. Of the 2,061 unique individuals, 1,731 (84.0%) were identified as one-admission clients, and 330 (16.0%) were identified as repeat clients. To identify any potential differences between one-admission and repeat clients, we analyzed associations at the individual-level (rather than the admission-level)[18] across client characteristics,

[18] The admissions data obtained from the TSC is collected in a long format, where information from each admission is represented in a single row. As such, repeat clients will be represented by multiple rows that contain information for each unique admission. To perform the analyses in this section, we took the

including gender, race/ethnicity, age, housing status, veteran status, primary substance, average BAC, and average location distance from the TSC. Bivariate and multivariate analyses are used to address three areas of interest associated with potential differences between one-admission clients and repeat clients: 1) the characteristics associated with being a repeat client, 2) the characteristics associated with the number of times each client has been admitted to the TSC, and 3) the characteristics associated with the timing to re-admission to the TSC. Bivariate analysis findings can be found in Appendix B.

Multivariate Analysis of Repeat Clients

Next, we conducted a multivariate analysis using logistic regression to identify the characteristics associated with being a repeat admit to the TSC while accounting for the influence of all other characteristics included in the model. Once again, analyses were estimated at the individual level, with each unique individual being identified as either a one-admission or repeat client. Once admission characteristics were simultaneously considered in the multivariate model, three characteristics were found to be significantly associated with repeat admissions to the TSC (see Table 4.4).

Table 4.4. Logistic Regression Results for Predicting Repeat TSC Clients (*n* = 1,439)

Variables	b	Standard Error	Odds Ratio
Male	0.160	0.176	1.174
Race/Ethnicity (White reference)			
African American	0.023	0.199	1.023
Hispanic/Latino	–0.597	0.337	0.550
Native American	0.120	0.247	1.127
Age	**0.014***	**0.006**	**1.014**
Unhoused	**1.036*****	**0.157**	**2.819**
Veteran	–0.023	0.231	0.978
Alcohol	0.0611	0.252	1.063
BAC × 100	**0.024***	**0.010**	**1.024**
Distance from TSC (miles)	–0.125	0.093	0.882
Intercept	–2.936	0.318	0.053

Notes: BAC has been multiplied by 100 to make the results more easily interpretable.
* $p<0.05$, ** $p<0.01$, *** $p<0.001$ (two-tailed test)

admissions database and transformed it into an individual database using the unique identifier collected by the TSC. Known as a wide format, each row in the transformed database represents a single client (based on their unique identifier). For repeat clients, data from subsequent admissions are displayed as additional columns in the database. Client characteristics, were obtained by calculating the average across admissions for each unique individual. It is those averages that are used in these analyses.

First, age was positively associated with repeat admissions. For each one-year increase in age, the logged odds of being a repeat client increase by 1.4%. Stated differently, with all other characteristics held at their averages, a 50-year-old client is found to have a predicted probability of being a repeat client of 19.7%, while the predicted probability of being a repeat client for a 30-year-old is 15.8%.

The second statistically significant predictor of being a repeat client to the TSC was the average BAC level. A 0.010 increase in BAC was associated with a 1.4% increase in the logged odds of being a repeat client. Examining predicted probabilities, we find an individual with a BAC of 0.000 has a 14.1% probability of being a repeat client with all other characteristics held constant. The predicted probability of being a repeat client for those at the legal BAC limit (0.08) is 16.4% and 19.0% for those who are twice the legal limit (0.160).

The last statistically significant predictor of being a repeat TSC client was housing status. In particular, the logged odds of being a repeat client are nearly three times greater for unhoused individuals compared to those who are housed. With all other characteristics held at their averages, individuals who are housed have an 11.3% probability of being a repeat client to the TSC. For individuals who are unhoused, the probability increases to 26.0%.

Analysis of Admissions Counts

As a supplemental analysis to the analysis of repeat clients, we explored what characteristics are associated with the number of TSC admissions per individual. While bivariate associations can be found in Appendix B, the multivariate analyses are shown here. Next, we used negative binomial regression to simultaneously examine the possible characteristics associated with the number of TSC admissions per individual.[19] The findings—shown in Table 4.5—reflect the same pattern observed in the logistic regression analysis above, with the addition of gender and race differences in admissions counts. Males are found to have an incident rate for TSC admissions that is 12.4% greater than that of females, Native Americans have an incident rate that is 36.7% greater than White clients, and the incident rate for unhoused clients is 45.5% greater than clients who are housed. The percent change in the incident rate of TSC admissions is a 0.6% increase for a 1-year increase in age and a 1.1% increase for an increase in BAC of 0.01. Like the previous analysis, there was no association by race/ethnicity (for African Americans and Hispanics/Latinos), veteran status, primary substance, or distance of location from the TSC.

[19] Negative binomial regression is the appropriate analytical technique for this analysis because these count data do not approximate a normal distribution. Furthermore, negative binomial is preferred over Poisson regression because there was evidence of overdispersion in the distribution of number of TSC admissions (see Long and Freese, 2006).

Table 4.5. Negative Binomial Regression on Number of TSC Admissions per Individual (*n* = 1,439)

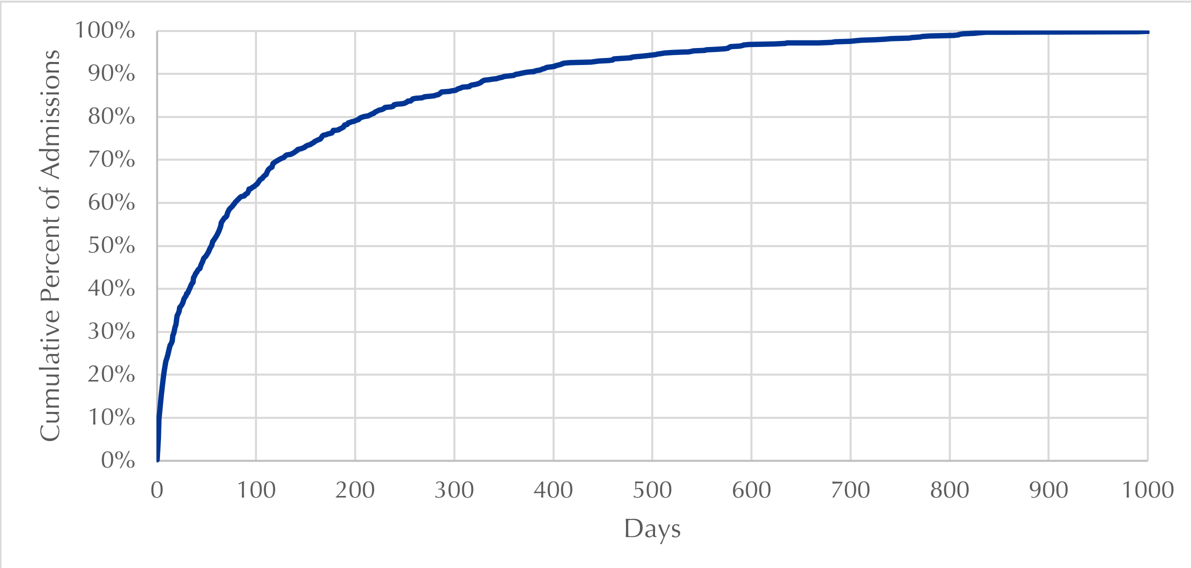
Variables	b	Standard Error	IRR
Male	**0.117***	**0.059**	**1.124**
Race/Ethnicity (White reference)			
African American	0.009	0.068	1.009
Hispanic/Latino	–0.084	0.093	0.919
Native American	**0.313*****	**0.079**	**1.367**
Age	**0.006****	**0.002**	**1.006**
Unhoused	**0.375*****	**0.052**	**1.455**
Veteran	–0.048	0.082	0.953
Alcohol	0.008	0.084	1.008
BAC × 100	**0.011****	**0.003**	**1.011**
Distance from TSC (miles)	–0.018	0.030	0.982
Intercept	–0.292	0.104	

Notes: BAC has been multiplied by 100 to make the results more easily interpretable. IRR = Incident Rate Ratio.
* $p<0.05$, ** $p<0.01$, *** $p<0.001$ (two-tailed test)

Analysis of Time to Re-Admission

To further understand repeat TSC clients, we explored how the individual characteristics of clients are related to the length of time since the previous admission for repeat clients. The average number of days between TSC admissions for repeat clients was 126.3 days, with a standard deviation of 176.2. The distribution ranges from 0 days to 1,007 days, with a median of 55 days. One-quarter of re-admissions occurred within 12 days of their last admission.

Figure 4.3. Days Between Sobering Center Admissions for Repeat Clients from 5/30/2018 to 10/14/2021 (*N* = 850 admissions)



We first analyzed bivariate associations between admission characteristics and the days since the last admission, these results can be found in Appendix B. Next, we analyzed whether any client characteristics predicted an earlier time to re-admission using survival analysis. Bivariate Cox proportional hazard models were estimated using gender, race/ethnicity, age, housing status, veteran status, primary substance, and BAC at intake as individual predictors. The results from these bivariate analyses are shown in the first results column in Table 4.6. Other than veteran status and primary substance, all predictors were statistically significantly associated with time to re-admission at a bivariate level.

It was indicated through these bivariate survival analyses that clients who are male (hazard ratio = 2.115; $p < 0.001$), unhoused (hazard ratio = 4.255; $p < 0.001$), and older (hazard ratio = 1.033; $p < 0.001$) tend to be re-admitted to the TSC faster than their female, non-unhoused, and younger client counterparts. For race/ethnicity, we found no significant difference in the risk of being re-admitted at any point between White and African American clients. Differences were observed, however, between White and Hispanic/Latino or Native American clients. The risk of re-admission at any point was less for Hispanic/Latino clients compared to White clients (hazard ratio = 0.250; $p = 0.002$), and the risk for Native American clients was greater than White clients (hazard ratio = 2.113; $p = 0.024$). Clients with a higher BAC (hazard ratio = 1.003; $p = 0.001$) were also found to be re-admitted to the TSC in a shorter amount of time compared to clients with a lower BAC.

Next, we estimate a multivariate Cox proportional hazard model using the same client characteristics included in the bivariate survival analyses. The third column in Table 4.6

presents the results from the multivariate analysis. Comparing the findings from the bivariate and multivariate analyses, we find that after taking into consideration the influence of other variables, the associations between Native American clients (relative to Whites) with risk for time to re-admission is no longer statistically significant. As with the bivariate analysis, there is no evidence of an association with veteran status or alcohol as a primary substance. After the adjustment for the influence of other client characteristics, **gender**, **race/ethnicity (Hispanic only)**, **housing status, age**, and **BAC at intake** were all still significantly associated with re-admission timing to TSC.

Holding all other client characteristics constant, males were found to have a risk of re-admission at any point in time that is 2.1 times greater compared to female clients (hazard ratio = 2.115; p = 0.008). While the association between White and Native American clients is no longer statistically significant, there continues to be a significant difference between White and Hispanic/Latino clients. Specifically, White clients tend to get re-admitted to TSC earlier after discharge than Hispanic/Latino clients (hazard ratio = 0.417; p = 0.046). The rate of timing to re-admission increases with age (hazard ratio = 1.022; p = 0.013). A one-year increase in age increases the rate by 2.2%. Unhoused clients tend to be re-admitted to TSC faster than clients who are housed (hazard ratio = 3.832; p < 0.001). Compared to non-unhoused clients, the rate of timing to re-admission for unhoused clients is 3.8 times greater. Finally, a higher BAC is associated with a higher risk for re-admission at any time than a lower BAC (hazard ratio = 1.036; p < 0.001). A 0.01 increase in BAC increases the rate of timing to re-admission by 3.6%.

Table 4.6. Bivariate and Multivariate Cox Proportional Hazard Regression of Re-admission Timing to TSC (*n* = 2,094 Admissions)

	Bivariate		Multivariate	
Variables	Hazard Ratio	Standard Error	Hazard Ratio	Standard Error
Male	**2.115*** **	**0.420**	**1.717** **	**0.349**
Race/Ethnicity (White reference)				
African American	0.906	0.229	0.897	0.222
Hispanic/Latino	**0.250** **	**0.109**	**0.417***	**0.183**
Native American	**2.113***	**0.702**	1.708	0.535
Age	**1.033*** **	**0.009**	**1.022***	**0.009**
Unhoused	**4.255*** **	**0.624**	**3.832*** **	**0.537**
Veteran	1.155	0.242	0.716	0.100
Alcohol	1.463	0.333	0.807	0.381
BAC × 100	**1.033*** **	**0.010**	**1.036*** **	**0.010**

Notes: BAC has been multiplied by 100 to make the results more easily interpretable. Analyses include clustered sandwich estimators for individual IDs to adjust for repeat clients.
* p<0.05, ** p<0.01, *** p<0.001 (two-tailed test)

Analysis of Client Length of Stay in the TSC

Next, we explored the characteristics that are associated with the amount of time individuals stay at the TSC during their visit. The distribution for length of stay at the TSC ranged from 0 to 23.55 hours, with an average length of stay of 11.28 hours and a median of 10.28 hours. Bivariate and multivariate statistical models were used to estimate these relationships. The client characteristics included in these analyses were gender, race/ethnicity, housing status, veteran status, age, primary substance, BAC at intake, first TSC admission compared to repeat admission, distance from TSC, TPD Division, time of day, day of the week, and season of the year. Bivariate associations can be found in Appendix B, and multivariate associations are shown here.

Multivariate Analysis of Length of Stay

Ordinary least squares (OLS) regression was used to observe the effects of our independent variables on the length of stay at the TSC, given the normal distribution of the dependent variable. In the multivariate model—which adjusts for the influence of all predictors simultaneously—time of day of the admission (beta = 0.174; $p < 0.001$), housing status (beta = 0.121; $p < 0.001$), and veteran status (beta = –0.054; $p = 0.015$) were found to be statistically significant predictors of length of stay. On average, individuals brought to the TSC during the day are predicted to stay 1 hour and 19 minutes longer than clients during the nighttime hours. Unhoused clients stay 54 minutes longer, on average, compared to clients who are housed. Finally, veterans of the United States military are found to have a length of stay at the TSC that is, on average, nearly 38 minutes shorter than their non-veteran counterparts.

Table 4.7. OLS regression on Number of Hours Spent at the TSC (*n* = 1,996)

Variables	b	Standard Error	Beta
Male	0.061	0.218	0.007
Race/Ethnicity (White reference)			
African American	–0.306	0.250	–0.029
Hispanic/Latino	–0.052	0.285	–0.004
Native American	0.091	0.304	0.008
Age	0.008	0.008	0.029
Unhoused	**0.902*** **	**0.184**	**0.121**
Veteran	**–0.645** **	**0.247**	**–0.054**
Alcohol	0.004	0.292	0.001
BAC × 100	0.007	0.011	0.019
Distance from TSC (miles)	–0.068	0.104	–0.015
First TSC Admission	0.388	0.233	0.049
Daytime Admission	**1.305*** **	**0.181**	**0.174**
Intercept	9.846	0.393	

Notes: BAC has been multiplied by 100 to make the results more easily interpretable. Analyses include clustered sandwich estimators for individual IDs to adjust for repeat clients.
* $p<0.05$, ** $p<0.01$, *** $p<0.001$ (two-tailed test)

Analysis of Client Referrals at Discharge

Upon discharge, the TSC may provide clients with referrals to various community organizations or centers.[20] The TSC began collecting information about admission referrals in April 2020. As such, these data are limited because of the lack of availability in the timeframe of data analyzed in this report (52.0% missing). Despite data limitations, we felt it was of interest to explore what factors might be associated with receiving a referral at discharge. Herein, we describe the logistic regression results on client referrals to community organizations or centers upon discharge from TSC, and bivariate results can be found in Appendix B.

We estimated a logistic regression model to predict the likelihood of receiving a referral at discharge. Four predictors were found to be statistically significantly associated with receiving a referral (see Table 4.8). First, BAC at intake was positively associated with receiving a referral. For each 0.01 increase in BAC level, the logged odds of receiving a referral are predicted to increase by 1.8%. Next, having alcohol as a primary substance decreased the logged odds of receiving a referral by 37.0%. Specifically, the predicted probability of receiving a referral for clients with a primary substance other than alcohol is

[20] Examples of referral locations include unhoused day centers, detox centers, Family and Child Services, behavioral health, HOW Foundation, Parkside, and Women in Recovery.

72.5%, while the predicted probability for alcohol users is 63.7%. Housing status increases the odds of receiving a referral at discharge by 50%. Unhoused individuals have a 70.0% predicted probability of receiving a referral, and individuals who are housed have a 61.9% predicted probability. Finally, differences in the odds of receiving a referral at discharge were observed across seasons. With winter as the reference category, the logged odds of receiving a referral at discharge decrease by 96% in the spring, 97% in the summer, and 98% in the fall. Considering predicted probabilities, the probability of receiving a referral at discharge for clients in the winter is 98.1%. In the spring, summer, and fall, the predicted probability decreases to 65.9%, 62.0%, and 47.0%, respectively.

Table 4.8. Logistic Regression Results for Predicting Receiving a Referral (*n* = 1,358)

Variables	b	Standard Error	Odds Ratio
Male	0.009	0.172	1.009
Race/Ethnicity (White reference)			
African American	–0.024	0.200	0.976
Hispanic/Latino	0.073	0.240	1.075
Native American	–0.210	0.221	0.810
Age	–0.001	0.006	0.999
Unhoused	**0.405****	**0.141**	**1.499**
Veteran	0.0601	0.214	1.063
Alcohol	**–0.456***	**0.205**	**0.634**
BAC × 100	**0.018***	**0.008**	**1.018**
First TSC Admission	–0.222	0.154	0.801
Season (Winter reference)			
Spring	**–3.311*****	**0.513**	**0.037**
Summer	**–3.481*****	**0.500**	**0.031**
Fall	**–4.103*****	**0.526**	**0.017**
Intercept	3.976	0.538	53.30

Notes: BAC has been multiplied by 100 to make the results more easily interpretable. Analyses include clustered sandwich estimators for individual IDs to adjust for repeat clients.
* $p<0.05$, ** $p<0.01$, *** $p<0.001$ (two-tailed test)

Summary of Findings from TSC Data

The purpose of these analyses was to gain a clearer understanding of the individuals in Tulsa who are diverted from jail and referred to the TSC. We explored how types of clients varied depending on when the admission occurred and explored the differences in the characteristics of one-admission clients and repeat clients and the timing to re-admission. Finally, we observed characteristics associated with a client's length of stay at the TSC and whether they received a referral to a community organization or center.

Our findings demonstrate that while TPD officers from the Riverside division refer the most clients to TSC (41%), it is still common for officers from Mingo Valley (32%) and Gilcrease (26%) to use it. Regardless, clients are likely to be picked up by TPD officers at a location relatively close to the TSC (88% of all clients are detained at a location less than two miles from the TSC). Many different TPD officers refer clients given that the sobering center is used agency-wide, but some officers are more likely to use the TSC than others. For example, only eight officers are responsible for 10% of referrals. Clients referred to the TSC are overwhelmingly male, White, and approximately 40 years old. The majority of clients are unhoused, and most are not veterans of the United States military. The clear majority are referred to the TSC because of alcohol use.

Table 4.9 summarizes many of the bivariate and multivariate results presented above. The characteristics associated with repeat clients include being male, unhoused, older, and having a high BAC at intake. For the most part, these client characteristics were also consistently related to having a greater count of admissions and being re-admitted to the TSC more quickly. Of note is the lack of statistically significant racial/ethnic differences in the multivariate models. In the bivariate analyses, Native Americans represented a greater proportion of repeat clients than expected, had greater admissions counts, and experienced re-admission in less time. When multivariate models were estimated, however, these effects were found to be largely explained by housing status.

Housing status is a driving factor in predicting the length of stay in the TSC and receiving a referral at discharge. Unhoused clients, on average, have durations at the TSC that last longer, and they are more likely to receive a referral to a community organization or center upon discharge. An additional finding of interest for the length of stay is the nonexistent association between length of stay and BAC at intake. These results suggest that BAC and sobriety monitoring do not play a role in how long a client is likely to stay.

Table 4.9. Summary of Chapter Findings

	Repeat Client		Admissions Count		Time to Re-Admission		Length of Stay		Referral at Discharge	
Client Characteristics	BV	MV	BV	MV	BV	MV	BV	MV	BV	MV
Male	+	×	+	+	–	–	×	×	×	×
White	+	ref	–	ref	ref	ref	–	ref	×	ref
African American	+	×	–	×	×	×	–	×	×	×
Hispanic/Latino	–	×	–	×	+	+	–	×	×	×
Native American	+	×	ref	+	–	×	ref	×	×	×
Unhoused	+	+	+	+	–	–	+	+	+	+
Veteran	×	×	×	×	×	×	×	–	×	×
Age	+	+	+	+	–	–	+	×	×	×
Alcohol Use	+	×	+	×	×	×	×	×	×	–
BAC	+	+	+	+	–	–	×	×	×	+
First TSC Admission	.	.	.	.	.	.	–	×	×	×
Distance from TSC	–	×	×	×	.	.	×	×	×	.
Riverside Division	.	.	.	.	.	.	×	.	×	.
Mingo Valley Division	.	.	.	.	.	.	×	.	×	.
Gilcrease Division	.	.	.	.	.	.	×	.	×	.
Daytime Admission	.	.	.	.	.	.	+	+	×	.
Weekend Admission	.	.	.	.	.	.	×	.	×	.
Winter Admission	.	.	.	.	.	.	×	.	+	ref
Spring Admission	.	.	.	.	.	.	×	.	×	–
Summer Admission	.	.	.	.	.	.	×	.	–	–
Fall Admission	.	.	.	.	.	.	×	.	–	–

Notes: BV = Bivariate Analysis; MV = Multivariate Analysis; + = positive association; – = negative association; × = non-significant association; . = not included in analysis; ref = reference category for analysis.

Analyses of Tulsa Police Data

The Tulsa study setting provides a unique opportunity to address and examine key issues related to the impact of sobering centers on police-civilian contacts. The police data ranged from January 2009 through December 2021. The Tulsa Sobering Center opened in May 2018, which provided the opportunity to conduct a pre/post analysis on changes in specific arrests (e.g., public intoxication arrest) that corresponded with the timing of the opening of the sobering center. This study context also provided a unique data source for understanding officer decision-making, collected by the Tulsa Police Department (TPD): a description of the reasons for intoxication-related arrests after the opening of the sobering center, which allowed for the examination of the various factors associated with intoxication-related arrests when an alternative existed.

When analyzing the official police data in Tulsa, we examined two primary questions:

1. *What proportion of arrests in Tulsa included charges likely to be impacted by a sobering center, including arrests for public intoxication (PI), operating a motor vehicle under the influence (OVI), drugs and/or drug possession (PO), and disorderly conduct (DC)?*
2. *What impact, if any, was seen in changes in arrests, including charges related to these behaviors after the opening of the Tulsa Sobering Center*?

Several analyses provided insight into the arrest patterns for these specific charge types (i.e., arrests where at least one of these charges emerged). For the entire distribution of arrests in Tulsa (Jan. 2009 - Dec. 2021), roughly 27% (N = 72,753) of the 270,491 total arrests for this period included at least one charge for PI, OVI, PO, and/or DC.

To assess the potential changes in official measures of arrests (i.e., arrests where at least one of the charges of interest-PO, PI, OVI, DC-were present within the arrest), we examined official TPD arrest (and charge) data. For the bivariate and regression models presented, arrest counts were specifically measured as outcome variables and were uniquely modeled as each month's arrest measure, operationalized as a composite variable, running from its first through its last day. Consistent with prior research on place-specific initiatives (see Corsaro, Brunson, and McGarrell, 2013), the total number of arrests (per month) was the outcome of interest.

The overlap among arrests where multiple charges for PI, OVI, PO and DC are also noteworthy. In 10.1% of the cases where a person was arrested for at least one specific charge of PI, OVI, PO, or DC (N = 7,369 specific arrests / 72,752 total arrests), the individual was charged with at least one other of these specific charges (e.g., a person arrested for PI was also charged with OVI or PO or DC).[21] Thus, while not uniform, there was a small degree of likelihood that a person charged with any one of these intoxication-related charges would also be charged with multiple disturbance, possession, or intoxication charges.

Additional analyses highlight that individuals charged with disorderly conduct were often (over 1/3 of the time) charged with multiple criminal offenses.[22] On the other hand, individuals charged with OVI, PI, and PO were overwhelmingly (85% to 90%) only charged with those criminal offenses. This suggests that many arrests made in Tulsa were possession only, OVI only, and public intoxication only. These were the types of arrests, at least within Tulsa, that may have been most likely to be impacted by the introduction and usage of a sobering center facility (which began operations in May 2018).

Assessing Impact on Arrests: Tulsa Trends and Interrupted Time Series

Bivariate Trends

In order to assess whether (and to what extent) alternatives to arrest, such as sobering centers, impact arrests, we examined the changes in arrest. The first step in any analysis to assess potential changes in arrest patterns was to examine total arrests over time. As seen in Figure 4.4, without controlling for any temporal, seasonal, or specific fluctuations in the trend data, we see that the average number of total arrests (per month) in Tulsa was 4,680.6 between January 2009 and April 2018. Comparatively, the average count of total arrests from May 2018 (the opening of the Tulsa sobering center) to December 2021 (conclusion of Tulsa data collection/submission) was 3,373.9 arrests per month.[23] Thus, the raw percentage change in total arrests for this pre/post sobering center period was -27.9%, indicating a moderate decline in all arrests for this period of inquiry, net of controlling for any trends, drifts, seasonal influences, or the COVID-19 pandemic).

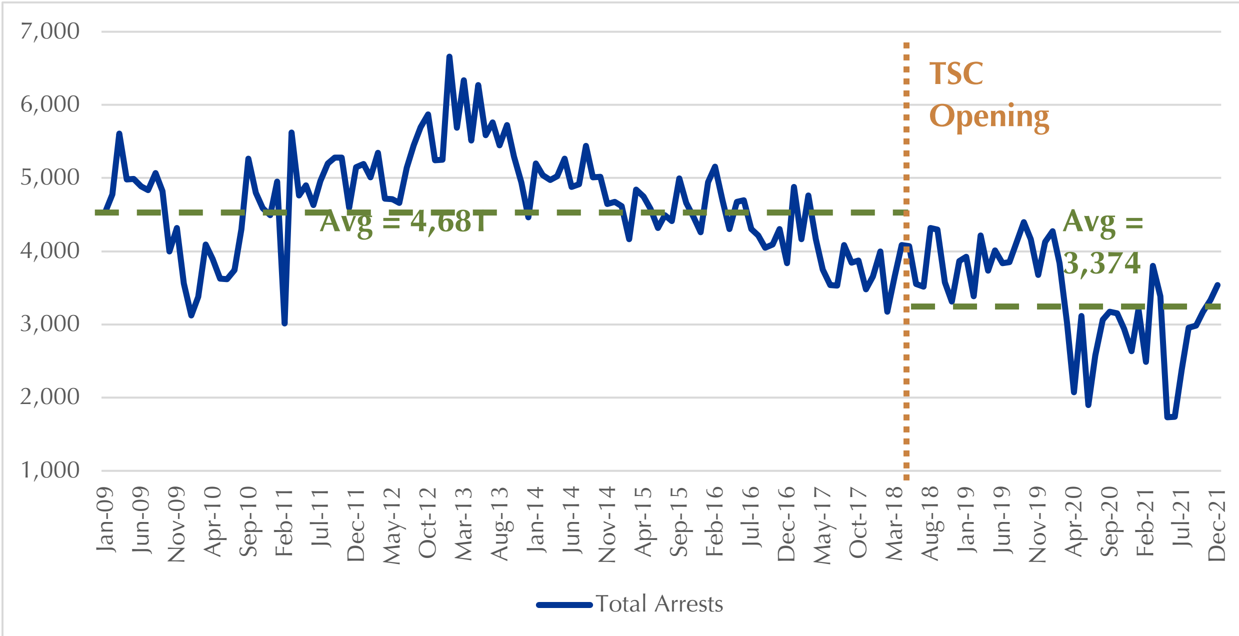
---

[21] In the 'post-sobering center' period only (beyond May 2018), the percent of these charges within arrests was 23.1% (15,045/65,955).

[22] The top ten 'other' charges for people arrested for disorderly conduct were: no driver's license, driving while suspended, trespassing, eluding police, domestic assault, no car insurance while driving, false impersonation, and assault and battery on a police officer. Thus, disorderly conduct charges were most likely associated with additional disruptive behavior.

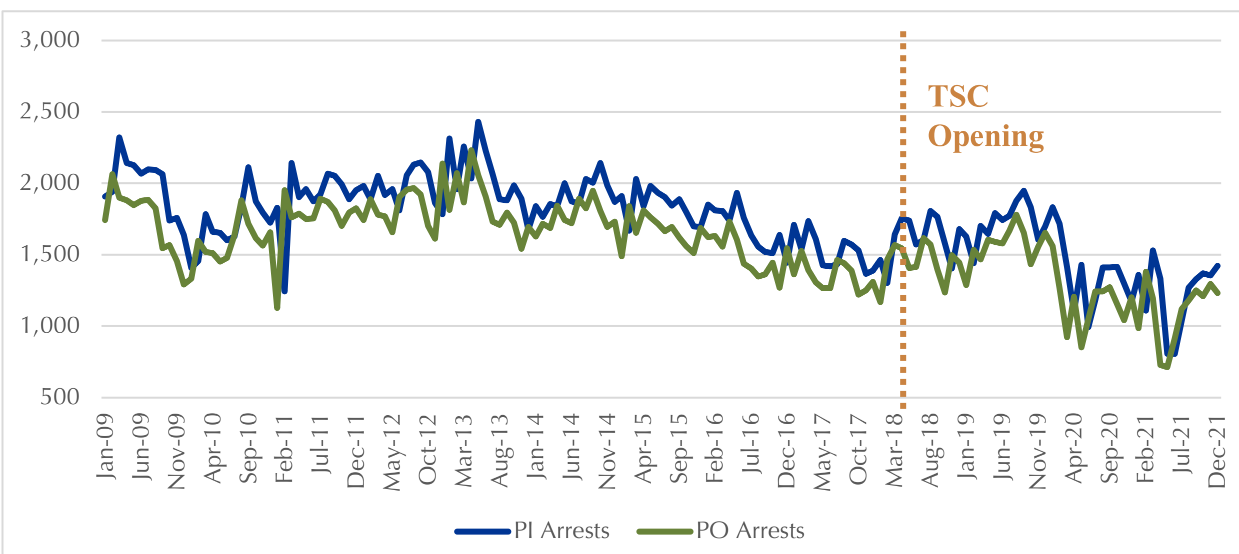
[23] It is important to note that arrests can include multiple charges. The arrest count is person-event specific and not charge specific (e.g., a person arrested for disorderly conduct, public intoxication, and driving under the influence has three charges but only a single custodial arrest, which in these data would equate to a single arrest event).

Figure 4.4. Total Arrests in Tulsa (2009-2021)



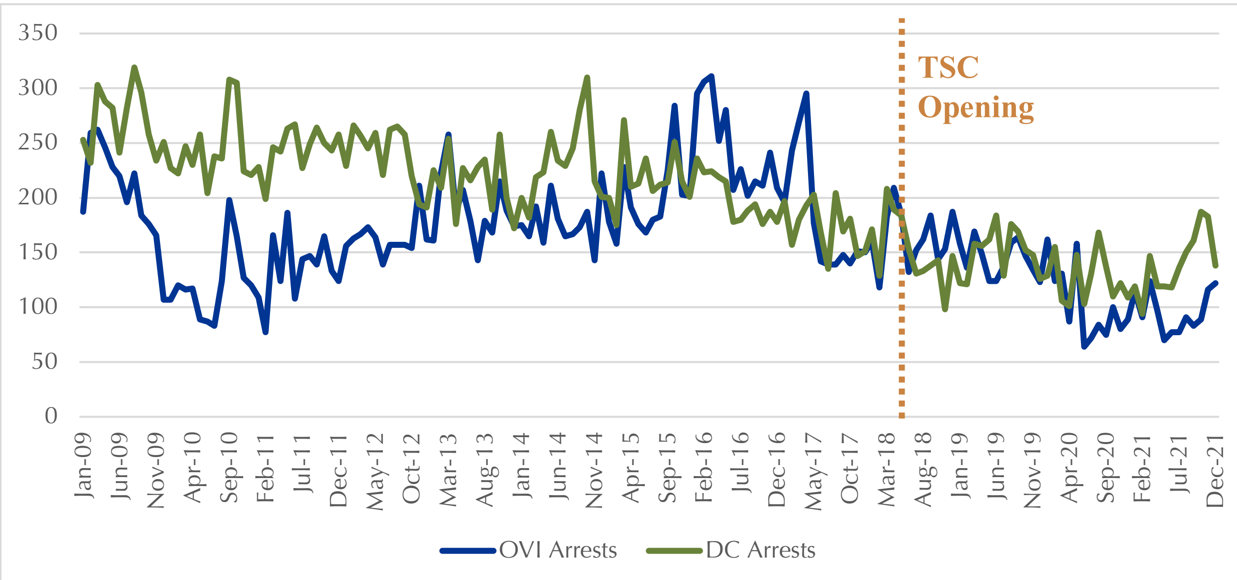
We next examined the four categories of arrests of interest to assess changes in patterns during the same period. The most common arrests where any of these charges were present (i.e., at least one charge was present) were for public intoxication (PI, 11.2% of total arrests) and possession of an illegal substance (9.8% of total arrests). Figure 4.5 demonstrates declines in each during the study period. Public intoxication arrests declined from an average of 1,835.2 per month to 1,476.2 per month in the pre/post sobering center period, which equates to a raw percentage reduction of -19.6%. Similarly, possession-related arrests declined from 1,662.9 to 1,309.4 (-21.3%).

Figure 4.5. Public Intoxication and Possession Arrests in Tulsa (2009-2021)



Additionally, we examined monthly trends in arrests involving operating under the influence (OVI, which comprised less than 4.0% of all total arrests) and disorderly conduct (DC, which comprised less than 6.0% of all total arrests). As seen in Figure 4.6, OVI arrests experienced a decline of 31.6% (from 179.5 per month to 122.7 per month), while DC arrests declined by nearly 38.0% (224.4 per month to 139.1 per month).

Figure 4.6. Public Intoxication and Possession Arrests in Tulsa (2009-2021)



Without controlling for any shifts or major divergences in the arrest patterns, the preliminary bivariate analyses suggest that overall arrests declined by 28%, while specific arrests declined slightly less (PI arrests and PO arrests), similar (OVI arrests), and greater (DC arrests) relative to overall arrests. This bivariate approach of percentage change comparisons has the potential to both under and overestimate percentage changes simply by examining the ebbs and flows without accounting for periods when such shifts are specific and predictable. While not without its own limitations, the most rigorous technical approach available to this study that controls for stationary and predictable temporal factors is to rely on an interrupted time series analysis from a multivariate framework, which we employ next. We specifically sought to examine, net of other temporal factors, which arrest types (if any) changed above and beyond overall arrest patterns.[24]

[24] Clogg-Z Coefficient difference tests allow for statistical comparison of specific arrests (e.g., PI arrests) relative to overall arrests (i.e., the baseline point of comparison). In this case, a statistically significant coefficient difference shows that specific arrests diverged *above and beyond* any changes in overall arrests.

Time Series

The primary covariate for each regression was operationalized as a *sobering center* onset reference measure; we used the sobering center's opening date of May 2018. This measure was created as an indicator variable where months prior to the intervention period (beginning in January 2009 through the month preceding sobering center onset) were defined as the pre-sobering center period (i.e., value = 0). Subsequently, the post-sobering center period (value = 1) serves as the point of divergence.

Additional covariates were included to have more fully specified models. First, the bivariate trend analyses clearly indicated that the total arrest count experienced noticeable and sizable shocks post-April 2020 (the onset of the COVID-19 pandemic, which had a direct impact on crime and arrests). Arrest counts (along with other police activities) declined significantly across the US because of the national shutdown (Nielson, Zhang, and Ingram, 2022). All analyses included a COVID-19 post-period covariate (value = 0 from 1/2009 to 3/2020 and value = 1 4/2020 to 12/2021). Thus, all interpretations of shifts in arrests were 'net of the COVID-19 shock in arrests.' Similarly, we included *monthly dummy variables,* using December as the reference month, to account for seasonal effects (i.e., seasonal shocks) that occurred during specific periods of the year (mostly in the late spring and early summer, which are also seen in the bivariate trend graphs). [25]

[25] A series of sensitivity tests were conducted on each of the models – though not all of the results were presented in the tables presented herein for parsimony. Given that count regression models rely on the use of Maximum Likelihood (ML) estimation and we include the same covariates to control for linear and curvilinear trends and seasonality, this is an appropriate statistical control to account for the first-order autocorrelation process (Harvey 1990). All regression analyses included the exploration of the possibility of broad potential trend influences by adding a simple linear *trend* variable (to account for linear trends) and a *trend-squared* variable ($trend^2$ to account for curvilinear trends) in each model and table presented below. At no point did the included trend-squared measures alter the results in any meaningful or substantive manner, and thus were excluded from the presentation. The count regression time-series model(s) can be written as follows: Monthly count outcomes = Intercept + Post-Sobering Center Onset + Post-COVID-19 pandemic shock + Trend (where statistically significant and thus where needed) + Monthly Seasonal Dummy Variables + Error Term

Table 4.10. Interrupted Time Series Analyses for Arrests in Tulsa Using Maximum Likelihood Negative Binomial Regression (1/2009-12/2021)

	Total Arrests	PI	OVI	PO	DC
	B (SE)	B (SE)	B (SE)	B (SE)	B (SE)
Intercept	8.54** (0.050)	5.02** (0.083)	7.41** (0.046)	5.55** (0.024)	7.61** (0.043)
Sobering Center	-0.104** (0.031)	-0.331** (0.065)	0.024 (0.029)	-0.185** (0.041)	0.045 (0.027)
Controls+					
COVID-19	-0.302** (0.041)	-0.528** (0.056)	-0.273** (0.038)	-0.006 (0.007)	-0.275** (0.035)
Linear Trend	-0.001** (0.000)	0.002** (0.000)	-0.001** (0.000)	-0.004** (0.000)	-0.001** (0.000)
Clogg-Z Coefficient Difference Test Relative to Total Arrests		-0.227** (0.072)	--	-0.081 (0.051)	--
+All regression models include February – December monthly dummy variables (included in models but excluded from tables for parsimony); *p < .05, ** p < .01					

Table 4.10 provides insights into several key patterns related to arrest over time. First, in terms of controls, the COVID-19 (April 2020 onward) indicator variable was statistically significant in all models – showing that arrests declined considerably during the pandemic period. Additionally, there were fluctuating linear trends in each of the estimated models, though the magnitude and size of the estimates were extremely minor across all models. The monthly seasonal measures, included in the models but excluded from the tables, consistently demonstrated seasonal fluctuations in arrest patterns. Second, net of controls, the timing of the sobering center corresponded with a 9.9% decline in total arrests, which for our analyses, served as the standard baseline of comparison in the full regression models.[26] More specifically, in the bivariate trend analysis, we estimated a reduction in overall arrests by -28%, but this was most likely associated with the trends, shifts, and COVID-19 impact of the study period. Once these factors were controlled for in the models, the estimated post-sobering center opening decline in all arrests was roughly -10%. Third, public intoxication arrests experienced a statistically significant decline of 28.2% (Exp(-.331)) after Tulsa's sobering center opened. Fourth, possession arrests experienced a statistically significant decline of 16.8% (Exp(-.185)) during this same

[26] To calculate percentage changes via the Poisson regression estimates, we first exponentiate the coefficients to calculate the incident rate ratio. Then we use the following formula to derive the percentage change: 1.00 - IRR = % change.

period. By contrast, neither OVI nor DC arrests experienced a statistically significant shift before and after the sobering center opened, net of controls.

As noted previously, the primary research question for this set of analyses was what impact the sobering center may have had (or at least corresponded with in terms of timing) on the specific types of arrests examined here. The final parameter included in Table 4.10 was the Clogg-Z Coefficient Difference test to assess whether any of the significant estimates (i.e., PI and PO arrests) declined above and beyond the changes in total arrests (parallel with a difference-in-difference estimation). The results showed that arrests with public intoxication charges experienced a statistically significant decline of 20.3% (Exp(-.227)) *above and beyond* the changes experienced in total arrests. Comparatively, the reduction in possession arrests occurred similarly (and thus not distinctly) to total arrests.

Supplemental Time Series on Arrest Changes by Race

Given that the time series analyses indicated there was an observed statistically significant decline in public intoxication arrests in Tulsa, above and beyond any changes in total arrests, we wanted to examine the change in public intoxication arrests for Black, White, and Hispanic arrestees during the same period of examination. The analyses indicate that the greatest reductions in public intoxication arrests were for Hispanic arrestees (-55.3%). White arrestees experienced the second largest decline in arrests for this arrest charge at -40.0%. Native American arrestees experienced a -30.8% decline in the post-sobering center period. During the post-COVID (April 2020 onward) period, the only racial/ethnic groups that experienced a decline specific to that period was among Native American arrestees by -32.6% and White arrestees by –22.2%. Finally, Black arrestees experienced the lowest decline in arrests for public intoxication charges at 20.7%. Each of the differences were divergent from one another.[27] In sum, while the benefit of a significant decline in arrests were observed for all racial/ethnic groups, Black arrestees experienced the lowest overall decline in public intoxication arrest changes. Additionally, only White and Native American arrestees were arrested at a significantly lower rate in the post-COVID period in this study period.

[27] Clogg-Z coefficient difference tests were run separately for each racial/ethnic group.

Table 4.11. Time Series Analysis of Public Intoxication Arrest Changes by Race in Tulsa

	White Public Intoxication Arrests	Hispanic Public Intoxication Arrests	Black Public Intoxication Arrests	Native Am Public Intoxication Arrests
	B (SE)	B (SE)	B (SE)	B (SE)
Intercept	4.24** (0.039)	2.37** (0.109)	3.93** (0.543)	3.24* (0.086)
Sobering Center	-0.524** (0.050)	-0.806** (0.099)	-0.233** (0.041)	-0.369* (0.075)
Controls+				
COVID-19	-0.251** (0.071)	-0.082 (0.131)	-0.088 (0.077)	-0.395* (0.106)
Linear Trend	-0.001 (0.001)	-0.000 0.000	-0.000 (0.000)	-0.000 (0.000)

+All regression models include February – December monthly dummy variables; *$p < .05$, ** $p < .01$

Summary of Time Series Findings

While total arrests, as well as PI, PO, DC, and OVI arrests, declined over the period of inquiry, the findings from the time series models show that for the majority of arrests (and specifically for OVI and DC arrests) this was due in varying degrees to the COVID-19 pandemic, linear trends, and seasonal fluctuations. Once these factors were accounted for, we still saw an overall reduction of 10% in total arrests, which served as a baseline point of comparison (since sobering centers are not designed to reduce total arrests but rather specific types of arrests). The coefficient difference test highlighted that public intoxication arrests declined by 20% above and beyond any changes in total arrests showing that where the sobering center had a potential impact as an alternative to arrest in Tulsa, it was for public intoxication arrests specifically.

Unique Data Source and Analysis: Public Intoxication Arrests in Tulsa Post-Sobering Center

Since March 2018 (the opening of the sobering center), TPD has collected information on all public intoxication arrests (i.e., what was the 'reason for the arrest' for public intoxication since there is an alternative to this arrest). Thus, the expectation is that officers will divert individuals to the sobering center rather than arrest them whenever possible. Given this, it is unsurprising there was a statistically significant decline in public intoxication arrests (only) in Tulsa. Among the five jurisdictions in this study, only TPD collects specific data on why a public intoxication arrest occurs after the sobering center was opened (as a mechanism to ensure that the TPD officers are following the agency policy on diverting intoxication-only arrests). This section summarizes key information about PI arrests in Tulsa post-sobering center onset. Some measures (e.g., reason for arrest) were available for the entire data collection period, while other information (e.g., unhoused status of arrestee) was not initially collected but later included as more comprehensive information became collected by TPD.[28]

Among the 3,210 individuals who were arrested for public intoxication (in lieu of being diverted to the sobering center) in Tulsa, the most common reason is for aggressive and/or violent behavior (i.e., assault, assault with a deadly weapon, resisting arrest, battery, domestic violence, and causing a disturbance). Roughly 12% were arrested for an outstanding warrant (removing officer discretion from the equation). Fewer than 10% were arrested for property crime or possession of drugs (i.e., beyond legal limit or with intent to sell). Roughly 38% were arrested for 'other' reasons.[29]

Table 4.12. Reasons for Public Intoxication Arrests in Tulsa (Post-Sobering Center Opening), March 2018 – July 2021

Reason for Arrest (Public Intoxication Charge)	Frequency	Percent
Aggression and Violent Crime	1,284	40.0%
Other (obstruction, refused officer orders, etc.)	1,220	38.0%
Warrant	385	12.0%
Property Crime and/or Trespassing	193	6.0%
Possession of Illegal Substance/Materials	128	4.0%
Total	3,210	100%

Summary of Findings from TPD Data

Given that sobering centers are an alternative to arrest, we anticipated a change (reduction) in specific types of arrests following the opening of the Tulsa Sobering Center. Specifically, we expected to see a decline in arrests where the person was under intoxication, under the influence of drugs and/or alcohol, or public disturbance arrests given that individuals under the influence are more at-risk for being involved in nuisance/disturbance arrests. The bivariate and multivariate time series analyses indicated

[28] There were 3,958 arrests for public intoxication between March 2018 and July 2021 (the end of the data submitted for this component of the study). For these events, 748 cases had missing data (and thus were excluded from graphs and figures), leaving a valid N = 3,210 arrests. It is also worth noting that TPD began collecting data later on unhoused status of arrestees, and the findings (N = 2,712 total) show that 41.2% were unhoused at the time of arrest.

[29] The 'other' category of arrests included the following distribution: 38.9% obstruction of justice charges, 35.7% of 'other' charges, 10.2% refusing to follow officer commands, and 8.3% refused to attend sobering center in lieu of arrest.

a pattern of findings consistent with our research hypotheses (i.e., that the opening of the sobering center would significantly impact these specific types of arrests).

Our examination of the impact on arrests after the opening of the sobering center in Tulsa point to three key findings. First, the 20% reduction in public intoxication arrests was statistically significant, above and beyond any and all changes in total arrests and net of time-varying controls. No other arrests related to intoxication experienced the same type of decline, net of controls. Second, after the sobering center was opened TPD documented (why officers were making public intoxication arrests. The vast majority of reasons were for violence (40% of the cases) and outstanding warrants (12% of the cases) that limited officer discretion. Thirdly, while public intoxication arrests for all racial and ethnic groups experienced significant declines, the greatest declines were observed for Hispanic and White arrestees in Tulsa.

Results of Focus Group with Tulsa Police

On August 22, 2022, we traveled to the Tulsa Police Department (TPD) to engage in a single focus group of TPD officers on the use of the Tulsa Sobering Center (TSC). This group was smaller and differed from other focus groups in this research in that it was comprised of only three male officers, including a deputy chief, one patrol officer, and one specialized task force officer (assigned to unhoused outreach). The officers were high-utilizers of the sobering center (based on sobering center officer ID data) and included their perceptions of other officers who are high-utilizers. The morning focus group lasted about 30 minutes. The conversation began with a short statement from the lead researcher about the purpose of the focus group, the scope of the conversation, and the officers' anonymity guarantees. Approximately nine open-ended questions were used to guide the conversation. The primary goal of this focus group was to understand TPD officer decision-making in using sobering centers in lieu of arrest.

Benefits and Obstacles

The focus group discussion began by asking officers to describe the benefits of using the sobering center in their city. Officers relayed that the sobering center is fast, easy, and relatively convenient, making time management one of its biggest benefits. The sobering center intake process is much more efficient than taking someone to jail, saving valuable officer time. One of the reasons why the sobering center saves time is the protocol for managing personal property. It is TPD policy that no property can be left behind after an individual has been detained. When an individual is taken to jail, all personal property must be properly booked, stored, and documented. Given that a large proportion of the sobering center clientele are unhoused, the list of personal property can become quite extensive (e.g., "Doesn't matter if it is a $4,000 TV or a cocktail napkin, it is personal property"). Clients will stay at the sobering center for only 10 hours. Because of this short duration, the sobering center can store the property without a thorough documentation process.

In addition to the time-saving benefits, officers who used the sobering center frequently stated that the sobering center provides a direct avenue to treatment for individuals. Officers will often try to encourage clients to begin a life-changing journey on the way to the sobering center to encourage them to get help (something that is far more infrequent when transporting civilians to jail). Unlike jail, the sobering center provides clients opportunities for help.

Next, officers were asked to describe challenges or obstacles to using the sobering center. The officers felt there were no major challenges or obstacles directly related to using the sobering center, however a few minor challenges were described. For instance, the officers highlighted that many officers (i.e., their peers) view a punitive response as more appropriate than a treatment response. As such, it is hard to get buy-in on the utility of the sobering center from these officers because they believe people need to be locked up.

Another concern of the officers was the procedure for searching clients for contraband before being admitted. The officers felt the pat down and search process of clients was not as thorough as it should be. The concern was that less thorough searches could lead to contraband getting into the sobering center, resulting in further substance use and potential overdose within the facility. It should be noted that there is a desk with a camera in the sobering center where all possible contraband should be removed from the person (e.g., personal property can be stored in a locker) before being admitted and taken back to the holding area.

In describing negative experiences officers have faced when using the sobering center, their main concern was what can happen after an individual has been admitted. Specifically, the officers felt the sobering center needed a more secure area to help prevent property damage within the facility. It was mentioned that there had been instances where clients have engaged in destructive behavior, such as tearing down drywall and clogging toilets. When such behavior occurs, TPD officers have to return to the sobering center to make an arrest and transport the individual to jail, which officers felt was an inconvenience. Officers had similar feelings regarding client welfare and suicidal ideation after being admitted to the sobering center. When these events occur, the sobering center often relies on TPD patrol officers to deal with them. The officers felt that this service would be better handled by a community partner available 24/7. The common theme of negative experiences identified by the officers was that they do not like having to come back to the sobering center to deal with clients after they have already been admitted.

Finally, the interviewed officers suggested there was a lingering concern that some peer officers are fairly pessimistic about chronic users getting treatment, and may not see the utility of continually dropping off at the sobering center. In terms of challenges, officers appear frustrated by the chronically intoxicated individuals they regularly transport to the sobering center. At times, they feel it is difficult to deal with the same person repeatedly. When dealing with chronic users, they sometimes resent the individual and feel sobering center resources could be better spent on individuals who want to get sober. Yet, at the same time, officers wish there was a way for them to hear feedback from the sobering center about some of the clients they have brought in. In short, perceived police cultural response to the sobering center persists as a concern for those interviewed (though to a much lesser extent than when the sobering center initially opened).

Officer Decision-Making

During the focus group discussion, officers were asked to describe their decision-making when faced with a publicly inebriated person. When deciding to intervene with an inebriated person in public, the driving factor was that the police had received a call for service about the individual. These calls for service are most often reported as a disturbance or failure to leave. As such, the decision to intervene is often not proactive; instead, the police respond when they are asked to respond. While it is uncommon for officers to intervene with inebriated individuals without a call for service, when they do, it is often because the individual is observed stumbling into the street, sleeping in problematic or dangerous locations (e.g., the street, train tracks, in front of entry ways to businesses or dwellings), or they are a chronic inebriate who is, "just not ready for society today."

When deciding to take an individual to the sobering center or jail, officers mentioned the sobering center is the preferred destination. As mentioned by one of the officers, when people have warrants or are aggressive, they need to be taken to the appropriate place—jail. Yet, those who have had a bad day or made a bad decision and are too intoxicated should have a place to go that matches their problem and does not have the consequences associated with being charged and going to jail. Aside from the decision between jail or sobering center, the officers mentioned that minimizing the number of inebriates who are taken to the hospital is a priority. Therefore, the hospital is only an option when an individual is faced with a medical emergency.

Supervision

Officers were asked to describe supervisory expectations regarding sobering center use. Overall, the officers did not have much to say regarding these expectations. They felt supervisors and administration supported the idea of the sobering center. Yet, they also felt there was limited supervisory emphasis on requiring the use of the sobering center in lieu of arrest. Notably, while the officers in the focus group felt there was little reinforcement by the administration, TPD officers are required by policy to document in an arrest report for a public intoxication arrest why they chose to forgo the sobering center. As such, the use of the sobering center is at least encouraged through policy by the TPD administration.

Impact of Geography

Lastly, officers were asked whether the location of the intoxicated citizen had any impact on the decision to take them to the sobering center or jail. Overall, the officers felt the intoxicant's location did not play a role in deciding what to do with individuals. They did note that geography does play a role in where most of the clients are coming from. From their perspective, most of the sobering clients do not come from the downtown area. Instead, most interactions with intoxicated individuals worthy of being taken to the sobering center occur outside town. The unhoused population is believed to be moving away from the downtown area to locations with highway access, liquor stores, and better opportunities for panhandling. Since these areas are away from downtown, there are fewer services available. The police, therefore, are often the ones responsible for handling problems that may arise with these individuals.

Officer Recommendations

Specifically, the officers felt it would be encouraging to hear “good” stories about clients who chose treatment and got sober. Such stories would help officers feel they are actually doing something good by using the sobering center. When the sobering center conducts internal analyses and follow-up with prior clients, and there is a story that resonates with the staff (e.g., a person completed treatment, gained housing, and has since been living sober and healthier), the TPD would benefit from the sharing of that information (to reinforce the importance of the sobering center as an alternative to arrest).

Concluding Remarks

Overall, the participating officers enjoy the availability of the sobering center and believe most of their colleagues feel the same. Officers find that the sobering center is much more efficient than taking publicly intoxicated individuals to jail. The efficiency of dropping off clients allows officers to save time and lets them get back to patrolling their beat, where they feel they can get back to “real police work.” Compared to jail, the officers perceive that the sobering center provides clients with better opportunities to get help.

CHAPTER 5: WICHITA, KANSAS

Wichita is the largest city in Kansas, with 395,699 residents in 2021. Located in the Midwest, Wichita is the 48th largest city in the United States. The majority of Wichita residents are White (62.5%), followed by Hispanic (18.2%), Black (10%), Asian (4.8%), two or more races (4.4%), and other (0.8%). The median household income in Wichita is $53,466.

Policing services are provided to the City of Wichita through the Wichita Police Department (WPD). The WPD is comprised of 612 sworn officers and 182 civilian employees, based on 2016 data, and is responsible for 139 square miles of jurisdiction. Based on the 2016 LEMAS statistics, the WPD receives about 234,000 calls for service each year and dispatches officers to all calls. In 2022, the WPD had a reported operating budget of 102 million dollars (Hack, 2022). Part of the Field Services Division, the Unhoused Outreach Team (HOT) at WPD is responsible for responding to 911 calls regarding unhoused individuals and focuses on diverting individuals from jail into other services, such as sobering facilities; they are the primary law enforcement partner of the Wichita sobering center.

Compared to the other case study sites, Wichita is unique because there is no state law prohibiting public intoxication in Kansas. However, when officers must respond to a person who is intoxicated and in need of assistance, guidance for diversion is included in WPD's Mental Health SOP 519. Additionally, due to the lack of criminal law in Kansas, officers are encouraged via WPD policy to divert individuals from court and jails in lieu of taking individuals in need to service providers and to the Sedgewick County Coordinating Crisis Center (CCC) in particular. Though officers in all four patrol bureaus can utilize the CCC, it is primarily used by the H.O.T. unit.

Sobering services in Wichita are provided by the Sedgewick County Coordinating Crisis Center (CCC), which is co-operated by COMCARE (mental health services provider) and the Substance Abuse Center of Kansas (SACK; substance abuse services provider). Located in downtown Wichita, the CCC opened in February 2015 to provide rapid stabilization for individuals to divert them from emergency departments and jails. Clients are brought to the CCC by WPD and various other emergency service providers, and staff at the CCC determine the most appropriate service(s) based on the client's needs. The CCC provides crisis services such as 24-hour crisis observation, sobering, detox, peer crisis, and local transportation.

The sobering unit referred to as "SACKSU" has four beds post-pandemic (8 beds, pre-pandemic) dedicated to sobering. The SACK sobering and detox units are funded through various municipal, county, and state funding sources. Staying in the SACKSU is voluntary, and clients can remain in the unit for up to 23 hours, although the average stay is about

10 hours. Open 24/7, the sobering unit staff rely on a short intake process to gather basic client information, administer a breathalyzer test, and ask about recent drug use. No clients are denied admittance based on substance alone, but instead may be denied if they are too intoxicated to participate in the intake process. No medical staff are on-site for the sobering unit, and clients are not typically provided any food. Instead, clients are encouraged to seek services for food, laundry, and other needs from resources in the surrounding area. As part of the discharge, SACKSU staff discuss plans with clients for the next steps and gather contact information for a client's follow-up call ten days post-discharge.

Analyses of Wichita Sobering Center

This section of the report relies on data collected by the sobering center in Wichita, known as the Substance Abuse Center of Kansas Sobering Unit (SACKSU). The primary unit of analysis is an individual admitted to the sobering center, referred to as a "client." The SACKSU began data collection on February 25, 2015. Variables captured since the start of data collection include the client referral source, if the client was transferred to detox, and the duration of stay. Additional variables have been incorporated in data collection efforts, including race/ethnicity, housing status, substances used at admission, and date of birth. The analyses in this report are based on SACKSU data collected through February 11, 2021. Table 1 in Appendix C presents a detailed description of all SACKSU variables used in the following analyses, including the variable definition, date range of availability, and how the variable was coded and used in analyses.

The purpose of analyzing these sobering center data is to understand SACKSU use and its clientele overall. As such, in this section, we explore five broad research questions:

1. *What are the trends in SACKSU admissions?*
2. *What are the characteristics of the SACKSU clientele?*
3. *Are there differences in the characteristics of one-admission and repeat-admission clients (those who have been admitted to the SACKSU on multiple occasions)?*
4. *What client characteristics are associated with differences in the length of stay per admission at the SACKSU?*
5. *What client characteristics are associated with a client being transferred to detox after discharge from the SACKSU?*

Several analyses provide insight into these research questions. Descriptive, bivariate, and multivariate analyses are all used to glean a clearer understanding of the use of the SACKSU and its clientele, who otherwise would likely be transported to jail if the SACKSU was not an available alternative.

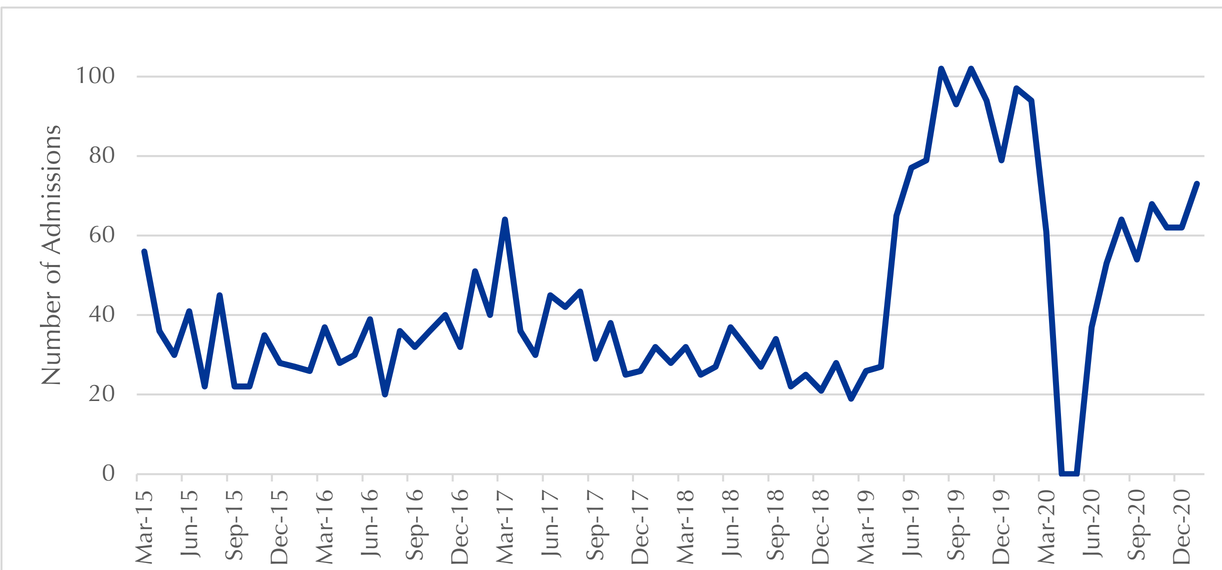
Trends in Sobering Center Client Admissions

This section provides a descriptive exploration of the trends in SACKSU's admissions. Specifically, charts and descriptive statistics are used to demonstrate the trends in admissions counts, characteristics of admissions and the use of SACKSU, and the characteristics of the clients referred to the SACKSU.

Trends in Admissions

From February 25, 2015, to February 11, 2021, the SACKSU had a total of 3,082 admissions. This corresponds to approximately 515 admissions per year or 43 admissions per month. Figure 5.1 displays the admission counts by month for all months with complete data. By observing the trend in admissions over this period, it is apparent that admissions were impacted by COVID-19. Specifically, SACKSU expanded its number of clients starting in May 2019. The following year, however, the COVID-19 outbreak began. Admissions to the SACKSU were put on hold, with no admissions in April or May 2020. In June 2020, admissions resumed, and the number of clients rose to near pre-COVID-19 counts.

Figure 5.1. SACKSU Admissions Counts by Month from 3/1/2015 to 1/31/2021 (*N* = 3,050)



Estimate of Jail Days Saved

Based on the SACKSU admission counts, we calculated an estimated number of "jail days" saved if each sobering center admission was a true diversion from an arrest and jail admission. The number of "jail days" saved was estimated by multiplying the number of yearly admissions by the average time spent in the sobering center per admission per year (measured in hours). This number was then divided by 24 to estimate the number of "days" saved. Table 5.1 shows the number of jail days saved per year. By our estimates, 3,082 clients over approximately six years stayed a total of 33,417 hours in the SACKSU.

This translates into approximately 1,571 days since the SACKSU has been in operation, although variation exists across years.

Table 5.1. Estimated Jail Days Saved by Diversion to Sobering Center by Year (*N* = 3,082 admissions)

	Jail Days Saved
2015*	117
2016	130
2017	150
2018	112
2019	402
2020	417
2021*	65

Note: * indicates when data does not cover the full calendar year.

Admission Characteristics

The SACKSU is available 24 hours a day, seven days a week. Table 5.2 displays the descriptive statistics for SACKSU admission characteristics. There were slightly more admissions occurring at night (from 7:00 PM to 6:59 AM) than during the day (52.6% versus 47.4%). Admissions across days of the week were fairly consistent, with the lowest proportion of admissions occurring on Saturday (11.1%) and the largest proportion occurring on Tuesday (16.2%). The admissions split between work days and weekends was about 2 to 1, with approximately 62.4% of admissions occurring during the work week (Monday, Tuesday, Wednesday, and Thursday) and 37.6% occurring over the weekend (Friday, Saturday, and Sunday). Admissions were relatively consistent across seasons, with 26.6% occurring in the fall, 26.7% in the winter, 19.8% in the spring, and 26.9% in the summer. It should be noted, however, that the distribution of counts by season is skewed due to data availability. For example, the SACKSU had no admissions during the start of the COVID-19 pandemic. Therefore, data for two months in Spring 2020 (April and May) are systematically missing. Nonetheless, a significant association was found between the time of day and whether the admission occurred during the work week or the weekend ($\chi^2 = 19.887$; $df = 1$; $p < 0.001$). As expected, a larger proportion of admissions over the weekend occurred during nighttime hours compared to the SACKSU admissions during the work week (57.8% vs. 49.5%).

The zip code for the place of residence for all SACKSU clients was collected in the SACKSU database. Nearly half (48.0%) of all clients were from the same zip code as the SACKSU—67203. In total, 136 unique zip codes are included in the SACKSU's database. Of note, however, was that 75% of clients resided within only nine unique zip codes, and approximately 90% of clients were from the same 27 zip codes.

The SACKSU collects detailed information regarding who referred the individual to be admitted to the sobering center. The most common referral source was the clients themselves (36.8% self-referrals). The next most common referral source was from places that provide recovery services (e.g., Alcoholics Anonymous, Oxford Houses, sobering living facilities, and substance abuse centers). Recovery services were responsible for 21.4% of SACKSU admissions referrals. Family or friends (17.7%) and hospitals or medical services (14.3%) were the next most popular sources of referrals. Of interest is the low count of direct referrals from law enforcement (6.3%).[30]

Table 5.2. SACK Sobering Unit Admission Characteristics (n=3,082)

	%
Daytime Admission	47.4
Day of the Week	
Sunday	12.2
Monday	15.0
Tuesday	16.2
Wednesday	15.5
Thursday	15.7
Friday	14.3
Saturday	11.1
Weekend Admission	37.6
Season of Year	
Winter	26.7
Spring	19.8
Summer	26.9
Fall	26.6
Referral Source (*N* = 3,075)	
Self	36.8
Family/Friend	17.7
Recovery Services	21.4
Community Services	1.1
Hospital/Medical	14.3
Law Enforcement	6.3
Corrections Agency	2.3

Client Characteristics

Table 5.3 contains descriptive information about clients admitted to the SACKSU. Individuals admitted during the data timeframe were overwhelmingly White (77.4%). Among other racial/ethnic groups, 11.0% of admissions were African American, 7.1%

[30] Due to the fact that the SACKSU is situated within the CCC, law enforcement typically drop off clients to the CCC. CCC staff decide the most appropriate placement for that individual based on their needs, such as admission to the SACKSU.

were Hispanic/Latino, and 4.2% of admissions were Native American (0.3% were identified as being Asian or "other"). Nearly half of the clients admitted (43.7%) were individuals who were identified as being unhoused at the time of admission. Unfortunately, information regarding the gender of the admitted client was not provided to our research team. Looking at age distribution at intake across all admissions, the average age was 39.12 years (nearly an 11-point standard deviation) with a median of 38 years.

The SACKSU started collecting information on the substances used by the client at the time of admission in May 2019 (53.6% missing in the timeframe of these data). For the 1,430 cases with valid data on this variable, the most common substances used by clients admitted to the sobering center were methamphetamine (54.6%) and alcohol (51.1%). Other substances are displayed in Table 5.3.

Given that the SACKSU collects information on all substances used by clients, information on multiple substance users can be examined. As such, 74.1% of clients were identified as being single substance users, while 25.9% were identified as using more than one substance at the time of their admission to the SACKSU. When considering how many substances were being used, 19.0% were identified as using two, 6.0% were using three, and 1.0% were identified as using four or five substances. Of the single substance users, 49.9% were identified as users of alcohol only, and 44.1% were identified as users of methamphetamine only.[31]

The SACKSU data collection efforts attempt to track individual clients. As such, a unique identifier is collected that corresponds to a specific individual that can then be used to track the individual across repeated visits. Of all admissions, 59.6% were first-time SACKSU clients. The remaining 40.4% were repeat clients. In total, 1,825 unique clients made up 3,063 SACKSU admissions.[32] The average number of admissions per individual equaled 1.7, with a standard deviation of 1.8. The median and modal frequency of admissions were equal to 1 (72.9% had only one admission), and the data ranged from a minimum of 1 to a high of 22.

Finally, variation exists for how long clients stay at the SACKSU. The average length of stay at the SACKSU per admission was 10.8 hours (standard deviation = 6.3). The distribution of data on the length of stay for admissions ranged from 0 to 28.5 hours, with a median duration of 10 hours. The majority (51.2%) of clients stay at the SACKSU for more than four but less than 13 hours before being released.

[31] While less frequent, the substance used by the remaining 6% of single substance users included heroin/opioids (1.5%), benzodiazepines (0.2%), and cocaine/crack (4.3%).

[32] *n* = 19 cases had a missing unique identifier. As such, these cases are removed for any analyses on repeat clients.

Table 5.3. SACKSU Client Characteristics

	Mean (SD) / %
Race (N=2,356)	
White	77.4
African American	11.0
Hispanic/Latino	7.1
Native American	4.2
Other	0.3
Unhoused (N=2,351)	43.7
Age (N=747)	39.12 (10.76)
Substance (N=1,430)	
Any Alcohol	51.1
Any Methamphetamine	54.6
Any Heroin/Opioids	9.1
Any Benzodiazepines	3.0
Any Marijuana	4.8
Any Cocaine/Crack	10.1
Other Substance	0.8
Number of Substances (N=1,430)	1.34 (0.64)
Multiple Substance User (N=1,430)	25.9
Repeat Visit (N=3,063)	40.4
Visit Number (N=1,825)	1.68 (1.78)
Stay Duration (hours) (N=3,081)	10.84 (6.28)

Admission Trends by Client Characteristics

Next, we analyzed the SACKSU data to test for potential bivariate associations between trends in admissions—including time of day, day of the week, and season of the year—and characteristics of the individuals admitted to the SACKSU and their length of stay at the SACKSU. The client characteristics explored include age, race/ethnicity, housing status, alcohol use, multiple substance use, repeat client, and referral source. The appropriate bivariate statistical test (i.e., chi-square test for independence, independent *t*-tests, or one-way analysis of variance) is used depending on the level of measurement of the two variables. Due to the length of these analyses, they are included in Appendix C at the end of this report.

Analysis of One-Admission vs. Repeat Clients

We next examined whether differences exist between clients who are admitted to the SACKSU only once ('one-admission client') compared to those who are admitted to the SACKSU two or more times ('repeat client'). As detailed above, 1,825 unique individuals were responsible for the 3,063 total admissions into the SACKSU during the timeframe of the data. Of the 1,825 unique individuals, 1,330 (72.9%) were identified as being single admits, and 495 (27.1%) were identified as repeat admits.

To identify any potential differences between single and repeat clients, we analyzed associations at the individual level (rather than the admission level)[33] across client characteristics, including age, race/ethnicity, housing status, use of alcohol, use of more than one substance, and whether the individual was a self-referral to the sobering center. Bivariate and multivariate analyses are used to address three areas of interest associated with potential differences between one-admission clients and repeat clients: 1) the characteristics associated with being a repeat client, 2) the characteristics associated with the number of times each client has been admitted to the SACKSU, and 3) the characteristics associated with the timing to re-admission to the SACKSU. Note that the bivariate associations can be found in Appendix C, and multivariate analyses are presented herein.

Multivariate Analysis of Repeat Clients

Next, we conducted a multivariate analysis using logistic regression to identify the characteristics associated with being a repeat client of the SACKSU while accounting for the influence of all other characteristics included in the model. Once again, analyses were estimated at the individual level, with each unique individual being identified as either a one-admission client or repeat client. Once all client characteristics were simultaneously considered in the multivariate model, three characteristics were significantly associated with being a repeat client to the SACKSU (see Table 5.4).

[33] The admissions data obtained from the SACKSU is collected in a long format, where information from each admission is represented in a single row. As such, repeat clients will be represented by multiple rows that contain information for each unique admission. To perform the analyses in this section, we took the admissions database and transformed it into an individual database using the unique identifier collected by the SACKSU. Known as a wide format, each row in the transformed database represents a single client (based on their unique identifier). For repeat clients, data from subsequent admissions are displayed as additional columns in the database. Client characteristics, were obtained by calculating the average across admissions for each unique individual. It is those averages that are used in these analyses.

Table 5.4. Logistic Regression Results for Predicting Repeat SACKSU Clients (*n* = 918)

Variables	*b*	Standard Error	Odds Ratio
Race/Ethnicity (White reference)			
African American	0.403	0.225	1.496
Hispanic/Latino	**–0.709***	0.349	0.492
Unhoused	**0.868*****	0.168	2.381
Alcohol User	**1.142*****	0.165	3.133
Multiple Substance User	–0.330	0.190	0.719
Self-referral	0.315	0.170	1.370
Intercept	–1.978	0.190	0.138

Note: Age is excluded because of missingness (listwise deletion results in a loss of *n* = 386 cases).
* p<0.05, ** p<0.01, *** p<0.001 (two-tailed test)

First, housing status was associated with being a repeat client of the SACKSU. The logged odds of being a repeat client are 2.4 times greater for unhoused individuals compared to those who are housed. With all other characteristics held at their averages, individuals who are housed have a 22.0% probability of being repeat clients of the SACKSU. For unhoused individuals, the predicted probability of being a repeat client increases to 38.6%.

The second statistically significant predictor of being a repeat client to the SACKSU was being a Hispanic/Latino compared to a White client. Being Hispanic/Latino reduces the logged odds of being a repeat client by half. In particular, the predicted probability of being a repeat client to the SACKSU for an individual who is Hispanic/Latino is only 17.0%. This predicted probability increases to 28.5% for clients who are White.

Finally, the last statistically significant predictor of being a repeat client was the use of alcohol. In these data, the logged odds of being a repeat client are 3.1 times greater for alcohol users than clients who do not use alcohol. Examining predicted probabilities for these variables, we found non-alcohol users have an 18.6% probability of being a repeat client, while the probability of being a repeat client increases to 40.3% for users of alcohol.

Analysis of Admissions Counts

As a supplemental analysis to the analysis of repeat clients, we explored what characteristics are associated with the number of SACKSU admissions per individual. The bivariate associations can be found in Appendix C. We used negative binomial regression to simultaneously examine the possible characteristics associated with the number of

SACKSU admissions per individual.[34] The findings in Table 5.5 mostly reflect the same pattern observed in the logistic regression analysis above. While race/ethnicity was not statistically significantly associated with admissions counts, housing status, alcohol use, multiple substance use, and referral source were statistically significantly associated. Unhoused clients are found to have an incident rate for SACKSU admissions that is 1.5 times greater than clients who are housed, alcohol users have an incident rate that is approximately 68% greater than that of non-alcohol users, the incident rate for multiple substance users is approximately 19% lower than single-substance using clients, and clients who are self-referrals have an incident rate that is approximately 17% greater than the rate of clients who are referred from a different source.

Table 5.5. Negative Binomial Regression on Number of SACKSU Admissions per Individual (*n* = 918)

Variables	*b*	Standard Error	IRR
Race/Ethnicity (White reference)			
African American	0.0590	0.088	1.061
Hispanic/Latino	–0.159	0.117	0.853
Unhoused	**0.401*****	0.063	1.494
Alcohol User	**0.519*****	0.060	1.680
Multiple Substance User	**–0.205****	0.072	0.814
Self-referral	**0.158***	0.066	1.171
Intercept	0.0890	0.069	1.093

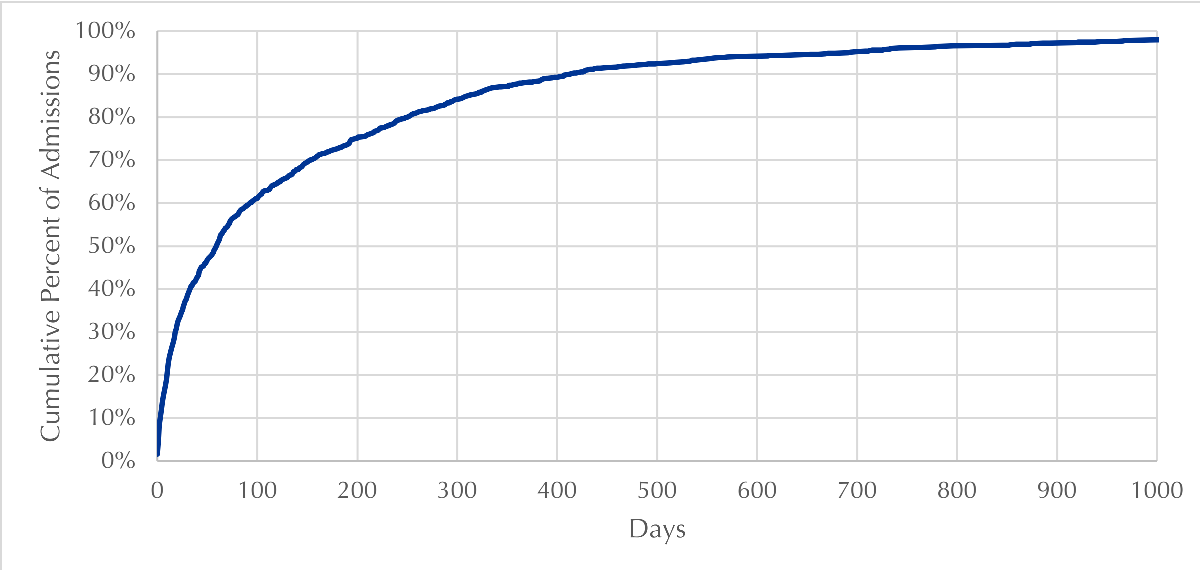
Notes: IRR = Incident Rate Ratio. Age is excluded as a covariate because of missingness (listwise deletion results in a loss of *n* = 386 cases). * $p<0.05$, ** $p<0.01$, *** $p<0.001$ (two-tailed test)

Analysis of Time to Re-Admission

To further understand repeat clients, we explored how the individual characteristics of clients are related to the length of time since the previous admission for repeat clients. The average number of days between SACKSU admissions for repeat clients was 158.2 days, with a standard deviation of 252.1. The distribution ranged from 0 to 1,979 days, with a median of 60 days. One-quarter of re-admissions occurred within 13 days of the last admission (see Figure 5.2).

[34] Negative binomial regression is the appropriate analytical technique for this analysis because these count data do not approximate a normal distribution. Furthermore, negative binomial is preferred over Poisson regression because there was evidence of overdispersion in the distribution of number of SACKSU admissions (see Long and Freese, 2006).

Figure 5.2. Days Between Sobering Center Admissions for Repeat Clients from 2/25/2018 to 2/11/2021 (*N* = 1,238)



We first analyzed bivariate associations between client characteristics and the number of days since the last admission; these can be found in Appendix C. Next, we analyzed whether any client characteristics predicted an earlier time to re-admission using survival analysis. Bivariate Cox proportional hazard models were estimated using race/ethnicity, age, housing status, alcohol use, multiple substance use, and referral source as individual predictors. The results from these bivariate analyses are shown in the first results column in Table 5.6. No bivariate association was observed for race/ethnicity, age, alcohol use, multiple substance use, or referral sources. Only housing status was statistically significantly associated with timing to re-admission at a bivariate level. Clients who are **unhoused** (hazard ratio = 1.738; $p < 0.001$) tend to be re-admitted to the SACKSU faster than their non-unhoused client counterparts. The next step was to estimate a multivariate Cox proportional hazard model using the same client characteristics included in the bivariate survival analyses. For more information on how bivariate and multivariate analyses are used in this report, please refer to the methodology chapter.

The second results column in Table 5.6 presents the results from the multivariate analysis. As with the bivariate analysis, no evidence of an association with race/ethnicity, alcohol use, multiple substance use, or referral source was observed. After considering the influence of other variables, we find that housing status s is still the only client characteristic associated with risk for time to re-admission. Unhoused clients tend to be re-admitted to the SACKSU faster than clients who are housed (hazard ratio = 1.793; $p < 0.001$). Compared to non-unhoused clients, the rate of timing to re-admission for unhoused clients is 1.8 times greater.

Table 5.6. Bivariate and Multivariate Cox Proportional Hazard Regression of Re-admission Timing to SACKSU (*n* = 1,369 Admissions)

	Bivariate		Multivariate	
Variables	Hazard Ratio	Standard Error	Hazard Ratio	Standard Error
Race/Ethnicity (White reference)				
African American	1.279	0.231	1.179	0.223
Hispanic/Latino	0.909	0.334	0.978	0.362
Age	1.010	0.009	—	—
Unhoused	**1.738*****	0.247	**1.793*****	0.258
Alcohol User	1.129	0.214	1.277	0.247
Multiple Substance User	1.026	0.154	0.942	0.141
Self-referral	1.205	0.134	1.199	0.133

Notes: For age, $n = 719$ for the bivariate analysis. Because of this reduction in sample size, age is excluded from the multivariate analysis. The analysis includes clustered sandwich estimators for individual IDs to adjust for repeat clients.

* $p<0.05$, ** $p<0.01$, *** $p<0.001$ (two-tailed test)

Analysis of Client Length of Stay in the SACKSU

Next, we explored the characteristics associated with the duration of individuals' stay at the SACKSU. The distribution for length of stay at the SACKSU ranged from 0 to 28.5 hours, with an average length of stay of 10.8 and a median of 10 hours. Bivariate and multivariate statistical models were used to estimate these relationships. Note that bivariate results can be found in Appendix C. The client characteristics included in these analyses were race/ethnicity, age, housing status, alcohol use, multiple substance use, first SACKSU admission compared to repeat admissions, referral source, time of day, day of the week, and season of the year.

Multivariate Analysis of Length of Stay

OLS regression was used to observe the effects of our independent variables on the length of stay at the SACKSU (results shown in Table 5.7). In the multivariate model—which adjusted for the influence of all predictors simultaneously—**alcohol user** (beta = –0.131; $p < 0.001$), **time of day of admission** (beta = 0.105; $p < 0.001$), **day of the week** (beta = 0.079; $p = 0.002$), **spring admission compared to winter** (beta = –0.223; $p < 0.001$), **summer admission compared to winter** (beta = –0.165; $p < 0.001$), and **fall admission compared to winter** (beta = –0.068; $p = 0.030$) were statistically significant predictors of length of stay.

On average, individuals brought to the SACKSU during the day stayed 1 hour and 22 minutes longer than clients brought during the nighttime. Weekend admissions, on average, stayed 1 hour and 4 minutes longer than clients during the work week. The

SACKSU clients in the winter stayed longer compared to clients in the spring (difference of 4.88 hours), summer (2.33-hour difference), and fall (0.94-hour difference). Finally, alcohol users stayed 1 hour and 42 minutes shorter, on average, than clients who were users of substances other than alcohol.

Table 5.7. OLS regression on Number of Hours Spent at the SACKSU (*n* = 1,369)

Variables	*b*	Standard Error	Beta
Race/Ethnicity (White reference)			
African American	0.430	0.537	0.022
Hispanic/Latino	–0.030	0.682	–0.001
Unhoused	0.235	0.349	0.018
Alcohol User	**–1.697*** **	0.407	–0.131
Multiple Substance User	0.706	0.399	0.048
First SACKSU Admission	–0.212	0.447	–0.016
Self-referral	–0.458	0.348	–0.035
Daytime Admission	**1.370*** **	0.338	0.105
Weekend Admission	**1.059** **	0.343	0.079
Season (Winter reference)			
Spring	**–4.877*** **	0.572	–0.223
Summer	**–2.334*** **	0.455	–0.165
Fall	–0.938*	0.433	–0.068
Intercept	15.588	0.696	

Notes: Age is excluded as a covariate because of missingness (listwise deletion results in a loss of *n* = 650 cases). The analysis includes clustered sandwich estimators for individual IDs to adjust for repeat admits.
* $p<0.05$, ** $p<0.01$, *** $p<0.001$ (two-tailed test)

Analysis of Client Transfer to Detox

Upon discharge, the SACKSU clients can be transferred to the associated detoxification unit. In the SACKSU database, 49.5% of clients were transferred to detox upon discharge. While bivariate associations can be found in Appendix C, we describe the multivariate logistic regression results on client transfer to the SACK detoxification unit below. **First SACKSU admission**, **referral source**, **time of day**, and **being admitted during the summer** were statistically significantly associated with being transferred to detox (see Table 5.8).

Table 5.8. Logistic Regression Results for Predicting Detox Transfer (*n* = 1,358)

Variables	*b*	Standard Error	Odds Ratio
Race/Ethnicity (White reference)			
African American	0.200	0.171	1.222
Hispanic/Latino	0.082	0.251	1.085
Unhoused	0.006	0.117	1.006
Alcohol User	0.122	0.134	1.129
Multiple Substance User	0.100	0.128	1.106
First SACKSU Visit	**0.618*****	0.137	1.855
Self-referral	**0.255***	0.114	1.291
Daytime Admission	**0.286***	0.119	1.331
Weekend Admission	0.190	0.116	1.209
Season (Winter reference)			
Spring	0.395	0.207	1.484
Summer	**–0.755*****	0.149	0.470
Fall	0.098	0.143	1.102
Intercept	–0.757	0.216	0.469

Notes: Age is excluded as a covariate because of missingness (listwise deletion results in a loss of *n* = 650 cases). The analysis includes clustered sandwich estimators for individual IDs to adjust for repeat admits.
* $p<0.05$, ** $p<0.01$, *** $p<0.001$ (two-tailed test)

Being a first-time client of the SACKSU increases the odds of being transferred to detox at discharge by approximately 86%. First-time clients have a 53.8% probability of being transferred to detox, and repeat clients have a 39.3% probability. Self-referrals were more likely to be transferred to detox than individuals referred through a different source. The predicted probability for those who self-referred is 50.9%, while those referred from a different source have a predicted probability of 44.9%. The logged odds for being transferred to detox upon sobering center discharge increase by 33% for clients admitted during the day compared to nighttime. Daytime clients have a predicted probability of 51.7% of being transferred to detox, while nighttime clients have a probability of 45.0%. Finally, the probability of being transferred to detox is associated with the season of the year. In particular, the logged odds of being transferred to detox upon discharge are roughly 53% lower for summertime admissions than winter. The predicted probability of being transferred to detox is 34.0% during the summer and 51.8% during the winter.

Summary of Findings from the SACKSU Data

The purpose of these analyses was to gain a clearer understanding of the individuals diverted from jail and referred to the SACKSU in Wichita. We explored how types of clients varied depending on when the admission occurred and examined the differences in the characteristics of one-admission clients and repeat clients and the timing to re-admission. Finally, we observed what characteristics were associated with a client's length of stay and whether they were transferred to detox after discharge.

Our findings demonstrate that over one-third of SACKSU clients are self-referrals, while just 6% are referred by law enforcement. Clients are likely to have a place of residence relatively close to the SACKSU. Nearly half (48%) of clients were noted as having a place of residence within the same zip code as the SACKSU. Further, 75% of clients come from nine unique local zip codes. Clients referred to the SACKSU are overwhelmingly White and have an average age of approximately 39. Many clients are unhoused (44%) and most commonly use either alcohol (51%) or methamphetamine (55%). One-quarter of the clients admitted reported using more than a single substance at admission.

Table 5.9 summarizes many of the bivariate and multivariate results presented above. The characteristics associated with repeat clients include being unhoused, age, and being a user of alcohol. For the most part, these client characteristics were also consistently related to having a greater count of admissions. We also found that unhoused clients were re-admitted to the SACKSU more quickly. Of note is the relative lack of statistically significant racial/ethnic differences in both bivariate and multivariate analyses.

When predicting the length of stay in the SACKSU, the type of substance used was the most important client characteristic. In particular, clients who used substances other than alcohol were found to have a longer stay in the SACKSU than alcohol users. Differences in the length of stay were also observed by season. The length of stay was significantly longer during the cold temperatures of winter than in the warmer seasons of spring and summer. Approximately half of SACKSU clients were transferred to detox. Clients were more likely to be transferred to detox upon discharge if they self-referred to the SACKSU or were first-time clients.

Table 5.9. Summary of Chapter Findings

	Repeat Client		Admissions Count		Time to Re-Admission		Length of Stay		Detox at Discharge	
Client Characteristics	*BV*	*MV*	*BV*	*MV*	*BV*	*MV*	*BV*	*MV*	*BV*	*MV*
White	×	ref	×	ref	ref	ref	–	ref	×	ref
African American	×	×	×	×	×	×	+	×	×	×
Hispanic/Latino	×	–	×	×	×	×	×	×	×	×
Unhoused	+	+	+	+	–	–	+	×	–	×
Age	+	.	+	.	×	.	×	.	×	.
Alcohol Use	+	+	+	+	×	×	–	–	×	×
Multiple Substance Use	×	×	–	–	×	×	+	×	×	×
Self-referral	+	×	×	+	×	×	+	×	×	+
First SACKSU Visit	.	.	.	.	.	.	×	×	+	+
Daytime Admission	.	.	.	.	.	.	×	+	+	+
Weekend Admission	.	.	.	.	.	.	×	+	×	×
Winter Admission	.	.	.	.	.	.	ref	ref	×	ref
Spring Admission	.	.	.	.	.	.	–	–	×	×
Summer Admission	.	.	.	.	.	.	–	–	–	–
Fall Admission	.	.	.	.	.	.	×	×	+	×

Notes: BV = Bivariate Analysis; MV = Multivariate Analysis; + = positive association; – = negative association; × = non-significant association; . = not included in analysis; ref = reference category for analysis.

Analyses of Wichita Police Data

The Wichita setting provides a unique opportunity to address and examine key issues related to the impact of opening the Substance Abuse Center of Kansas (SACKSU) sobering and detox center in February 2015. The Wichita Police Department provided arrest data which ranged from January 2010 through July 2021. Thus, a significant advantage of the Wichita setting is that we can conduct a pre/post analysis on changes in specific arrests (e.g., public intoxication arrest) that corresponded with the timing of the opening of the SACKSU. However, WPD did not provide information about the race and ethnicity of arrestees. Thus we could not examine whether any changes in arrests related to the opening of the SACKSU varied by race and ethnicity. Additionally, as noted in the prior Research Methodology section, we did not conduct focus group interviews in Wichita, given that the primary direct utilizers of SACKSU from WPD involved the specialized Unhoused Outreach Team (HOT). We did conduct a site visit (included in this section at various points) to provide context to the metrics and counts of usage presented herein.

We examined two primary questions using the official police data in Wichita:

1. *What proportion of arrests in Wichita included charges likely to be impacted by the opening and administration of SACKSU, including arrests for public intoxication (PI), driving a vehicle while under the influence (DUI), drugs and/or drug possession (PO), and disorderly conduct (DC)?*

2. *What impact, if any, was seen in changes in arrests, including charges related to PI, DUI, PO, or DC arrests after SACKSU's opening?*

Several analyses provided insight into the arrest patterns for these specific charge types (i.e., arrests where at least one of these charges emerged). For arrests in Wichita during the data period examined here (1/2010 - 7/2021), roughly 24.5% (N = 55,330 specific arrests) of all arrests (n = 170,230) included at least one charge for public intoxication[35], operating a vehicle while under the influence, possession, and/or disorderly conduct.[36]

[35] In Wichita there is no public intoxication charge that is applicable to civilians. There are carry open container and pedestrian under the influence charges (which are only applicable to pedestrians who are intoxicated and walking on a street. We kept our operational definition of public intoxication (PI) in Wichita to be consistent across sites (i.e., for study consistency). The specific charges we looked at were: consumption of intoxicating liquor in a public space; consumption of intoxicating liquor by minor; possession and/or under control of marijuana/hallucinogens; possession and/or control of opium, opiates, or narcotics; or possession and/or control of methamphetamine; and transportation of open alcohol/liquor in an occupied area.

[36] It is important to note that the arrest by charge specific counts do not combine to equal the total number of arrests here due to overlap of charges within a single arrest.

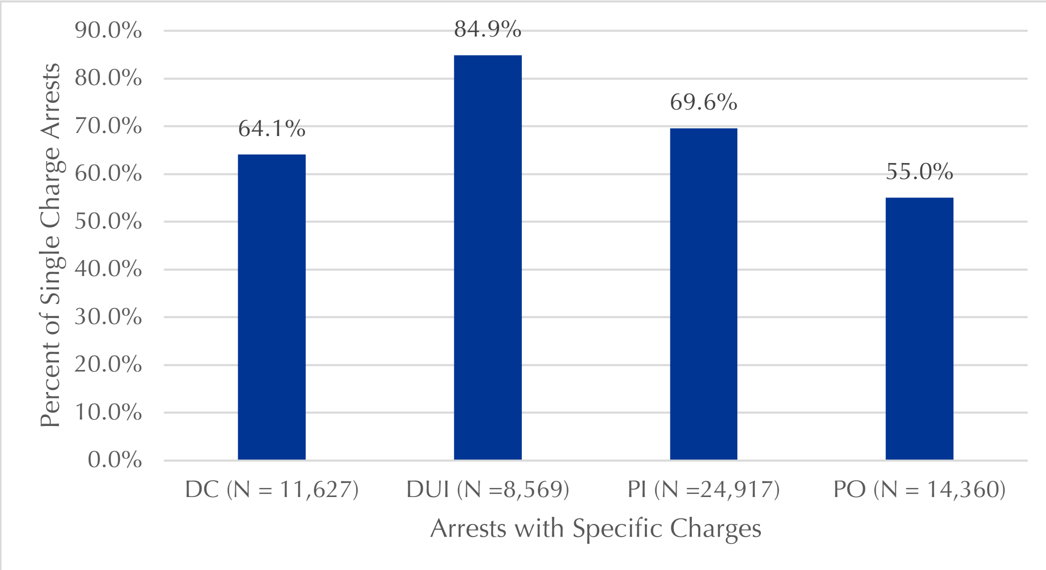
The overlap among arrests where multiple charges for public intoxication (PI), driving under the influence (DUI), drug possession (PO), and disorderly conduct (DC) were also observed in Wichita. In 39.6% of the cases where a person was arrested for at least one specific charge of public intoxication, operating a vehicle while under the influence, possession of illegal substance, or disorderly conduct (N = 21,935 specific arrests / 55,330 total arrests), the individual was charged with at least one other of these specific charges (e.g., a person arrested for intoxication was also charged with possession, disorderly conduct, or driving while under the influence).[37] Thus, where individuals were levied with arrest charges such as public intoxication, they were somewhat likely (roughly half of the time) to be charged with any additional intoxication-related charges such as disturbance, possession, driving under the influence, or multiple types of intoxication charges. In sum, there is a high degree of interrelationship between these charges among people arrested for any of these offenses.

Figure 5.3 shows the percentage of arrests by charge type that involved only a single charge. As shown, individuals charged with driving under the influence were much more likely to be charged only with that singular charge (84.9%) than arrestees charged with other offenses. Specifically, individuals charged with public intoxication were solely charged with that offense in 69.6% of PI arrests. Individuals charged with disorderly conduct were charged with that singular offense in 64.1% of arrests (meaning that nearly 1/3 times individuals charged with disorderly conduct were charged with multiple intoxication-related offenses). Finally, when an individual was charged with possession of an illegal substance or paraphernalia, in roughly half of the cases, they were charged with an additional offense (solo charges occurred in N = 7,898 of the 14,360 total possession arrests).[38]

[37] In the 'post-sobering center' period only (beyond February 2015) these four arrest charge types encompassed roughly 21.3% of all arrest charges (26,548 / 72,378). Comparatively, the pre-sobering center period (prior to February 2015) encompassed roughly 29.4% of all arrests (28,782/97,852).

[38] It was common for individuals charged with public intoxication to be charged with possession; however, individuals charged with possession were more likely to be charged with a variety of charges beyond intoxication.

Figure 5.3: Percent of Arrests with a Single Charge by Charge Type, Wichita



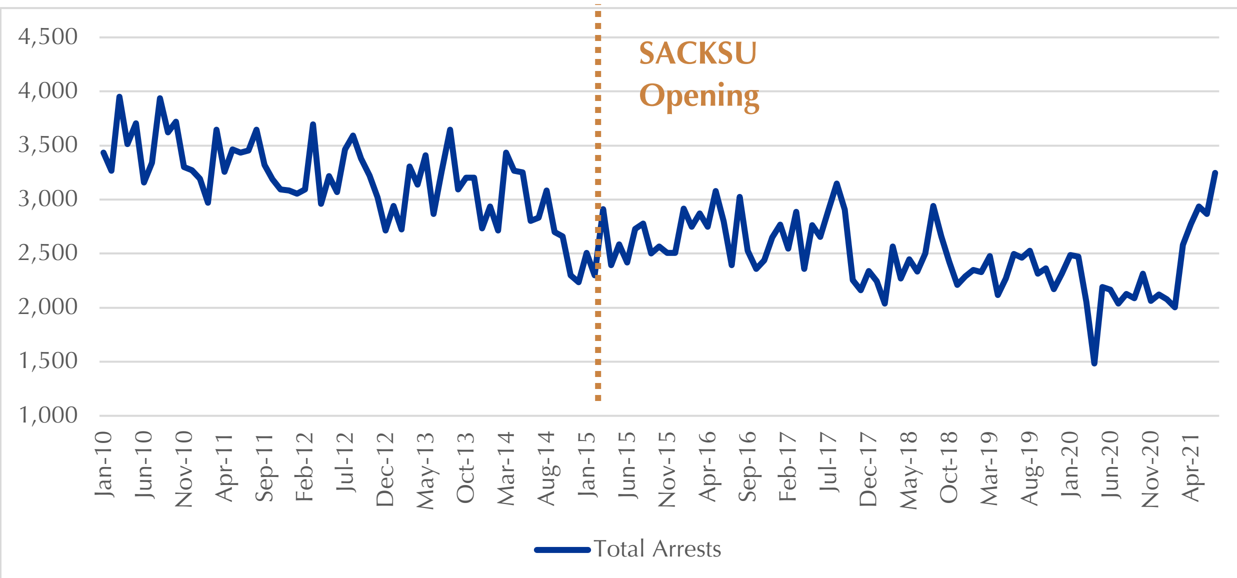
In summary, the descriptive analysis regarding the proportion of single vs. multiple charges levied against individuals charged with arrests of interest (disorderly conduct, DUI, public intoxication, and possession) showed varying patterns. First, many (nearly 40%) of the individuals charged with any of these charges often faced multiple charges – though people charged with operating a vehicle under the influence in Wichita were often only charged with single or multiple violations of criminal law *within* those offense categories. Additionally, when individuals were charged with public intoxication (at least relative to the other categories of offense examined here), they were also highly likely only to be charged with a singular offense. Comparatively, individuals charged with disorderly conduct and possession were more frequently (between one-half to one-third of the time) charged beyond that particular offense category (demonstrating a greater diversity of illicit/illegal behaviors while being publicly intoxicated).

Assessing Impact on Arrests: Wichita Trends and Interrupted Time Series

Bivariate Trends

We examined the changes in total arrest patterns to assess whether there were any changes in arrests at the time of the opening of the SACKSU. The first step was to assess potential changes in arrest patterns by examining changes in the total number of arrests over time. Without controlling for temporal, seasonal, or specific fluctuations in the trend data, the average number of total arrests (per month) in Wichita was roughly 3,200 between 1/2010 and 1/2015 compared to a monthly average count of nearly 2,500 arrests from 2/2015 (the opening of Wichita SACKSU) to 7/2021 (conclusion of Wichita data collection/submission).[39] Thus, the raw percentage change in total arrests for this pre/post sobering center period was -22.5%, indicating a moderate general decline in all arrests for this period of inquiry, net of controlling for any trends, drifts, seasonal influences, or the COVID-19 pandemic. All multivariate models in Wichita should control for many of these natural fluctuations before estimating the change in intoxication-related arrests (specifically).

Figure 5.4: Total Arrest Trends in Wichita (1/2010-7/2021)



A total of 225,560 arrests occurred during the study period. We next examined the 55,330 singular arrests based on the four specific charges of interest displayed in Table 5.10 to assess whether changes in arrest patterns for these charges were observed in Wichita during the same period. Of these arrests, the most common charge was for public intoxication (45.0% of intoxication-related arrests), followed by possession of an illegal substance and/or drug paraphernalia (14,360 arrests, roughly 26.0% of the arrests of interest), disorderly conduct (11,627 arrests, 21.0% of arrests of interest), and DUI arrests (8,569 arrests, 15.5% of arrests of interest).

[39] As noted previously, arrests can include multiple charges. The arrest count is person-event specific and not charge specific (e.g., a person arrested for disorderly conduct, public intoxication, and driving under the influence has three charges but only a single custodial arrest, which in these data would equate to a single arrest event).

Table 5.10: Intoxication-Related Arrest Charges in Wichita (1/2010-7/2021)

Arrest Charges	N	% Intoxication-Related Arrests (n=55,330)	% Total Arrests (n=225,560)
Public Intoxication	24,917	45.0%	11.0%
Possession	14,360	26.0%	6.4%
Disorderly Conduct	11,627	21.0%	5.2%
DUI	8,569	15.5%	3.8%

Comparing raw (univariate) percentage changes for the pre/post sobering center (based on February 2015's onset), Figure 5.5 shows that public intoxication arrests declined by roughly -12% (from 192.9 per month to 168.5 per month); possession arrests also declined by approximately the same amount, -12%, from 111.3 per month to 97.0 per month.

Figure 5.5: Trends in Charges of Intoxication and Possession in Wichita (1/2010-7/2021)

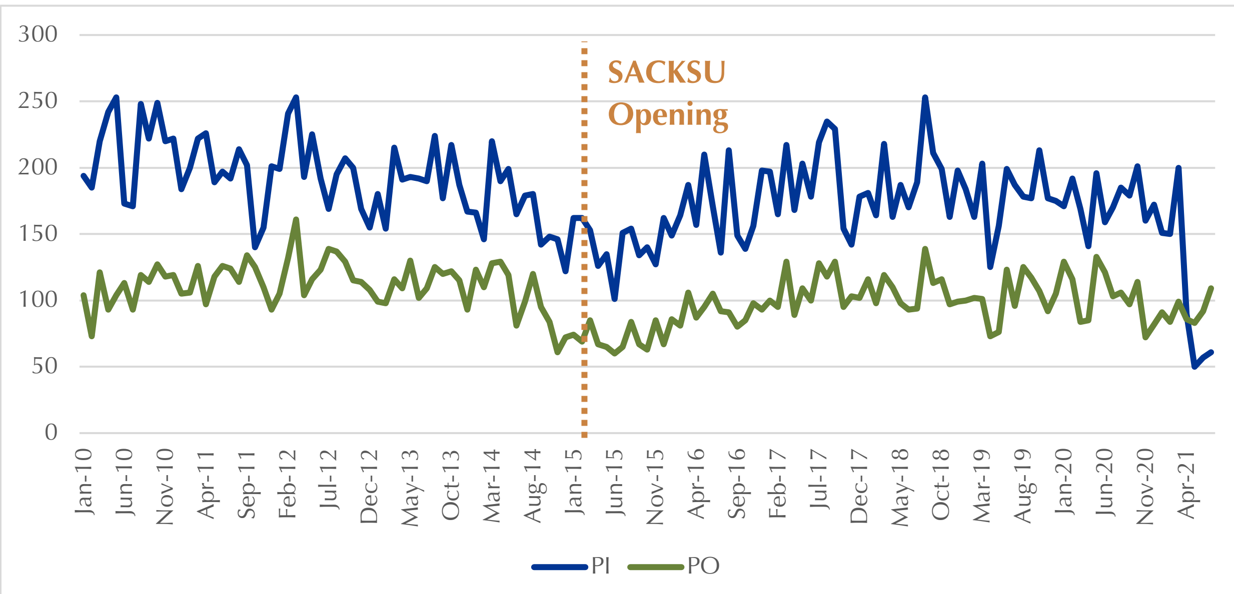
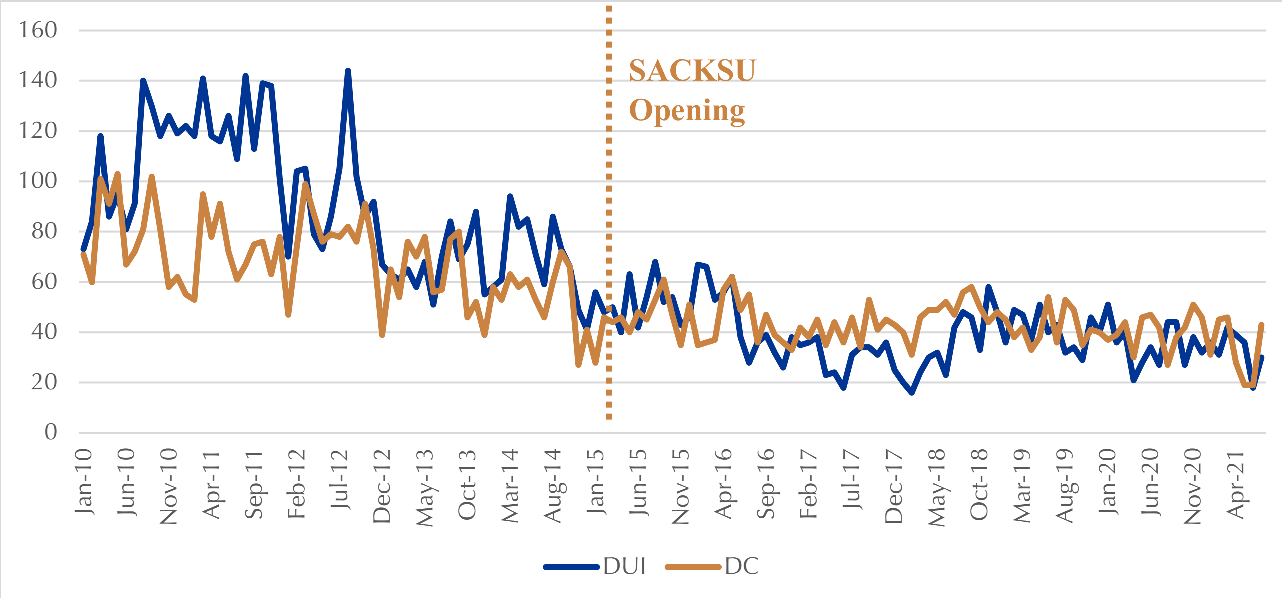


Figure 5.6 below shows that DUI arrests experienced the largest overall decline 38.7% (from 90.9 per month to 38.7 per month), while disorderly conduct arrests declined by 37.1% (from 68.0 per month to 42.7 per month).

Figure 5.6: Trends in Charges of DUI and Disorderly Conduct in Wichita (1/2010-7/2021)



Bivariate Summary

While the bivariate trend analyses do not control for shifts or systematic divergences in the arrest patterns, the preliminary analyses suggest there is evidence of a decline in total arrests (23%), DUI and disorderly conduct arrests (-39% and -37%, respectively), and to a lesser degree, public intoxication and possession arrests (-12% for each).

Time Series

To better understand what impact the opening of the sobering centers may have had on arrests with these specific charges, we next sought to examine, net of other temporal factors, which arrest types (if any) changed above and beyond overall arrest patterns using time series analyses. The primary independent variable in the analyses was operationalized as a *sobering center onset* reference measure, which we measured as a transitional period on and after February 2015 (the date of the SACKSU opening and usage by WPD). This measure was created as an indicator variable where months before the intervention period (from January 2010 through January 2015 were coded as the pre-sobering center period, value = 0). Subsequently, the post-sobering center period (value = 1) serves as the point of divergence from February 2015 to July 2021.

Additional covariates were included to have more fully specified models. First, the bivariate trend analyses indicated that the total arrest count experienced noticeable and sizable shocks post-April 2020; the onset of the COVID-19 pandemic, which resulted in a national shutdown of unprecedented heights in the U.S., directly impacted crime and arrests (Nielson, Zhang, and Ingram, 2022). All analyses included a COVID-19 post-period covariate (value = 0 from 1/2010 to 3/20 and value = 1 from 4/2020 to 7/2021).

Thus, all interpretations of shifts in arrests were net of the COVID-19 shock in arrests. Similarly, we included *monthly dummy variables,* using December as the reference month, to account for seasonal effects that occurred during specific periods of the year (mainly in the late spring and early summer, which are also seen in bivariate trend graphs).[40] It is also noteworthy that we could not obtain the arrest (or criminal offense charge) events by race of the suspect/arrestee in Wichita. Thus, we did not analyze changes in arrest type by race/ethnicity in Wichita.

For the time series analyses, we examined the potential influence of the opening of the sobering center in Wichita on specific types of arrests (i.e., arrests where at least one of the charges of interest — PO, PI, DUI, DC), net of the previously outlined covariates.

Table 5.11: Interrupted Time Series Analyses for Arrests in Wichita Using Maximum Likelihood Negative Binomial Regression (1/2010-07/2021)

	Total Arrests	PI	DUI	PO	DC
	B (SE)	B (SE)	B (SE)	B (SE)	B (SE)
Intercept	6.97** (0.02)	5.26** (0.038)	4.67** 0.101	4.63** (0.047)	3.38** (0.055)
Sobering Center	0.007 (0.027)	-0.053 (0.063)	-0.236** (0.075)	-.259** (0.073)	-0.121* (0.065)
Controls+					
COVID-19	0.034 (0.047)	-0.142* (0.081)	0.199* (0.081)	-0.067 (0.055)	-0.004 (0.086)
Linear Trend	-0.004** (0.000)	-0.000 0.000	-0.009** (0.001)	0.001* (0.000)	-0.002* (0.001)
+All regression models include February – December monthly dummy variables (included in models but excluded from tables for parsimony); *p < 0.05, ** p < 0.01					

Table 5.11 shows that the opening of the Wichita sobering center corresponded with three statistically significant declines in the arrests of interest examined here: DUI arrests,

[40] A series of sensitivity tests were conducted on each of the models – though not all of the results were presented in the tables presented here-in for parsimony. Given that count regression models rely on the use of Maximum Likelihood (ML) estimation, and we include the same covariates to control for linear and curvilinear trends and seasonality, this is an appropriate statistical control to account for the first-order autocorrelation process (Harvey 1990). All regression analyses included the exploration of the possibility of broad potential trend influences by adding a simple linear *trend* variable (to account for linear trends) and a *trend-squared* variable ($trend^2$ to account for curvilinear trends) in each model and table presented below. At no point did the included trend-squared measures alter the results in any meaningful or substantive manner, and thus were excluded from presentation. The count regression time-series model(s) can be written as follows: Monthly count outcomes = Intercept + Post-Sobering Center Onset + Post-COVID-19 pandemic shock + Trend (where statistically significant and thus where needed) + Monthly Seasonal Dummy Variables + Error Term

possession arrests, and disorderly conduct arrests. Equally important, total arrests did not experience any statistically significant changes that corresponded with the opening of the sobering center, indicating that overall arrests declined in a linear fashion (linear trend estimate = -0.004, $p < 0.01$) between 2010 and 2021. Thus, for any arrest that had a significant change that corresponded with the onset of the Wichita sobering center, we can view it as unique and distinct to those arrest types (i.e., there is no need for a coefficient difference test since the baseline of comparison—total arrests—did not experience a significant shift). It is noteworthy that public intoxication (the most common of the arrest charges examined here) did not experience a statistically significant change in event counts in the post-SACKSU period. There are several potential confounders (which are difficult to measure quantitatively) that we speculate might explain this lack of a significant decline in the most common possession/usage-based arrest counts in the discussion section.

For arrests that did correspond with the opening of the sobering center, we observed a statistically significant decline in DUI arrests by 21.0% (Exp(-0.236)), a substantial reduction in possession arrests of 22.8% (Exp(-0.259)), and a decline of 11.4% in disorderly conduct arrests (Exp(-0.121)). Beyond these key findings, several control variables exerted influence on the estimates. The monthly seasonal measures, included in the models but excluded from the tables, consistently demonstrated seasonal fluctuations in arrest patterns for each outcome. It is interesting to note that the direct impact of the COVID-19 pandemic was primarily calibrated with significant declines in public intoxication ($b = -0.142$, $SE = 0.081$) and significant increases in DUI arrests ($b = 0.199$, $SE = 0.081$), which had marginal increases in mid-2021 onward (i.e., the post-COVID transitional period). None of the other outcomes of interest appeared to shift in any discernable manner related to a potential COVID-19 impact.

Summary of Findings from Wichita Data

Given that SACKSU is designed to serve as a client treatment and recovery center and an alternative to arrest, we anticipated a change (reduction) in specific types of intoxication-related arrests. The findings, however, demonstrated mixed support for the impact of the SACKSU opening on intoxication-related arrests. The bivariate and multivariate time series analyses indicated a pattern of findings consistent with some of our research hypotheses (i.e., that the opening of the sobering center would significantly impact these specific types of arrests). In contrast, other hypotheses were not supported. For example, public intoxication arrests appeared stable over this period.

The data on arrests post sobering center in Wichita showcase three primary findings. First, overall arrests did not change at the time of the sobering center opening in Wichita. Thus any changes in intoxication-specific arrests did not appear to be influenced by a global reduction in arrests.

Second, public intoxication arrests did not decline in the post-SACKSU period. We anticipated a decline in Wichita for intoxication-related arrests that were not observed. However, a more detailed review of the SACK data indicated that a very small percentage of intakes was a product of WPD directly. Indeed, as demonstrated in the next section of this chapter, SACKSU accepted most of their clients from other alternatives to arrest sites. Additionally, the WPD patrol officers were not responsible for the primary intakes of SACKSU. Our on-site visit indicated that a specialized unhoused outreach team was most likely to work with SACKSU. However, they emphasized finding permanent housing for clients to address the broader unhoused problems in Wichita. The drugs used by individuals admitted at SACKSU were less likely to be alcohol and marijuana and more likely to be different types of substances (see the following section on SACKSU data). Thus, it is possible that this setting is less likely to impact public intoxication-only arrests directly and is more likely to assist with chronic and severe drug usage.

Third, disorderly conduct arrests, DUI arrests, and possession arrests all experienced statistically significant divergences when the sobering center opened, net of controls. These findings show that WPD officers suddenly and permanently (at least for a six-year follow-up period) shifted their arrest counts for charges typically associated with chronic inebriation and drug/alcohol usage.

CHAPTER 6: AUSTIN, TEXAS

Austin is the capital of Texas and the fourth largest city in the state, with 964,177 residents in 2021 (US Census, 2022). Located in the Southern region of the US, Austin is the 11th most populous city in the United States. The population has a majority of White residents (48.2%), followed by Hispanic (33.3%), Asian (7.7%), Black (7.4%), mixed race (2.9%), and other races (0.5%). The median household income in Austin is $75,752.

Policing services are provided to Austin through the Austin Police Department (APD). The APD comprises 1,809 sworn personnel, 675 civilians, 24 canines, and 16 horses, though the APD currently works at a deficit of more than 250 officers (Lee, 2022). The APD jurisdiction is approximately 296.2 square miles. The APD patrol is divided across ten sectors and includes over 35 specialized policing units. According to the 2016 LEMAS data, the APD receives 930,691 calls for service each year and dispatches officers to 432,013 of those calls. In 2022, the APD annual operating budget was approximately $360 million, which is $30 million lower than the reported operating budget from 2016.

Per APD Policy 309, *Handling Publicly Intoxicated Persons*, APD officers who encounter a publicly intoxicated person eligible for the sobering center shall divert those individuals to a responsible adult or the sobering center as an alternative to arrest. Officers who decide to make an in-custody arrest of a publicly intoxicated person eligible for the center must consult with an on-duty supervisor for approval of the arrest.

The Sobering Center of Austin (SCA) serves as the primary sobering facility for the city. Founded in September 2018, the SCA provides community members with a safe place to recover from intoxication in lieu of jail or the emergency room. The SCA was modeled after the Houston (TX) Recovery Center. Clients 18 or older can be brought to the SCA via law enforcement, emergency services personnel, or through one of the SCA's other referral partners; walk-ins are not accepted. The SCA is a non-medical, non-treatment facility that can connect clients seeking treatment. The SCA is funded through an inter-local agreement, as the City of Austin covers operating costs, but the county donated the building. The SCA operates with three people per shift, one of whom must be an EMT. In addition, the SCA relies on private security (sometimes off-duty law enforcement) consisting of a single security officer each shift; this officer typically stays out of sight but can assist SCA staff as needed.

The SCA can hold a maximum of 20 clients post-COVID (capacity of 40 pre-COVID), although this capacity changes based on staffing. The SCA provides two rooms for sobering clients: stimulant and depressive. This design relies on a "brain" model as opposed to a gender model and is based on the needs of the client and the intoxicant from which they are sobering[41]. The stimulant room has games, a television, and other items for clients where resting is unlikely. In contrast, the depressive room is dark and primarily used for sleeping. The hold within the SCA is voluntary, and clients can leave whenever they want. Once admitted to the SCA, a screening protocol is used to assign clients a need level from one through four; this designates their monitoring frequency by SCA staff. During their stay, SCA clients can access water, snacks, showers, and lockers for personal items and phones. There is also a laundry room with donated clothing that clients may use.

Analyses of Austin Sobering Center

This section of the report relies on data collected by the Sobering Center of Austin (SCA). The primary unit of analysis is an individual admitted to the sobering center, referred to as a "client." The SCA began data collection on October 1, 2018, including variables such as race and ethnicity, gender, age, BAC, primary substance used, housing status, military or veteran status, student status, source of transportation to the SCA, and treatment after discharge. Additional variables have been incorporated over time, including EMS/PD sector information, annual income, secondary substance used, polysubstance use, and duration of stay. This report uses SCA data collected through September 30, 2021. Table 1 in Appendix D presents a detailed description of all SCA variables used in the following analyses, including the variable definition, date range of availability, and how the variable was coded and used in analyses.

The purpose of analyzing these sobering center data is to understand SCA use and its clientele overall. As such, in this section, we explore four broad research questions[42]:

- *What are the trends in SCA admissions?*
- *What are the characteristics of the SCA clientele?*

---

[41] Design details described directly by the SCA executive director in April 2022.

[42] The quantity and quality of SCA's data collection has improved over time. Unfortunately, while the SCA collects a unique identifier for repeat individual clients, those data are too unreliable to perform any one-admission versus repeat-admission client analyses. As such, we are unable to explore the research question explored in other case study sites related to whether there are differences in the characteristics of one-admission clients and repeat-admission clients.

The SCA changed their records management system in October 2020. With this change came a change in unique identifier. Unfortunately, there was no way to match the previous unique identifier to the new numbers. Furthermore, we came across issues of data reliability when considering the pre-October 2020 unique identifier. Individuals identified under the same unique identifier would have inconsistencies across demographic data that did not seem plausible (e.g., drastic changes in age and changes in gender and race). As such, we were not comfortable performing any analyses based off the previous identifier. While the new identifier is reliable, aside from the limited sample size, there were concerns over the left censoring of the data. This issue made it where any analyses considering one-admission versus repeat-client admissions would likely be biased because we would have no record of their pre-October 2020 admissions. As such, repeat clients would incorrectly be identified as first-time clients.

- *What client characteristics are associated with differences in the length of stay per admission at the SCA?*
- *What characteristics are associated with a client going to treatment upon discharge from the SCA?*

Several analyses provide insight into these research questions. Descriptive, bivariate, and multivariate analyses are all used to glean a clearer understanding of the use of the SCA and its clientele, who otherwise would likely be transported to jail if the SCA was not an available alternative.

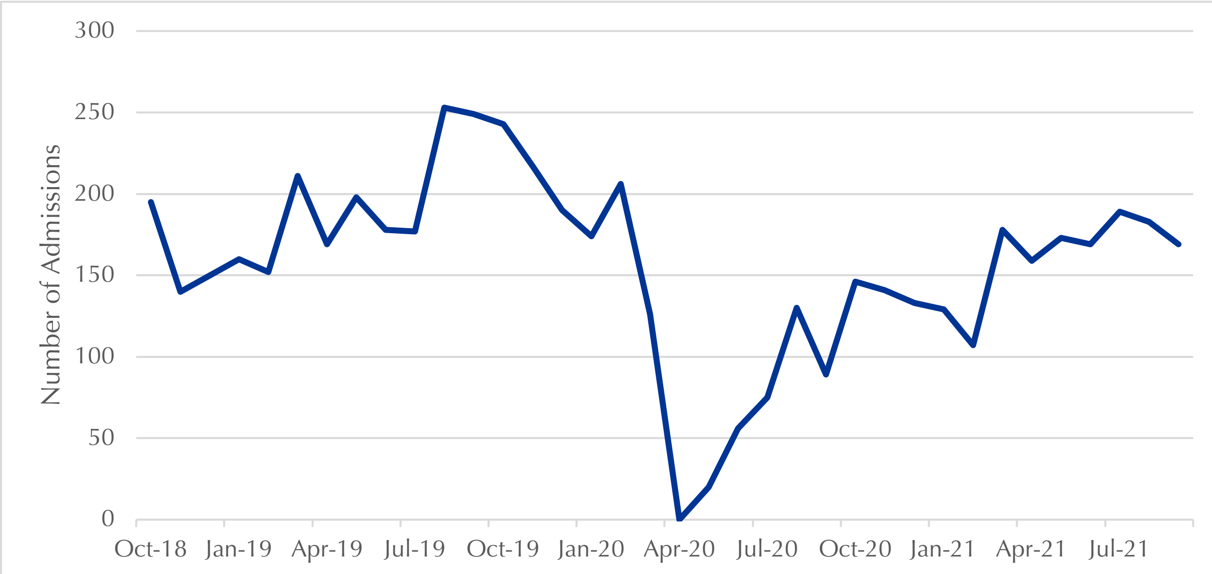
Trends in Sobering Center Client Admissions

This section provides a descriptive exploration of the trends in the SCA's admissions. Specifically, charts and descriptive statistics are used to demonstrate the trends in admissions counts, characteristics of admissions and the use of SCA, and the characteristics of the clients referred to the SCA.

Trends in Admissions

From October 1, 2018, to September 30, 2021, the SCA had 5,484 admissions. This corresponds to approximately 1,880 admissions per year or 157 admissions per month. Figure 6.1 displays the admissions counts by month for this period. By observing the trend, it is apparent that COVID-19 impacted admissions. Specifically, from January 2019 to February 2020, the average number of monthly admissions was just under 200. The lowest number of admissions during this timeframe was in February, with 152. Starting in March 2020, the number of admissions dropped to 126. The sobering center was closed from April 1, 2020, to May 19, 2020. As such, there were only 20 admissions in May, and reduced admissions continued in June (56) and July (75). From August 2020 through September 2021, the average number of monthly admissions was about 150.

Figure 6.1. SCA Admissions Counts by Month from 10/1/2018 to 9/30/2021 (*N* = 5,484)[43]



Estimate of Jail Days Saved

Based on the SCA admissions counts, we calculated an estimated number of "jail days" saved if each sobering center admission were a true diversion from an arrest and jail admission. The number of "jail days" saved was estimated by multiplying the number of yearly admissions by the average number of hours spent in the sobering center per admission per year.[44] This number was then divided by 24 to estimate the number of "jail days" saved. According to the data recieved 5,484 clients admitted over 36 months stayed 40,128 hours in the SCA, which amounts to a toal of 1,672 days as shown in Table 6.1 below.

Table 6.1. Estimated Jail Days Saved by Diversion to Sobering Center by Year (*N* = 5,484 admissions)

	Jail Days Saved
2018*	96
2019	684
2020	403
2021*	489

Note: * indicates data that does not cover the full calendar year.

[43] Note that admission data is missing for December 2018. The SCA confirmed that data for this month was not properly maintained and is unavailable for analysis.

[44] Some clients were reported in the database as having very long stays at the sobering center. This is because the SCA will allow clients to stay as a "holdover" until they can be transferred to a treatment facility (i.e., a detox program). Given that these long durations would bias the calculation of the average length of stay per year, we restricted the calculation of the average length of stay to only admissions that were less than 24 hours (95.4% of admissions).

Admissions Characteristics

The SCA is available 24 hours a day, seven days a week. Table 6.2 displays the descriptive statistics for SCA admissions characteristics. There were slightly more admissions occurring at night (from 7:00 PM to 6:59 AM) than during the day (55.9% versus 44.1%). Admissions across days of the week varied according to whether it was the work week or the weekend. The lowest proportion of admissions occur on Tuesdays (10.0% of admissions), and the largest proportion occurs on Saturdays (21.1%). Admissions were more common on the weekend than during the work week, 44.3% of admissions occurred during the work week (Monday, Tuesday, Wednesday, and Thursday), and 55.7% occurred over the weekend (Friday, Saturday, and Sunday). A significant association existed between the time of day for admission and whether the admission occurred during the work week or the weekend ($\chi^2 = 49.113$; $df = 1$; $p < 0.001$). As expected, a larger proportion of admissions over the weekend occurred during nighttime hours compared to the SCA admissions during the work week (60.1% vs. 50.6%).

Admissions were also relatively consistent across seasons, with 25.1% of admissions occurring in the winter, 20.9% in the spring, 27.5% in the summer, and 26.5% in the fall. It should be noted, however, that the distribution of counts by season was skewed due to data availability. As discussed above, admissions into the SCA were largely impacted by the COVID-19 pandemic, and the impact on admissions counts was predominantly in Spring of 2020.

The SCA collects detailed information regarding who transported the client to the sobering center. The most common transport source was the police. Specifically, 66.4% of clients were transported to the SCA by police officers from any agency. Of those officers, 67.9% were from Austin Police Department, and the remaining 32.1% were from other law enforcement agencies or non-specified law enforcement. The next most common transporting source was emergency medical services (EMS), responsible for transporting 24.2% of the SCA admissions. While police and EMS were responsible for transporting the vast majority of clients, other sources of transportation reported in the database included a sobering center van (2.8%), walk-in clients (2.1%), and "other" (4.6%).

The city and zip code of the place of residence for SCA clients is collected in the SCA database. Of those who provided a city of residence (22.6% of cases were missing) over two-thirds (69.1%) identified Austin as their city of residence. Like city of residence, a large proportion of clients in the database were missing zip code information (33%). For those with valid zip code information, 16.9% reported a residence that was within the same zip code as the SCA—78701. Furthermore, 50% of clients resided within 11 unique local zip codes and approximately 75% of clients were from 50 zip codes.

To further understand where clients were transported from, information on the Austin Police Department sector in which the client was detained is collected. For clients transported to the SCA by the police, sector information was missing in 42.3% of the cases. For the cases with valid sector information, it was observed that the largest proportion of clients were transported from GEORGE (28.8%). GEORGE is the smallest geographic police sector, but it is also home to the downtown entertainment district. Following GEORGE in sharing a larger proportion of SCA transports were BAKER (13.4%) and DAVID (11.5%).

Table 6.2. Sobering Center of Austin Admission Characteristics

	%	*N*
Daytime Admission	44.1	5,484
Day of the Week		5,484
Sunday	20.3	
Monday	11.9	
Tuesday	10.0	
Wednesday	10.5	
Thursday	11.9	
Friday	14.3	
Saturday	21.1	
Weekend Admission	55.7	5,484
Season of Year		5,484
Winter	25.1	
Spring	20.9	
Summer	27.5	
Fall	26.5	
Transportation Source		5,096
Police	66.4	
EMS	24.2	
SC Van	2.8	
Walk-in	2.1	
Other	4.5	
Austin resident	69.1	4,260
APD Sector		1,951
ADAM	7.5	
BAKER	13.4	
CHARLIE	7.7	
DAVID	11.5	
EDWARD	9.0	
FRANK	7.6	
GEORGE	28.8	
HENRY	7.4	
IDA	6.8	
APT	0.3	

Client Characteristics

Table 6.3 contains descriptive information about clients admitted to the SCA. During the data timeframe, individual admissions to the SCA were overwhelmingly male (74.7%), and White clients made up 50.2% of all admissions. Nearly one-third (31.7%) of admissions were Hispanic/Latino individuals, 11.7% were African American, 1.7% were Asian, and 1.3% were Native American. The remaining 3.4% of admissions were identified as either Native Hawaiian/Pacific Islander (0.3%), two or more races (0.7%), or "other" (2.4%). Nearly 30% of clients were unhoused at the time of their admission to the SCA. Few SCA clients were veterans or active military members (8.4%) or students (10.0%). The SCA has also attempted to collect information on the annual income of their clients, but this data field suffers from a high degree of missing data (40.7%). Of those who provided income information, most clients (57.4%) reported an annual income under $15,000 (46.2% reported having no income). The average age at intake was 36 years (nearly a 13-point standard deviation) with a median of 32 years. The youngest age at intake was 15, and the oldest was 83.

The SCA collects information on the substances the client is using at the time of admission to the SCA. Alcohol (85.0%) was overwhelmingly the most common substance used by SCA clients. The use of other substances was infrequently reported, but of these substances, methamphetamine (5.7%) and marijuana or synthetic marijuana (4.2%) were the most common. The remaining admissions involved substances such as heroin or other opioids, crack/cocaine, benzodiazepines, hallucinogens, unknown substances, "other" substances, and no substances. The SCA collects information on multiple substances used by clients, and only 1.3% of clients were identified as using more than one substance at the time of their admission to the SCA.

During the SCA admissions process, all clients receive a blood alcohol concentration (BAC) test. For all admissions (including the individuals who were not using alcohol), the average BAC at intake was over twice the legal limit (0.178), with a median of 0.192. The average is slightly skewed, given the number of clients who were not using alcohol but were still breathalyzed. For example, approximately 22% of admits had a BAC below the legal limit of 0.08, and 16% of clients recorded a BAC of 0.000. When restricting the sample to only the clients who reported using alcohol, the average BAC increases to 0.210, with a median of 0.212.

Finally, variation exists for how long clients stay at the SCA. The average stay at the SCA per admission was 12.1 hours (standard deviation = 44.7), with a median of 7.1 hours. These data are skewed given that the distribution of the data on the length of stay for admissions ranged from 0 hours to approximately 35 days. Yet only 5.5% of the sample had a recorded length of stay that was greater than 24 hours. Additionally, 8.8% of clients brought to the SCA were not formally admitted and an additional 7.9% were admitted but then transferred away before completing their admissions. The explanations for non-admittance included transfer to hospital (39.1%), transfer to jail (25.7%), the client was not intoxicated (13.0%), the client was non-compliant (8.9%), the client walked out (7.0%), and "other" (6.2%). Similarly, reasons for admission followed by transfer included transfer to hospital (39.5%), the client walked out (28.1%), transfer to jail (18.6%), the client was non-compliant (5.1%), transfer to a treatment facility (1.2%), and "other" (7.6%). When the sample is restricted to only the clients who stayed for less than 24 hours and were admitted and not transferred before completing their stay, we observe a distribution with an average length of stay of 7.8 hours and a median of 7.2 hours.

Table 6.3. Sobering Center of Austin Client Characteristics

	Mean (SD) / %	*N*
Gender		5,433
Male	74.7	
Female	24.9	
Transgender/Non-Binary	0.4	
Race/Ethnicity		5,207
White	50.2	
African American	11.7	
Hispanic/Latino	31.7	
Asian	1.7	
Native American	1.3	
Pacific Islander	0.3	
Two or more races	0.7	
Other	2.4	
Unhoused	29.7	4,841
Active Military/Veteran	8.4	4,347
Student	10.0	4,422
Annual Income		3,262
No Income	46.2	
Less than $15,000	11.3	
$15,000 – $24,999	8.4	
$25,000 – $34,999	7.2	
$35,000 – $49,999	9.3	
$50,000 – $74,999	8.7	
$75,000 – $99,999	3.5	
$100,000 – $149,999	3.1	
$150,000 – $199,999	0.7	
More than $200,000	1.8	
Age	35.56 (12.60)	5,446
Substances		5,170
Any Alcohol	85.0	

Any Methamphetamine	5.7	
Any Heroin/Opioids	1.9	
Any Crack/Cocaine	1.0	
Any Marijuana/Synthetic	4.2	
Any Hallucinogens	0.3	
Any Benzodiazepines	0.5	
Any Other	1.7	
Any Unknown	0.8	
None	0.4	
Multiple Substance User	1.3	5,170
BAC	0.178 (0.112)	4,899
Stay Duration (hours)	7.89 (4.55)	4,148

Admissions Trends by Client Characteristics

Next, we analyzed the SCA data to test for potential associations between trends in admissions—including time of day, day of the week, and season of the year—and characteristics of the individuals admitted to the SCA. The client characteristics explored include age, gender, race/ethnicity, housing status, active military/veteran status, student status, annual income, city of residence, alcohol use, BAC, and transportation source to the SCA. The appropriate bivariate statistical test (i.e., chi-square test for independence, independent *t-tests*, or one-way analysis of variance) is used depending on the level of measurement of the two variables. Due to the length of this section, it has been moved to Appendix D in this document.

Analysis of Police vs. EMS Admissions

As detailed above, approximately 66.4% of clients are transported to the SCA by police and 24.2% by EMS. We examined whether significant differences in client characteristics exist between clients transported to the SCA by the police compared to EMS. Significant associations were observed for **gender** ($\chi^2 = 16.607$; $df = 1$; $p < 0.001$), **housing status** ($\chi^2 = 5.869$; $df = 1$; $p = 0.015$), **student status** ($\chi^2 = 53.496$; $df = 1$; $p < 0.001$), **annual income** ($\chi^2 = 18.510$; $df = 1$; $p < 0.001$), **any alcohol use** ($\chi^2 = 4.753$; $df = 1$; $p = 0.029$), whether the client was **not admitted** ($\chi^2 = 23.030$; $df = 1$; $p < 0.001$), and whether the client was **admitted but transferred** before completing their stay ($\chi^2 = 5.647$; $df = 1$; $p = 0.017$). Race/ethnicity, age, active military/veteran, city of residence, and BAC at intake were not associated with transportation source, as shown in Table 6.4 below.

A greater proportion of male clients were transported to the SCA by police compared to EMS. A greater proportion of clients transported to the SCA by EMS were unhoused, compared to those by the police. Students made up only 8.4% of the clients transported to the SCA by the police, but 16.7% of the clients transported by EMS. For annual income, 51.5% of clients transported to the SCA by the police were identified as making less than $15,000 a year, compared to 60.7% of clients transported by EMS.

A greater proportion of clients transported by the police were alcohol users compared to clients transported by EMS. In other words, a greater proportion of non-alcohol users were brought to the SCA by EMS compared to the police. Ten percent of clients transported by the police were ultimately not admitted to the SCA. Only 6% of clients transported by EMS were not admitted. Yet, of those admitted to the SCA but then transferred before completing their stay, a greater proportion of clients brought to the SCA by EMS were transferred compared to clients brought by the police.

Table 6.5. Differences in Characteristics of Clients Transported by Police and EMS

	Transported by Police	Transported by EMS
Male (n = 4,570)	76.0%	70.0%
Unhoused (n = 4,027)	26.4%	30.3%
Student (n = 3,744)	8.4%	16.7%
Income less than $15,000 ($n$ = 2,702)	51.5%	60.7%
Alcohol User (n = 4,354)	87.8%	85.3%
Not Admitted (n = 4,614)	10.5%	5.8%
Admitted but Transferred (n = 4,614)	6.4%	8.4%

Analysis of Client Length of Stay in the SCA

Next, we explore the characteristics associated with how long individuals stay at the SCA during their visit. As discussed above, variation exists for how long clients stay at the SCA. When the sample is restricted to only the clients who stayed less than 24 hours and were admitted and not transferred before completing their stay, the distribution for the length of stay has an average length of stay of 7.8 hours and a median of 7.2 hours. Bivariate and multivariate statistical models were used to estimate these relationships. Note that the bivariate associations can be found in Appendix D, and multivariate analyses are presented herein.

Multivariate Analysis of Length of Stay

OLS regression was used to observe the effects of our independent variables on the length of stay at the SCA. These findings can be found in Table 6.5. In the multivariate model—which adjusts for the influence of all predictors simultaneously—**gender** (beta = 0.047; p = 0.014), **age** (beta = 0.118; $p < 0.001$), **housing status** (beta = 0.174; $p < 0.001$), **any alcohol use** (beta = –0.130; $p < 0.001$), **BAC** (beta =0.200; $p < 0.001$), **transportation source** (beta = –0.115; $p < 0.001$), **time of day of admission** (beta = 0.130; $p < 0.001$), **day of the week of admission** (beta = 0.044; p = 0.027), and **spring admission** compared to winter (beta = 0.056; p = 0.016) were statistically significant predictors of length of stay.

In interpreting the findings from Table 6.6, we see that, on average, male clients brought to the SCA are predicted to stay 27 minutes longer than clients who are not male. Age was positively associated with the length of stay at the SCA. For each one-year increase in age, the length of stay is predicted to increase by 2 minutes. Stated differently, with all other characteristics held at their averages, the predicted length of stay for a 30-year-old is 7 hours and 31 minutes, while a 50-year-old client has a predicted length of stay of 8 hours and 19 minutes. Clients who are unhoused are predicted to stay 1 hour and 40 minutes longer, on average, than clients who are housed, while alcohol users are predicted to stay 1 hour and 40 minutes shorter, on average, than clients who are users of substances other than alcohol. Yet, while alcohol users have a length of time that is shorter on average, a positive association is observed between length of stay at the SCA and BAC level. For a 0.010 increase in BAC level, the length of stay is predicted to increase by 5 minutes. The predicted length of stay for clients with a BAC of 0.000 is 6 hours and 11 minutes. The predicted length of stay for clients at the legal limit (0.08) is 6 hours and 50 minutes, while those who have a BAC that is twice the legal limit (0.160) have a predicted length of stay of 7 hours and 29 minutes. Next, clients transported to the SCA by police are predicted to have a length of stay that is 1 hour and 6 minutes shorter than clients transported by EMS. Clients admitted to the SCA during the day are predicted to stay 1 hour and 5 minutes longer than clients admitted during the nighttime hours, while weekend clients are predicted to stay 22 minutes longer than weekday clients. Finally, SCA clients admitted during the winter are predicted to stay for a shorter duration compared to clients admitted in the spring (difference in 33 minutes).

Table 6.6. OLS Regression on Number of Hours Spent at the SCA (*n* = 2,434)

Variables	*b*	Standard Error	Beta
Male	**0.457***	0.187	0.047
Race/Ethnicity (White reference)			
African American	0.276	0.260	0.021
Hispanic/Latino	0.255	0.173	0.029
Age	**0.040*****	0.007	0.118
Unhoused	**1.672*****	0.194	0.174
Active Military/Veteran	0.056	0.293	0.004
Student	-0.217	0.276	-0.016
Any Alcohol Use at Admission	**-1.663*****	0.315	-0.130
BAC (x 100)	**0.080*****	0.010	0.200
Transported by Police	**-1.108*****	0.185	-0.115
Daytime Admission	**1.091*****	0.163	0.130
Weekend Admission	**0.370***	0.167	0.044
Season (Winter Reference)			
Spring	**0.545***	0.225	0.056
Summer	0.397	0.215	0.044
Fall	0.193	0.237	0.018
Intercept	5.230	0.436	

Notes: BAC has been multiplied by 100 to make the results more easily interpretable.
* $p<0.05$, ** $p<0.01$, *** $p<0.001$ (two-tailed test)

Analysis of Client Transferred to Treatment at Discharge

Upon discharge, the SCA clients have the opportunity to be transferred to treatment.[45] Only 4.4% of clients in the SCA database were identified as going to treatment after discharge. While the small number of clients identified as going to treatment limits the ability to perform robust analyses, we felt it was still of interest to explore what factors might be associated with a client going to treatment after discharge. Herein, we describe the logistic regression results on client transfers to treatment upon discharge from the SCA; bivariate results can be found in Appendix D.

We estimated a logistic regression model to predict the likelihood of going to treatment at discharge. Of the included independent variables, five predictors were statistically significantly associated with going to treatment at discharge (see Table 6.7). First, age at intake was positively associated with going to treatment. For each 1-year increase in age, the logged odds of going to treatment are predicted to increase by 2.4%. For example, the predicted probability of a 25-year-old client going to treatment is 1.9%. For 50-year-old clients, the predicted probability of going to treatment increases to 3.3%. For race/ethnicity, it is found that the logged odds of going to treatment are predicted to be greater for White clients compared to African American clients. Specifically, the predicted probability of a White client going to treatment is 3.2%. For African American clients, the predicted probability decreases to 0.6%. With the influence of all other predictors accounted for, an association between going to treatment and active military/veteran status is observed. Specifically, the logged odds of an active military/veteran going to treatment upon discharge are nearly 2.5 times greater compared to non-military clients. Active military/veterans have a predicted probability of going to treatment of 5.5%, while non-military clients have a predicted probability of 2.4%. The logged odds for going to treatment after sobering center discharge are greater for clients admitted during the day compared to nighttime (odds ratio = 2.61). Daytime clients have a predicted probability of going to treatment of 3.8%, while nighttime clients have a probability of going to treatment of 1.5%. The odds of going to treatment are also smaller for individuals who are admitted to the sobering center during the weekend compared to those admitted during the work week (odds ratio = 0.45). Specifically, the probability of going to treatment for weekend clients is 1.7% compared to 3.6% for work week clients.

[45] Example of treatment locations found in the data include 15th Street Respite, A New Entry, Cenikor, Oxford House, Recovery Unplugged, and Victory Outreach.

Table 6.7. Logistic Regression Results for Predicting Treatment at Discharge (*n* = 2,415)

Variables	*B*	Standard Error	Odds Ratio
Male	–0.407	0.317	0.666
Race/Ethnicity (White reference)		.	
African American	**–1.713***	0.734	0.180
Hispanic/Latino	–0.208	0.292	0.812
Age	**0.024***	0.011	1.024
Unhoused	0.393	0.276	1.481
Active Military/Veteran	**0.905***	0.363	2.472
Student	–0.598	0.746	0.550
Any Alcohol Use at Admission	–0.819	0.463	0.441
BAC × 100	0.0132	0.015	1.013
Transported by Police	–0.285	0.282	0.752
Daytime Admission	**0.958*****	0.289	2.606
Weekend Admission	**–0.800****	0.280	0.449
Intercept	–3.811	0.621	

Notes: BAC has been multiplied by 100 to make the results more easily interpretable.
* $p<0.05$, ** $p<0.01$, *** $p<0.001$ (two-tailed test)

Summary of Findings from SCA Data

The purpose of these analyses was to gain a clearer understanding of the individuals in Austin who are diverted from jail and referred to the SCA. We explored how types of clients varied depending on when the admission occurred and whether the client was brought to the SCA by police or EMS. We also observed what characteristics were associated with a client's length of stay at the SCA and whether a client went to treatment upon discharge from the SCA.

Our findings demonstrate that the clientele brought to the SCA varies depending on when they were brought in and who brought them in. Austin is a city that attracts tourists, has a vibrant nightlife, and is the home to a large university. While not directly measured, our results suggest these city characteristics play a large role in the observed differences in SCA admissions across time of day and day of the week. Specifically, a larger proportion of those admitted during the night and on the weekend are younger individuals who are housed, are students, have an income greater than $15,000 a year, are using alcohol, are not residents of Austin, and were brought to the SCA by EMS rather than police. As such, these findings point to the likelihood that these individuals are likely one-time sobering center users who had too much to drink while enjoying what Austin has to offer. Daytime and work week admissions, however, are likely those who are more chronic utilizers of the SCA, characterized by being older, unhoused, having lower incomes, hard drug use, and living in Austin.

Unique to the Austin data is the variability regarding who transported the client to the SCA. This variability allowed us to observe differences in the clientele transported to the SCA by police versus those transported by EMS. Compared to those brought in by EMS, a greater proportion of those brought to the SCA by the police are male, housed, not students, have incomes greater than $15,000 a year, and are alcohol users. That is, EMS brings in a greater proportion of non-male, unhoused, student, low-income, and drug-using clients. The characteristics suggest that client demographics vary depending on the transportation source.

Table 6.8 summarizes the bivariate and multivariate results presented above regarding client length of stay at the SCA and whether they went to treatment after discharge. When considering length of stay, we found that the driving characteristics for a longer stay are being male, older, unhoused, and having a higher BAC at intake. Looking at clients who went to treatment after discharge, the pattern of findings follows the hypothesized theme of one-admission users versus chronic users of the SCA. Specifically, those who are admitted during the daytime hours and during the work week are more likely to go to treatment.

Table 6.8. Summary of Sobering Center Findings

	Length of Stay		Treatment at Discharge	
Client Characteristics	*BV*	*MV*	*BV*	*MV*
Male	+	+	x	x
White	x	ref	x	ref
African American	x	x	x	–
Hispanic/Latino	x	x	x	x
Age	+	+	+	+
Unhoused	+	+	+	x
Active Military/Veteran	x	x	x	+
Student	–	x	–	x
Income less than $15,000	+	.	+	.
From Austin	+	.	+	.
Alcohol User	–	–	–	x
BAC	+	+	–	x
Transported by Police	–	–	–	x
Treatment at Discharge	+	.	.	.
Daytime Admission	+	+	+	+
Weekend Admission	–	+	–	–
Winter Admission	x	ref	x	.
Spring Admission	x	+	x	.
Summer Admission	x	x	x	.
Fall Admission	x	x	x	.

Notes: BV = Bivariate Analysis; MV = Multivariate Analysis; + = positive association; – = negative association; × = non-significant association; . = not included in analysis; ref = reference category for analysis.

Analyses of Austin Police Data

The Austin setting provided several unique opportunities to assess key issues related to the impact of the Sobering Center of Austin (SCA), which opened on September 30, 2018. The police data range from January 1, 2010, through June 30, 2022, allowing for a pre/post analysis to directly gauge its impact on public intoxication and related arrests by APD. For the Austin setting, we examined official police data focusing on two primary questions:

1. *What proportion of arrests in Austin included charges likely to be impacted by the SCA, including arrests for public intoxication (PI), driving a motor vehicle under the influence (DUI), drugs and/or drug possession (PO), and disorderly conduct (DC)?*
2. *What impact, if any, did the opening of the SCA have on arrests that included charges related to PI, DUI, PO, or DC?*

For arrests in Austin for the data examined (1/2010 - 6/2022), roughly 30.5% (N = 119,757) of the 392,793 total arrests included at least one public intoxication charge, driving a motor vehicle under the influence, possession, and/or disorderly conduct.

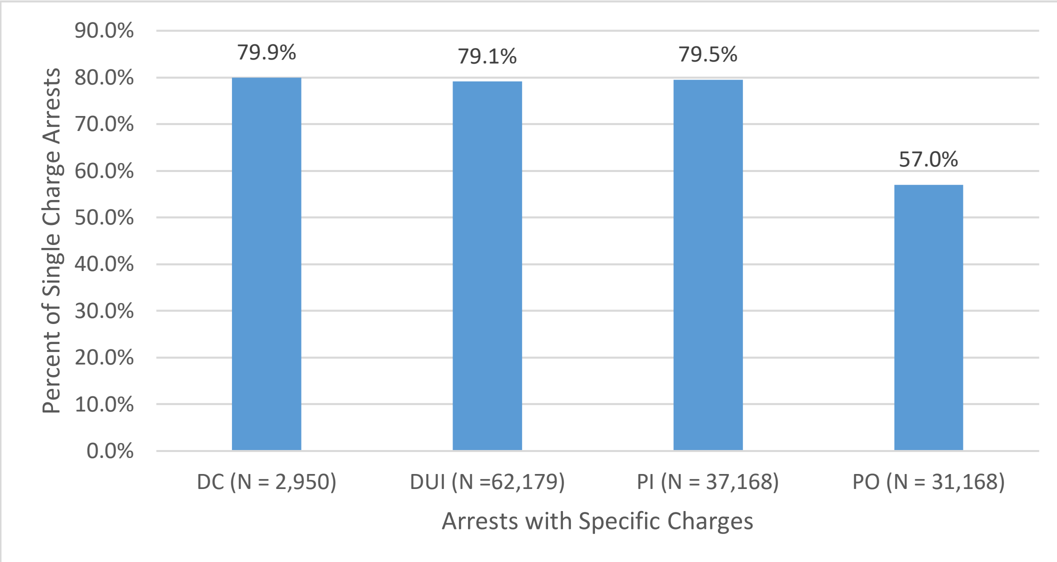
The overlap among arrests where multiple charges for PI, DUI, PO, and DC was also observed in Austin. In roughly 22.4% (n=26,826/119,757) where a person was arrested for at least one specific charge of PI, DUI, PO, or DC, the individual was charged with at least one other among these specific charges (e.g., a person arrested for intoxication was also charged with possession, or disorderly conduct, or driving while under the influence).[46]

Figure 6.2 shows the percentage of arrests by charge type involving only a single charge. As shown, the pattern of singular arrest charges (among these four specific groups of charges) was consistent for disorderly conduct, public intoxication, and driving under the influence. Approximately 79-80% of individuals arrested for each of these offenses (DC, PI, and DUI) were likely only to be charged with that offense. Comparatively, individuals charged with possession of illegal drugs and/or paraphernalia were much less likely to be arrested based only on a singular charge (only 57.0% of cases) among these four categories (and thus were charged with multiple charges nearly half of the time).

---

[46] The total charges by type displayed in the graphics do not equate to the total N (119,757) because of multiple charges within a single arrest. Additionally, the pre-SCA percent of intoxication-related arrests was roughly 29.2% (21,792/74,630) while the post-SCA percent of intoxication-related arrests was roughly 30.7% (97,965/318,163). Thus, there was strong stability in the overall distribution of arrests over time.

Figure 6.2: Percent of Arrests with a Single Charge by Charge Type, Austin



In summary, the descriptive statistical analyses regarding the proportion of single vs. multiple charges levied against individuals charged with offenses of interest (DC, DUI, PO, and PI) showed divergent patterns. Individuals charged with possession of drugs and/or paraphernalia were often charged with multiple offenses, whereas individuals charged with disorderly conduct, driving under the influence, and/or public intoxication were most frequently charged only with those charges.

Assessing Impact on Arrests: Austin Trends and Interrupted Time Series

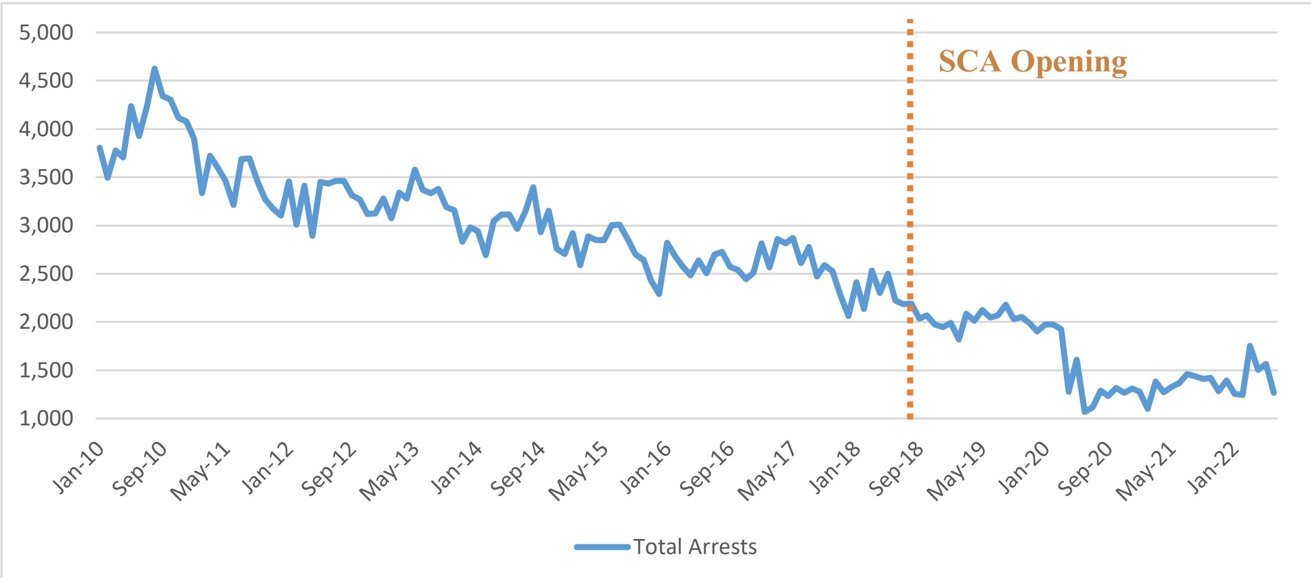
Bivariate Trends

To assess changes in arrest patterns potentially related to the opening of the SCA, we examined changes in the total number of arrests over time. As seen in Figure 6.3 below, without controlling for any temporal, seasonal, or specific fluctuations in the trend data, we see that the average number of total arrests (per month) in Austin was roughly 3,042 between 1/2010 and 10/2018. Comparatively, the average count of total arrests from 10/2018 (the opening of the SCA occurred on September 30, 2018) to 6/2022 was 1,597 arrests per month.[47] Thus, the raw percentage change in total arrests for this pre/post sobering center period was -47.5% (i.e., there was a major decline in all arrests, net of controlling for any trends, drifts, seasonal influences, or the COVID-19 pandemic). A general examination of the graph shows a clear linear trend (reduction) in arrests during the majority of this period. This means that all multivariate models in Austin should

[47] Arrests can include multiple charges. The arrest count is person-event specific and not charge specific (e.g., a person arrested for disorderly conduct, public intoxication, and driving under the influence has three charges but only a single custodial arrest, which in these data would equate to a single arrest event).

account/control for many of these natural fluctuations before estimating the change in intoxication-related arrests, specifically.

Figure 6.3: Total Arrest Trends in Austin (1/2010-6/2022)



We next examined the intoxication-related arrests of interest in Austin to assess changes in patterns during the same period of inquiry. For the 392,793 total unique arrests examined during this study period, there were 119,757 singular arrests.[48] DUI and possession arrest charges were among the most common (roughly 16% each of total arrests), followed by public intoxication (9.5%). Disorderly conduct charges were much less frequent (less than 3% of total arrests). Within the 119,757 intoxication-related arrests, possession (51.1%) and DUI charges were the most common (51.9%).

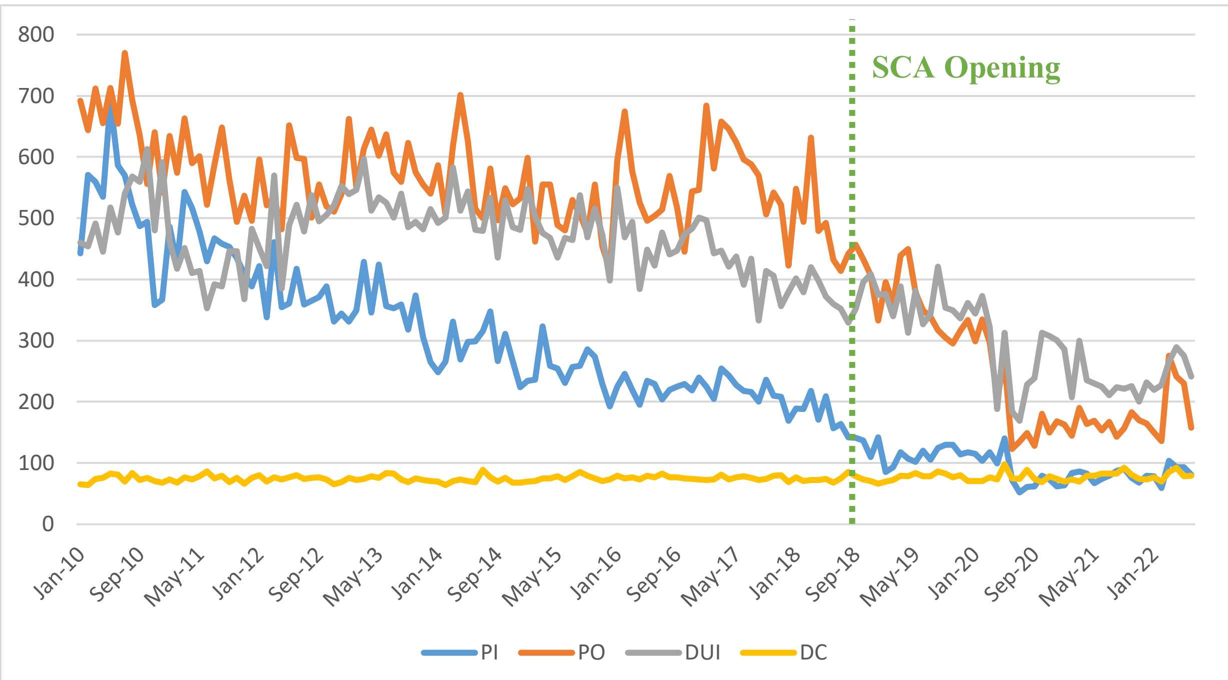
Table 6.9: Intoxication-Specific Charges Among Arrests of Interest in Austin (1/2010-6/2022)

Arrests Charges	N	% Intoxication Arrests (N = 119,757)	% Total Arrests (N = 392,793)
Public Intoxication	37,168	31.0%	9.5%
Possession	61,215	51.1%	15.5%
Disorderly Conduct	11,327	9.4%	2.8%
DUI	62,179	51.9%	15.8%

[48] As noted previously, total arrests are person-event specific and not charge specific. In the data, a person arrested on a given day and charged with three offenses is only arrested one time (and thus appears once in these data). For the ‘charges’ of interest, the categories are not mutually exclusive (and thus arrests with specific traits of charges can overlap in arrest counts with other categories (e.g., a person arrested for disorderly conduct and DUI will appear in both of these trends since the trends are arrests with that trait of interest).

In terms of raw (univariate) percentage changes for the pre/post-SCA (centering on the October 2018 break in the series), we saw that public intoxication arrests declined by roughly 70% (from 321 per month to 93 per month); possession arrests also declined by nearly 56% (from 563 per month to 245 per month). DUI arrests experienced a sizable decline by roughly 38% (from 468 per month to 290 per month). Comparatively, disorderly conduct arrests remained stable over this period (increasing approximately 4% from 74 per month to 77 per month).

Figure 6.4: Bivariate Changes in Intoxication-Related Arrests in Austin (1/2010 to 6/2022)



While the bivariate trend analyses do not control for significant trends or shifts in arrest patterns, the preliminary analyses suggest there is evidence of a decline in overall arrests and declines in intoxication and possession arrests.

Time Series

To better understand what impact the opening of the SCA may have had on arrests with these specific charges, we next examined, net of other temporal factors, which arrest types (if any) changed above and beyond overall arrest patterns using time series analyses. Each regression model was arrest specific in that the outcome variables were uniquely modeled as each month’s arrest measure, operationalized as a composite variable, running from its first through its last day.

The analysis's primary independent variable was operationalized as a *sobering center onset* reference measure, which we measured as a transitional period on and after

October 2018 (given the Austin sobering center's September 30, 2018 opening date). This indicator variable measures the months before the intervention period (from January 2010 through September 2018, defined as the pre-sobering center period). Subsequently, the post-sobering center period serves as the point of divergence from October 2018 to June 2022.

Additional covariates were included to have more fully specified models. First, the bivariate trend analyses in Austin showed that the total arrest count experienced noticeable and sizable shocks post-April 2020, the onset of the COVID-19 pandemic (Nielson, Zhang, and Ingram, 2022). In Austin, overall, they remained lower post-April 2020 for at least two full years. Thus, similar to other analyses, all analyses included a COVID-19 post-period covariate, which means all interpretations of shifts in arrests were 'net of the COVID-19 shock in arrests.' Similarly, we included monthly dummy variables, using December as the reference month, to account for seasonal effects (i.e., seasonal shocks) that occurred during specific periods of the year (mostly in the late spring and early summer, which are also seen in bivariate trend graphs). A trend variable was also included in all analyses, given the linear reduction in arrests (for each type) observed during this examination period.[49]

Table 6.10: Interrupted Time Series Analyses for Arrests in Austin Using Maximum Likelihood Negative Binomial Regression (1/2010-06/2022)

	Total Arrests	PI	DUI	PO	DC
	B (SE)	B (SE)	B (SE)	B (SE)	B (SE)
Intercept	8.29* (0.016)	6.22* (0.039)	6.27* (0.038)	6.50 (0.027)	2.45* (0.113)
Sobering Center	-0.074* (0.017)	-0.275* (0.042)	-0.151* (0.030)	-0.335* (0.039)	0.074 (0.077)
Controls+					
COVID-19	-0.294*	-0.138*	-0.342*	-0.679*	0.074

[49] A series of sensitivity tests were conducted on each of the models – though not all of the results were presented in the tables presented here-in for parsimony. Given that count regression models rely on the use of Maximum Likelihood (ML) estimation and we include the same covariates to control for linear and curvilinear trends and seasonality, this is an appropriate statistical control to account for the first-order autocorrelation process (Harvey 1990). All regression analyses included the exploration of the possibility of broad potential trend influences by adding a simple linear *trend* variable (to account for linear trends) and a *trend-squared* variable ($trend^2$ to account for curvilinear trends) in each model and table presented below. At no point did the included trend-squared measures alter the results in any meaningful or substantive manner, and thus were excluded from the presentation. The count regression time-series model(s) can be written as follows: Monthly count outcomes = Intercept + Post-Sobering Center Onset + Post-COVID-19 pandemic shock + Trend (where statistically significant and thus where needed) + Monthly Seasonal Dummy Variables + Error Term

	(.026)	(0.054)	(0.035)	(0.049)	(0.081)
Linear Trend	-0.005* (0.000)	-0.011* (0.003)	-0.001* (0.000)	-0.001* (0.000)	0.001 (0.000)
Clogg-Z Coefficient Difference Test Relative to Total Arrests		-0.201* (0.045)	-0.077* (0.034)	-0.261* (0.042)	--
+All regression models include February – December monthly dummy variables (included in models but excluded from tables for parsimony); *p < 0.05, ** p < 0.01					

Table 6.10 shows that the opening of the SCA corresponded with statistically significant declines in most arrest outcomes examined here: total arrests, public intoxication, driving under the influence, and possession. Following the opening of the sobering center in Austin: 1) public intoxication arrests, net of other confounders, declined by 24.0% (Exp(-0.275)), 2) DUI arrests significantly declined by 14.0% (Exp(-0.151)), and 3) possession arrests significantly declined by 28.4% (Exp(-0.335)). By contrast, disorderly conduct arrests did not shift during the time of the SCA opening.

As a frame of reference, we also modeled the potential decline/change in total arrests. We saw that net of confounders, total arrests declined by 7.2% (Exp(-0.074)). This analysis suggested a general trend reduction in arrests during this same period. It, therefore, became important to treat the overall decline in arrests as a potential conservative benchmark of a general trend in the data due to shifts in Austin police use of arrests.[50]

The Clogg-Z coefficient difference tests indicate that the declines in PI, DUI, and PO arrests occurred above and beyond any changes in total arrests during this period. Thus, the most robust and rigorous analyses suggest that the observed declines in these three arrest types most likely correspond with the opening of the SCA, net of other factors (trends, seasonality, COVID-19) over time. The COVID-19 impact was observed in declines in total arrests by 25% (Exp(-0.294), public intoxication by 12.8% (Exp(-0.138), DUI by 28.9% (Exp(-0.342), and most measurably, possession arrests by 49.3% (Exp(-0.679). In short, the impact of COVID-19 likely impacted DUI and possession arrests relative to all other charges examined here.

[50] We also examined the remaining total number of arrests (i.e., total number of arrests – any charge of possession, public intoxication, driving under the influence, or disorderly conduct (N = 273,036)). The post-sobering center estimate of this model was a nonsignificant increase of 0.04 (or 4%) of the remaining charges. We did not use this as the benchmark as the frame of reference in the main body of the study because while we suspected the sobering center would likely impact only these four types of arrests, we cannot definitively say what arrests would be directly related (beyond public intoxication, but this presumes public intoxication charges *only* given the criterion for sobering center applicability). Thus, the -7% benchmark as a frame of reference is likely a conservative and a overestimate of a general trend in the data to compare against. However, we erred on the side of caution for this study.

Supplemental Time Series on Arrest Changes by Race

Given that the time series analyses indicated statistically significant declines in PI, PO, and DUI arrests, we wanted to examine the change in public intoxication arrests for Black, White, and Hispanic arrestees during the same period.[51] The analyses presented in Tables 6.11 to 6.13 indicate that the greatest reductions in public intoxication arrests were for White arrestees (28.4%). Black arrestees experienced the second largest decline in arrests for this arrest charge at 21.2%. Hispanic arrestees experienced the lowest decline in public intoxication charges at 16.5%. A significant decline in intoxication arrests occurred during the COVID-19 pandemic for both White and Black but not for Hispanics arrestees. Net of these effects, the difference for White arrestees was significantly divergent from all other groups (i.e., the greatest decline), while Black and Hispanic divergences were similar.[52] In sum, while the benefit of a significant decline in arrests was observed for Whites, Blacks, and Hispanics, White arrestees experienced the largest overall decline in public intoxication arrest changes.

Table 6.11. Time Series Analysis of Public Intoxication Arrest Changes in Austin by Race/Ethnicity

	White PI Arrests	Hispanic PI Arrests	Black PI Arrests
	B (SE)	B (SE)	B (SE)
Intercept	5.64* (0.044)	3.95* (0.093)	5.11* (0.048)
Sobering Center	-0.335* (0.045)	-0.180* (0.083)	-0.239* (0.053)
Controls+			
COVID-19	-0.187* (0.061)	-0.086 (0.097)	-0.122* (0.061)
Linear Trend	-0.001* (0.000)	-0.007* (0.000)	-0.011* (0.000)
+All regression models include February – December monthly dummy variables (included in models but excluded from tables for parsimony); *$p < 0.05$, ** $p < 0.01$			

The results of the DUI arrest changes by race/ethnicity indicated no statistically significant differences in DUI arrest during the post-sobering center period. Specifically, White DUI arrests declined by 16.1% (Exp(-0.175)), net of controls. Hispanic DUI arrests declined by 12.0% (Exp(-0.128)). Black DUI arrests declined by 17.5% (Exp(-0.193)). None of the difference coefficient tests indicated any group divergence from one another, indicating

[51] Roughly 98.8% of all arrestees were classified as either Black, White, or Hispanic. There was insufficient statistical power to detect effects by any other racial and ethnic group in Austin given this distribution.

[52] Clogg-Z coefficient difference tests were run separately for each racial/ethnic group.

the reductions in DUI arrests were proportionally similar for all three racial/ethnic groups examined here.

Table 6.12. Time Series Analysis of DUI Arrests Changes in Austin by Race/Ethnicity

	White DUI Arrests	Hispanic DUI Arrests	Black DUI Arrests
	B (SE)	B (SE)	B (SE)
Intercept	5.56* (0.042)	5.40* (0.051)	3.63* (0.058)
Sobering Center	-0.175* (0.039)	-0.128* (0.039)	-0.193* (0.054)
Controls+			
COVID-19	-0.496* (0.044)	-0.237* (0.042)	-0.301* (0.058)
Linear Trend	-0.003* (0.000)	-0.001* (0.000)	0.003* (0.000)
+All regression models include February – December monthly dummy variables (included in models but excluded from tables for parsimony); *p < 0.05, ** p < 0.01			

The results of the possession arrest changes by race/ethnicity similarly indicated no statistically significant differences during the post-sobering center period. Specifically, net of controls, White possession arrests declined by 23.5%, Hispanic possession arrests declined by 25.4%, and Black possession arrests declined by 27.8%. Again, none of the difference coefficient tests indicated any group divergence from one another, indicating the reductions in possession arrests were proportionally similar for all three racial and ethnic groups examined. Finally, we highligt that the largest decline in DUI arrests corresponding with the COVID-19 pandemic was for White DUI arrests by 39.1%, which was significantly larger in magnitude than DUI arrests for Blacks or Hispanics. There were no differences in magnitude for possession arrests among Blacks, Whites, or Hispanics.

Table 6.13. Time Series Analysis of Possession Arrest Changes in Austin by Race/Ethnicity

	White PO Arrests	Hispanic PO Arrests	Black PO Arrests
	B (SE)	B (SE)	B (SE)
Intercept	5.28* (0.049)	5.42* (0.056)	5.47* (0.048)
Sobering Center	-0.268* (0.047)	-0.293* (0.054)	-0.326* (0.041)
Controls+			
COVID-19	-0.675* (0.054)	-0.748* (0.066)	-0.615* (0.056)
Linear Trend	-0.002* (0.000)	-0.002* (0.000)	-0.001* (0.000)

+All regression models include February – December monthly dummy variables (included in models but excluded from tables for parsimony) *p < 0.05, ** p < 0.01

Summary of Findings from Austin Police Data

Considering that many sobering centers are designed as an alternative to arrest, we anticipated a reduction in specific types of arrests, primarily those that are directly associated with intoxication (via alcohol or drugs). The bivariate and multivariate time series analyses indicated a pattern of findings consistent with our research hypotheses; these results suggested an overall targeted reduction in the arrest types most likely to be influenced by the opening and utilization of the SCA.

Our examination of the impact on arrests following the opening of the sobering center in Austin shows several important findings. In the post-sobering center period, we observed ***statistically significant declines*** in possession arrests (27%) and public intoxication arrests (24%), net of controls, and the impact of COVID-19 on arrests. DUI arrests also declined at a greater rate (14%) than overall arrests (7%). These changes in arrests of interest suggest their declines were greater in magnitude than the change in overall arrests (7%), net of the same controls. No such divergence was observed for disorderly conduct arrests, which had a smaller frequency in event counts than all other outcomes of interest.

The supplemental race and ethnicity analyses for arrests indicated some divergent impacts across various outcomes. For public intoxication, White arrestees experienced larger reductions in arrests than did Black and Hispanic arrestees. Conversely, DUI and possession arrests declined at a similar (non-divergent) rate for Whites, Blacks, and Hispanics. Thus, there were mostly commensurate declines among these arrest types across racial and ethnic groups, though for public intoxication arrests more so for White arrestees.

Results of Focus Groups with Austin Police

On August 10, 2022, two members of our research team traveled to the Austin Police Department (APD) to engage in two focus group discussions with APD officers on the use of the Sobering Center of Austin (SCA). Both sessions were held in the afternoon, with one group of seven patrol officers from the day shift (zero supervisors) and one group of ten participants from the night shift (seven patrol officers and three supervisors). All officers were assigned to the George sector, the primary downtown patrol area of APD. Each session lasted about 30 minutes. As with all focus groups for this project, the conversation began with a short statement from the lead researcher about the purpose of the focus group, scope of the conversation, and the officers' guarantees to anonymity. The results of the focus groups are discussed below.

Benefits and Obstacles

Officers were asked about the benefits and obstacles to using the sobering center in Austin. Officers agreed that sobering centers were a good alternative to jail and felt that their "hands were forced" before the sobering center opened in late 2018. Before the SCA, officers could only take publicly intoxicated persons to jail or emergency departments. Officers also agreed that processing at the SCA is much faster than at the jail; officers may have to spend five to 30 minutes at the SCA, but they reported processing at the jail would take at least two hours. If officers had to transport to the hospital, officers stated that they were required to stay with the intoxicated person for a minimum of four hours due to APD policy. Officers indicated that the SCA was more frequently used for bar patrons and younger adults who become overly intoxicated. The City of Austin is well known for its large bar scene that attracts many visitors. A final benefit the officers mentioned was that the SCA sometimes sent staff to assist in areas with busy bars (6th Street) and use street outreach to bring inebriated persons directly to the sobering center. The officers thought this greatly benefited both APD and local EMS.

Discussions also identified challenges to officer use of sobering centers. Officers disclosed that determining the appropriate "level" of intoxication for individuals to be sent to the SCA was difficult. The officers viewed this as a narrow window—where the person is somehow a danger to themselves but not behaving badly enough for jail. Reasons for non-admission to the SCA experienced by officers included rejection because they were too inebriated, on a no-admit list, or had a type of head injury. All night shift focus group officers reported being called back to the SCA to deal with a problem. This was primarily an issue for the night shift, as the day shift was infrequently called to handle issues at the SCA. A final challenge that some officers encountered in diverting individuals to the SCA was if the person has additional charges or warrants or if, during a search before transport, they are found with contraband, the person is no longer eligible for the SCA and must be taken to jail.

Officer Decision-Making

In dealing with a publicly inebriated person, officers agreed that they preferred to release the individual to a responsible party (e.g., a friend, family member, etc.) rather than taking them to a sobering center or jail. However, the officers also try to gauge how well the individual knows the responsible party; if it appears they do not, then the officer will not release them—for example, if an over-intoxicated female is with an male companion. If no responsible party is available, then the second preference is to transport that person to the SCA. APD policy requires officers to use the center over the use of arrest, and officers must justify to supervisors if they want to use jail instead. Officers said they also considered the person's effect on the public while on the scene; if they are causing problems, officers will remove them from the scene. Additionally, if they appear agitated or non-compliant, that person may be transported to jail over the SCA. Officers also felt the SCA was safer to take inebriated persons into protective care, particularly if the person is young, a tourist, or a possible target for victimization.

When it comes to handling chronic inebriates, such as individuals experiencing being unhoused, decision-making is slightly different. Officers viewed these individuals as less likely to be victimized. Instead, they would be transported to the SCA if there was a call for service or complaint. Additionally, officers may have to call EMS for any medical concerns. Officers note that when dealing with the unhoused population, which is more frequent during the day shift, these unhoused individuals sometimes want to be sent to the SCA because they are cold or want a safe place to rest. However, officers try to suggest other options if they are not intoxicated and are simply looking to be transported. Officers note that this happens sometimes, and officers offer other alternatives beyond the center, usually other shelters.

Supervision

There is a direct supervisory expectation that officers use sobering centers for non-violent, non-criminal inebriates. Officers must get supervisor approval to take eligible inebriates to the jail rather than the SCA. Officers noted that supervisors trust officer judgments, but if they arrest for public intoxication (PI) only, the officer has to justify the decision in their written report. Officers also suggested many senior officers are assigned to the downtown area command; these officers can intervene if they see a rookie officer who may not be diverting eligible individuals to the SCA.

In terms of command staff expectations, officers noted a more pronounced command staff support of diverting individuals to the SCA when it opened in 2019. Since then, little has been done to promote the use of this resource at the command level. Officers noted that over the last few years, revised policies were released that refined the criteria and expectations for officer use of the SCA.

Impact of Geography

Most intoxicated individuals are picked up in the George sector, and all officers in the Austin focus groups were assigned to the George Sector. This sector contains Austin's entertainment districts, including Sixth Street and Rainey Street. Officers noted that they often get calls for service about intoxicated persons from private security and bouncers on these streets. When asked about other areas with concentrations of inebriated individuals, officers reported that the "domain area" was also common. However, officers noted that this was far away and officers do not always patrol in cars; therefore, transporting to the SCA was not always an option. Officers also identified the Adams sector as an area with a high concentration of inebriates, although transports from that sector are less likely. In this area, off-duty contract officers are often dealing with inebriated individuals, but they do not have a vehicle for transport and have to call someone on duty.

Officer Recommendations

Officers viewed the sobering center as a helpful resource for the most part, in that it required less time and less paperwork on the officer's behalf. The officers felt that the more options for handling intoxicated persons, the better. However, officers also agreed that it was sometimes difficult to decide whether to take an inebriated person to the SCA, to jail, or to the hospital. This was framed as a "fine line" for the officer to walk. If taking intoxicated individuals to the jail, officers noted that jail wait times to see a nurse can be very long, especially during the day. However, ultimately the inebriated person has to agree to go to the SCA. If they refuse, the next option is jail.

Officers noted throughout both discussions that they often experience pushback from individuals who are being told they will be transported to the sobering center. This pushback may stem from believing that the SCA is in jail and/or is associated with legal consequences. Officers noted that this challenge often results in them spending significant time convincing the individual to agree to go to the SCA. Officers recommended the development of a communication sheet of SCA benefits to read to intoxicated persons.

Regarding recommendations to cities considering developing sobering centers, officers recommended that the center be located as closely as possible to the highest concentration of PI arrests and/or near the jail.

Concluding Remarks

In conclusion, the primary goal of this focus group was to understand APD officer decision-making in using sobering centers in lieu of arrest. The APD officers who participated in the focus groups agreed that the Sobering Center of Austin (SCA) was a helpful resource, saving officer time and paperwork compared to jail transports. Officers also try to gauge the person's effect on the public in their decision-making; if they appear agitated, they may be transported to jail over the SCA. However, the person must agree to go to the SCA. Officers noted it was sometimes challenging to convince inebriated persons to go to the sobering center, often because they are unfamiliar with what these facilities entail. Indeed, this challenge led to officers suggesting that creating a short document highlighting SCA benefits might be helpful while on patrol and can be used to persuade intoxicated individuals to agree to be transported there. Officers voiced some frustration about deciding whether an individual is best suited for the SCA, the hospital, or the jail. They described a "fine line" in determining whether a person was too drunk to be in public but not so intoxicated that they needed to go to the hospital. Further, the diminished capacity of individuals, due to their level of intoxication, made it challenging to persuade individuals to agree to go to the sobering center. We elaborate on this issue and its connection to other findings and recommendations in the Discussion section of this report.

CHAPTER 7: HOUSTON, TEXAS

Houston is the largest city in the State of Texas, with 2,288,250 residents in 2021 (US Census, 2022). Located in the West South Central sub-region of the South, Houston is the 4th most populous city in the US. The population has the largest majority of Hispanic residents (44.5%), followed by White (24.1%), Black (22.3%), Asian (6.8%), Mixed Race (1.9%), and Other races (0.40%). In addition, approximately 28.9% of the residents were born outside of the US, which is more than twice the national average of 13.5%. The median income for a household in Houston is $53,600.

Policing services are provided to Houston through the Houston Police Department (HPD). According to 2019 statistics, the HPD is comprised of 5,257 sworn officers and 895 civilians. The HPD is responsible for more than 671 square miles of police jurisdiction. According to the 2016 LEMAS data, the HPD receives 2,445,080 calls annually and dispatches officers to 1,168,383 calls. In 2016, the HPD reported an annual operating budget of approximately $806 million.

In handling publicly intoxicated persons, officers are guided by HPD policy. Under the appropriate circumstances[53], HPD advises officers to divert publicly intoxicated individuals to the custody of a responsible adult or to the sobering center in Houston as an alternative to arrest. HPD requires supervisor approval to place a publicly intoxicated person in jail instead of taking the person to the center or releasing them into the custody of a responsible adult.

The sobering services in Houston are provided by the Houston Recovery Center (HRC), located in the same building in Downtown Houston as the HPD Mental Health Division. The HRC opened in April 2013 and was modeled after the San Antonio Sobering Center. The HRC is operated as a non-profit and is funded and managed by the City of Houston. In addition to the sobering center program, the HRC also provides programs for addiction recovery and peer support and Public Intoxication Transport, a program giving proactive patrols for intervention, wellness checks, and transport by emergency medical technicians and peer recovery specialists.

The capacity of the HRC is 84 people, with approximately 16 beds dedicated to female clients. While all client holds are voluntary, the average stay at the HRC is about 4-6 hours. Those with long-term addiction issues can stay at the HRC until a spot opens at a treatment facility, sometimes taking more than 30 days. Clients are primarily brought to the HRC by law enforcement, but the HRC also seeks out clients through street outreach

[53] Individuals must be over 18, have no medical issues, and are not displaying signs of active aggression or have active warrants.

(also considered proactive intervention) and HRC staff stationed in local hospitals. Once a client enters the facility, the intake procedure includes a brief medical screen conducted by a staff emergency medical technician. Clients can be intoxicated on alcohol or other drugs, except for bath salts or phencyclidine (PCP). While in the sobering center, clients receive water, electrolyte drinks, crackers, and a safe place to sleep. Upon release from the HRC, staff gather discharge information and use a follow-up protocol to assess client needs and recommend appropriate services.

Analyses of Houston Sobering Center

This report section relies on data collected by the Houston Recovery Center (HRC). The primary unit of analysis is an individual admitted to the sobering center, referred to as a "client." The HRC began collecting descriptive data on April 10, 2013, when the facility opened, for most variables included in this analysis. However, over time other variables were added to the data collection efforts. For example, on August 15, 2017, the HRC began including a measure of blood alcohol content taken at admission, self-reported arrest history, and employment status. Additional variables were added in 2018 and again in 2019. The analyses in this report are based on HRC data collected through March 31, 2021. Table 1 in Appendix E presents a detailed description of all HRC variables used in the following analyses, including the variable definition, data range of availability, and how the variable was coded for use in analyses.

The purpose of analyzing these sobering center data is to understand HRC use and its clientele overall. As such, in this section, we explore five broad research questions:

- *What are the trends in HRC admissions?*
- *What are the characteristics of the HRC clientele?*
- *Are there differences in the characteristics of one-admission clients and repeat-admission clients (those who have been admitted to the HRC on multiple occasions)?*
- *What client characteristics are associated with differences in length of stay per admission at the HRC?*
- *What client characteristics are associated with a client enrolling in a recovery program upon discharge from the HRC?*

Several analyses provide insight into these research questions. Descriptive, bivariate, and multivariate analyses are used to glean a clearer understanding of the use of the HRC and its clientele, who otherwise would likely be transported to jail if the HRC was not an available alternative.

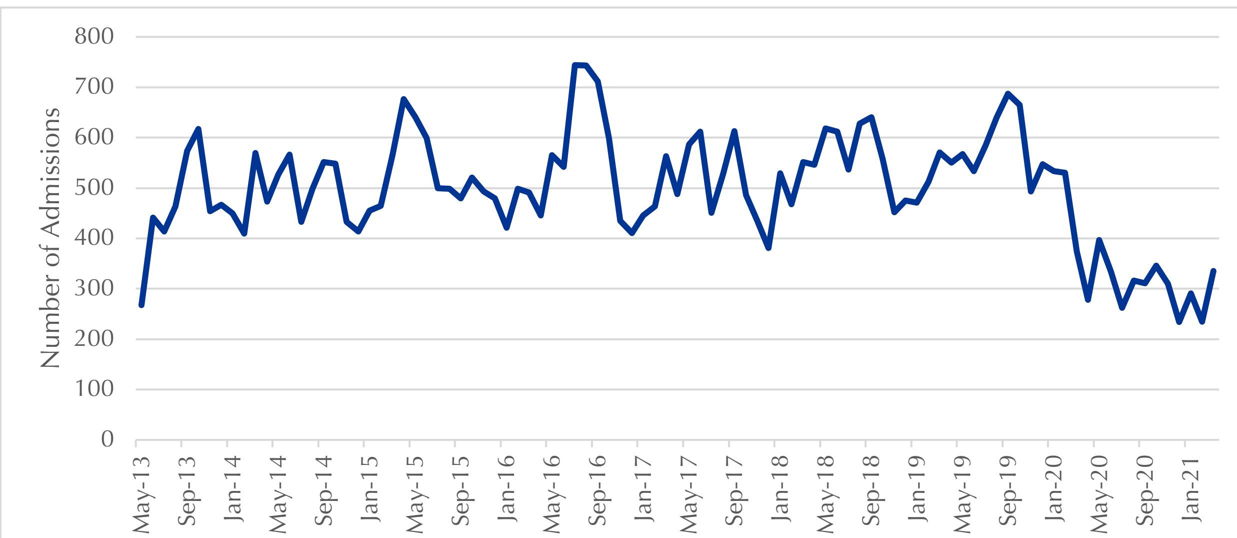
Trends in Sobering Center Client Admissions

This section provides a descriptive exploration of the trends in the HRC's admissions. Specifically, charts and descriptive statistics are used to demonstrate the trends in admissions counts, characteristics of admissions and the use of the HRC, and the characteristics of the clients referred to the HRC.

Trends in Admissions

From April 10, 2013, until March 31, 2021, the HRC had 47,182 admissions. This corresponds to approximately 5,973 admissions per year or 498 per month. Figure 7.1 displays the monthly admissions counts for all months with complete data. As can be seen, much variation exists for admissions counts across time. Specifically, from June 2013 to the month preceding the COVID-19 pandemic (March 2020), the average number of monthly HRC admissions 529 admissions. In April 2020, when the COVID-19 pandemic began, intakes dropped precipitously and remained lower than the pre-COVID average throughout the duration of our data collection period. From April 2020 through March 2021, the average number of HRC admissions was approximately 303 per month.

Figure 7.1. HRC Admissions Counts by Month from 5/1/2013 to 3/31/2021 (*N* = 47,124)



Estimate of Jail Days Saved

Based on the HRC admission counts, we calculated an estimated number of "jail days" saved if each sobering center admission was a true diversion from an arrest and jail admission. The number of "jail days" saved was estimated by multiplying the number of yearly admissions by the average number of hours spent in the sobering center per admission per year.[54] This number was then divided by 24 to estimate the "days" saved. Table 7.1 shows the number of jail days saved per year. According to our estimates, 47,182 clients admitted over eight years stayed an estimated total of 232,597 hours in the HRC. This translates to approximately 9,692 days since the HRC has been in operation. When considering the six full calendar years (not including 2020 because of COVID-19) in the available data, an average estimate of 1,278 jail days per year are saved by diverting individuals from jail to the HRC.

Table 7.1. Estimated Jail Days Saved by Diversion to Sobering Center by Year(*N* = 47,182)

Year	Jail Days Saved
2013*	854
2014	1,182
2015	1,176
2016	1,249
2017	1,239
2018	1,340
2019	1,481
2020	966
2021*	205

Note: * indicates when data does not cover the full calendar year.

Admissions Characteristics

The HRC is available 24 hours a day, seven days a week. Table 7.2 displays the descriptive statistics for HRC admissions characteristics. There were slightly more admissions occurring at night (from 7:00 PM to 6:59 AM) than during the day. Admissions across days of the week were fairly consistent, with the lowest proportion of admissions occurring on Thursdays (13.5%) and the largest proportion occurring on Saturdays (15.5%). Admissions are split almost evenly between work days and weekends, with approximately 55% of admissions occurring during the work week (Monday, Tuesday, Wednesday, and Thursday) and 45% occurring over the weekend (Friday, Saturday, and Sunday).

Admissions are also relatively consistent across seasons, with 24.3% of admissions occurring in the fall, 23.0% in the winter, 25.6% in the spring, and 27.1% in the summer. A significant association was found between the time of day for admission and whether the admission occurred during the work week or the weekend ($\chi^2 = 1997.430$; $df = 1$; $p <$

[54] Some clients were reported in the database as having very long stays at HRC. Given that these long durations would bias the calculation of average length of stay per year, we restricted the calculation of the average length of stay to only admissions that were less than or equal to 24 hours (97.6% of admissions).

0.001). As expected, a larger proportion of admissions over the weekend occurred during nighttime hours compared to the HRC admissions during the work week (54.7% vs. 45.3%). A significant—but not very substantive— association was also observed between the time of day and season (χ^2 = 11.427; *df* = 3; *p* = 0.010). Daytime admissions comprised 47.7% of overall admissions, but 47.2% in winter, 48.5% in spring, 48.2% in summer, and 46.6% in fall. Variation was also observed between the time of day and season of the admission (χ^2 = 14.294; *df* = 3; *p* = 0.003); 44.9% of all admissions to HRC occurred during the weekend. The respective proportions were 44.6% in the winter, 43.7% in the spring, 45.9% in the summer, and 45.7% in the fall.

The HRC collects information regarding the source of the client's admission to the sobering center. The most common source was law enforcement. Specifically, 80.7% of clients were admitted to the HRC by law enforcement officers. When considering the law enforcement agencies responsible for the referral to HRC, the majority were from Houston Police Department (HPD) (81.2%). The remaining referrals from law enforcement came from Metro-Transit (6.9%), Harris County Constables (5.5%), Harris County Sherriff (3.5%), university-affiliated police (1.5%), Veteran Affairs Police (0.2%), school district police (0.1%), and "other" agencies (1.1%). While law enforcement was the source for the majority of clients, other sources of admission included court, probation, or jail (6.7%), Public Intoxication Transport (5.9%), community or family members (4.5%), mental health or substance abuse services (1.1%), and "other" (1.2%).

Table 7.2. Houston Sobering Center Admission Characteristics

	%	*N*
Daytime Admission	47.7	47,182
Day of the Week		47,182
Sunday	14.6	
Monday	14.1	
Tuesday	13.9	
Wednesday	13.6	
Thursday	13.5	
Friday	14.8	
Saturday	15.5	
Weekend Admission	44.9	47,182
Season of Year		47,182
Winter	23.0	
Spring	25.6	
Summer	27.1	
Fall	24.3	
Admission Source		47,182
Law Enforcement	80.7	

Public Intoxication Transport	5.9	
Court/Probation/Jail	6.7	
Community/Family	4.5	
Mental Health/Substance Use Services	1.1	
Other	1.1	
Law Enforcement Agency		37,915
Houston PD	81.2	
Harris County Sherriff	3.5	
Metro-Transit	6.9	
Harris County Constables	5.5	
University-affiliated Police	1.5	
School District Police	0.1	
Veteran Affairs Police	0.2	
Other	1.1	

The HPD assigns officers to geographically-based beats. When applicable, the information for these beats is collected by the HRC during the intake process. Overall, beat information was available for 30,841 admissions to HRC that listed HPD as the source of admission. Approximately 43% of these admissions came from just six beats. Of note, these beats are all geographically contiguous with the HRC (see Table 7.3).[55] Houston's central business district is found within Beat 1A10, which is also the beat where the HRC is located; this beat made up the greater proportion of Houston PD admissions from a single beat (14.3%). When considering the other most prominent beats, it is clear that distance to the HRC is inversely related to the number of clients admitted to the HRC from the HPD. In other words, the closer the beat is to the HRC, the higher proportion of clients. While other factors are likely involved—such as the density of bars and night clubs and unhoused populations—this finding suggests that proximity to the HRC plays a critical role in the decision of police officers to divert an individual to the HRC.

Table 7.3. HPD Referrals to the HRC by Beat from 4/10/2013 to 3/31/2021 (*N* = 30,841)

HPD Beat	HPD District, Division	Percentage of referrals	Count of referrals
1A10	Downtown Division, District 1	14.3	4,396
1A20	Central Division, District 1, 2	9.3	2,856
10H40	South Central Division, District 10	7.6	2,352
2A10	Central Division, District 1, 2	6.1	1,871
2A50	Central Division, District 1, 2	3.0	915
1A30	Central Division, District 1, 2	2.8	854

[55] The Houston PD patrol map is available at: https://www.houstontx.gov/police/pdfs/hpd_beat_map.pdf.

Remaining Beats	56.9%	17,597

Client Characteristics

Table 7.4 contains descriptive information about clients admitted to the HRC. Individuals admitted to the HRC during the data timeframe were overwhelmingly male (82.2%). Among racial/ethnic groups, 40.8% of clients were White, 36.0% were African American, and 21.2% were Hispanic/Latino. The remaining 2% of admissions were made up of clients who identified as either Asian, Native American, Pacific Islander, two or more races, or "other". The average age at intake was 39.5 years (nearly a 13-point standard deviation) with a median of 38 years. The youngest age at intake was 17 years, and the oldest was 86 years.

Approximately 42% of clients were identified as unhoused at admission to the HRC. Few clients were identified as United States military veterans (8.5%). The vast majority (83.8%) were identified as having low-income status at the time of admission (missing for 41.3% of admissions), and 60.8% were unemployed (missing for 68.5% of admissions). Furthermore, the HRC began collecting data on educational attainment in February 2019 (missing for 86.9%). While these data are limited, most clients (55.8%) during this timeframe had completed high school or received a GED. Yet, approximately 24% had not completed high school. Approximately 8% of clients had completed an Associate's degree or a Bachelor's degree, respectively, while 2.8% had completed a professional or advanced degree.

The HRC also collects client details regarding self-reported mental health issues, history of visits to the emergency room, treatment history, and history of arrest. Of the HRC clients with available mental health data, 34.1% self-reported having at least one mental health issue. Of those who identified a mental health issue, the most common examples were anxiety, depression, and bipolar disorder. Twenty percent of HRC clients stated during admissions that they had been to the emergency room at least once in the last 90 days, while 18.6% stated they had received treatment for substance use or mental health within the last 12 months. Approximately two-thirds of the HRC clients reported having been previously arrested. Although this number is significantly higher than the prevalence of arrest in the general population, it is consistent with those reported in other substance-using samples (Brame et al., 2012).

The HRC collects information on the substance the client is using at the time of admission to the HRC. Alcohol (79.6%) was overwhelmingly the most common substance used by admitted clients. Marijuana or synthetic marijuana ("kush") was the next most common substance used among HRC clients (20.8%), followed by crack or cocaine (7.8%). The use of other substances was infrequently reported, but of these substances, methamphetamine and heroin or other opioids were the most common. The remaining admissions involved substances such as MDMA, PCP, benzodiazepine, barbiturates, and "other" substances.

Since the HRC collects data on all substances used by a client at the time of their admissions, information on multiple substance users can be examined. As such, 87.2% of clients were identified as being single substance user, while 12.8% were identified as using more than one substance at the time of their admission to the HRC. When considering the number of substances being used, 8.8% were identified as using two substances, 2.3% were using three substances, and 1.7% were using between four and nine substances. Of single substance users, alcohol was the predominant substance of choice, with 80.0% of clients identified as users of just alcohol. The next most common substance used by single-substance clients was marijuana or synthetic marijuana (13.2%).[56]

Table 7.4. Houston Sobering Center Client Characteristics

	Mean (SD) / %	*N*
Gender		47,158
Male	82.2	
Female	17.6	
Transgender	0.3	
Race/Ethnicity		42,208
White	40.8	
African American	36.0	
Hispanic/Latino	21.2	
Asian	1.3	
Native American	0.2	
Pacific Islander	0.1	
Two or more	0.1	
Other	0.3	
Age	39.46 (12.71)	47,167
Unhoused	41.9	45,821
Veteran	8.5	46,234
Low Income Status	83.8	27,700
Unemployed	60.8	14,854
Educational Attainment		6,191
Less than High School	24.4	
High School/GED	55.8	
Associate's Degree	7.9	
Bachelor's Degree	8.0	

[56] While less frequent, the substance used by the remaining 6.8% of single substance users included cocaine/crack (2.7%), heroin/opioids (1.4%), methamphetamine (1.2%), PCP (0.5%), benzodiazepine (0.3%), barbiturates (0.1%), MDMA (0.1%), and "other" substances (0.6%).

Professional or Advanced Degree	2.8	
Other Education	1.1	
Mental Health Issue	34.1	36,996
ER Visit in Las 90 Days	20.0	37,010
Treatment in Last Year	18.6	14,680
Ever Arrested	66.6	37,255
Substance		42,168
Alcohol	79.6	
Marijuana/Synthetic	20.8	
Cocaine/Crack	7.8	
Methamphetamine	3.6	
Heroin/Opioids	3.5	
MDMA	1.1	
PCP	1.4	
Benzodiazepine	1.6	
Barbiturates	1.0	
Other	0.5	
Number of Substances	1.21 (0.71)	42,168
Multiple Substance User	12.8	42,168
BAC at Intake	0.127 (0.114)	17,491
Readiness for Treatment		34,508
Ready for Treatment	58.5%	
Unsure	19.9%	
Not Ready for Treatment	21.6%	
Repeat Visit	37.8	47,182
Admissions Count	1.61 (2.96)	29,373
Stay Duration (hours)	4.91 (3.90)	43,250

During the HRC admissions process, all clients receive a blood alcohol concentration (BAC) test. For all admissions (including the individuals who were not using alcohol), the average BAC at intake was .127. This average, however, is slightly skewed by the non-alcohol users who are inflating BACs equal to 0.000. Specifically, 99.4% of the clients who reported using substances other than alcohol (*n* = 3,293) had a BAC equal to .000. When considering only the clients with alcohol identified as their primary substance, the average BAC increases to 0.173, with a minimum BAC of 0.000 and maximum of 0.405. For all clients who had a BAC test at intake that was positive for alcohol (i.e., not equal to 0.000) regardless of primary substance used, the average BAC was 0.191. Clients report their readiness for treatment. Of the clients in the HRC database, 58.5% reported they were ready for treatment, 19.9% stated they were unsure, and 21.6% said they were not ready.

The HRC data collection efforts attempt to track individual clients by assigning a unique identifier to track individuals across repeated visits. Of all admissions, 62.3% were the first HRC admission for that specific individual. The remaining 37.8% were repeat visits. Overall, 29,373 unique individuals (clients) made up the 47,182 total HRC admissions during the data timeframe. The average number of admissions per individual equaled 1.61 with a standard deviation of 2.96. The median and modal frequency of admissions were equal to 1 (81.1% had only one admission) and the highest number of admissions for a single individual was 173 admissions during the nearly 8-year time period.

Finally, variation exists for how long clients stay at the HRC. The average length of stay at the HRC per admission was 6.8 hours (standard deviation = 19.3), with a median of 4.1 hours. These data are skewed given that the distribution of the data on the length of stay for admissions ranged from 0 hours to approximately 48 days. Yet only 2.3% of the sample had a recorded length of stay that was greater than 24 hours. When the sample is restricted to only the clients who stayed for 24 hours or less, we observe a distribution with an average length of stay of 4.9 hours and a median of 4.1 hours. Of note, the HRC began to identify clients who were held over for services in July 2018. During this timeframe, 14.6% of HRC clients were holdovers. The average length of stay at the HRC with holdovers excluded was 5.5 hours.

Characteristics of Non-Admissions to the HRC

The HRC collects data on incidences when the referred client is not formally admitted to the HRC. Contained within a separate database, the HRC documents information such as the date, the unique ID for the client, and the client's age, gender, and race/ethnicity. These data also include information about the source of the referral, the source of transportation, the law enforcement agency, beat, and reason for the non-admission. During the timeframe of our study, 1,998 clients were referred to the HRC but not admitted.

The most common reason that clients were refused admission to the HRC was client non-compliance (47.5%). Medical (13.4%) or COVID-19 symptoms (10.5%) were the next most common reasons, followed by law enforcement (8.1%), mental health (7.4%), and use of a restricted drug (5.4%). Other reasons for non-admission were infrequently reported but include client refusal of services (2.8%), client had no identification (1.8%), client was non-ambulatory (1.4%), client had an outstanding warrant (0.6%), client was underage (0.6%), or that no officer was on site (0.1%).

We examined whether any client characteristics were associated with whether a client was admitted to the HRC. **Time of day of the admission** ($\chi^2 = 88.402$; $df = 1$; $p < 0.001$**)**, **day of the week** ($\chi^2 = 4.734$; $df = 1$; $p = 0.03$), **source of admission** ($\chi^2 = 9.812$; $df = 1$; $p = 0.002$), and **race/ethnicity** ($\chi^2 = 20.821$; $df = 2$; $p < 0.001$) were statistically significantly associated with being admitted or not admitted to the HRC, while season of the year, gender, or age were not. As shown in Table 7.5, a greater proportion than expected of those not admitted to the HRC, compared to those admitted, were brought to the HRC during the nighttime hours and on the weekend. A greater proportion of those not admitted to the HRC had a non-law enforcement referral source compared to those who were admitted. Finally, a greater proportion than expected of clients not admitted to the HRC were either White or African American, while a smaller proportion of those not admitted were Hispanic/Latino.

Table 7.5. Characteristics of Admission and Non-Admissions to the HRC

	Percent of Clients (N = 49,180)	
Not Admitted to the HRC	4.1%	
Admitted to the HRC	95.9%	
	Not Admitted	Admitted
Nighttime Admission (n = 49,180)	63.1%	52.3%
Weekend Admission (n = 49,180)	47.5%	45.0%
Police Referral (n = 49,154)	83.5%	80.7%
White (n = 43,010)	42.9%	41.7%
African American (n = 43,010)	40.0%	36.8%
Hispanic/Latino (n = 43,010)	17.0%	21.6%

Admission Trends by Client Characteristics

Next, we analyzed the HRC data to test for potential bivariate associations between trends in admissions—including time of day, day of the week, and season of the year—and characteristics of the individuals admitted to the HRC. The client characteristics explored include gender, age, race/ethnicity,housing status, veteran status, educational attainment, employment, low-income status, mental health issue, treatment history, arrest history, alcohol use, multiple substance use, BAC, repeat client, and referral source. The appropriate bivariate statistical test (i.e., chi-square test for independence, independent *t*-tests, or one-way analysis of variance) is used depending on the level of measurement of the two variables. Due to the length of this section, it may be found in Appendix E at the end of this document.

Analysis of One-admission vs. Repeat Clients

Of particular interest for trends in admissions is whether differences exist between clients who are admitted to the HRC only once ('one-admission client') compared to those who are admitted to the HRC two or more times ('repeat client'). As detailed above, 29,373 unique individuals were responsible for the 47,182 total admissions to the HRC during the timeframe of the data. Of the 29,373 unique individuals, 23,817 (81.1%) were identified as one-admission clients and 5,556 (18.9%) were identified as repeat clients. To identify any potential differences between one-admission and repeat clients, we analyzed associations at the individual-level (rather than the admission-level)[57] across client characteristics, including gender, age, race/ethnicity, housing status, veteran status, educational attainment, employment, low-income status, mental health issue, treatment history, arrest history, alcohol use, multiple substance use, BAC, and referral source. Bivariate and multivariate analyses are used to address three areas of interest associated with potential differences between one-admission clients and repeat clients: 1) the characteristics associated with being a repeat client, 2) the characteristics associated with the number of times each client has been admitted to the HRC, and 3) the characteristics associated with the timing to re-admission to the HRC. Note that the bivariate associations can be found in Appendix E, and multivariate analyses are presented herein.

Multivariate Analysis of Repeat Clients

Next, we conducted a multivariate analysis using logistic regression to identify the characteristics associated with being a repeat client to the HRC while adjusting for the influence of all other characteristics included in the model. Once again, analyses were estimated at the individual level with each unique individual being identified as either a one-admission client or repeat client. Once all client characteristics were simultaneously considered in the multivariate model, all characteristics aside from having police as the source of the HRC referral were significantly associated with being a repeat client to the HRC (see Table 7.6).

Table 7.6. Logistic Regression Results for Predicting Repeat HRC Clients (*n* = 18,088)

Variables	*b*	Standard Error	Odds Ratio
Male	**0.340*** **	0.050	1.406
Race/Ethnicity (White reference)			
African American	**0.232*** **	0.043	1.261
Hispanic/Latino	**0.391*** **	0.052	1.478
Age	**0.019*** **	0.002	1.019
Unhoused	**1.514*** **	0.043	4.547
Veteran	**0.183** **	0.069	1.200
Mental Health Issue	**0.373*** **	0.043	1.452
Ever Arrested	**0.492*** **	0.047	1.636

[57] The admissions data obtained from the HRC is collected in a long format, where information from each admission is represented in a single row. As such, repeat clients will be represented by multiple rows that contain information for each unique admission. To perform the analyses in this section, we took the admissions database and transformed it into an individual database using the unique identifier collected by the HRC. Known as a wide format, each row in the transformed database represents a single client (based on their unique identifier). For repeat clients, data from subsequent admissions are displayed as additional columns in the database. Client characteristics, were obtained by calculating the average across admissions for each unique individual. It is those averages that are used in these analyses.

Alcohol User	**–0.373*** **	0.054	0.689
Multiple Substance User	**–0.233*** **	0.064	0.792
Police Referral	–0.076	0.062	0.927
Intercept	–2.874	0.100	0.057

Notes: * $p<0.05$, ** $p<0.01$, *** $p<0.001$ (two-tailed test)

Being male compared to female or transgender increases the logged odds of being a repeat client by approximately 41%. With all other characteristics held at their averages, the predicted probability of being a repeat client at the HRC is 21.3% for female or transgender clients. For males, the probability increases to 26.5%. Race/ethnicity was also associated with being a repeat client of the HRC. Specifically, the logged odds of being a repeat client are greater for African American and Hispanic/Latino clients compared to White clients. For example, with all other characteristics held constant, the probability of being a repeat client is 22.9% for White clients. This probability increases to 26.5% and 29.1% for African American and Hispanic/Latino clients, respectively. Age was positively associated with repeat admissions. For each one-year increase in age, the logged odds of being a repeat client increase by 1.9%. Stated differently, with all other characteristics held at their averages, a 50-year-old client has a predicted probability of being a repeat client of 28.7%, compared to a 30-year-old's predicted probability of being a repeat client at 22.6%.

Housing status was the strongest predictor of being a repeat HRC client. The logged odds of being a repeat client are 4.5 times greater for unhoused individuals compared to those who are housed. With all other characteristics held at their averages, individuals who are housed have a 16.8% probability of being a repeat client to the HRC. For individuals who are unhoused, the probability increases to 46.0%. Veterans are also more likely to be repeat clients at the HRC compared to clients who are not military veterans (Odds Ratio = 1.20). The predicted probability of being a repeat client is 28.1% for veterans and 25.2% for non-veterans. For those who self-reported mental health issues, the logged odds of being a repeat client are nearly 1.5 times greater for those with a mental health issue compared to those without. The predicted probability of being a repeat client is 29.3% for those with mental health issues compared to 23.2% for those without such issues. Clients with a history of arrest also have greater logged odds of being a repeat client compared to clients without an arrest history (OR = 1.64). With all characteristics held constant, clients with an arrest history have a predicted probability of being a repeat client that is equal to 27.9%. Clients who have never been arrested have a predicted probability of being a repeat client equal to 20.2%.

Another predictor of being a repeat client was the use of alcohol. In these data, being a user of alcohol decreases the logged odds of being a repeat client by 31% compared to clients who do not use alcohol. Considering predicted probabilities, non-alcohol users have a 30.2% probability of being a repeat client compared to 23.9% probability for users of alcohol. A similar pattern is found for multiple substance use. Specifically, after adjusting for the influence of all other variables (alcohol use in particular), the logged odds of being a repeat HRC client are less for multiple substance users compared to single substance users (Odds Ratio = 0.72). For multiple substance users, the predicted probability of being a repeat client is 22.4%, and 26.0% for single substance users.

Analysis of Admissions Counts

As a supplemental analysis to the analysis of repeat clients, we explored what characteristics are associated with the number of HRC admissions per individual. Note that the bivariate associations can be found in Appendix D, and multivariate analyses are presented herein.

We used negative binomial regression to simultaneously examine the characteristics associated with the number of HRC admissions per individual.[58] The findings—shown in Table 7.7—mirror the patterns observed in the logistic regression analyses above, with the addition of the source of admission significantly impacting admissions counts. After adjusting for the influence of all other client characteristics, males have an incident rate for HRC admissions that is 18.2% greater than that of female or transgender clients. African American and Hispanic/Latino clients have an incident rate that is 3.6% and 14.1% greater that White clients. The percent change in the incident rate of HRC admissions is a 0.7% increase for a 1-year increase in age. Unhoused clients have an incident rate of HRC admissions that is 2.4 times greater than clients who are housed, and the incident rate for admissions for veterans is 14.2% greater than non-veteran clients. The incident rate of HRC admissions is greater for clients who have a self-reported mental health issue (IRR = 1.13) and for clients who have previously been arrested (IRR = 1.22). Alcohol users (IRR = 0.93) and multiple substance users (IRR = 0.82) have an incident rate that is lower than non-alcohol and single substance-using clients. Finally, clients whose admission source is the police have an incident rate of HRC admission that is 8.6% greater than those admitted through a source other than the police.

Table 7.7. Negative Binomial Regression on Number of HRC Admissions per Individual (*n* = 18,225)

Variables	*b*	Standard Error	IRR
Male	**0.167*** **	0.019	1.182

[58] Negative binomial regression is the appropriate analytical technique for this analysis because these count data do not approximate a normal distribution. Furthermore, negative binomial is preferred over Poisson regression because there was evidence of overdispersion in the distribution of number of HRC admissions (see Long and Freese, 2006).

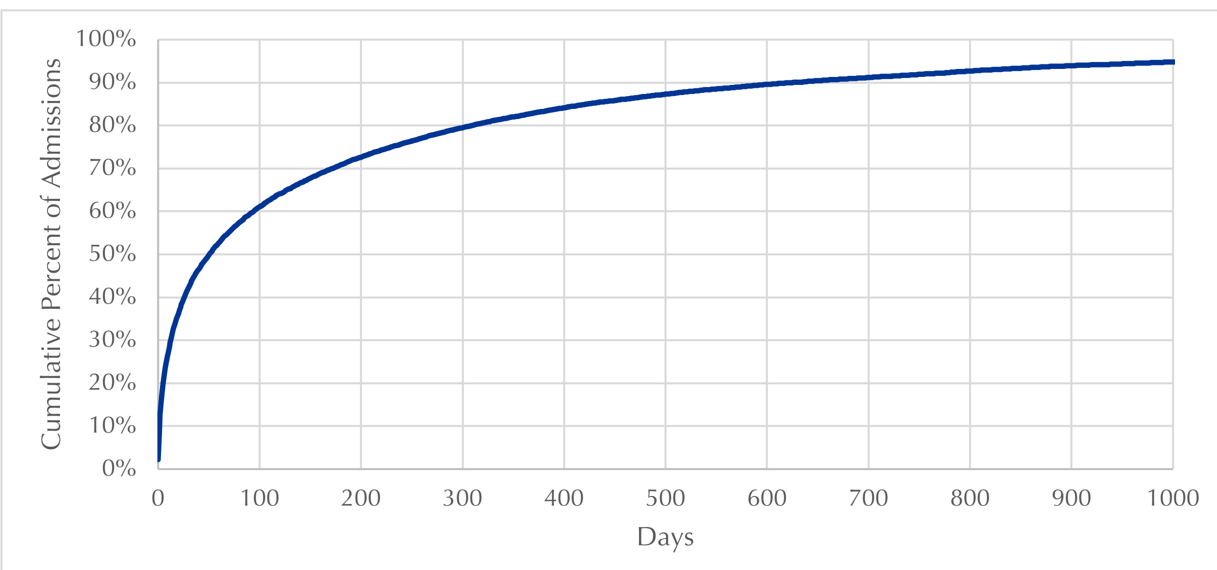
Race/Ethnicity (White reference)			
African American	**0.035***	0.016	1.036
Hispanic/Latino	**0.132*****	0.019	1.141
Age	**0.007*****	0.001	1.007
Unhoused	**0.882*****	0.018	2.417
Veteran	**0.132*****	0.026	1.142
Mental Health Issue	**0.121*****	0.017	1.128
Ever Arrested	**0.196*****	0.018	1.216
Alcohol User	**–0.070****	0.022	0.932
Multiple Substance User	**–0.197*****	0.027	0.822
Police Referral	**0.083****	0.026	1.086
Intercept	–0.310	0.038	0.733

Notes: IRR = Incident Rate Ratio.
* $p<0.05$, ** $p<0.01$, *** $p<0.001$ (two-tailed test)

Analysis of Time to Re-Admission

To further understand repeat HRC clients, we explored how the individual characteristics of clients are related to the length of time since the previous admission for repeat clients. The average number of days between HRC admissions for repeat clients was 207.1 days, with a standard deviation of 362.6. The distribution ranged from 0 days to 2,807 days, with a median of 51 days. One-quarter of re-admissions occurred within nine days of the last admission (see Figure 7.2).

Figure 7.2. Days Between Sobering Center Admissions for Repeat Clients from 5/1/2013 to 3/31/2021 (*N* = 17,809)



We first analyzed bivariate associations between client characteristics and the number of days since their last HRC admission. Significant associations are presented in Table 7.8.

Of the observed characteristics, all characteristics other than age and educational attainment were statistically significantly associated with days between HRC admissions.

HRC repeat clients who were male returned to the HRC faster than female and transgender clients. African American and Hispanic/Latino clients had an average length of time between admission that was longer than White clients. There was no significant difference in average number of days between HRC admissions between African American and Hispanic/Latino clients. Unhoused clients returned to the HRC an average of nearly 150 days earlier than repeat clients who were housed. Repeat clients who were veterans also returned to the HRC faster, on average, than repeat clients who were not veterans. Compared to the average number of days between admissions for repeat clients employed at the time of admission and those not of low-income status, unemployed and low-income clients returned to the HRC in a shorter number of days. Similarly, clients with a self-reported mental health issue and those who received treatment for substance use or mental health issues in the past year returned to the HRC faster than clients without a mental health issue and those who did not receive treatment in the last year. On average, repeat clients who have been arrested have more days between HRC admission than repeat clients who have never been arrested.

On average, the number of days between return visits to the HRC was 56 days longer for alcohol users compared to clients who were not users of alcohol. Similarly, clients who use only a single substance returned an average of 78 days faster than repeat clients who are multiple substance users. Furthermore, the number of days between admissions is positively associated with BAC at intake (r = .08). As such, the number of days between admissions is greater, on average, for the clients who have higher BACs. Repeat clients who stated they were ready to receive treatment for their substance use were re-admitted to the HRC an average of 24 days later than clients who were either not ready or unsure if they were ready for treatment. Clients whose source of admission is the police have, on average, 21 more days between admissions compared to clients admitted through a source other than the police. Finally, the average number of days between visits was longer when the previous visit was an individual’s first HRC admission. That is, individuals who have been admitted to the HRC multiple times returned to the HRC faster than those who have only been admitted once before.

Table 7.8. Average Number of Days Between Admissions by Client Characteristics

		Days Between Admissions
Gender (n = 17,809)	Male	200.7
	Female or Transgender	253.7
Race/Ethnicity (n = 16,620)	White	172.7
	African American	218.7
	Hispanic/Latino	230.8

Housing Status (*n* = 17,372)	Unhoused	158.7
	Housed	307.7
Veteran Status (*n* = 17,687)	Veteran	152.8
	Not Veteran	215.2
Employment Status (*n* = 5,655)	Employed	394.6
	Not Employed	358.5
Low-Income Status (*n* = 10,299)	Low Income	212.2
	Not Low Income	354.5
Mental Health (*n* = 13,054)	Mental Health Issue	192.9
	No Mental Health Issue	212.4
Treatment History (*n* = 5,590)	Treatment in Last Year	234.5
	No Treatment in Last Year	308.3
Arrest History (*n* = 13,158)	Prior Arrest	207.2
	Never Arrested	190.8
Alcohol Use (*n* = 15,566)	Alcohol User	226.6
	Non-Alcohol User	170.2
Multiple Substance Use (*n* = 15,566)	Multiple Substance User	279.6
	Single Substance User	201.8
Treatment Readiness (*n* = 12,655)	Ready for Treatment	183.4
	Not Ready or Unsure	207.3
Source of Admission (*n* = 17,809)	Police Source	212.2
	Non-Police Source	191.0
Admission Number (*n* = 17,809)	Second Admission	360.7
	3rd Admission or more	137.5

Next, we analyzed whether any client characteristics predicted an earlier time to re-admission using survival analysis. Bivariate Cox proportional hazard models were estimated using gender, race/ethnicity, age, housing status, veteran status, mental health issues, arrest history, alcohol use, multiple substance use, readiness for treatment, and source of admission as individual predictors. The results from these bivariate analyses are shown in the first and second columns in Table 7.9. Other than readiness for treatment, all predictors were statistically significantly associated with timing to re-admission at a bivariate level.

Bivariate analyses only take into consideration the effect of a single predictor on the outcome of interest. As a point of origin, they provide a reasonable baseline estimation of a single measure. Conversely, multivariate analyses are capable of simultaneously assessing the effects of several predictor variables while taking into consideration the effects of those additional predictors. Specifically, in a multivariate framework, the associations between specific variables can be observed while holding constant the influence of all other included variables on the outcome of interest. The ability to simultaneously account for the influence of all predictor variables on the outcome is what makes multivariate analysis a stronger analytical strategy than bivariate analysis. As such, the next step was to estimate a multivariate Cox proportional hazard model.

Table 7.9. Bivariate and Multivariate Cox Proportional Hazard Regression of Re-admission Timing to HRC (*n* = 25,088 Admissions)

	Bivariate		Multivariate	
Variables	Hazard Ratio	Standard Error	Hazard Ratio	Standard Error
Male	**1.889*** **	0.141	**1.532*** **	0.115
Race/Ethnicity (White reference)				
African American	**1.459*** **	0.103	1.133	0.083
Hispanic/Latino	**1.372*** **	0.117	**1.666*** **	0.142
Age	**1.036*** **	0.002	**1.019*** **	0.003
Unhoused	**5.802*** **	0.209	**4.188*** **	0.185
Veteran	**1.758*** **	0.160	**1.283** **	0.122
Mental Health Issue	**1.931*** **	0.089	**1.328*** **	0.070
Ever Arrested	**2.725*** **	0.106	**1.768*** **	0.076
Alcohol User	**0.492*** **	0.027	**0.882* **	0.053
Multiple Substance User	**1.157** **	0.053	**0.874** **	0.046
Police Referral	**0.496*** **	0.021	**0.884** **	0.042
Ready for Treatment	1.049	0.044	**0.908* **	0.42
Low Income^	**4.892*** **	0.319	—	—
Unemployed^	**3.351*** **	0.207	—	—
Non-High School Graduate^	**1.290** **	0.121	—	—
Treatment in Last Year^	**1.782*** **	0.134	—	—
BAC × 100^	**0.985*** **	0.005	—	—

Notes: ^ Low Income (*n* = 18,288), unemployment (*n* = 10,685), non-high school graduate (*n* = 4,538), treatment in last year (*n* = 10,611), and BAC (*n* = 9,664) are excluded from the multivariate analyses because of their impact on the sample size when using listwise deletion. BAC has been multiplied by 100 to make the results more easily interpretable. Analysis includes clustered sandwich estimators for individual IDs to adjust for repeat clients.
* $p<0.05$, ** $p<0.01$, *** $p<0.001$ (two-tailed test)

The third and fourth columns in Table 7.9 present the multivariate analysis results. Comparing the findings from the bivariate and multivariate analyses, we find that after considering the influence of other variables, the association between African American clients (relative to Whites) with risk for time to re-admission is no longer statistically significant. Moreover, after adjusting for the influence of other client characteristics, treatment readiness—which was nonsignificant in its bivariate model—is now significantly associated with risk for time between re-admission. Aside from these differences, the associations observed in the bivariate models continued to be significantly associated with re-admission timing to the HRC.

Holding all other client characteristics constant, males have a risk of re-admission at any point in time that is 1.5 times greater than female and transgender clients. While the association between White and African American clients is no longer statistically significant in the multivariate model, there continues to be a significant difference between White and Hispanic/Latino clients. Specifically, Hispanic/Latino clients tend to be re-admitted to the HRC earlier after discharge than White clients (hazard ratio = 1.666; $p < 0.001$). The rate of timing to re-admission also increases with age (hazard ratio = 1.019; $p < 0.001$). A one-year increase in age increases the rate by 1.9%. Unhoused clients tend to be re-admitted to HRC faster than non-unhoused clients (hazard ratio = 4.188; $p < 0.001$). Compared to non-unhoused clients, the rate of timing to re-admission for unhoused clients is nearly 4.2 times greater. The rate of timing to re-admission is greater for veteran clients than for non-veteran clients (hazard ratio = 1.283; $p = 0.009$). Clients with a self-reported mental health issue have a risk of re-admission at any point in time that is 1.3 times greater than those without mental health issues (hazard ratio = 1.328; $p < 0.001$). Similarly, clients who have previously been arrested tend to get re-admitted to the HRC faster than clients who have never been arrested (hazard ratio = 1.768; $p < 0.001$). Clients whose source of admission is the police have a rate of timing to readmission that is shorter, on average, compared to clients referred to the HRC by sources other than the police (hazard ratio = 0.884; $p = 0.010$). Clients who use alcohol or use multiple substances have a rate of timing to re-admission that is lower than clients who are not users of alcohol (hazard ratio = 0.882; $p = 0.036$) or who are users of only a single substance (hazard ratio = 0.874; $p = 0.010$). Finally, clients who identify themselves as being ready to quit their substance use have a lower risk of re-admission at any point in time compared to clients who are either not ready to quit or are unsure if they are ready (hazard ratio = 0.908; $p = .039$).

Analysis of Client Length of Stay in the HRC

Next, we explored the characteristics that were associated with the amount of time individuals stay at the HRC during their visit. As discussed above, variation existed for how long clients stay at the HRC. When the sample is restricted to only the clients who stayed for 24 hours or less, the distribution for the length of stay has an average length of stay of 4.91 hours and a median of 4.08 hours. Bivariate and multivariate statistical models were used to estimate these relationships. The client characteristics included in these analyses were gender, race/ethnicity, age, housing status, veteran status, educational attainment, employment status, low-income status, mental health issues, treatment history, arrest history, referral source, treatment readiness, alcohol use, multiple substance use, BAC at intake, first HRC admission compared to repeat admission, time of day, day of the week, and season of the year. Note that the bivariate associations can be found in Appendix E, and multivariate analyses are presented herein.

Multivariate Analysis of Length of Stay

OLS regression was used to observe the effects of our independent variables on the length of stay at the HRC (results shown in Table 7.10). In the multivariate model—which adjusts for the influence of all predictors simultaneously—time of day of admission, housing status, gender, age, treatment readiness, visit number to the HRC, source of admission, African American compared to White clients, mental health issue, history of arrest, alcohol use, summer and spring admission compared to winter, multiple substance use, and day of the week of admission were all statistically significant predictors of length of stay at the HRC. The only characteristics not associated with length of stay at the HRC were veteran status, Hispanic/Latino compared to White, and fall compared to winter.

On average, male clients brought to the HRC are predicted to stay 1 hour and 4 minutes less than clients who are not male. African American clients stay approximately 25 minutes less, on average, compared to White HRC clients. Age was positively associated with length of stay at the HRC. For each one-year increase in age, the length of stay is predicted to increase by about 2 minutes. Stated differently, with all other characteristics held at their averages, the predicted length of stay for a 30-year-old is approximately 5 hours, while a 50-year-old client has a predicted length of stay of 5 hours and 34 minutes. Clients who are unhoused are predicted to stay 54 minutes longer, on average, than clients who are housed. On average, clients who self-reported a mental health issue are predicted to stay 24 minutes longer compared to clients without mental health issues. On average, clients with a history of arrest are predicted to stay 22 minutes longer than clients who have never been arrested.

Alcohol users are predicted to stay 26 minutes longer than clients who are not users of alcohol, and multiple substance users have a length of stay at the HRC that is an average of 17 minutes longer than clients who only use one substance. Furthermore, clients who report they are ready for treatment and want to quit their substance use stay, on average, 43 minutes longer than clients who are either not ready or unsure. Additionally, first-time visits to the HRC tend to be shorter than repeat visits by an average of 40 minutes. Clients who are referred by police stay an average of 1 hour and 2 minutes shorter than clients referred to the HRC by another source.

Clients admitted to the HRC during the night are predicted to stay 1 hour and 23 minutes longer than those admitted during the daytime, while weekend clients are predicted to stay six minutes shorter than weekday clients. Finally, HRC clients admitted during the winter are predicted to stay longer than clients admitted in the spring (10-minute difference) or summer (11-minute difference).

Table 7.10. OLS regression on Number of Hours Spent at the HRC (*n* = 23,505)

Variables	*b*	Standard Error	Beta
Male	**–1.071*****	0.097	–0.101
Race/Ethnicity (White reference)			
African American	**–0.408*****	0.081	–0.051
Hispanic/Latino	–0.151	0.086	–0.016
Age	**0.028*****	0.003	0.094
Unhoused	**0.901*****	0.068	0.116
Veteran	–0.146	0.122	–0.012
Mental Health Issue	**0.394*****	0.070	0.049
Ever Arrested	**0.371*****	0.054	0.046
Alcohol User	**0.440*****	0.093	0.045
Multiple Substance User	**0.280***	0.111	0.020
Ready for Treatment	**0.715*****	0.056	0.093
First HRC Visit	**–0.671*****	0.079	–0.086
Police Referral	**–1.041*****	0.133	–0.085
Daytime Admission	**–1.379*****	0.058	–0.179
Weekend Admission	**–0.092***	0.047	–0.012
Season (Winter reference)			
Spring	**–0.170***	0.072	–0.019
Summer	**–0.183****	0.071	–0.021
Fall	–0.049	0.080	–0.005
Intercept	5.141	0.215	

Notes: Analysis includes clustered sandwich estimators for individual IDs to adjust for repeat clients.
* *p*<0.05, ** *p*<0.01, *** *p*<0.001 (two-tailed test)

Analysis of Client Enrollment in an HRC Recovery Program

Upon discharge, some HRC clients are enrolled in an HRC Recovery Program. Such programs include Substance Use Treatment with Case Management and Recovery Coaching (PART[59]), Recovery Coaching only (PRS)[60], or Reach, which is the same program as PART but with additional HIV, hepatitis C, or trauma treatment or counseling. In the HRC database, 14.9% of clients (n=7,014) were identified as being enrolled in an HRC Recovery Program after discharge. Of these, 67.7% were enrolled in PART, 27.5% in PRS, and 4.8% in Reach. Herein, we describe the logistic regression results on client enrollment in an HRC Recovery Program upon discharge from the HRC; bivariate findings

[59] PART is Personal Addiction Recovery Team

[60] PRS is Peer Recovery Support

can be found in Appendix E. When considering bivariate relationships, aside from educational attainment, all observed characteristics were significantly associated with enrollment in an HRC recovery program after discharge.

We estimated a logistic regression model to predict the likelihood of being enrolled in an HRC recovery program after discharge from the HRC. Table 7.11 shows ten characteristics significantly associated with enrolling in an HRC recovery program after discharge.

First, compared to being female or transgender, being male decreases the logged odds of being enrolled in an HRC recovery program by 43%. Specifically, the predicted probability of being enrolled for males is 14% and increases to 20% for female and transgender clients. Age at intake was positively associated with being enrolled in an HRC recovery program. For each one-year increase in age, the logged odds increase by 2%. The logged odds of being enrolled in a recovery program are also greater for clients who have previously been arrested. The probability of enrolling in a recovery program is 11% for clients who have never been arrested and 16% for those who have been arrested in the past. The logged odds of enrolling in a recovery program are 3.3 times greater for clients who identify they are ready for treatment compared to those who are not ready or unsure. Clients who are ready for treatment have an 18% predicted probability, and individuals who are not ready or unsure only have an 8% predicted probability. A similar observation is made for repeat HRC clients. The logged odds of being enrolled in a recovery program are 2.4 times greater for clients who have been to the HRC previously compared to those who have experienced their first HRC admission. Specifically, repeat clients have a predicted probability of enrollment of 19%. This probability decreases to 11% for first-time HRC clients. Multiple substance users are also predicted to be more likely to enroll in an HRC recovery program. The predicted probability for single-substance users is 13%, and 25% for multiple-substance users. The logged odds are also greater for clients whose source of admission was a referral other than the police. The predicted probability of enrolling in a recovery program for clients with a police referral is 10%. For those with a non-police referral, the predicted probability increases to 32%.

Differences in the logged odds of enrolling in an HRC recovery program at discharge were observed depending on when the admission took place. For time of day, the logged odds are 1.2 times greater for those who are admitted during the day compared to during the night. The predicted probability of enrollment is 16% for daytime admission and 14% for nighttime admissions. Clients admitted during the weekend are less likely to be enrolled in a recovery program, with a predicted probability of 13% compared to 16% for clients admitted during the work week. Finally, seasonal differences were observed. With winter as the reference category, the logged odds of enrolling in an HRC recovery program at discharge increased by 28% in the spring. Considering predicted probabilities, the probability of enrolling at discharge for clients in the winter is 14%, and it increases to 17% in the spring. No other significant seasonal differences were observed.

Table 7.11. Logistic Regression Results for Predicting Enrollment in an HRC Recovery Program (n = 25,088)

Variables	*b*	Standard Error	Odds Ratio
Male	**–0.563*****	0.122	0.570
Race/Ethnicity (White reference)			
African American	–0.234	0.169	0.792
Hispanic/Latino	–0.357	0.215	0.700
Age	**0.020****	0.007	1.020
Unhoused	0.009	0.077	1.009
Veteran	0.496	0.271	1.642
Mental Health Issue	0.187	0.116	1.206
Ever Arrested	**0.515*****	0.096	1.674
Ready for Treatment	**1.184*****	0.103	3.266
Alcohol User	–0.126	0.105	0.882
Multiple Substance User	**1.045*****	0.073	2.844
Repeat HRC Visit	**0.891*****	0.098	2.437
Police Referral	**–1.779*****	0.076	0.169
Daytime Admission	**0.198****	0.070	1.219
Weekend Admission	**–0.322*****	0.047	0.725
Season (Winter reference)			
Spring	**0.249*****	0.074	1.283
Summer	0.004	0.076	1.004
Fall	–0.036	0.094	0.965
Intercept	–2.640	0.317	0.071

Notes: Analysis includes clustered sandwich estimators for individual IDs to adjust for repeat admits.
* p<0.05, ** p<0.01, *** p<0.001 (two-tailed test)

Summary of Findings from the HRC Data

The purpose of these analyses was to better understand the individuals in Houston who are diverted from jail and admitted to the HRC. We explored how types of clients varied depending on when the admission occurred and explored the differences in the characteristics of one-admission clients and repeat clients and the timing to re-admission. Finally, we observed what characteristics were associated with a client's length of stay at the HRC and whether they enrolled in an HRC recovery program after discharge.

Our findings demonstrate that the clear majority of clients are admitted to the HRC by local law enforcement and that HPD officers complete the majority of law enforcement admissions. Client admissions from HPD were more likely to occur at locations relatively close to the HRC. Our analysis of beat information determined that approximately 43% of these admissions came from just six beats that were all geographically contiguous with the HRC (14.3% of admissions were from the beat within which the HRC is located). While other factors are likely involved—such as the density of bars and night clubs and unhoused populations—this finding suggests that proximity to the HRC plays a critical role in the decision of police officers to divert an individual to the HRC.

Clients referred to the HRC are overwhelmingly male and have an average age of approximately 40 years old. Approximately 41% of clients were White, 36% were African American, and 21% were Hispanic/Latino, reflecting the racial/ethnic heterogeneity of the city of Houston. Many clients are unhoused, of low-income status, unemployed, and have previously been arrested. Furthermore, the clear majority of clients are users of alcohol; just 12% of clients are users of multiple substances. Unlike other sobering centers, the HRC tracks data on people not admitted into the HRC. The most common reason for refusal was non-compliance by the client (48% of all non-admissions).

Table 7.12 summarizes many of the bivariate and multivariate results presented above. The characteristics associated with repeat clients include being male, African American or Hispanic/Latino compared to White, unhoused, older, having self-reported mental health issues, previously being arrested, and using substances other than alcohol. For the most part, these client characteristics were also consistently related to having a greater count of admissions and being re-admitted to the HRC more quickly. Additionally, it was observed that clients who identified they were ready for treatment and ready to quit their substance use tended to have a longer amount of time between admissions compared to those who were not ready or unsure if they were ready.

Being male, unhoused, admitted to the HRC during the day, having a source of referral other than the police, and being ready for treatment were major driving factors in predicting the length of stay in the HRC. Approximately 1 in 20 clients enrolled in an HRC recovery program upon discharge. An important predictor of enrollment in an HRC recovery program was a client identifying they were ready for treatment. Other important predictors of being enrolled in a recovery program included being a repeat client and being a multiple substance user. Male clients, on the other hand, are less likely to enroll in a recovery program, as are clients who have an admission source to the HRC that is not the police.

Table 7.12. Summary of Chapter Findings

	Repeat Client		Admissions Count		Time to Re-Admission		Length of Stay		Recovery Program	
Client Characteristics	*BV*	*MV*	*BV*	*MV*	*BV*	*MV*	*BV*	*MV*	*BV*	*MV*
Male	+	+	+	+	–	–	–	–	–	–
White	–	ref	–	ref	ref	ref	ref	ref	+	ref
African American	+	+	ref	+	–	×	–	–	+	×
Hispanic/Latino	–	+	–	+	–	–	–	×	–	×
Age	+	+	+	+	–	–	+	+	+	+
Unhoused	+	+	+	+	–	–	+	+	+	×
Veteran	+	+	+	+	–	–	+	×	+	×
Mental Health Issue	+	+	+	+	–	–	+	+	+	×
Ever Arrested	+	+	+	+	–	–	+	+	+	+
Alcohol Use	–	–	–	–	+	+	+	+	–	×
Multiple Substance Use	+	–	–	–	–	+	×	+	+	+
Police Referral	+	×	+	+	+	+	–	–	–	–
Ready for Treatment	.	.	.	.	×	+	+	+	+	+
No HS Completion	+	.	+	.	–	.	+	.	×	.
Unemployed	+	.	+	.	–	.	+	.	+	.
Low Income	+	.	+	.	–	.	+	.	+	.
Treatment in Last Year	+	.	×	.	.	.	.	.	+	.
BAC	–	.	–	.	+	.	+	.	–	.
First HRC Admission	.	.	.	.	.	.	–	–	–	–
Daytime Admission	.	.	.	.	.	.	–	–	+	+
Weekend Admission	.	.	.	.	.	.	–	–	–	–
Winter Admission	.	.	.	.	.	.	ref	ref	+	ref
Spring Admission	.	.	.	.	.	.	–	–	+	+
Summer Admission	.	.	.	.	.	.	×	–	–	×
Fall Admission	.	.	.	.	.	.	×	×	–	×

Notes: BV = Bivariate Analysis; MV = Multivariate Analysis; + = positive association; – = negative association; × = non-significant association; . = not included in analysis; ref = reference category for analysis.

Analysis of Houston Police Data

Due to data limitations, the analyses conducted in Houston are distinct from the other sites. While the opening of the Houston Recovery Center is relatively recent (April 2013), the Houston Police Department (HPD) experienced a change in its data collection system (from a report writing system pre-June 2014) to a Tiburon-produced system (or Record Management System) in June 2014 onward. This change eliminated the opportunity for a pre/post-time series analysis to assess the impact of public intoxication and related arrests.

A report by the Houston Recovery Center (HRC) indicates a likely 97% decline in public intoxication county jail intakes after the sobering center became a viable police alternative, demonstrating that the impact on arrests was immediate and sustained over time.[61] While this is a limited assessment impact, the Houston setting did provide an opportunity to examine sobering center intakes by the geographic context compared to the geographic distribution of arrests by HPD.

For the Houston setting (i.e., post-sobering center period only), we examined official police data with a focus on the following question:

- What proportion of charges in Houston reflect intoxication-related arrests: public intoxication (PI), driving a motor vehicle under the influence (DUI), drugs and/or drug possession (PO), and disorderly conduct (DC)?

For the period examined (1/2016 - 6/2022), HPD reported a total of 240,758 arrests; roughly 15.1% (n=36,354) of all arrests included at least one charge for public intoxication, driving a motor vehicle while under the influence, possession, and/or disorderly conduct. Table 7.13 provides more information about these arrests. Although the data from HPD did not allow for a precise pre/post impact assessment of the opening of the sobering center, the results indicating the small proportion of arrests related to these charges are suggestive of such impact, particularly for public intoxication arrests. The majority of intoxication-related arrests were for DUI charges (65% of intoxication arrests and roughly 10% of total arrests). In comparison, possession charges were also common (33% of intoxication arrests and approximately 5% of total arrests). Disorderly conduct and public intoxication arrests comprised fewer than 1% of total intoxication arrests.

---

[61] Data were obtained from the *Houston Recovery Center Report: A Proactive Solution for Substance Misusing Individuals Detained by Law Enforcement* made at the International Association of Chiefs of Police Meeting in Washington DC (2021): The Houston Sobering Center report showed that public intoxication jail-intakes ranged from between 1,000 to 2,000 per month (minimum/maximum range values) between 1/2010 and 3/2013; however post-April 2013, the highest monthly count of public intoxication jail intakes was 200 or fewer after April 2013 (with some as few as 15 per month). These results suggest that the impact of the sobering center was immediate, significant, and sustained.

Table 7.13. Intoxication-Specific Charges Among Arrests of Interest in Houston (1/2016-6/2022, Total N = 240,758)

Arrests Charges	N	% Intoxication Arrests (N = 36,354)	% Total Arrests (N =240,758)
Public Intoxication[62]	80	<1%	<0.1%
Possession	12,263	33.7%	5.1%
Disorderly Conduct	132	<1%	<0.1%
DUI	23,879	65.7%	9.9%

Neighborhood-Level Analyses of Sobering Center Intakes

The data in Houston were unique in that the HRC collected information about which HPD beat a client was transported from. This data from the HSC, linked with HPD official data (arrest, offense, and calls for service) and census measures, provided an opportunity to examine the contextual neighborhood conditions that potentially correspond with police diversions for intoxication in Houston.

There were 118 police beats where information was readily available in Houston, providing the framework for a unique 'neighborhood context' analysis. In the context of the sobering center sites examined here, HPD does not collect information regarding where (as well as when and how often) a civilian is transported by the police to the sobering center since this alternative to arrest (i.e., drop-off) is not viewed as an official police action (e.g., citation, arrest, offense reporting, or use of force). The only information collected by police agencies that we examined in this study includes where civilians are arrested, where citizen-generated calls for police assistance occur, and the locations of offenses reported to the police are derived.

By integrating the information collected at the sobering center (such as the demographics of the person transported to the sobering center, their frequency of attendance, their residency/unhoused status at the time of transport), and the structural and social characteristics of the police beats from where transportation occurred, we can examine which neighborhood conditions are associated with sobering center intake points of onset.

Background

Social scientists, and criminologists in particular, have examined crime's social and physical distribution across space. The literature strongly suggests that the distribution of crime across places is strongly related to neighborhood structure. For example, social disorganization theory suggests that neighborhoods characterized by high levels of poverty

[62] For the 80 PI arrests, one involved a case where either additional charges were filed against the suspect, while the other 79 involved suspects who had been arrested for public intoxication three or more times in the past 24 months, leading to a class B offense according to Texas law.

and unemployment, residential instability, and racial/ethnic heterogeneity traditionally have weakened social bonds between residents (Sampson et al., 1997). The lack of social connections weakens informal social control and reduces the ability of communities to address problems collectively. The lack of social control in disadvantaged neighborhoods contributes to higher rates of both lower-level crimes and physical/social incivilities (Silver & Miller, 2004; Wilson & Kelling, 1982).

These conditions provide a context that may help drive place-based associations in arrests. Specifically, as residents become unwilling to exercise informal social control, they become more reliant on formal actors, such as the police, to resolve issues relating to crime and disorder (Boggess & Maskaly, 2014). Low-level crimes and disorder have drawn increased scrutiny from public officials, leading to targeted enforcement (Fagan & Davies, 2000). Disadvantaged neighborhoods are also more at risk for drug overdoses (Chichester et al., 2020), further emphasizing drug problems in these areas and placing them at greater risk of police deployment.

The Houston context provides a unique social setting to examine which structural, social, and police deployment factors are most likely associated with sobering center intakes, an alternative to arrest. An analysis such as the one provided herein is particularly salient, given that criminal justice scholarship has paid considerable attention to unraveling which neighborhood structural, social, and criminogenic conditions are associated with official police actions (i.e., citations, arrests, and uses of force). There has been no examination to date, of which we are aware, that disentangles neighborhood conditions of sobering center intakes where police contact serves as the point of origin for admission.

Data, Methods, and Analytical Strategy

The neighborhood-level context of this study component was derived from 118 police beats in the City of Houston, which had a population range of 2,700 persons per beat to 49,000 persons per beat (with an average of 19,024 people per beat). The following outcomes were examined at the neighborhood level:

1) Total arrests between 1/2016 and 6/2022 (including total arrests, Black arrests, White arrests, and Hispanic arrests);
2) Sobering center intakes between 1/2016 and 6/2022 (total intakes, Black intakes, White intakes, and Hispanic intakes); and
3) Sobering center intake counts where the housing information, economic conditions, and type of intoxication the clients were under were aggregated to the neighborhood level (e.g., unhoused at intake, those with a residence at intake, those under the influence of alcohol only at intake, and those under the influence of multiple substances).

In terms of covariates, the following independent variable measures were collected and analyzed:

1) Indicators of social disruption (U.S. Census measures of the percent of households in poverty in 2010;[63] the percent of female-headed households with children under 18; and the unemployment rate);
2) Demographics of the police beats (i.e., the total population count per beat; the percent of the population not White (percent minority population); and the percent (youth) population aged 15-24 years old.
3) Neighborhood-level crime/calls for service counts as an indicator of police activity in the beats (2015 total CFS count before the opening of the HSC; the 2015 total crime rate per beat via the HPD, and the total possession/narcotic offenses in 2015 as an indicator of proactive police enforcement of drug/narcotics crime in the beats).[64]

The descriptive statistics for each of these neighborhood (beat) level outcomes and independent variables are presented in Table 7.14 below. The HPD beats averaged 152.6 intakes in total per beat, while they averaged 1,854 arrests per beat. Black intake counts per neighborhood averaged 46 per beat, while Black arrests averaged 950.8 per beat. White intake counts averaged 50 per beat, while White arrests averaged 243 per beat. Hispanic intake counts averaged 53 per beat, with 243 average arrests per beat.

Table 7.14. Descriptive Statistics (N = 118 Beats)

Outcomes	Mean	St. Deviation
Total Intake Count	152.6	328.0
Total Arrest Count	1,854.0	1539.9
Black Intake Count	46.0	127.8
Black Arrest Count	950.8	1070.3
White Intake Count	50.1	114.9
White Arrest Count	243.2	230.1
Hispanic Intake Count	53.2	89.7
Hispanic Arrest Count	243.2	230.0
Private Residence Intakes	87.1	128.9
Unhoused Intakes	61.6	208.6
Alcohol Only Intakes	78.5	119.4
Multiple Substance Intakes	49.2	172.7

[63] All US Census measures in this study rely on 2010 data. The reason is two-fold: First, the majority of the years here (2016 to 2022) occurred prior to the 2020 census. Second, the 2020 Census was plagued with a variety of measurement issues related to the COVID-19 pandemic. Thus, we chose 2010 for robust consistency in Houston neighborhoods.

[64] The models would have had some degree of overlap/measurement error had we selected a variety of minority population estimates per beat (e.g., percent Black, percent Hispanic, percent Asian/Pacific Islander, etc.). For parsimony, we selected a single indicator of percent minority to reflect the more standard indicator of population heterogeneity.

Independent Variables		
Indicators of Disruption		
Percent in Poverty	0.19	0.09
Percent Female-Headed Home	0.19	0.11
Unemployment Rate	0.04	0.01
Demographics Indicators		
Total Population	19,024	11,401
Percent Minority	0.42	0.18
Youth Population	0.09	0.04
Neighborhood Crime		
Pre-Sobering CFS Count	9,952.6	5904.7
Total Crime Rate	71,582.7	53,258.1
Total Possession/Narcotics Offenses	2,094.1	1772.2

The outcomes for the analyses were model specific. Each model contained two outcomes for relative frameworks of comparison. In this case, the point estimates from the incidents rate ratios (IRRs) from the Poisson regressions of event counts could be compared (in terms of size and magnitude).[65] Poisson regression is a specialized generalized linear modeling technique used to analyze counts of non-negative integers and, thus, is most appropriate for arrest analyses. For each model, we provide relative comparison rates to provide context regarding the different neighborhood dynamics that correspond with arrests versus alternatives to arrest. We used Wald tests for model comparisons to examine the association of covariates between two groups, net of other parameters (Wooldridge, 2010). Significant Wald tests indicate that the difference in magnitude of the two effect sizes being compared is unlikely due to chance alone. In this case, we are directly testing whether there is a significant difference between each independent variable and its effect on sobering center intakes versus arrests (or certain types of intakes from others, which were model specific).

In Table 7.15 below, we examine which neighborhood correlates were most strongly associated with total Houston sobering center intakes compared to the total number of HPD arrests per beat. Two social disruption indicators (percent in poverty and female-headed households) were considerably stronger predictors of total arrests than total sobering center intakes (via the Wald tests). However, as noted by the Wald test, beats with higher levels of unemployment had more sobering center intakes than arrests. Notably, the percent minority was a significantly stronger predictor of arrests, consistent with numerous criminological studies, than sobering center intakes (an outcome unique to this study). Based on the Wald tests, beats with higher rates of youth population had

[65] A correction parameter for overdispersion was included, where necessary via the model fit statistics.

higher levels of sobering center intakes than arrests. In sum, most disadvantage indicators and percent minority were greater predictors of arrests than sobering center intakes, while youthful population and unemployment rates corresponded with intakes over arrests.

Table 7.15. Total Sobering Center Intake Estimates vs. Total Arrest Estimates

Measures	Total Intake Count		Total Arrest Count		Wald
Indicators of Disruption	IRR	S.E.	IRR	S.E.	
Percent in Poverty	0.900*	0.131	4.13*	0.148	*
Female-Headed Home	0.004*	0.000	0.158*	0.007	*
Unemployment Rate	103.1*	89.55	22.89*	4.85	*
Demographics Indicators					
Total Population	0.999*	0.000	1.00*	0.002	
Percent Minority	0.231*	0.015	0.924*	0.015	*
Youth Population	3.085*	0.543	0.861*	0.039	*
Neighborhood Crime					
Pre-Sobering CFS Count	1.00*	0.000	1.00*	0.000	
Total Crime Rate	1.00*	0.000	0.999*	0.002	
Total Possession/Narcotics Offenses	1.00*	0.000	1.00*	0.000	
Constant	128.98*	4.78	529.91*	5.84	
Pseudo R-Square	0.825		0.827		

*p<0.05

We next wanted to examine patterns of arrests to diversion based on the racial and ethnic composition of arrestees relative to those admitted to the sobering center. Similar to the findings for total intakes and arrests, many disadvantage indicators (poverty and female-headed households) and percent minority per beat were greater predictors of arrests for Blacks and Whites than sobering center intakes for Blacks and Whites, while the population aged 15-24 and unemployment rates corresponded with sobering center intakes over arrests for Blacks and Whites (via Wald tests), seen in Table 7.16 below. However, in a supplemental analysis, we found that the magnitude of the unemployment rate and youth population was considerably higher for sobering center intakes for Blacks than sobering center intakes for Whites.

By contrast, the results in Table 7.15 are slightly different for intakes versus arrests for Hispanics (particularly when compared to the earlier intakes to arrests for Whites and Blacks). For Hispanics, percent in poverty was strongly and positively correlated with sobering center intakes, above and beyond the positive association between poverty and arrests. Thus, unique to intakes for Hispanics, higher poverty levels correspond to sobering center intakes. Likewise, the youth population was a stronger predictor of Hispanic arrests than Hispanic intakes (the opposite was true for Black and White intakes/arrests).

In sum, the traditional correlates predicting Black and White arrest rates (which hold true in Houston for arrests) predict Hispanic intakes versus Hispanic arrests. Intakes of

Hispanics are most strongly associated with neighborhood disadvantage and residential instability, which is not as true for intakes of Blacks and Whites.

Table 7.16: Sobering Center Intake Estimates vs. Arrest Estimates by Race/Ethnicity

	Blacks					Whites					Hispanics				
Measures	Intake Count		Arrest Count		Wald	Intake Count		Arrest Count		Wald	Intake Count		Arrest Count		Wald
Indicators of Disruption	IRR	S.E.	IRR	S.E.		IRR	S.E.	IRR	S.E.		IRR	S.E.	IRR	S.E.	
Percent in Poverty	0.332*	0.098	1.780*	0.094	*	0.329*	0.091	1.301*	0.133	*	4.754*	1.011	1.301*	0.133	*
Female-Headed Home	0.002*	0.000	0.143*	0.009	*	0.001*	0.000	0.015*	0.002	*	0.143*	0.004	0.015*	0.002	*
Unemployment Rate	3,240.0*	538.7	64.17*	19.06	*	2.467*	4.022	15.07*	9.32	*	65.574*	90.06	15.07*	9.32	*
Demographics Indicators															
Total Population	0.999*	0.000	0.999*	0.000		0.999*	0.000	1.00*	0.000		0.999*	0.001	1.000*	0.000	
Percent Minority	0.900*	0.122	3.362*	0.003	*	0.167*	0.021	.335*	0.016	*	0.110*	0.019	0.335*	0.016	*
Youth Population	6.211*	1.544	0.943*	0.051	*	1.829*	0.710	0.982*	0.148	*	0.441*	0.162	0.982*	0.148	*
Neighborhood Crime															
Pre-Sobering CFS Count	1.00*	0.000	1.00*	0.000		1.000*	0.000	1.00*	0.000		1.000*	0.000	1.000*	0.000	
Total Crime Rate	1.00*	0.000	0.999*	0.000		1.000*	0.000	1.00*	0.002		1.000*	0.000	1.000*	0.000	
Total Possession / Narcotics Offenses	1.00*	0.000	1.00*	0.000		1.000*	0.000	1.00*	0.000		1.006*	0.000	1.000*	0.000	
Constant	19.93*	1.44	179.6*	0.000		86.06*	0.000	221.15*	0.000		44.43*	2.75	221.15*	6.13	
Pseudo R-Square	0.822		0.800			0.758		0.696			0.589		0.696		

Next, we compare the composition of the neighborhoods/beats from which individuals were taken to the sobering center to assess whether differences exist between those who were unhoused at intake and those who had private residences. The beat-level correlates that most significantly distinguish unhoused intakes from private residence intakes include the percent in poverty, female-headed households, and unemployment rate, all of which were higher for unhoused intakes. In short, intakes of unhoused residents come from more disadvantaged neighborhoods. Private residence intakes were higher in higher minority neighborhoods than unhoused intakes (suggesting that a higher minority population matters more for private residence intakes). Likewise, private residence intakes are more prevalent in higher youth population neighborhoods. The demographic composition of neighborhoods is more strongly correlated with private intakes than unhoused intakes.

Table 7.17. Private Residence Intake Estimates vs. Unhoused Intake Estimates

Measures	Private Residence Intakes		Unhoused Intakes		Wald
Indicators of Disruption					
Percent in Poverty	0.613*	0.112	3.76*	0.992	*
Female-Headed Home	0.016*	0.003	0.020	0.000	*
Unemployment Rate	29.33*	31.69	152.6*	234.9	*
Demographics Indicators					
Total Population	0.999*	0.000	0.999*	0.000	
Percent Minority	0.312*	0.026	0.137*	0.016	*
Youth Population	5.72*	1.32	1.35*	0.396	*
Neighborhood Crime					
Pre-Sobering CFS Count	1.00*	0.000	1.00*	0.000	
Total Crime Rate	1.00*	0.000	1.00*	0.000	
Total Possession/Narcotics Offenses	1.00*	0.000	1.00*	0.000	
Constant	66.67	3.17	53.24	3.44	
Pseudo R-Square	0.655		0.821		

*$p<0.05$

Finally, the beat-level correlates that most significantly distinguish alcohol-only intakes from multiple substance intakes include several measures of disadvantage: the percent in poverty, female-headed households, and unemployment rate, all of which were higher for multiple substance intakes (unemployment, in particular, was considerably higher for multiple substance intakes). Demographic characteristics of neighborhoods also significantly distinguished alcohol-only intakes from multiple-substance intakes. For example, alcohol-only intakes were more likely to come from higher minority neighborhoods, while multiple-substance intakes were more likely in neighborhoods with a higher youth population.

Table 7.18. Alcohol-Only Intake Estimates vs. Multiple Substance Intake Estimates

Measures	Alcohol Only Intakes		Multiple Substance Intakes		Wald
Indicators of Disruption					
Percent in Poverty	0.907*	0.153	1.901*	0.538	*
Female-Headed Home	0.008*	0.001	0.001*	0.000	*
Unemployment Rate	9.62*	9.81	5,080.0*	863.8	*
Demographics Indicators					
Total Population	0.999*	0.000	0.999*	0.000	
Percent Minority	0.321*	0.025	0.109*	0.015	*
Youth Population	0.999*	0.000	2.13*	0.650	*
Neighborhood Crime					
Pre-Sobering CFS Count	1.000*	0.000	1.000*	0.000	
Total Crime Rate	1.000*	0.000	1.000*	0.000	
Total Possession/Narcotics Offenses	1.000*	0.000	1.000*	0.000	
Constant	81.84	3.62	37.69	2.71	
Pseudo R-Square	0.703		0.823		

*p<.05

Summary

The Houston setting did not allow for a pre/post analysis of the impact of the HRC on intoxication-related arrests (similar to other sites in this study) due to records management and data systems changes. For the post-only period examined here, intoxication-related arrests encompassed roughly 15% of all Houston arrests, which makes the setting generalizable to many of the other case-study sites included in this study (Austin, Tulsa, Oklahoma City, and Wichita). Comparatively, a unique strength of the Houston setting was the ability to compare (at the beat level) where intakes originated (via the HRC) and where arrests occurred (via the HPD). The net findings of this component of the Houston study suggest the following patterns emerge from a neighborhood structural level. The beat-level correlates of most arrests (total arrests, Black arrests, and White arrests) appear to be social disruption (poverty, female-headed households), and the percent minority and neighborhood youth population. These same correlates, however, do not predict sobering center intakes, in total or for Black and White individuals. However, for Hispanic individuals, the same predictors of arrests for Blacks and Whites predict sobering center intakes for Hispanics. These findings suggest that the contextual conditions corresponding to intakes vary between Blacks/Whites and Hispanics.

Additionally, the findings clearly indicate, regardless of outcome (arrests versus intakes), police activity in the beats (citizen-generated calls for assistance), crime rates, and the number of possession/narcotics criminal offenses had virtually no bearing when delineating arrests from sobering center admissions. The logical conclusion of these findings is that what the police are called for, how often they are called, and how often they make narcotics arrests in the beats did not have any bearing on their use of the sobering center instead of arrest.

Finally, our findings show that certain structural and social conditions correspond with alcohol-only versus multiple-substance intakes. Individuals admitted to sobering centers for multiple substances were admitted from neighborhoods more likely to result in police arrests (i.e., more poverty-based, higher female-headed households, and higher unemployment rates). On the other hand, individuals more likely to be admitted for alcohol only were admitted from places with higher levels of minority populations. These findings suggest that where inebriants are more diverse in their alcohol/drug usage, the same correlates that explain criminal arrest correspond with their sobering center admissions. However, alcohol-only individuals admitted to a sobering center are more likely to come from less distressed and socially diverse neighborhoods. In sum, the context of sobering center admissions is not explained by arrest correlates (except for Hispanic admissions). More work must unravel the context by which different populations and users are brought to sobering centers by police.

Results of Focus Groups with Houston Police

On August 9, 2022, we traveled to the Houston Police Department (HPD) to engage in a single focus group of HPD officers on the use of the Houston Recovery Center (HRC). This group included a total of 17 officers, with 3 supervisors and 2 female officers in the room. Officers were from a variety of the 22 HPD districts, representing perspectives across patrol districts and experiences. The early evening focus group lasted about 40 minutes. As with all focus groups for this project, the conversation began with a short statement from the lead researcher about the purpose of the focus group, scope of the conversation, and the officers' guarantees to anonymity. The results of the focus groups are discussed below.

Benefits and Obstacles

The focus group discussion began by asking officers to describe the benefits of using the sobering center in their city. Officers relayed that it is the most time-efficient option—dropping inebriated individuals at the jail, the Harris County Joint Processing Center (JPC), can take several hours. The officers noted that the JPC serves the county and is shared by the Houston Police Department and Harris County Sheriff's Office—some of the largest law enforcement agencies in the US[66]—thereby increasing processing times. Fortunately, the jail is located down the street from the sobering center, so it is an easy alternative to

[66] HPD has 6,345 personnel and HCSO has 5,071 personnel. Personnel counts are listed by the Council of State Governments. https://csgjusticecenter.org/projects/law-enforcement-mental-health-learning-sites/

the jail. Officers also suggest the sobering center is a good option for a person who just needs to "sleep it off" without the trouble and associated costs of being arrested and charged with a crime.

Second, officers were asked to describe challenges or obstacles to using the sobering centers. Officers first expressed frustration with chronic unhoused populations frequently picked up for public intoxication. These individuals are dropped off frequently at the HRC and do not seem to be getting the help they need. The next issue that officers identified was when officers dropped off at the HRC and did not understand what substance the person had used. This sometimes results in the person being rejected during processing at the Center, to which HPD must respond. In the case of a person denied admission at the HRC, officers from the HPD downtown division are called to respond—not the officer responsible for the individual's drop-off. This was a major challenge in some officers' view; there were strong sentiments in the room that this hindered officers assigned to the downtown division. HPD officers in the downtown division also must deal with issues of release of clients who sometimes are still not yet sober. This challenge is not due to HPD policy but rather the location of the HRC.

In describing negative experiences officers have faced when using the sobering center, many participants described that inebriated individuals are often confused about what a sobering center is and mistakenly believe that officers are still taking them to jail. The jail is close to the sobering center, and sometimes individuals recognize the location and become concerned. Notably, the HRC has distinct signs at intake saying "THIS IS NOT JAIL" in both English and Spanish. Officers also relayed that it sometimes takes a lot of effort to convince an individual to agree to go to a sobering center. This is often complicated by the nature of the individuals they are dealing with – who are intoxicated and not thinking rationally.

Officer Decision-Making

During the focus group discussion, officers were asked to describe their decision-making when faced with a publicly inebriated person—specifically, a person who does not appear to be a chronic inebriate. Officers unanimously described that their priority is to find a person's family or friends to serve as a safe guardians. If a person is not belligerent or violent, and there is no capable guardian available, an officer then instructs the inebriated individual that they are going to a sobering center. The officers suggested they express this as a directive (i.e., "This is what is going to happen to you."). In circumstances where an officer prefers to rely on a sobering center over a capable guardian, this depends on the inebriated individual and the circumstances. Officers agreed upon the example of an inebriated young woman with a male companion—officers often believe a sobering center is a safer option for the young woman compared to an officer guessing about the intentions of the male companion.

Officers were also asked to describe their decision to take a chronic intoxicant (defined as an individual that they know has frequented the sobering center) to the sobering center over jail, and if any situational factors impacted this decision. Officers suggested they would usually only do this if they received a call complaining about the chronic intoxicant. Diverting the individual from jail to the sobering center is preferred by both HPD policy and the staff at the JPC (county jail). If an officer brings a non-aggressive, intoxicated person to the JPC, they must obtain supervisory approval to complete processing there. Therefore, unless there is a medical reason a person cannot go to the HRC, which officers described as extremely rare, the intoxicated individual will always be brought to the sobering center if they are eligible. Officers also noted it was very rare that the HRC would not accept an intoxicated person brought to them; issues of limited space or banned lists were extremely rare.

Supervision

Officers were asked to describe supervisory expectations regarding sobering center use. Officers in the room indicated that there was no specific set of expectations, and rather the discretionary decision to use sobering centers was in the hands of the officer. However, if an officer responds to an intoxicated person who is belligerent or violent, the officer will call a supervisor for approval prior to bringing that person to the JPC. Within this focus group, there were three supervisors present. One supervisor, who appeared to be a strong advocate of the HRC, indicated that the use of the sobering center was always reinforced with new officers throughout their field training officer (FTO) program. Additionally, supervisors in the room stated they would remind officers of this option if they were on scene.

When asked about command staff expectations, officers noted that HPD typically reinforces sobering center use through the distribution of “circulars” – department-wide memos that are used to remind officers of this resource. Officers estimated about two or three circulars on the Houston Recovery Center had been distributed agency-wide over the past four years. Officers also suggested that circulars are more likely after an incident where a sobering center could have been used but was not.

Impact of Geography

In our quantitative analyses of sobering center admissions, we found that approximately 15% of the admissions were concentrated in the patrol beat containing the sobering center. Another 45% of sobering center admissions came from five adjacent beats. Focus group officers were asked to describe the context of these beats. Officers described these areas as Downtown and “central,” with a big entertainment district, including many bars. Additionally, there are large congregations of unhoused individuals. Social service providers are also concentrated downtown, partially driving the unhoused population's concentration.

Officer Recommendations

At the conclusion of the focus groups, participants were asked if they had any advice to provide to a police officer who had never dropped off at a sobering center. They emphasized how the facility was a faster and easier alternative than processing a person in jail. Officers also agreed that this was a better alternative for most people—a place to “sleep it off” and not result in criminal charges. Officers were also asked to provide suggestions for any cities that are considering implementing a sobering facility. They recommended cities consider opening a few small sobering centers because having a single facility increases the chances that a particular division of a police department gets overloaded due to the location of that facility. Additionally, with more centers across different areas of town, this may reduce the transport distance for some officers who are not downtown. Officers also suggested the importance of ensuring the sobering facility is well-staffed to handle inebriated persons so that officers do not have to return to the sobering center. For example, one officer recommended centers have a police officer assigned to the location. They also believed sobering centers should offer more resources, such as showers and medical treatment. Officers likened the idea to a “one-stop shop” for the chronic inebriates.

Concluding Remarks

In conclusion, the primary goal of this focus group was to understand HPD officer decision-making in using sobering centers in lieu of arrest. We found that officers were very amenable to the use of sobering centers for intoxicated individuals if that person did not have a capable guardian available. Officers believed processing at the HRC was a much faster alternative than jail, adding that they are required to receive supervisory approval to take a non-aggressive and otherwise compliant individual for a public intoxication arrest. The HRC is the preferred drop-off location in lieu of the jail by HPD policy, jail staff, and sobering center staff. For chronic intoxicants, HPD officers typically do not transport them to the HRC unless they receive a complaint about the person. The most common issues for officers to transport an individual to a sobering center included individuals unfamiliar with the concept of a sobering center and believing they were being taken to jail and frustration with chronic inebriates who do not seem to be getting the help that they need.

Supervisory and command expectations also guide officer decision-making. The use of the HRC is reinforced to officers through HPD memos, field training, and supervisors directly. By HPD policy, all officers who attempt to arrest a person solely for a PI charge must receive supervisory approval—and supervisors always prefer that individuals be diverted to the HRC when possible.

Additionally, a policy-related issue was revealed during discussions about HPD response to HRC rejections. Officers expressed strong frustrations that only officers from HPD downtown division are called to respond to HRC rejections—particularly when they were not the officer responsible for initial drop-off. Officers felt that this was a difficulty in being assigned to the downtown division and believed this standard procedure needed to change. We elaborate upon this issue and other findings in the Discussion section of this report.

CHAPTER 8: FEASIBILITY ASSESSMENT

In this section, we provide recommendations for collecting and analyzing sobering center data to promote robust research on the utility of sobering centers and how their use may be elevated.

Sobering Center Data Collection

Our analysis of data collection efforts across sites found considerable variability in the type and quality of data collected. Some locations collect vast data, much of which seems unnecessary. Other sites collect rich and meaningful data but do so in a way that makes analyses more difficult and cumbersome by requiring a wide array of data cleaning procedures to ensure accurate and reliable data. This section guides sites wishing to collect valid, usable data in efficient ways that lend themselves to future analyses.

The recommendations include measures that we believe all sobering centers should collect, along with recommended response sets that streamline data collection. Some sites may find these recommendations of interest, while others may not. We urge future sobering centers to consider the information they collect from clients carefully, the methods they use to collect the data, and the future use of collecting data. We strongly encourage sobering centers to consult with experts before establishing collection methodologies. These experts should balance the needs and data collection capacities of the sobering center against the costs, efficiencies, and utility of collecting specific data.

Recommended Measures for All Sobering Centers

This section suggests specific measures we contend all sobering centers should consider collecting. These items provide centers with necessary information about the individuals using the center and center performance. In all cases, we recommend making the data collected as seamless and efficient as possible.

Importantly, all who enter the sobering center need to be assigned a unique ID number that can be used to track individuals across repeat admissions. Identification numbers can be simple, and centers should avoid using numeric strings of sensitive or confidential information, such as birth dates and especially social security numbers. A unique identifier is a must to consider any analyses dealing with repeat clients.

Information about the date and time is also important for both intake and discharge. Using information on the time and date of intake and discharge will also allow for data collection on each client's length of stay at the sobering center. To conduct thorough analyses on the clients who use (and often reuse) the sobering center, it is necessary to collect data on client characteristics. Characteristics that should be collected include gender, race, ethnicity, age, housing stability, employment status, educational attainment, substance use, and blood alcohol content. If possible, we also think it would be interesting to gauge BAC levels upon discharge. This would help understand whether alcohol-using clients are being released while still intoxicated.

Finally, not all clients transported to the sobering center are formally admitted, and it should be in the interest of sobering centers to understand the patterns of non-admittance (beyond speculating non-compliance). As such, data regarding reasons for non-admissions should be collected. Further description of these variables, their definition, and recommendations for operationalizing the data in an admissions database are presented in Table 1 in Appendix F.

Recommended Ancillary Measures

Many sobering centers will be interested in collecting ancillary data on clients and program performance. The measures we recommend are presented in Table 2 in Appendix F and include items collected by some (not all) sobering centers and items that would be helpful to measure. Again, our advice is to collect only pertinent information useful to the center's goals, and to do so in ways that maximize ease and accuracy of entry and the ability to perform analyses. Potential ancillary measures may include a source of referral to the sobering center, location information, and additional details on client background information such as arrest/incarceration history, mental health issues, veteran status, and student status. More thorough information regarding substance abuse may also be of interest, such as the history of diagnosis with a substance abuse disorder, history of treatment for substance abuse, frequency of use, and readiness to stop substance use. Finally, some sobering centers may be interested in documenting the circumstances of the client discharge and departure, including whether the individual received a treatment recommendation, where the client was transported, and whether the client was formally discharged.

When compiling a list of potential measures to collect from clients, information collectors within sobering centers must consider two questions. First, "do these measures provide valuable information about the clients using the sobering center or the performance of the sobering center?" If the answer here is "no," we recommend that the sobering center discard these measures. To encourage the accuracy of data collection, it needs to be focused and efficient. More data is not always better. And collecting unnecessary measures may make the data collection efforts too cumbersome for staff, which could lead to errors in data collection. If the answer to the first question is "yes," the following question is, "Are these measures difficult to collect efficiently?" If the answer here is "no," then the measure is good to go and should be included in the database. Yet, if the answer is "yes," careful consideration is needed to decide whether the variable is needed or how to lessen the burden of collecting the data and the potential ways to make collection of the data more accessible.

Analyzing Sobering Center Data

While there are many reasons for collecting data on the individuals brought to the sobering center and the circumstances of their admission, one of the most important reasons to analyze the data is to summarize observed trends and patterns across admissions. Such analyses will allow sobering centers to make data-driven decisions with evidence directly tied to their own needs as documented by their data. For a sobering center to get the most satisfactory answers to their questions, they should look within. Aside from using data to answer internal questions and to adjust internal policies and procedures, data analysis can also be used to answer the questions of individuals external to the sobering center. Quality data can be analyzed to glean answers that can quickly be turned into quality responses to partners of the sobering center, law enforcement executives, city managers, and sources of sobering center funding. In other words, the analysis of available data should not be overlooked (particularly considering that sobering centers serve as an alternative to arrests for police).

Outcomes to Examine

The outcomes examined in an analysis of sobering center data largely depend on the question of interest. When outlining research questions, they have to be directly linked to the availability of the data collected. Given the vast array of data that a sobering center can collect, many outcomes could be considered.

A simple analysis of trends in admissions is a good place to start. Here, the outcome would be the number of admissions. How these admissions counts are explored depends on the question. To observe long-term admissions trends, one should look at monthly admission counts over time. It is then possible to observe months where admissions were either higher or lower than normal, and reasons for these pattern changes (e.g., COVID-19 restrictions, large music festivals) can be considered. Furthermore, to document admissions characteristics, it may be interesting to observe seasonal differences in sobering center use and in use across days of the week and time of day. Such analyses can help a sobering center organize staff and make decisions to ensure the sobering center is effectively and efficiently run at all times.

Beyond trends in admissions counts, sobering centers may also be interested in describing the characteristics of the clientele who use the sobering center. Here, a sobering center could use much of the information regarding client background information to present patterns of sobering center use. Beyond a simple description of who uses the center, differences in the clientele depending on admissions characteristics such as time of day, day of the week, and season of the year can also be explored. If data are collected regarding individuals not admitted to the sobering center, analyses can be conducted to find patterns across client characteristics and reasons for not being admitted. Another potential outcome of interest would be differences in the duration of a client's stay at the sobering center. Differences in length of stay could be observed across client characteristics to understand patterns in average duration. Once again, all this information can be used to tailor the policies and procedures of the sobering center to fit better the needs of the sobering center, its staff, and its clientele.

The Limitation of Admissions-Level Analysis

Sobering centers will likely collect their data at the admissions level, where each admission is documented in the database as its entry. While it is essential to assess research questions at the admissions level, there is at least one limitation to these analyses. Some clients will be repeated visitors to the sobering center. Analyses at the admissions level often assume that each admission is unique and independent from the other admissions. In the case of repeat clients, the expectation of independence is violated. As a result, some observed associations might be because of repeat individuals in the database rather than the actual client characteristics. This is why it is critical for sobering centers to collect an individual identifier for each client. This will allow sobering centers to track repeat visitors and account for those repeat visitors in any analyses they may want to perform. Furthermore, tracking individuals and repeat admissions opens the door to more research questions and analyses beyond trends in admissions characteristics, such as differences in single-time and repeat clients and timing to re-admissions.

Additionally, one of the critical questions related to the development and use of sobering centers is, does it reduce the likelihood of recidivism for clients (versus those who would be arrested for public intoxication offenses). While we examined these patterns at an aggregate level, we could not examine them at the individual level. The inability to link the client sobering center intake history with arrest history makes the feasibility of this question impossible to answer. We suggest that sobering centers consider developing a client name release form to analyze arrest patterns using law enforcement arrest data (where such information is waived or agreed upon). Given that the sobering center is an alternative to arrest, these information source comparisons are more than feasible – they are invariably linked. However, client confidentiality related to broader health and medicine issues hampers the ability to address this question more fully.

Moving Beyond Basic Analyses

When dealing with only admissions-level variables, a sobering center may limit itself to the examination of basic counts in admissions and crosstabulations between outcomes such as the timing of the admission or length of stay and various client or admissions characteristics variables. While these are essential first steps, they should be recognized as being just that—a first step. The use of multivariate statistics is required to assess sobering center data more fully. This is because multivariate analyses can account for the simultaneous influence of multiple characteristics on the outcomes of interests. For example, what factors predict clients who accept referral services? These analyses provide more rigorous results that can better assess the use of the sobering center and guide decision-making for changes in policy and procedures. If needed, sobering centers should consult with experts or data analysts to perform some of these more advanced analyses.

Summary

Much of data collection is an art. Sobering centers will need to carefully consider what information they are interested in collecting and how to ensure data are collected efficiently and accurately. In all, the goal of data collection is to have a system of data entry that is easy, well-organized, and not prone to errors. This is best accomplished by automating the process as much as possible to ensure that all relevant information can be quickly and accurately entered into the database. To evaluate the reliability and validity of data collection efforts, sobering centers should routinely examine their data for quality assurance. If needed, modifications to existing data structures should further seek to reduce the human error caused by either inaccurate reporting (e.g., spelling errors) or incomplete reporting (e.g., omissions, abbreviations). With quality data comes accurate analyses. With accurate analyses comes a more robust understanding of the patterns and trends in using the sobering center and those using it. Altogether, this information can be used to enhance the efficiency of how the sobering center is run and to highlight the practicality of the center to key stakeholders and communities.

CHAPTER 9: DISCUSSION

This report documents the findings from the second phase of a broader research study designed to examine the utility of sobering centers as an alternative to arrest. Using five jurisdictions as case study sites, we conducted comprehensive examinations of sobering center operations and police use of this arrest alternative in Oklahoma City, OK; Tulsa, OK; Wichita, KS; Austin, TX; and Houston, TX. Using admission data from these five sobering centers, we examined the individuals diverted from jail and emergency services to the sobering center. The analyses explored sobering center admission patterns and the factors predicting whether clients were admitted more than once, time to re-admission, and whether clients received a referral at discharge. Using official police data in each jurisdiction, we examined the impact of the sobering center on official intoxication-related arrests over time and assessed if intoxication-related arrest charges were reduced more than others. We conducted six focus groups across four case study sites to understand officer decision-making regarding this arrest alternative, their perceptions of the benefits and challenges of sobering center use, and the organizational support for sobering centers within their agencies.

This report's final section summarizes the findings based on official data from sobering centers and police agencies and our qualitative focus group interviews. In this synthesis of the findings, we compare and contrast the results across the five case study sites. Following that, we acknowledge the limitations of the current research. We conclude by highlighting the strengths of this study in comparison to previous research and identify how our research builds the knowledge base regarding sobering centers as an alternative to arrest.

Overview of the Findings

The primary purpose of this phase of the research study was to address the following research questions:

1. What are the general trends in sobering center admissions, and what are the characteristics of the clientele?
2. What patterns among the information provided by the sobering centers emerged that delineated one-admission from repeat clients, and what client characteristics are associated with the length and stay and receiving a referral for service?
3. What impact did the sobering center have on official arrests?
4. What types of arrests were reduced the most if diversion to the sobering center was used as an alternative to arrest?

5. Were the potential changes in alternatives to arrest consistent across different demographic groups in different settings?

Trends in Sobering Center Admissions and Client Characteristics

We obtained admissions data from the sobering center facilities within each case study site. Depending on available data and its quality, descriptive, bivariate, and multivariate analyses were used to glean a clearer understanding of the use of sobering centers and their clientele, who otherwise would have likely been transported to jail if the sobering center was not an option.

All case study sites operate a sobering center available 24 hours a day, seven days a week. The majority of clients across all five case study sites were admitted to the sobering center during nighttime hours. Most admissions in Houston, Oklahoma City, Tulsa, and Wichita occurred during the work week, whereas more admissions occurred on the weekend in Austin. The impact of the COVID-19 pandemic on admissions varied across sites. In Oklahoma City and Tulsa, the effect was negligible. Austin, Houston, and Wichita were highly impacted and either closed during parts of the pandemic or significantly decreased their admissions.

Our findings suggest that there are geographic patterns in sobering center admissions. Individuals admitted to the sobering center tended to be detained or picked up at locations relatively close to the sobering center. In Houston, for example, 43% of the admissions came from clients detained in six police beats geographically contiguous with the HRC. In Tulsa, 33% of all admissions were of clients picked up less than one mile from the sobering center, and 88% had a location less than two miles away. This was likely due to city officials' strategic placement of these facilities. Officers in the focus groups articulated that the sobering center in their respective jurisdictions was strategically located, either in the areas with the most publicly intoxicated individuals or near a mental health facility or the jail. They also perceived that the sobering center's efficiency and convenience compared to jail would increase officers' likelihood of using the sobering center regardless of location.

Client Characteristics

Patterns also emerge for the characteristics of the clientele brought to sobering centers. Across all sites, males made up a much larger proportion of admissions than females (or transgender). The average age across the sites ranged between 35 and 43. Across all sobering centers, White clients constituted the largest proportion of admissions. Client race/ethnicity, however, was highly dependent on the corresponding demographics of the surrounding city and area. For example, a greater proportion of admissions in Austin and Houston were Hispanic/Latino, while in Houston and Oklahoma City, a greater proportion of clients were African American. Finally, a much larger proportion in Oklahoma City and Tulsa were Native American.

Housing status was an important factor across all sites, although the distribution of services rendered to unhoused clients at the time of admission varied across sites. For Oklahoma City and Tulsa, the majority of clients admitted were unhoused, while about one-third in Austin and two-fifths in Houston and Wichita were unhoused. Alcohol was the predominant substance used in Austin, Houston, and Tulsa. In these sites, alcohol was often followed by either methamphetamine or marijuana/synthetic marijuana, but at a much lower frequency. Compared to the other sites, the substance use in Wichita was unique. Here, over half of the admitted clients were users of methamphetamine.

Repeat Admissions

We examined whether differences existed between clients admitted to a sobering center only once compared to those admitted two or more times. Three sites—Houston, Tulsa, and Wichita—collected data that allowed our research team to observe these possible differences. Repeat visits comprised approximately 38% of all admissions in Houston, 29% in Tulsa, and 40% in Wichita. We explored how client characteristics were related to being a repeat client, the number of times a client was admitted, and the timing of re-admission to the sobering center. Table 9.1 below summarizes the findings from the multivariate analyses of these outcomes. A plus (+) sign and green highlight indicate a positive statistically significant association between the client characteristic and the outcome variable. A negative (–) sign and orange highlight indicate a negative statistically significant association. Cells containing "X" and blue highlight indicate no statistically significant association, and cells containing " . " and gray highlight indicate the variable was not included in the analysis due to missingness or because that site does not collect the data.

Table 9.1. Summary of Repeat Client Multivariate Analysis Findings Across Sobering Center Sites

Client Characteristics	**Repeat Client**			**Admissions Count**			**Time to Re-Admission**		
	HRC	*TSC*	*SACK*	*HRC*	*TSC*	*SACK*	*HRC*	*TSC*	*SACK*
Male	+	x	.	+	+	.	–	–	.
White	ref	ref	Ref	ref	ref	ref	ref	ref	ref
African American	+	x	x	+	x	x	x	x	x
Hispanic/Latino	+	x	–	+	x	x	–	+	x
Native American	.	x	.	.	+	.	.	x	.
Unhoused	+	+	+	+	+	+	–	–	–
Veteran	+	x	.	+	x	.	–	x	.
Age	+	+	.	+	+	.	–	–	.
Alcohol Use	–	x	+	–	x	+	+	x	x
Multiple Substances	–	.	x	–	.	–	+	.	x
BAC	.	+	.	.	+	.	.	–	.
Mental Health Issue	+	.	.	+	.	.	–	.	.
Ever Arrested	+	.	.	+	.	.	–	.	.
Police Referral	x	.	.	+	.	.	+	.	.
Self-Referral	.	.	x	.	.	+	.	.	x
Ready for Treatment	.	.	.	.	.	.	+	.	.

Notes: HRC = Houston Recovery Center; TSC = Tulsa Sobering Center; SACK = Wichita Substance Abuse Center of Kansas; + = positive association; – = negative association; X = non-significant association; . = not included in analysis; ref = reference category for analysis.

As shown in Table 9.1, some similarities emerge across sites for each of the observed outcomes. **The probability of a client being a repeat is greatest when an individual is unhoused and older.** Being unhoused and older were also associated with a greater risk of having more admissions. Focus group participants expressed concern that unhoused clients were abusing the system by purposefully trying to get admitted to the sobering center because of the provision of food, a bed, and a shower. **In addition to being unhoused and age, across sites, males were at a significantly greater risk for more admissions, and multiple substance use was associated with a lower risk**. **Finally, across sites, the rate of timing to re-admission was greater (i.e., returned faster) for older, unhoused, and male clients compared to younger, housed, and non-male clients.**

Length of Stay and Post-Stay Outcomes

We also explored the association between client characteristics and the length of stay at the sobering center, and the likelihood of going to treatment or receiving a referral for services upon discharge from the sobering center. Data to address these outcomes were available in all sites but Oklahoma City. The average length of stay at sobering centers varied across sites. Houston had the shortest length of stay at just under 5 hours, followed by Austin at approximately 8 hours. The average stay in Wichita was just under 11 hours, while in Tulsa it was just over 11 hours.

Table 8.2 below summarizes the findings from the multivariate analyses that correspond to these outcomes. As shown, several similarities exist across sites. **In all sites but Wichita, unhoused clients had a longer average stay at the sobering center than clients who were housed**. **In Austin and Houston, older clients had a longer stay, on average, compared to younger clients. In all sites but Houston, the average stay in the sobering center was longer for clients admitted during the day**. Spring and summer admissions had a shorter average length of stay than winter admissions in Houston and Wichita.

Table 9.2 also shows the key characteristics associated with receiving treatment or a referral for services upon discharge from the sobering center. While some patterns are observed, direct comparisons are somewhat arbitrary with this outcome because it was different across sites. For instance, this outcome was measured as whether the client went to treatment (Austin), was enrolled in an in-house recovery program (Houston), received a referral for community services (Tulsa), and whether the client was transferred to detox (Wichita). **Nevertheless, older clients in Austin and Houston were more likely to receive treatment or a referral for services upon discharge than younger clients. In all sites but Tulsa, clients admitted during the daytime were more likely to receive treatment or a referral than those admitted during the night**. **Similarly, clients admitted during the weekend in Austin and Houston were less likely to receive treatment or a referral than**

those admitted during the work week. Clients in Tulsa and Wichita admitted during the winter were more likely to receive treatment or a referral than those admitted during the summer.

Table 9.2. Summary of Multivariate Analysis Findings for Length of Stay and Treatment/Referral at Discharge Across Sobering Center Sites

Client Characteristics	**Length of Stay**				**Treatment/Referral at Discharge**			
	SCA	*HRC*	*TSC*	*SACK*	*SCA*	*HRC*	*TSC*	*SACK*
Male	**+**	**–**	**x**	**.**	**x**	**–**	**x**	**.**
White	**ref**	**ref**	**ref**	**ref**	**ref**	**ref**	**ref**	**ref**
African American	**x**	**–**	**x**	**x**	**–**	**x**	**x**	**x**
Hispanic/Latino	**x**	**x**	**x**	**x**	**x**	**x**	**x**	**x**
Native American	**.**	**.**	**x**	**.**	**.**	**.**	**x**	**.**
Unhoused	**+**	**+**	**+**	**x**	**x**	**x**	**+**	**x**
Active Military/Veteran	**x**	**x**	**–**	**.**	**+**	**x**	**x**	**.**
Age	**+**	**+**	**x**	**.**	**+**	**+**	**x**	**.**
Alcohol Use	**–**	**+**	**x**	**–**	**x**	**x**	**–**	**x**
Multiple Substances	**.**	**+**		**x**	**.**	**+**	**.**	**x**
BAC	**+**	**.**	**x**	**.**	**x**	**.**	**+**	**.**
Mental Health Issue	**.**	**+**	**.**	**.**	**.**	**x**	**.**	**.**
Ever Arrested	**.**	**+**	**.**	**.**	**.**	**+**	**.**	**.**
Police Referral	**–**	**–**	**.**	**.**	**x**	**–**	**.**	**.**
Self-Referral	**.**	**.**	**.**	**x**	**.**	**.**	**.**	**+**
Ready for Treatment	**.**	**+**	**.**	**.**	**.**	**+**	**.**	**.**
Student	**x**		**.**	**.**	**x**	**.**	**.**	**.**
First Admission	**.**	**–**	**x**	**x**	**.**	**–**	**x**	**+**
Daytime Admission	**+**	**–**	**+**	**+**	**+**	**+**	**.**	**+**
Weekend Admission	**+**	**–**	**.**	**+**	**–**	**–**	**.**	**x**
Winter Admission	**ref**	**ref**	**.**	**ref**	**.**	**ref**	**ref**	**ref**
Spring Admission	**+**	**–**	**.**	**–**	**.**	**+**	**–**	**x**
Summer Admission	**x**	**–**	**.**	**–**	**.**	**x**	**–**	**–**
Fall Admission	**x**	**x**	**.**	**x**	**.**	**x**	**–**	**x**

Notes: SCA = Sobering Center of Austin; HRC = Houston Recovery Center; TSC = Tulsa Sobering Center; SACK = Wichita Substance Abuse Center of Kansas; + = positive association; – = negative association; X = non-significant association; . = not included in analysis; ref = reference category for analysis.

Impact of Race and Housing Status

Notably, while client race and ethnicity were sometimes associated with sobering center outcomes within the site, a consistent pattern across sites was not observed. However, exclusively focusing on only sobering center data may exclude essential components of the larger story. Indeed, the relative lack of racial and ethnic differences across sobering center outcomes may be driven by differences in who gets diverted to the sobering center compared to those who get arrested.

The findings from the sobering center analyses underscore the importance of dealing with housing when it comes to sobering center operations. Across multiple outcomes—the likelihood of being a repeat client, the number of sobering center admissions, the timing to re-admission, or the length of stay—unhoused clients tended to have a greater risk of experiencing more contact with the sobering center than clients who have housing. These results demonstrate that sobering centers play an important role in diverting unhoused members of the public away from the criminal justice system for minor offenses.

Jail Days Saved

By our estimates, these five sobering center sites combine to save approximately 3,894 days spent in jail per year if sobering center admissions are a true diversion from jail. As such, sobering centers reserve jail resources and services for matters more serious than public intoxication. However, diverting individuals from jails and placing them in a sobering center does not necessarily save money. Our review of these sites indicates that sobering centers most likely shift the costs and resources from one entity (jails) to another (sobering centers) due to chronic, repeat usage and services by clients most at risk. However, a major benefit of sobering centers is that they can be expected to help alleviate problems associated with limited law criminal justice resources and connect clientele to additional resources.

Officer Decision-Making and the Impact of Sobering Centers on Police Arrest Rates

We obtained official arrest data from the police agencies within our case study sites. The timeframes examined for each case study site varied from a minimum of six years in Houston to a maximum of 23 years in Oklahoma City. Tulsa, Wichita, and Austin data were provided for 12-13 years. Depending on the availability and quality of data, descriptive, bivariate, and multivariate analyses were used to understand how the availability of a sobering center impacted arrests. We also conducted focus groups with officers in four of the five case study sites to understand their experiences with using the sobering center as an alternative to arrest for publicly intoxicated individuals.

Officer Decision-Making

In each case study site, the police departments guided officer decision-making regarding sobering centers by policy. In each focus group interview, officers noted that they rarely proactively police publicly intoxicated individuals for the sole reason to obtain treatment for individuals. Moreover, officers said they are almost always called to a scene by a citizen-generated request for someone who appears publicly intoxicated or disorderly. Police policies in each location we examined require officers to use the sobering center for eligible individuals upon the voluntary approval of the intoxicated person and the sobering center. In Austin and Houston, officers must obtain supervisory approval to take a publicly intoxicated person eligible for the sobering center to jail instead. Officers in the focus groups specifically cited department policy as influencing their decision-making in responding to calls for service for intoxicated individuals.

To understand why officers arrest individuals for public intoxication instead of using the sobering center, we examined two data sources: official Tulsa PD data and focus groups conducted in four case study sites. First, the TPD requires officers who make a public intoxication arrest to document the reason for arrest, given the department policy and expectation that officers divert individuals to the sobering center whenever possible. These data show that the most cited reason was for aggressive or violent behavior. This is consistent with the findings from the focus groups conducted across four sites. Officers described the sobering center as the preferred destination for intoxicated individuals. Still, they noted that the decision of where to take an intoxicated individual is typically made based on the availability of a capable guardian for the individual and the inebriated individual's behavior (e.g., violence, belligerence), state of well-being (e.g., level of intoxication, injuries, victimization risk), and warrant history (e.g., violent crime vs. misdemeanor offenses).

Aggregate Impact of Sobering Centers on Arrests

Given that sobering centers are used as an alternative to arrest in the agencies included in this study, we anticipated a reduction in total arrests and intoxication-related arrests following the opening of each jurisdiction's sobering center. Specifically, we expected to observe a decline in arrests for public intoxication (PI), drug possession (PO), driving under the influence of drugs or alcohol (DUI), or public disturbance/disorderly conduct (DC).

For three of the five sobering center locations included in this study—Tulsa, Wichita, and Austin—the arrest data provided by the city police department preceded the opening of the affiliated sobering centers, which allowed for pre/post-arrest analyses. Table 9.3 summarizes the findings from bivariate and multivariate time series analyses assessing the impact of a sobering center opening on arrests in these three sites. The bivariate approach to percentage change comparisons can both under and overestimate percentage changes by examining the ebbs and flows without accounting for periods when such shifts are specific and predictable (e.g., seasonal shifts, the impact of COVID-19). Multivariate interrupted time series analysis controls for stationary and predictable temporal factors and, while typically more conservative, can be viewed as the most likely change in the outcomes of interest (net of time-variant control variables).

Table 9.3. Summary of Bivariate and Multivariate Time Series Analysis Findings for Sobering Center Impact on Arrest Rates

Arrest Type	**Bivariate**			**Multivariate**		
	Tulsa PD	Wichita PD	Austin PD	Tulsa PD	Wichita PD	Austin PD
Total	-28%	-23%	-48%	-10%	X	-7%
Public Intoxication (PI)	-20%	-12%	-70%	-20%	X	-24%
Possession of Drugs (PO)	-21%	-12%	-56%	X	-23%	-28%
Driving Under the Influence (DUI)	-32%	-39%	-38%	X	-21%	-14%
Disorderly Conduct (DC)	-38%	-37%	+4%	X	-11%	X

Notes: + = statistically significant increase in arrests; – = statistically significant decline in arrests; X = no statistically significant impact on arrests. The multivariate findings for PI, PO, DUI, and DC arrests reflect statistically significant reductions *above and beyond* any changes in overall arrests as calculated by the Clogg-Z Coefficient difference tests.

As shown in Table 9.3, the bivariate and multivariate time series analyses indicated a pattern of findings largely consistent with the hypothesis that opening a sobering center would significantly impact specific arrests. There was, however, some variation across sites. The bivariate findings across sites indicated that total arrests and PI, PO, DUI, and DC arrests declined over the period of inquiry. The results from the multivariate time series models show that much of this decline was due in varying degrees to the COVID-19 pandemic, linear trends, and seasonal fluctuations.

Once these factors were accounted for, we still saw an overall reduction in total arrests of 10% in Tulsa and 7% in Austin. These served as baseline points of comparison (since sobering centers are not designed to reduce total arrests but rather specific types). **In Tulsa and Austin, public intoxication arrests declined by 20% and 24%, respectively, above and beyond any changes in total arrests and net of time-varying controls**. In Tulsa, no other arrests related to intoxication experienced the same type of decline, net of controls. In Austin, however, possession and DUI arrests declined at a greater rate than overall arrests by 27% and 14%, respectively, net of controls and the impact of COVID-19 on arrests.

By contrast, once other factors were controlled for in Wichita, overall arrests did not change at the time of the sobering center opening. In line with our hypotheses, disorderly conduct, DUI, and possession arrests experienced statistically significant divergences when the sobering center opened, net of controls. Contrary to our hypotheses and the findings for Tulsa and Austin, public intoxication arrests did not significantly decline in the post-SACKSU period. We attribute this to several unique factors of the WPD-SACKSU relationship and the clientele of the SACKSU. WPD use of the SACKSU is primarily limited to specialized unhoused outreach team officers rather than patrol officers, and WPD accounts for a small percentage of direct SACKSU referrals. Instead, WPD appears to utilize various alternative resources in Wichita above and beyond SACKSU. Finally, the substances used by individuals admitted at SACKSU were less likely to be alcohol and marijuana and more likely to be more serious drugs, making it less likely that the SACKSU opening would impact public intoxication-only arrests.

While our case study analyses showed that sobering centers have the potential to reduce arrests related to public intoxication, the establishment of a sobering center will not eliminate arrests for public intoxication violations. For example, the patterns that emerged in Oklahoma City clearly show that even with a well-established alternative to public intoxication, public intoxication, and other related behaviors will likely remain criminal arrest issues for police departments between ¼ (25%) and 1/3 (33%) of the time. Thus, public intoxication arrests persist within Oklahoma City, even in a setting with the longest-standing sobering center in the United States. Across the five case study sites, the percentage of arrests for PI, PO, DUI, and DC charges varied between 15% to 30%, with most sites ranging between 20% to 25%.

Role of Race/Ethnicity

Given that the time series analyses indicated statistically significant declines in specific intoxication-related arrests, we also examined whether these changes varied by arrestee race/ethnicity. Of the sites where a pre-post analysis was conducted, this analysis was only possible for Tulsa and Austin because Wichita did not provide arrestees' demographic characteristics. Table 9.4 summarizes these findings.

In Tulsa and Austin, public intoxication arrests significantly declined for all racial and ethnic groups, but to varying degrees. In Tulsa, the greatest reductions were observed for Hispanic (-55%) and White (-40%) arrestees, while the reduction for Native American and Black arrestees was 31% and 21%, respectively. Additionally, only White and Native American arrestees were arrested at a significantly lower rate in the post-COVID period. In Austin, the greatest reductions in public intoxication arrests were for White arrestees (-28%), while the decrease for Black and Hispanic arrestees was 21% and 17%, respectively. Although there were slight racial/ethnic differences in the decline of possession and DUI arrests after the sobering center opening in Austin, these were not statistically significant.

Table 9.4. Summary of Racial/Ethnic Differences in Time Series Analysis Findings for Sobering Center Impact on Arrest Rates[67]

Race/Ethnicity	Tulsa				Austin		
	White	Black	Hispanic	Native American	White	Black	Hispanic
Public Intoxication	-40%*	-21%	-55%	-31%	-28%*	-21%	-17%
Possession of Drugs	NA	NA	NA	NA	-24%	-28%	-25%
DUI	NA	NA	NA	NA	-16%	-18%	-12%

Notes: *Statistically significant difference across racial/ethnic groups in the decline in arrests based on Clogg-Z coefficient difference tests.

Finally, although the Houston setting did not allow for a pre/post analysis of the impact of the HSC on intoxication-related arrests, the setting did enable us to conduct a beat-level comparison of where arrests versus sobering center intakes occurred. These structural analyses indicated that neighborhood disadvantage measures were heavily associated with crime and arrests but not necessarily public intoxication diversions. There were some racial/ethnic differences in this analysis. For Hispanic individuals, the same predictors of arrests for Blacks and Whites predict sobering center intakes for Hispanics. These findings

[67] No statistically significant declines in disorderly conduct were observed in the time series analyses, net of other controls, following the opening of the sobering center in Tulsa or Austin, so it is excluded from this table.

suggest that the contextual conditions corresponding to intakes vary between Blacks/Whites and Hispanics. In short, the context of the surrounding community clearly impacts sobering center intakes by race/ethnicity.

Limitations

This research provides critical insights into the impact of sobering centers on intoxicated-related arrests and the trends in sobering center admissions and client characteristics. Nevertheless, it is important to acknowledge the limitations of the current research.

First, our case study jurisdictions may not represent all cities or counties with sobering centers available as an alternative to arrest. Our five sites are in the Midwest and South, but the first phase of our research found that more than half of the sobering centers nationally are in the West. Three case study jurisdictions are large cities with law enforcement agencies of more than 1,000 sworn personnel serving more than 500,000 residents. Comparatively, jurisdictions with these characteristics represent just one-third of those with sobering centers nationally.

Second, due to data limitations, we could not address one of the original research questions—whether diverting individuals to sobering centers in lieu of arrest alters their relative risk of recidivism or future contact with police. The interrupted time series analyses in this report demonstrate that counts of intoxication-based charges experienced statistically significant declines upon the opening of the recently created sobering centers, but these reductions in arrests and charges are citywide trends at an aggregate level of analysis. These analyses do not provide any insight or precision regarding the change in arrest patterns or trajectories among individuals. The only way to discern whether individual-level differences in arrest patterns shift would be to examine individuals' arrest and intake histories to assess whether treatment in sobering centers corresponds with a behavior change across multiple individuals and relative to an individual's prior arrest history before the sobering center. However, the arrest data made available to the research team across sites did not contain any specific identifiers (i.e., name of the person arrested), nor did any sobering center provide us any unique identifying information based on Health Insurance Portability and Accountability Act (HIPAA) requirements. Future research would improve our understanding of the impact of sobering centers on individuals if such data were shared across entities and corresponding analyses were conducted.

Third, our ability to compare outcomes across the case study sites was limited by the variation in data availability, differences in variable definitions, and quality in each jurisdiction's police agency and sobering center. For the police arrest data, each site captured somewhat similar information on arrestees, locations of incidents, and charges levied against suspects. However, two sites (Wichita and Houston) chose not to provide our team with demographic identifiers among arrestees. This hampered our ability to discern which groups of individuals were most likely to experience the most sizable reductions in arrests across sites in the post-sobering center period. Additionally, we were unable to test whether the sobering center had an impact on intoxication-based arrests in two sites (Oklahoma City and Houston) due to a records management change (Houston) and due to the longevity of the sobering center (Oklahoma City). In short, it was difficult to examine changes in arrests in two of our five sites using what is readily available in most police agencies.

A similar variation in data quality existed *across* and *within* sobering center sites. The Tulsa and Houston sites provided detailed and rich accounts, including self-reported hospitalizations, contacts with law enforcement, and living status (unhoused vs. residential). In contrast, others collected minimal information electronically (e.g., a unique, non-name identifier, intoxication substance, date of admission and release). Some sites did not collect information initially but progressively became more refined and precise with their data measures. For example, in the latter half of Austin's data collection submitted to our research team, the site began collecting information on whether the individual admitted to the sobering center was transported by law enforcement (and, if so, which agency). By contrast, the sobering center in Oklahoma City, which has been operational for fifty years, just recently began collecting data electronically rather than relying on written documentation.

Finally, although our research is the first to assess how the COVID-19 pandemic impacted police and sobering center operations in multiple sites, we cannot fully account for the impact on arrests, crime, and sobering center admissions resulting from the pandemic.

Conclusion

Our research seeks to build the evidence base regarding the aggregate patterns in sobering center admissions and the impact of sobering centers on police arrests. Our work fills several gaps in previous research. Like the first phase of this study, our research builds on previous literature that has almost exclusively focused on sobering centers' operations by incorporating the police perspective through analyses of official police data and focus groups with officers who divert publicly intoxicated individuals to sobering centers.

Our research team traveled to each sobering center and police department to meet with sobering and police executives to gain first-hand knowledge of operations and partnerships at each site. The current study is the first to investigate officer decision-making in diverting intoxicated persons instead of arrest. Overwhelmingly, the focus group participants across the case study sites echoed the perceptions identified in the Phase I national survey. Officers voiced positive perceptions of the utility and benefits of sobering centers as an arrest alternative in terms of saving officer time. They also agreed that it is the best option for most individuals because it provides protective care, the opportunity for additional resources and treatment, and avoids the costs and consequences of being arrested. Focus group participants identified only minor obstacles to sobering center use in their jurisdictions.

Our research extends previous case study research focused on single jurisdictions by comparing and contrasting police and sobering center operations across five case study sites. Most previous research has not been methodologically or statistically rigorous, relying on exploratory or descriptive analyses. Our study employs a sophisticated quasi-experimental research design and more robust data analyses that improve our understanding of the long-term effects of sobering centers, namely that opening a sobering center can significantly impact arrests for several specific intoxication-related charges. Furthermore, in several case study sites, we assessed the impact of race and ethnicity on police enforcement outcomes and sobering center admissions, an area that previous research has yet to explore.

Collectively, the findings from this phase of the research study provide important insights into the beneficial impact of sobering centers on individual sobering center clients and intoxication-related arrest rates within these five cities. Sobering centers represent a promising approach to diverting publicly intoxicated individuals from jails to sobering centers, thereby shrinking the net rather than widening it. Based on the findings in this report and the overall study, we offer a series of recommendations for police agencies, sobering centers, policymakers, and future research in *Examining the Utility of Sobering Centers: Project Summary and Recommendations for the Future,* the third and final report in the current series.

REFERENCES

Corsaro, N., Brunson, R. K., & McGarrell, E. F. (2013). Problem-oriented policing and open-air drug markets: Examining the Rockford pulling levers deterrence strategy. *Crime & Delinquency*, *59*(7), 1085-1107.

Fletcher, C. (1990). *What Cops Know*. New York, NY: Routledge.

Fox, J. (2016). *Applied Regression Analysis and Generalized Linear Models* (3rd ed.). Sage Publishing.

Fox, J. (2019). *Regression diagnostics: An introduction*. Sage publications.

Hack, C. (2022, May 20). Wichita's budget passes in August. Here's how you can get involved in shaping it now. *Wichita Beacon*. https://wichitabeacon.org/stories/2022/05/20/wichitas-budget-process/

Hanafi, S., Bahora, M., Demir, B.N, & Compton, M.T. (2008). Incorporating Crisis Intervention Team (CIT) knowledge and skills into the daily work of police officers: A focus group study. *Community Mental Health Journal, 44,* 427-432.

Jarvis, S. V., Kincaid, L., Weltge, A. F., Lee, M., & Basinger, S. F. (2019). Public intoxication: sobering centers as an alternative to incarceration, Houston, 2010–2017. *American Journal of Public Health*, *109*(4), 597-599.

King, G. (1988). Statistical models for political science event counts: Bias in conventional procedures and evidence for the exponential Poisson regression model. *American Journal of Political Science*, 838-863.

Lee, J. (2022, July 21). 'We are in a crisis right now.' APD Assistant Chief Jerry Bauzon speaks on patrol officer shortage. *KVUE*. Retrieved from https://www.kvue.com/article/news/investigations/defenders/austin-police-patrol-officer-shortage/269-16f38194-2ffb-4f02-becc-3b4db6375f20

Lee, T.W. (1999), *Using Qualitative Methods in Organizational Research*. Thousand Oaks, CA: Sage Publications.

Long, J. S. (1997). Regression models for categorical and limited dependent variables (vol. 7). *Advanced Quantitative Techniques in the Social Sciences*, 219.

Long, J. S., & Freese, J. (2006). *Regression models for categorical dependent variables using Stata* (Vol. 7). Stata press.

Long, J. S., & Freese, J. (2014). *Regression Models for Categorical Dependent Variables Using Stata* (3rd ed.). Stata Press.

Merton, R. K. & Kendall, P. L. (1949). The focused interview. *American Journal of Sociology*, Vol. 51, pp. 541-57.

Nielson, K. R., Zhang, Y., & Ingram, J. R. (2022). The impact of COVID-19 on police officer activities. *Journal of Criminal Justice*, *82*, 101943.

OKC Metro Alliance (n.d.). *What is P.I.A.?* http://okcmetroalliance.com/p-i-a/

Sampson, R. J., Raudenbush, S. W., & Earls, F. (1997). Neighborhoods and violent crime: A multilevel study of collective efficacy. *Science*, *277*(5328), 918-924.

Silver, E., & Miller, L. L. (2004). Sources of informal social control in Chicago neighborhoods. *Criminology*, *42*(3), 551-584.

Sullivan, C. & Baranauckas, C. (2020, June 26). Here's how much money goes to police departments in largest cities across the US. *USA Today*. *https://web.archive.org/web/20200714185818/https:/www.usatoday.com/story/money/2020/06/26/how-much-money-goes-to-police-departments-in-americas-largest-cities/112004904/*

Turner, A. (2015). Alternatives to criminalizing public intoxication: Case study of a sobering centre in calgary, AB. *SPP Research Paper*, *8*(27).

Wilson, J. Q., & Kelling, G. L. (1982). Broken Windows. *The Atlantic Monthly,* 249, 29-38.

APPENDICES

Appendix A. Oklahoma City Sobering Center Supplemental Details and Analyses

Table 1. Description of PIA Variables

Variable Name	Definition	Date Range	Coding for Analysis
Day of the Week	The day of the week (i.e., Sunday, Monday, Tuesday, Wednesday, Thursday, Friday, and Saturday) was identified from all admissions dates.	1/1/2019 – 10/31/2021	Recoded into binary variable: work week (Monday-Thursday) or the weekend (Friday-Sunday). *Weekend admission* is coded as 0 = work week and 1 = weekend.
Season of Year	Seasons of the year were identified from all admissions dates. Winter (December 21 - March 20), spring (March 21 - June 20), summer (June 21 - September 21), and fall (September 22 - December 20).	1/1/2019 – 10/31/2021	*Season* is coded where 1 = winter, 2 = spring, 3 = summer, and 4 = fall. For multivariate analyses, *winter* is used as the reference category.
Time of Day	Time of intake for all client admissions is collected using the 24-hour clock.	1/1/2019 – 10/31/2021	Recoded into a binary variable. *Daytime admission* is coded as 0 = night admission (between 7:00 PM and 6:59 AM) and 1 = day admission (between 7:00 AM and 6:59 PM).
Gender	Gender of the admitted client. PIA database includes male and female.	1/1/2019 – 10/31/2021	Gender was coded into a *male*, where 1 = male and 0 = female.
Race/Ethnicity	Race/ethnicity of the admitted client. PIA race categories included: White (Not Hispanic); Black (Not Hispanic); Hispanic-Mexican; Hispanic-Cuban; Hispanic-Puerto Rican; American Indian; Alaska Native; Asian/Pacific Islander; and Unknown.	1/1/2019 – 10/31/2021	*Race/ethnicity* is coded 1 = White, 2 = African American, 3 = White Hispanic/Latino, and 4 = Native American. Due to low case counts, Asian/Pacific Islander was removed for analyses.
Age	Age of the client at the time of the admission is collected as the number of years.	1/1/2019 – 10/31/2021	*Age* is a continuously measured in years.
BAC	All clients receive a blood alcohol concentration (BAC) test at intake and the results are entered into the PIA admissions database.	1/1/2019 – 10/31/2021	*BAC at Intake* is a continuous measure.
Transport from Hospital	Identified whether the client was transported to PIA from a hospital.	1/1/2019 – 10/31/2021	*Transport from Hospital* is coded where yes = 1 and no = 0.
Unhoused	Identified whether the admitted client was unhoused (yes or no)	9/1/2021 – 10/31/2021	*Unhoused* coded as 1 = unhoused and 0 = housed.

Appendix B. Tulsa Sobering Center Supplemental Details and Analyses

Table 1. Description of TSC Variables

Variable Name	Definition	Date Range	Coding for Analysis
Day of the Week	The day of the week (i.e., Sunday, Monday, Tuesday, Wednesday, Thursday, Friday, and Saturday) was identified from all admissions dates.	5/30/2018 – 10/14/2021	Recoded as binary variable reflecting whether the admission occurred during the work week (Monday-Thursday) or the weekend (Friday-Sunday). *Weekend admission:* 0 = work week and 1 = weekend.
Season of Year	Seasons of the year were identified from all admissions dates. Winter (Dec 21 - Mar 20), spring (March 21 - June 20), summer (June 21 - Sept 21), and fall (Sept 22 - Dec 20).	5/30/2018 – 10/14/2021	*Season* is coded where 1 = winter, 2 = spring, 3 = summer, and 4 = fall. For multivariate analyses, *winter* is used as the reference category.
Time of Day	Time of intake for all client admissions is collected using the 24-hour clock.	5/30/2018 – 10/14/2021	Recoded into a binary variable. *Daytime admission* is coded as 0 = night admission (between 7:00 PM and 6:59 AM) and 1 = day admission (between 7:00 AM and 6:59 PM).
TPD Division	Identifies the TPD police division of the referring officer. Division responses included Riverside, Mingo Valley, Gilcrease, and Other.	3/1/2020 – 10/14/2021	*TPD division* is coded 1 = Riverside, 2 = Mingo Valley, and 3 = Gilcrease. Due to low case counts, Other was removed for analyses.
Distance from TSC	The address of the location from which the individual being brought to the TSC was detained is collected by the TSC. Addresses were geocoded and the distance between the address and the TSC was measured using a straight line.	5/30/2018 – 10/14/2021	*Distance from TSC* is measured continuously, with miles as the unit of measurement.
Gender	Gender of the admitted client. TSC database includes male and female.	5/30/2018 – 10/14/2021	Gender was recoded into *male*, where 1 = male and 0 = female.

Race/Ethnicity	Race/ethnicity of the client. Original TSC race/ethnicity categories included: Caucasian, African American, Hispanic/Latino, Native American, Asian, and Other.	5/30/2018 – 10/14/2021	*Race/ethnicity:* 1 = White, 2 = Black[68], 3 = Hispanic/Latino, and 4 = Native American. Due to low case counts, Asian and Other were removed for analyses.
Unhoused	Identifies whether the admitted client was unhoused (yes or no).	6/1/2019 – 10/14/2021	*Unhoused:*1 = unhoused and 0 = housed.
Veteran	Identifies whether the admitted client was a veteran of the United States military (yes or no).	6/1/2019 – 10/14/2021	*Veteran*: 1 = veteran and 0 = non-veteran.
Age	Age of the client at the time of the admission is collected as the number of years.	5/30/2018 – 10/14/2021	*Age* is a continuously measured in years.
Primary Substance	Identifies the primary substance used by the client at admission. Original TSC substances include alcohol, heroin, pharma, methamphetamine, benzos, opioids, THC, cocaine, inhalants, and unknown.	5/30/2018 – 10/14/2021	Primary substance variable was recoded into a binary variable (*alcohol*), where 1 = alcohol as the primary substance and 0 = substances other than alcohol as the primary substance.
BAC	All clients receive a blood alcohol concentration (BAC) test at intake	5/30/2018 – 10/14/2021	*BAC at Intake* is a continuous measure. For regression analyses, the original BAC is multiplied by 100 for interpretational purposes.
Stay Duration	The number of hours a client stayed at the TSC from intake to discharge.	5/30/2018 – 10/14/2021	*Length of stay* is measured continuously, reflecting the number of hours (with decimals) the client stayed within the TSC.
Admissions Count	Identifies the total number of times each individual client has been admitted to the TSC.	5/30/2018 – 10/14/2021	The *admissions count* is a continuous measure.
Repeat Client	Identifies whether an individual client has been admitted to the TSC on more than one occasion.	5/30/2018 – 10/14/2021	Admissions counts variable was recoded into binary variable *repeat client*, where 1 = repeat client (two or more admissions) and 0 = one-admission client.

[68] Note that TSC collects the race of African-American, which we refer to as Black.

Admission Number	Identified the admission number of a specific admission is for an individual.	5/30/2018 – 10/14/2021	Used to create two measures. *First TSC admission* identifies whether the admission is the first for an individual (1= first admission and 0 = repeat). *Second admission* identifies whether the admission is a second admission (=1) or third or more (=0). One-admission clients are coded missing.
Time to Re-Admission	The time to re-admission was measured by calculating the days between one admission and the next using unique identifiers.	5/30/2018 – 10/14/2021	*Days between admissions* is measured continuously, reflecting the number of days between subsequent TSC admissions for repeat clients.
Referral at Discharge	Indicates whether the client received a referral to community organizations or centers.	4/16/2020 – 10/14/2021	Recoded into a binary variable where cases with a referral =1, cases without an identified referral=0.

Bivariate Association Between Client Characteristics and Trends in Admissions

The client characteristics explored include age, gender, race/ethnicity, housing status, veteran status, primary substance type, BAC at intake, repeat client, TPD division, and distance from the TSC. The appropriate bivariate statistical test (i.e., chi-square test for independence, independent *t*-tests, or one-way analysis of variance) is used depending on the level of measurement of the two variables.

Day vs. Night

Table 2 shows the significant associations observed between characteristics of the individual admitted to the TSC and whether the admission occurred during the day (between 7:00 AM and 6:59 PM) or at night (7:00 PM to 6:59 AM). The observed significant associations were for **age** (t = 6.10; p < .001), **race/ethnicity** (χ^2 = 44.156; df = 3; p < .001), **houseing status** (χ^2 = 44.156; df = 1; p < .001), **repeat client** (χ^2 = 17.377; df = 1; p < .001), **primary substance** (χ^2 = 40.598; df = 1; p < .001), **BAC** (t = 1.96; p = .05), and **distance from TSC** (t = 2.64; p = .008). As such, factors such as gender, veteran status, and TPD division were not associated with whether an admission occurred during the day or at night. The significant associations are detailed below.

The average age of daytime admissions was 42.68 years, which was significantly greater than the average age of those admitted to the TSC during the nighttime hours (39.79 years). For differences in admissions by race and ethnicity, a larger proportion of Native American clients were admitted during the day compared to nighttime admissions. Conversely, a larger proportion of nighttime admissions were Hispanic/Latino compared to daytime admissions. The proportion of daytime and nighttime admissions did not meaningfully differ for White or African American clients.

Next, a larger proportion of daytime clients were identified as unhoused compared to admissions at night. Unhoused individuals only make up approximately 48% of all admissions at night. A similar trend was observed for one-time TSC clients compared to repeat clients. Repeat clients made up a larger proportion of daytime admissions compared to admissions at night.

For the relationship between primary substance and time of day, it was observed that a greater proportion than expected of daytime admissions involved a primary substance other than alcohol. During the night, admissions were predominately alcohol-related. The average BAC at intake also reflects the increase in non-alcohol-related admissions during daytime hours. Specifically, the average BAC was approximately 6% higher during the night than the day.

Finally, clients brought to the TSC during the day were, on average, detained at locations slightly closer to the TSC than clients brought in at night. In particular, the average location distance from TSC for daytime clients was 1.25 miles, while the average distance for nighttime clients was 1.34 miles.

Table 2. Differences in Characteristics of Daytime and Nighttime Admissions

	Day	Night
Age (n = 2,911)	42.68	39.79
Hispanic/Latino (n = 2,864)	5.8%	9.2%
Native American (n = 2,864)	14.8%	10.7%
Unhoused (n = 2,141)	62.3%	47.9%
Alcohol (n = 2,911)	71.5%	81.5%
Repeat Client (n = 2,911)	44.9%	37.2%
BAC (n = 2,892)	.136	.144
Distance from TSC (miles) (n = 2,770)	1.25	1.34

Work Week vs. Weekend

Table 3 displays the significant associations observed between characteristics of clients admitted to the TSC and whether the admission occurred during the work week or over the weekend. Significant associations were observed for **race/ethnicity** (χ^2 = 17.304; df = 3; p = 0.001), **housing status** (χ^2 = 11.462; df = 1; p = 0.001), **repeat client** (χ^2 = 7.193; df = 1; p = 0.007), and **distance from TSC** (t = 3.07; p = 0.002). As such, gender, age, veteran status, primary substance, BAC, repeat client, and TPD division were not associated with work week or weekend TSC admissions.

For the association between the day of the week and race/ethnicity, it was observed that a larger proportion of African American and Hispanic/Latino clients were brought to the TSC over the weekend (and a smaller proportion brought during the work week) than would be expected if no such relationship existed. The opposite was true for White and Native American clients. White and Native American clients made up a greater proportion of work week and a smaller proportion of weekend admissions than expected.

A larger proportion of clients during the work week were identified as unhoused compared to admissions during the weekend. As such, unhoused individuals were more likely to be brought to the TSC during the week, while an increased number of non-unhoused individuals were brought on the weekend. Once again, a similar trend was observed for one-time TSC clients compared to repeat clients.

Finally, clients brought to the TSC during the work week were, on average, detained at locations that are slightly closer to the TSC compared to clients brought in during the weekend. In particular, the average location distance from TSC for work week clients was 1.26 miles, while the average distance for weekend clients was 1.35 miles.

Table 3. Differences in Clients Admitted during the Work Week Compared to Weekend

	Work Week	Weekend
White (*n* = 2,911)	67.0%	61.6%
African American (*n* = 2,911)	13.7%	17.1%
Hispanic/Latino (*n* = 2,911)	6.4%	9.4%
Native American (*n* = 2,911)	12.9%	11.9%
Unhoused (*n* =2,141)	57.5%	50.2%
Repeat Client (*n* = 2,911)	42.8%	37.9%
Distance from TSC (miles) (*n* = 2,911)	1.26	1.35

Season of the Year

Trends regarding characteristics of TSC clients were also observed across seasons of the year and are shown in Table 4. Significant associations were observed for **housing status** ($\chi^2 = 9.820$; $df = 3$; $p = 0.02$), **primary substance** ($\chi^2 = 13.348$; $df = 3$; $p = 0.004$), and **repeat client** ($\chi^2 = 12.289$; $df = 3$; $p = 0.006$). Gender, race/ethnicity, age, veteran status, BAC, and distance from TSC were not found to be associated with admissions by season.

A larger proportion of clients during the winter were identified as unhoused compared to not being unhoused than would be expected if no such relationship existed. In the spring, the proportion of admissions of individuals who are unhoused was less than expected. Admissions in both the summer and fall nearly match what would be expected. As such, admissions of unhoused individuals increase during the winter and decrease during the spring.

A similar trend is observed for one-admission clients and repeat clients, yet the divergence occurs in the winter and summer. Specifically, repeat clients made a larger proportion of admissions than expected during the winter. In the summer, repeat clients were less common. Finally, for the relationship between primary substance and seasons, it was observed that the proportion of admissions involving a primary substance other than alcohol was greater in the summer than expected. Conversely, the proportion of admissions for substances other than alcohol was lower than expected in the winter.

Table 4. Differences in Clients Admitted by Season of the Year

	Winter	Spring	Summer	Fall
Unhoused (*n* = 2,141)	58.1%	49.8%	56.4%	51.2%
Alcohol (*n* =2,911)	81.8%	77.2%	73.9%	77.1%
Repeat Client (*n* = 2,911)	45.8%	40.9%	37.1%	39.3%

Bivariate Associations between Client Characteristics and Repeat Admission

First, we analyzed bivariate associations between client characteristics and one-admission or repeat clients. Of the observed characteristics, **gender** ($t = 2.16$; $p = 0.031$), **race/ethnicity** ($\chi^2 = 10.016$; $df = 3$; $p = 0.018$), **age** ($t = 5.39$; $p < 0.001$), **housing statu** ($t = 8.18$; $p < 0.001$), **primary substance** ($t = 1.97$; $p = 0.049$), **average BAC** ($t =3.62$; $p < 0.001$), and **average location distance from the TSC** ($t = 2.08$; $p = 0.038$) were all found to be significantly related to being either a single or repeat admit to the TSC. Veteran status was the only characteristic not associated with repeat admissions. Due to the length of this section, the detailed analyses are include in Appendix A. Significant associations are shown in Table 5 and detailed in the text below.

A greater proportion of repeat clients were male compared to one-admission clients. A greater proportion than expected of White, African American, and Native American clients were repeat clients compared to one-admission clients, while a smaller proportion than expected of Hispanic/Latino clients were repeats compared to one-admission clients. The average age of repeat clients was four years older than one-admission clients. Being unhoused was also associated with repeat clients; approximately two-thirds of repeat clients were identified as unhoused, while two-fifths of one-admission clients were unhoused. Repeat clients were more likely to have alcohol as their primary substance than one-admission clients, and the average BAC level at intake was 0.022 higher for repeats. Finally, repeat clients, on average, were detained at locations that were one-tenth of a mile closer to the TSC than one-admission clients.

Table 5. Differences in Characteristics of One-admission and Repeat Clients

	One-admission Client	Repeat Client
Male (*n* = 2,059)	74.2%	79.8%
White (*n* = 1,984)	66.0%	68.2%
African American (*n* = 1,984)	15.5%	16.8%
Hispanic/Latino (*n* = 1,984)	10.4%	4.8%
Native American (*n* = 1,984)	8.1%	10.3%
Age (*n* = 2,061)	38.74	42.73
Unhoused (*n* = 1,492)	40.3%	65.6%
Alcohol (*n* = 2,016)	73.4%	78.5%
BAC (*n* = 2,051)	0.124	0.146
Distance from TSC (miles) (*n* = 1,975)	1.33	1.23

Bivariate Associations between Client Characteristics and Number of Admissions

Table 6 shows the significant bivariate associations. Of the observed characteristics, **gender** (t = 2.73; p =0.007), **race/ethnicity** (F = 5.46; p = 0.001), **age** (r = 0.10; p < 0.001), **housing statu** (t = 5.85; p < 0.001), **primary substance** (t = 3.03; p = 0.003), and **average BAC** (r = 0.10; p < .001) were all significantly related TSC admissions counts. Veteran status and distance from TSC were the only characteristics not associated with admissions counts.

The average number of TSC admissions was greater for males than females. Racial/ethnic differences were also evident. Native American clients averaged 1.80 TSC admissions, which is greater than the average number for White (1.33), African American (1.38), and Hispanic/Latino (1.12) clients. Age and admissions counts were positively correlated, which suggests the number of admissions counts increases with age. Unhoused clients averaged more TSC admissions compared to clients who were housed. Clients with alcohol as a primary substance had more TSC admissions, on average, compared to clients who used substances other than alcohol. BAC at intake and admissions counts were positively correlated. As such, individuals with a higher average BAC at intake tended to have more TSC admissions than individuals with lower BAC levels.

Table 6. Average Number of TSC Admissions by Client Characteristics

	Admissions Counts
Gender (*n* = 2,059)	
Male	1.48
Female	1.22
Race/Ethnicity (*n* = 1,984)	
White	1.33
African American	1.38
Hispanic/Latino	1.12
Native American	1.80
Housing Status (*n* = 1,492)	
Unhoused	1.68
Housed	1.11

Primary Substance (n = 2,016)	
Alcohol	1.44
Not Alcohol	1.16

Bivariate Associations Between Client Characteristics and Time Between Admissions

Significant associations are presented in Table 7. Of the observed characteristics, **gender** (t = 3.37; $p < 0.001$), **race/ethnicity** (F = 4.33; p = 0.005), **housing statu** (t = 4.90; $p <$ 0.001), **primary substance** (t = 3.12; p = 0.002), **BAC at intake** (r = –0.13; $p < 0.001$), **TPD division** (F = 4.88; p = 0.008), and **second admission** (t = 9.33; $p < 0.001$) were all found to be significantly related to the length of time since last TSC admission. Age and veteran status were not associated with time between TSC admissions.

Males had a shorter time between re-admissions, on average, compared to females. The only statistically significant pairwise difference by race/ethnicity was between White and Native American clients. Native American clients, on average, returned to the TSC for a repeat admission 48.1 days sooner than White clients. TSC repeat clients who were unhoused returned to the TSC an average of 83.6 days earlier than those who were housed. Repeat clients with alcohol as a primary substance were re-admitted to the TSC faster than individuals who used substances other than alcohol. BAC at intake and the number of days since the last TSC admission were negatively correlated. As such, individuals with a higher BAC at intake tended to have fewer days between admissions than individuals with lower BAC levels.

At the TPD division level, no significant differences were observed in the number of days between admissions for individuals detained in Riverside compared to Gilcrease or Mingo Valley. A significant difference, however, was observed between individuals detained in Mingo Valley compared to Gilcrease. Finally, the average number of days between visits was longer when the previous visit was an individual's initial TSC admission. Stated differently, individuals who have been admitted to the TSC multiple times had less time between visits than those who were admitted only once before.

Table 7. Average Number of Days Between Admissions by Client Characteristics

	Days Between Admissions
Gender (n = 850)	
Male	118.6
Female	179.3
Race/Ethnicity (n = 843)	
White	134.7
African American	129.3
Hispanic/Latino	176.0
Native American	86.6
housing status (n = 684)	
Unhoused	125.7

Housed	209.3
Primary Substance (*n* = 850)	
Alcohol	118.3
Not Alcohol	170.4
TPD Division (*n* = 446)	
Riverside	155.8
Mingo Valley	211.7
Gilcrease	130.1
Admission Number (*n* = 850)	
Second Admission	193.9
3rd Admission or more	83.6

Bivariate Associations Between Client Characteristics and Length of Stay

We analyzed bivariate associations between client characteristics and length of stay per admission in the TSC. Statistically significant associations are presented in Table 8. Of the observed characteristics, **race/ethnicity** ($F = 3.34$; $p = 0.019$), **housing status** ($t = 7.44$; $p < 0.001$), **age** ($r = 0.09$; $p < 0.001$), **time of day of admission** ($t = 11.36$; $p < 0.001$), and **being a first-time TSC client** ($t = 5.63$; $p < 0.001$) were found to be significantly related to the length of stay in the TSC. Thus, no bivariate association was observed between the length of stay at the TSC and other characteristics of interest including gender, veteran status, primary substance, BAC at intake, TPD division, distance from TSC, day of the week, and season of the year.

For the specific significant associations, Native American clients had a length of stay at the TSC that was approximately 34 minutes longer, on average, compared to White clients, and 51 minutes longer, on average, compared to Hispanic/Latino clients. No other meaningful differences were observed across racial/ethnic groups. Unhoused individuals had a length of stay at the TSC that was, on average, 1.18 hours longer than clients who were housed. Age and length of stay are positively associated, which means older clients were likely to stay in the TSC for a longer duration per admission than younger clients. Compared to clients who were brought to the TSC during nighttime hours (i.e., 7 PM to 7 AM), individuals who were admitted during the day stayed at the TSC for 1.53 hours longer on average. Finally, first-time clients stayed at the TSC 50 minutes shorter, on average, than TSC clients during a repeat admission.

Table 8. Average Length of Stay at the TSC by Client Characteristics

	Average Length of Stay (hours)
Race/Ethnicity (*n* = 2,856)	
White	11.25
African American	11.15
Hispanic/Latino	10.97
Native American	11.82
Housing status (*n* = 2,140)	

Unhoused	11.86
Housed	10.67
Time of Day of Admission (*n* =2,903)	
Day	12.15
Night	10.63
Repeat Visit (*n* = 2,901)	
First TSC Admission	11.04
Repeat client	11.88

Bivariate Associations on Client Characteristics and Referrals to Service Providers

Associations were assessed using the variables of gender, race/ethnicity, housing status, veteran status, age, primary substance, BAC at intake, first TSC admission compared to repeat admission, admission count, distance from TSC, TPD division, time of day of admission, day of the week of admission, and season of admission. From April 2020 to October 2021, 66.1% of clients received a referral from the TSC upon discharge. When considering bivariate relationships, the only statistically significant associations with receiving a referral were **housing status** ($\chi^2 = 9.625$; $df = 1$; $p = 0.002$) and **season of the year** ($\chi^2 = 142.7944$; $df = 3$; $p < 0.001$).

As shown in Table 9, a greater proportion of unhoused clients received a referral than would be expected by chance compared to clients who were housed. A greater proportion of clients admitted in the winter receive referrals than would be expected by chance. Yet, the opposite is observed for fall and summer admissions. No meaningful differences were observed for admissions in the spring.

Table 9. Client Referrals at Discharge (*N* = 1,396)

	Percent of Admissions	
Referral at Discharge	66.1%	
No Referral at Discharge	33.9%	
	Percent with No Referral	Percent with Referral
Unhoused	48.3%	57.1%
Winter Admission	1.1%	22.6%
Spring Admission	32.3%	31.9%
Summer Admission	39.2%	33.8%
Fall Admission	27.4%	11.7%

Appendix C. Wichita Sobering Center Supplemental Details and Analyses

Table 1. Description of SACKSU Variables

Variable Name	Definition	Date Range	Coding for Analysis
Day of the Week	The day of the week (i.e., Sunday, Monday, Tuesday, Wednesday, Thursday, Friday, and Saturday) was identified from all admissions dates.	2/25/2015 –2/11/2021	Recoded into binary variable reflecting whether the admission occurred during the work week (Monday-Thursday) or the weekend (Friday-Sunday). *Weekend admission* is coded as 0 = work week and 1 = weekend.
Season of Year	Seasons of the year were identified from all admissions dates. Winter (December 21 - March 20), spring (March 21 - June 20), summer (June 21 - September 21), and fall (September 22 - December 20).	2/25/2015 – 2/11/2021	*Season* is coded where 1 = winter, 2 = spring, 3 = summer, and 4 = fall. For multivariate analyses, *winter* is used as the reference category.
Time of Day	Time of intake for all client admissions is collected using the 24-hour clock.	2/25/2015 – 2/11/2021	Recoded into a binary variable. *Daytime admission* is coded as 0 = night admission (between 7:00 PM and 6:59 AM) and 1 = day admission (between 7:00 AM and 6:59 PM).
Referral Source	Identifies the source of the client's referral to the SACKSU. Sources include self, family/friend, recovery services, community services, hospital, police, and corrections.	2/25/2015 – 2/11/2021	*Referral source* was recoded into 1 = Self-referral and 0 = Another referral source.
Race/Ethnicity	Race/ethnicity of the admitted client. Original SACKSU race/ethnicity categories included: Caucasian, African American, Hispanic/Latino, Native American, Asian, Pacific Islander, Mixed, and Other.	1/1/2017 – 2/11/2021	*Race/ethnicity* is coded 1 = White, 2 = African American, and 3 = Hispanic/Latino. Due to low case counts, the remaining categories were removed for analyses.
Unhoused	Identifies whether the admitted client was unhoused (yes or no).	1/1/2017 – 2/11/2021	*Unhoused* is coded as 1 = unhoused and 0 = housed.
Age	Age of the client at the time of the admission is collected as the number of years.	1/1/2020 – 2/11/2021	*Age* is continuously measured in years.
Substance	Identifies the substances (more than one could be identified) used by the client at admission. Examples of original SACKSU substances include alcohol, methamphetamine, heroin, opioids, cocaine, marijuana,	5/1/2019 – 2/11/2021	Individual variables were created for substances listed in the database. These substances included any alcohol, any methamphetamine, any heroin/opioids, any cocaine/crack, any marijuana,

	benzodiazepines, and other substances.		any benzodiazepines, and any other. For analyses a binary variable (*alcohol*) is used where 1 = any alcohol use and 0 = no alcohol use.
Multiple Substance User	All substances used by the client were listed in the database.	5/1/2019 – 2/11/2021	Clients with more than one substance listed were recoded as a *multiple substance user* (1 = yes; 0 = no).
Stay Duration	The number of hours a client stayed within the SACKSU from intake to discharge.	2/25/2015 – 2/11/2021	*Length of stay* is measured continuously, reflecting the number of hours (with decimals) the client stayed within the SACKSU.
Admissions Count	Identifies the total number of times each individual client has been admitted to the SACKSU.	2/25/2015 – 2/11/2021	The *admissions count* is a continuous measure.
Repeat Client	Identifies whether an individual client has been admitted to the SACKSU on more than one occasion.	2/25/2015 – 2/11/2021	Admissions counts variable was recoded into binary variable *repeat client*, where 1 = repeat client (two or more admissions) and 0 = one-admission client.
Admission Number	Identified the admission number of a specific admission is for an individual.	2/25/2015 – 2/11/2021	Used to create two measures. *First SACKSU admission* identifies whether the admission is the first for an individual (1= first admission and 0 = repeat). *Second admission* identifies whether the admission is a second admission (=1) or third or more (=0). One-admission clients are coded missing.
Time to Re-Admission	The time to re-admission was measured by calculating the days between one admission and the next using unique identifiers.	2/25/2015 – 2/11/2021	*Days between admissions* is measured continuously, reflecting the number of days between subsequent SACKSU admissions for repeat clients.
Detox at Discharge	Indicates whether the client was identified as being transferred to detox after discharge from SACKSU.	2/25/2015 – 2/11/2021	Recoded into a binary variable that reflects whether the client went to detox (1 = yes; 0 = no).

Bivariate Association Between Client Characteristics and Trends in Admissions

Day vs. Night

No statistically significant associations at $p = 0.05$ were observed between characteristics of the individual admitted to the SACKSU and whether the admission occurred during the day (between 7:00 AM and 6:59 PM) or at night (7:00 PM to 6:59 AM). Table 2 shows the associations between admissions characteristics and whether the client was admitted during the day or night. A larger proportion of clients during the night were self-referrals compared to admissions during the day. A greater proportion of daytime clients use alcohol compared to clients at night. A similar pattern is observed for single versus multi-substance users. Specifically, multiple substance users account for 28.3% of admissions during the day, but 24.1% of nighttime admissions.

Table 2. Differences in Characteristics of Daytime and Nighttime Admissions

	Day	Night
Self-referral (n = 3,075)	35.0%	38.4%
Alcohol User (n = 1,430)	53.7%	48.9%
Multiple Substance User (n = 1,430)	28.3%	24.1%

Work Week vs. Weekend

No statistically significant associations at $p = 0.05$ were observed between characteristics of the individual admitted to the SACKSU and whether the admission occurred during the work week or weekend.

Season of the Year

Trends regarding characteristics of the SACKSU clients were also observed across seasons of the year and are shown in Table 3. Significant associations were observed for **multiple substance use** ($\chi^2 = 36.151$; $df = 3$; $p < 0.001$) and whether the client was a **referral source** ($\chi^2 = 17.596$; $df = 3$; $p = 0.001$). No associations were observed for race/ethnicity, age, housing status , alcohol use, or repeat client.

For the association between season and users of multiple substances, the proportion of clients who were users of more than one substance was greater than expected in the fall and winter and less than expected in the spring and summer. Variation was also found between the seasons and whether the client was a self-referral. The proportion of self-referrals did not differ from what would be expected by chance in the winter or summer. The proportion did differ, however, in the spring and fall. Fewer admissions in the spring were clients who were self-referred, and a greater proportion of clients in the fall were self-referred individuals.

Table 3. Differences in Clients Admitted by Season of the Year

	Winter	Spring	Summer	Fall
Multiple Substance User (n = 1,430)	28.3%	13.0%	19.7%	33.6%
Self-Referral (n = 3,075)	37.6%	29.7%	38.3%	39.8%

Bivariate Associations between Client Characteristics and Repeat Admission

First, we analyzed bivariate associations between client characteristics and single-time or repeat clients. Of the observed characteristics, **unhoused** (t = 6.32; p < 0.001), **age** (t = 3.27; p = 0.001), **alcohol use** (t = 6.35; p < 0.001), and **referral source** (t = 3.63; p < 0.001) were all significantly related to being either a single or repeat client to the SACKSU. Race/ethnicity and multiple substance use were the only characteristics not associated with repeat admissions. Significant associations are shown in Table 4 and detailed in the text below.

A larger proportion of repeat clients were unhoused compared to one-admission clients. The average age of repeat clients was approximately three years older than one-admission clients. Repeat clients were more likely to use alcohol compared to one-admission clients. Finally, repeat clients were more likely to self-refer to the SACKSU than one-admission clients.

Table 4. Differences in Characteristics of Single-time and Repeat Clients

	Single-time Client	Repeat Client
Age (n = 565)	37.5	40.7
Unhoused (n = 1,457)	32.8%	49.5%
Alcohol User (n = 973)	41.9%	63.3%
Self-referral (n = 1,822)	31.6%	39.9%

Bivariate Associations between Client Characteristics and number of admissions

Table 5 shows the significant bivariate associations. Of the observed characteristics **age** (r = 0.14; p = 0.001), **unhoused** (t = 4.58; p < 0.001), **alcohol use** (t = 6.50; p < 0.011), and **multiple substance use** (t = 3.55; p < 0.001) were significantly related to SACKSU admissions counts. Race/ethnicity and referral source was not associated with admissions counts.

Age and admissions counts were positively correlated, which suggests that the number of admissions counts increases with age. Unhoused clients averaged more SACKSU admissions compared to clients who were housed. Clients who use alcohol had more SACKSU admissions, on average, compared to clients who used substances other than alcohol. On average, clients who use multiple substances have fewer admissions than clients who use only one substance.

Table 5. Average Number of SACKSU Admissions by Client Characteristics

	Admissions Counts
housing status (n = 1,320)	

Unhoused	1.67
Housed	1.34
Alcohol Use (n = 933)	
Alcohol User	2.19
Non-alcohol User	1.33
Multiple Substance Use (n = 889)	
Multiple Substance User	1.23
Single Substance User	1.73

Bivariate Associations Between Client Characteristics and Days Since Last Admission

We first analyzed bivariate associations between client characteristics and the number of days since the last admission, these can be found in Appendix B. Significant associations are presented in Table 6. Of the observed characteristics, **housing status** (t = 3.51; p < 0.001), **alcohol use** (t = 4.07; p < 0.001), **referral source** (t = 2.02; p = 0.04), and **second admission** (t = 4.21; p < 0.001) were significantly related to the length of time since last SACKSU admission. Race/ethnicity, age, multiple substance use, and being transferred to detox during past admission were not associated with time between SACKSU admissions.

SACKSU repeat clients who were unhoused returned to the SACKSU an average of 62 days earlier than repeat clients who were housed. On average, the number of days between return visits to the SACKSU was 109 days longer for alcohol users than clients who were not using alcohol. Self-referred clients, on average, returned 29 days faster than clients referred from other sources. Finally, the average number of days between visits was longer when the previous visit was an individual's first SACKSU admission. That is, individuals admitted more than once returned faster than those admitted only once.

Table 6. Average Number of Days Between Admissions by Client Characteristics

	Days Between Admissions
Housing Status (n = 975)	
Unhoused	150.1
Housed	211.8
Alcohol Use (n = 566)	
Alcohol User	234.4
Non-alcohol User	125.4
Referral Source (n = 1,236)	
Self-Referred	143.0
Another Referral Source	172.0
Admission Number (n = 1,238)	
Second Admission	195.0
3rd Admission or more	133.7

Bivariate Associations Between Client Characteristics and Length of Stay

We analyzed bivariate associations between client characteristics and length of stay per admission in the SACKSU. Of the observed characteristics, **race/ethnicity** (F = 4.88; p = 0.008), **housing status** (t = 4.28; p <0 .001), **alcohol use** (t = 4.92; p < 0.001), **use of multiple substances** (t = 2.99; p = 0.003), **referral source** (t = 7.28; p < 0.001), and **season of year** (F = 49.83; p < 0.001) were the variables significantly related to length of stay in the SACKSU. No bivariate association was observed between the length of stay and client age, being a first-time client to the SACKSU, time of day, and day of the week of admission. Table 7 displays these results.

White clients had an average stay of approximately 1 hour and 11 minutes shorter than African American clients. No other meaningful differences were observed across racial/ethnic groups. Unhoused individuals had a length of stay, on average, 1.16 hours longer than clients who were housed. With regard to substances used, alcohol users had a duration of stay 1 hour and 41 minutes shorter, on average, than non-alcohol users. Similarly, single substance users had an average length of stay of 1 hour and 10 minutes shorter than clients using two or more substances. Self-referred individuals stayed, on average, 1.69 hours longer than those referred through a different source. Length of stay at the SACKSU was found to vary across seasons. The length of stay was significantly longer in the winter compared to the spring and summer, yet no significant difference was found between winter and fall. The average stay in the summer and fall was longer than the average stay in the spring. Finally, the average length of stay in the fall was significantly longer than the summer.

Table 7. Average Length of Stay at the SACKSU by Client Characteristics

	Average Length of Stay (hours)
Race (n = 2,248)	
White	11.53
African American	12.71
Housing Status(n = 2,350)	
Unhoused	12.35
Housed	11.19
Alcohol Use (n = 1,430)	
Alcohol User	13.39
Non-alcohol User	15.08
Multiple Substances Use (n = 1,430)	
Single Substance User	13.91
Multiple Substance User	15.08
Referral Source (n = 3,074)	
Self-Referred	11.92
Another Referral Source	10.23
Season of Year (n = 3,081)	
Winter	11.66
Spring	8.37
Summer	10.62
Fall	12.10

Bivariate Associations Between Client Characteristics and Transfer to Detox

Associations were assessed using the variables of race/ethnicity, age, housing status, alcohol use, multiple substance use, first SACKSU admission compared to repeat admission, referral source, time of day, day of the week, and season of the year. When considering bivariate relationships, **housing statuss** ($\chi^2 = 5.082$; $df = 1$; $p = 0.024$), **one admission clients** ($\chi^2 = 7.255$; $df = 1$; $p = 0.007$), **time of day** ($\chi^2 = 18.357$; $df = 1$; $p < 0.001$), and **season** ($\chi^2 = 38.171$; $df = 3$; $p < 0.001$) were associated with transfer to the detox unit.

As shown in Table 8, unhoused clients were transferred to detox at a lower proportion than expected, while first-time clients made up a greater proportion of detox transfers than would be expected by chance. Differences in the proportion of clients transferred to detox were also found when considering the time of day of the admission. In particular, 51% of clients transferred to detox were admitted to the SACKSU during the day. Of those not transferred to detox, only 44% were daytime admissions. When considering differences in detox transfers across seasons, no meaningful differences were present in the winter or spring. A lower proportion of transferred clients, however, occurred in the summer. The opposite pattern was observed in the fall.

Table 8. Client Transfer to Detox at Discharge

	Percent of Admissions ($N = 3{,}052$)	
Transfer to Detox	66.1%	
No Detox Transfer	34.9%	
	No Detox Transfer	Transfer to Detox
Unhoused ($n = 2{,}325$)	46.1%	41.5%
First SACKSU Admission ($n = 3{,}033$)	57.1%	61.9%
Daytime Admission ($n = 3{,}052$)	43.6%	51.4%
Season of Year ($n = 3{,}052$)		
Winter Admission	26.3%	26.8%
Spring Admission	20.5%	19.5%
Summer Admission	31.1%	23.2%
Fall Admission	22.2%	30.5%

Appendix D. Austin Sobering Center Supplemental Details and Analyses

Table 1. Description of SCA Variables

Variable Name	Definition	Date Range	Coding for Analysis
Day of the Week	The day of the week (i.e., Sunday, Monday, Tuesday, Wednesday, Thursday, Friday, and Saturday) was identified from all admissions dates.	10/1/2018 – 9/30/2021	Recoded into binary variable reflecting whether the admission occurred during the work week (Monday-Thursday) or the weekend (Friday-Sunday). *Weekend admission* is coded as 0 = work week and 1 = weekend.
Season of Year	Seasons of the year were identified from all admissions dates. Winter (December 21 - March 20), spring (March 21 - June 20), summer (June 21 - September 21), and fall (September 22 - December 20).	10/1/2018 – 9/30/2021	*Season* is coded where 1 = winter, 2 = spring, 3 = summer, and 4 = fall. For multivariate analyses, *winter* is used as the reference category.
Time of Day	Time of intake for all client admissions is collected using the 24-hour clock.	10/1/2018 – 9/30/2021	Recoded into a binary variable. *Daytime admission* is coded as 0 = night admission (between 7:00 PM and 6:59 AM) and 1 = day admission (between 7:00 AM and 6:59 PM).
Transportation Source	Identifies the source of the client's transfer to the SCA. Sources include police, EMS, SC van, walk-in, and "other."	10/1/2018 – 9/30/2021	*Transportation Sources* was recoded to 1 = Police and 0 = EMS. Due to low case counts, remaining sources were removed for analyses.
City of Residence	The client's residential address was collected by the SCA. Included in the address was the city or residence.	11/1/2018 – 9/30/2021	City was recoded to reflect whether the client was an Austin resident (=1) or not (=0).
APD Sector	Identifies the APD police sector for the location of where the client was detained.	1/1/2019 – 9/30/2021	Used for descriptive purposes only. Sectors include ADAM, BAKER, CHARLIE, DAVID, EDWARD, FRANK, GEORGE, HENRY, IDA, and APT.
Gender	Gender of the admitted client. SCA database includes male, female, and transgender.	10/1/2018 – 9/30/2021	Gender was coded into a *male*, where 1 = male and 0 = female or transgender.
Race/Ethnicity	Race/ethnicity of the admitted client. SCA race categories included: White; Black, African American, or African; Hispanic/Latino, American Indian, Alaska Native, or Indigenous; Asian or Asian American; Native Hawaiian or Pacific Islander; Client doesn't know; Client refused; Data not	10/1/2018 – 9/30/2021	*Race/ethnicity* was created by combining information from the SCA's original race and ethnicity variables and was coded where 1 = White, 2 = African American, and 3 = White Hispanic/Latino (Black Hispanic/Latino clients were coded as African American). Due to low case counts, Native American, Asian and Pacific

	collect. Ethnicity was collected separately with the response categories of Hispanic/Non-Latin(a)(o)(x), Non-Hispanic/Non-Latin(a)(o)(x), Client doesn't know, Client refused, and Data not collected.		Islander were removed for analyses.
Unhoused	Identifies whether the admitted client was unhoused (yes or no).	10/1/2018 – 9/30/2021	*Unhoused* is coded such coded as 1 = unhoused and 0 = housed.
Active Military/ Veteran	Identifies whether the admitted client is active military or a veteran of the United States military (yes or no).	10/1/2018 – 9/30/2021	*Active military/veteran* is coded as 1 = active military/veteran and 0 = non-active military/veteran.
Student	Identifies whether the admitted client is a student (yes or no).	10/1/2018 – 9/30/2021	*Student* is coded as 1 = student and 0 = non-student.
Annual Income	Annual income is originally collected by the SCA as a raw value. We binned the existing values into manageable categories: No income, less than $15,000, $15,000 - $24,999, $25,000 - $34,999, $35,000 - $49,999, $50,000 - $74,999, $75,000 - $99,999, $100,000 - $149,999, $150,000 - $199,999, and More than $200,000.	2/1/2019 – 9/30/2021	For analyses, the binned annual income measure was recoded into a binary variable (*low income*), where 1= Less than $15,000 or No income and 0 = More than $15,000.
Age	Age of the client at the time of the admission is collected as the number of years.	10/1/2018 – 9/30/2021	*Age* is a continuously measured in years.
Substance	Identifies the substances (more than one could be identified) used by the client at admission. Examples of original SCA substances include alcohol, methamphetamine, heroin, opioids, crack, cocaine, marijuana, synthetic marijuana, benzodiazepines, hallucinogens, and no substances.	10/1/2018 – 9/30/2021	Individual variables were created for substances listed in the database. These substances included any alcohol, any methamphetamine, any heroin/opioids, any crack/cocaine, any marijuana/synthetic, any hallucinogens, any benzodiazepines, any other, any unknown, and no substances. For analyses a binary variable (*alcohol*) is used where 1 = any alcohol use and 0 = no alcohol use.
Multiple Substance User	All substances used by the client were listed in the database.	10/1/2018 – 9/30/2021	Clients with more than one substance listed were recoded as a *multiple substance user* (1 = yes; 0 = no).
BAC	All clients receive a blood alcohol concentration (BAC) test at intake and the results are	10/1/2018 – 9/30/2021	*BAC at Intake* is a continuous measure. For regression analyses,

	entered into the SCA admissions database.		the original BAC is multiplied by 100 for interpretational purposes.
Not Admitted into the SCA	Indicates if a client transported to the SCA was not formally admitted. Provides the reason for the non-admittance (hospital, jail, client was not intoxicated, client was noncompliant, client walked out, and "other").	10/1/2018 – 9/30/2021	The variable *not admitted* reflects whether a client was not formally admitted to the SCA (=1) or if they were admitted (=0).
Admitted but Transferred from the SCA	Indicates if a client was formally admitted into the SCA but transferred elsewhere before completing their stay. Provides the reason for the transfer (hospital, client walked out, jail, client was noncompliant, transfer to treatment facility, and "other").	10/1/2018 – 9/30/2021	The variable *admitted but transferred* reflects whether a client was transferred after admission to the SCA (=1) or if they were not transferred (=0).
Stay Duration	The number of hours a client stayed within the SCA from intake to discharge.	10/1/2018 – 9/30/2021	*Length of stay* is measured continuously, reflecting the number of hours (with decimals) the client stayed within the SCA.
Treatment at Discharge	Indicates whether the client went to treatment upon discharge from the SCA.	10/1/2018 – 9/30/2021	Binary variable that reflects whether the client went to treatment upon discharge (=1) or not (= 0).

Bivariate Association Between Client Characteristics and Trends in Admissions

Day vs. Night

Significant associations were observed between the characteristics of the individual admitted to the SCA and whether the admission occurred during the day (between 7:00 AM and 6:59 PM) or at night (7:00 PM to 6:59 AM). The observed significant associations were for **gender** ($\chi^2 = 10.004$; $df = 1$; $p = 0.002$), **race/ethnicity** ($\chi^2 = 15.277$; $df = 2$, $p < 0.001$), **age** ($t = 12.832$; $p < 0.001$), **housing status** ($\chi^2 = 36.553$; $df = 1$; $p < 0.001$), **student status** ($\chi^2 = 21.738$; $df = 1$; $p < 0.001$), **annual income** ($\chi^2 = 31.18$; $df = 1$; $p < 0.001$), **city of residence** ($\chi^2 = 59.150$; $df = 1$; $p < 0.001$), and **any alcohol use** ($\chi^2 = 17.798$; $df = 1$; $p < 0.001$). As such, active military/veteran status, BAC, and transportation source were not related to daytime or nighttime SCA admissions. The significant associations are detailed below.

Table 2 shows the statistically significant associations between admissions characteristics and whether the client was admitted during the day or night. For the association between time of day and gender, male clients made up a greater proportion of daytime than nighttime admissions. A larger proportion of clients admitted during the day were White than at night. Conversely, a greater proportion of clients admitted during the night were Hispanic/Latino compared to the day. The proportion of daytime and nighttime admissions for African American clients did not meaningfully differ from what would be expected. On average, individuals admitted to the SCA during the night were four years younger than those admitted during the day.

A larger proportion of clients during the day were identified as being unhoused compared to admissions at night. The opposite trend was observed for clients who are students. Student clients made up a larger proportion of nighttime admissions compared to the admissions during the day. For annual income, a larger proportion of daytime admissions were clients who reported making less than $15,000 a year compared to nighttime clients. A greater proportion of daytime admissions also involved clients who lived in Austin compared to nighttime admissions. For the relationships between substances used and time of day, it was observed that a greater proportion of clients who were using alcohol were admitted to SCA at night compared to the day.

Table 2. Differences in Characteristics of Daytime and Nighttime Admissions

	Day	Night
Male (*n* = 5,430)	76.9%	73.1%
White (*n* = 4,872)	56.2%	51.5%
Hispanic/Latino (*n* = 4,872)	31.0%	36.3%
Age (*n* = 5,446)	38.0	33.6
Unhoused (*n* = 4,841)	34.2%	26.2%
Student (*n* = 4,422)	7.6%	11.9%
Income Less Than $15,000 (*n* = 3,262)	62.7%	53.0%
From Austin (*n* = 4,260)	75.2%	64.3%
Alcohol User (*n* = 5,167)	82.6%	86.8%

Work Week vs. Weekend

Significant associations were observed between the characteristics of the individual admitted to the SCA and whether the admission occurred during the work week or over the weekend. Significant associations were observed for **gender** (χ^2 = 13.441; df = 1; p < 0.001), **age** (t = 15.217; p < 0.001), **housing status** (χ^2 = 112.772; df = 1; p < 0.001), **active military/veteran status** (χ^2 = 4.911; df = 1; p = 0.027), **student status** (χ^2 = 85.544; df = 1; p < 0.001), **annual income** (χ^2 = 85.544; df = 1; p < 0.001), **city of residence** (χ^2 = 110.437; df = 1; p < 0.001), **any alcohol use** (χ^2 = 50.144; df = 1; p < 0.007), **BAC** (t = 2.546; p = 0.011), and **transportation source** (χ^2 = 18.883; df = 1; p < 0.001). As such, race/ethnicity was the only client characteristic not associated with being admitted to the SCA during the work week or the weekend.

Table 3 shows the statistically significant associations between admission characteristics and whether the client was admitted during the work week or the weekend. For the association with gender, it was found that a greater proportion of male clients were admitted during the work week compared to the weekend. The average age of SCA clients was 5 years older during the work week compared to the weekend.

A larger proportion of clients during the work week were identified as unhoused compared to weekend admissions. As such, unhoused individuals were more likely to be brought to the SCA during the week, while an increased number of individuals who were housed were brought to the SCA on the weekend. Active military or veteran clients and students made up a greater proportion of weekend admissions compared to SCA admissions during the work week. Annual income followed the same pattern as housing status. A greater proportion of work week admissions involved clients who make less than $15,000 a year compared to clients on the weekend. Furthermore, work week admissions were more likely to be from Austin compared to admissions during the weekend.

When considering the type of substances used at admission to the SCA, a greater proportion of weekend clients had been alcohol users compared to clients during the work week. The average BAC at intake reflects the increase in non-alcohol-related admissions during the work week. Specifically, the average BAC was approximately 5% higher during the weekend compared to the average BAC during the work week. Finally, a greater proportion of admissions during the weekend were transported to the SCA by EMS rather than police. Conversely, clients transported by police made up a larger proportion of work week admissions compared to weekend admissions.

Table 3. Differences in Clients Admitted During the Work Week Compared to Weekend

	Work Week	Weekend
Male (n = 5,430)	77.2%	72.8%
Age (n = 5,446)	38.4	33.3
Unhoused (n = 4,841)	37.6%	23.5%
Active Military/Veteran (n = 4,347)	7.4%	9.2%
Student (n = 4,422)	5.2%	13.7%
Income Less Than $15,000 ($n$ = 3,262)	66.6%	50.4%
From Austin (n = 4,260)	77.5%	62.6%
Alcohol User (n = 5,167)	81.0%	88.1%
BAC (n = 4,899)	0.173	0.181
Transported by Police (n = 2,911)	76.5%	70.8%

Season of the Year

Trends regarding characteristics of SCA clients were also observed across seasons of the year. Significant associations were observed for **student status** ($\chi^2 = 8.500$; $df = 3$, $p = 0.037$), **annual income** ($\chi^2 = 12.104$; $df = 3$, $p = 0.007$), **any alcohol use** ($\chi^2 = 58.805$; $df = 3$, $p < 0.001$), **BAC** ($F = 44.46$; $p < 0.001$), and **transportation source** ($\chi^2 = 29.452$; $df = 3$, $p < 0.001$). As such, no significant associations were observed for gender, race/ethnicity, age, housing status, military status, and city of residence.

Table 4 displays the statistically significant associations regarding season of the year for client admissions. A larger proportion of clients during the winter and fall were identified as being students compared to not being students than would be expected by chance if no such relationship existed. Specifically, student clients made up 10.0% of all admissions. During the winter and fall, around 11.0% of admissions were by student clients, while the proportion of spring admissions of individuals who are students was lower than expected. Admissions in the summer nearly matched what would be expected. As such, admissions of student clients increased during the fall and winter and decreased during the spring.

For the association between season and annual income, it was observed that the proportion of clients who make less than $15,000 was greater than expected in the spring (61.6%) and less than expected in the winter (52.9%). Specifically, 57.4% of all clients were identified as making less than $15,000 a year.

The percentage of clients admitted to SCA who were using alcohol at their admission varied across seasons. While the proportion of alcohol-using clients did not differ from what would be expected in the spring, winter and fall both had a greater proportion of alcohol users than expected if there was no relationship with the year's season. In the summer, a greater proportion of non-alcohol users were admitted to the SCA than would be expected by chance. This pattern of alcohol use was also reflected in seasonal differences in average BAC. Specifically, the average BAC levels in the winter and fall did not significantly differ, but they were significantly higher than those in the spring and summer. No significant difference in average BAC level was observed between spring and summer.

Finally, variation was also found between season of the year and whether the client was transported to the SCA by the police or EMS. The proportion did not differ from what would be expected by chance in the winter or summer. The proportion did differ, however, in the spring and fall. More admissions in the spring were from clients who were transported by the police than those in the fall. In other words, EMS transported more clients to the SCA in the fall than in the spring.

Table 4. Differences in Clients Admitted by Season of the Year

	Winter	Spring	Summer	Fall
Student (*n* = 4,422)	11.4%	8.0%	9.5%	11.0%
Income less than $15,000 (*n* = 3,262)	52.9%	61.6%	57.2%	57.4%
Alcohol User (*n* = 5,167)	87.8%	83.8%	79.6%	89.0%
Transported by Police (*n* = 2,911)	74.3%	77.5%	73.8%	67.2%
BAC (*n* = 4,899)	0.196	0.165	0.154	0.194

Bivariate Associations Between Client Characteristics and Length of Stay

We analyzed bivariate associations between client characteristics and length of stay per admission in the SCA. Statistically significant associations are presented in Table 5. Of the observed characteristics, **gender** (t = 5.01; $p < 0.001$), **age** (r = 0.23; $p < 0.001$), **housing status** (t = 11.13; $p < 0.001$), **student status** (t = 4.98; $p < 0.001$), **annual income** (t = 13.15; $p < 0.001$), **city of residence** (t = 10.11; $p < 0.001$), **any alcohol use** (t = 5.65; $p < 0.001$), **BAC** (r = 0.05; p = 0.003), **transportation source** (t = 5.48; $p < 0.001$**), treatment after discharge** (t = 7.39; $p < 0.001$), **time of day** (t = 10.50; $p < 0.001$), and **day of the week** (t = 4.24; $p < 0.001$) were significantly related to the length of stay in the SCA. Thus, no bivariate association was observed between the length of stay at the SCA and race/ethnicity, active military/veteran status, and season of the year.

For the specific significant associations, male clients had a length of stay at the SCA that was approximately 49 minutes longer, on average, compared to clients who were not male. Age and length of stay were positively associated, which means older clients were likely to stay in the SCA for a longer duration than younger clients. Unhoused individuals had a length of stay at the SCA that was, on average, 1 hour and 46 minutes longer than clients who were housed. The length of stay at the SCA for student clients was 1 hour and 10 minutes shorter, on average, than the length of stay for non-student clients. Clients who earn more than $15,000 a year stayed approximately 2 hours and 11 minutes longer than clients who make less than $15,000 a year. On average, clients who identify as living in Austin stayed longer at the SCA compared to clients not from Austin. Alcohol users had a duration at the SCA that was 1 hour and 12 minutes shorter than non-alcohol users. Yet, BAC and length of stay were slightly positively correlated; clients who had a higher BAC at intake stayed longer than those with lower BAC levels. Clients transported to the SCA by EMS stayed longer, on average, than clients transported by the police. Clients who went to treatment after being discharged from the SCA stayed nearly 3.5 hours longer, on average than clients who did not go on to treatment. Compared to clients who were transported to the SCA during nighttime (i.e., 7PM to 7AM), individuals admitted during the day stayed 1.48 hours longer on average. Finally, the average length of stay at the SCA was approximately 36 minutes shorter for clients admitted to the SCA on the weekend compared to clients admitted during the work week.

Table 5. Average Length of Stay at the SCA by Client Characteristics

	Average Length of Stay (hours)
Gender (n = 4,129)	
Male	8.11
Non-Male	7.30
Housing Status (n = 3,895)	
Unhoused	9.23
Housed	7.46
Student Status (n = 3,615)	
Student	6.86
Non-student	8.04
Annual Income (n = 2,834)	
Less than $15,000	9.13
More than $15,000	6.94

City of Residence (n = 3,470)	
From Austin	8.48
Not from Austin	6.84
Alcohol Use (n = 4,014)	
Alcohol User	7.73
Non-alcohol User	8.92
Transportation Source (n = 3,576)	
Police	7.43
EMS	8.31
Treatment after Discharge (n = 3,441)	
Went to Treatment	11.30
Did not go to Treatment	7.98
Time of Day (n = 4,143)	
Daytime Admission	8.74
Nighttime Admission	7.26
Day of the Week (n = 4,143)	
Work Week Admission	8.24
Weekend Admission	7.64

Bivariate Associations of Clients Transferred to Treatment at Discharge

When considering bivariate relationships, **age** (t = 6.66; $p < 0.001$), **housing status** (χ^2 = 22.956; df = 1; $p < 0.001$), **student status** (χ^2 = 8.708; df = 1; p = 0.003), **annual income** (χ^2 = 34.200; df = 1; $p < 0.001$), **city of residence** (χ^2 = 18.892; df = 1; $p < 0.001$), **alcohol use** (χ^2 = 60.242; df = 1; $p < 0.001$), **BAC at intake** (t = 6.69; $p < 0.001$), **transportation source** (χ^2 = 5.392; df = 1; p = 0.020), **time of day** (χ^2 = 17.452; df = 1, $p < 0.001$), and **day of the week** (χ^2 = 43.177; df = 1; $p < 0.001$) were all associated with a client going to treatment after discharge. No association was observed for gender, race/ethnicity, active military/veteran status, and season of the year.

Clients who went to treatment after discharge were of older age, on average, compared to the clients who did not go on to treatment. Specifically, clients who went to treatment were an average of seven years older than those who did not. Unhoused clients made up a greater proportion of those who went to treatment than would be expected. A similar pattern was observed for annual income. Student clients made up a smaller proportion of clients who went to treatment than would be expected by chance. A greater proportion of clients who reported Austin as their city of residence went to treatment compared to clients who did not go to treatment. Alcohol users made up a smaller proportion of clients who went to treatment than would be expected. This pattern was also reflected in the relationship between BAC at intake and clients going to treatment. Specifically, the clients who went to treatment, on average, had a BAC at intake that was 38% lower than those who did not go to treatment. A smaller proportion of clients who went to treatment were brought to the SCA by police compared to those who did not go to treatment. Furthermore, differences in the proportion of clients who went to treatment were also found when considering the time of day of the admission. In particular, a greater proportion of clients who went to treatment were admitted during the daytime compared to those who did not go to treatment. When considering differences in going to treatment across days of the week, it is observed that a smaller proportion of clients who go to treatment are admitted during the weekend than would be expected by chance.

Table 6. Client Going to Treatment at Discharge

	Percent of Admissions (*N* = 4,221)	
Treatment after Discharge	4.4%	
No Treatment after Discharge	95.6%	
	No Treatment	Treatment
Age (*n* = 4,202)	35.1	41.4
Unhoused (*n* = 3,955)	28.8%	45.7%
Student (*n* = 3,731)	10.7%	3.3%
Income less than $15,000 (*n* = 2,802)	55.9%	81.2%
From Austin (*n* = 3,564)	67.6%	84.1%
Any Alcohol Use at Admission (*n* = 4,055)	85.8%	64.2%
BAC (*n* = 3,857)	0.177	0.120
Transported by Police (*n* = 3,635)	73.6%	62.5%
Daytime Admission (*n* = 4,221)	43.6%	59.2%
Weekend Admission (*n* = 4,221)	56.7%	32.1%

Appendix E. Houston Sobering Center Supplemental Details and Analyses

Table 1. Description of HRC Variables

Variable Name	Definition	Date Range	Coding for Analysis
Day of the Week	The day of the week (i.e., Sunday, Monday, Tuesday, Wednesday, Thursday, Friday, and Saturday) was identified from all admissions dates.	4/10/2013 – 3/31/2021	Recoded into binary variable reflecting whether the admission occurred during the work week (Monday-Thursday) or the weekend (Friday-Sunday). *Weekend admission* is coded as 0 = work week and 1 = weekend.
Season of Year	Seasons of the year were identified from all admissions dates. Winter (December 21 - March 20), spring (March 21 - June 20), summer (June 21 - September 21), and fall (September 22 - December 20).	4/10/2013 – 3/31/2021	*Season* is coded where 1 = winter, 2 = spring, 3 = summer, and 4 = fall. For multivariate analyses, *winter* is used as the reference category.
Time of Day	Time of intake for all client admissions is collected using the 24-hour clock.	4/10/2013 – 3/31/2021	Recoded into a binary variable. *Daytime admission* is coded as 0 = night admission (between 7:00 PM and 6:59 AM) and 1 = day admission (between 7:00 AM and 6:59 PM).
Admissions Source	Identifies the source of the client's admission to the HRC. Sources include law enforcement, public intoxication transport, courts, jail, probation, family, mental health services, substance use services, community, and "other."	4/10/2013 – 3/31/2021	*Police referral* was recoded to 1 = Police and 0 = Source other than Police.
Law Enforcement Agency	Identifies the law enforcement agency involved in the jail diversion incident. Agencies include, Houston PD, Harris County Sherriff, Harris County Constable, Metro-Transit Police, university-affiliated police, school district police, veteran affairs police, and "other."	4/10/2013 – 3/31/2021	Similar agencies are collapsed into distinct groups for descriptive purposes.
HPD Beat	Identifies the district and/or beat of the jail diversion incident.	4/10/2013 – 3/31/2021	Used for descriptive purposes only.
Gender	Gender of the admitted client. HRC database includes male, female, and transgender.	4/10/2013 – 3/31/2021	Gender was coded into a *male*, where 1 = male and 0 = female or transgender.
Race/Ethnicity	Race/ethnicity of the admitted client. HRC race categories included: White; Black, Asian; American Indian/Alaska Native; Native Hawaiian/Pacific Islander; and "other." Ethnicity was	4/10/2013 – 3/31/2021	*Race/ethnicity* was created by combining information from the HRC's original race and ethnicity variables and was coded where 1 = White, 2 = African American, and 3 = White Hispanic/Latino

	collected separately with the response categories of Hispanic and Not Hispanic.		(Black Hispanic/Latino clients were coded as African American). Due to low case counts, other racial/ethnic categories were removed for analyses.
Living Status	Identifies the living status of the client. Options include unhoused, private residential, shelter / residential facility, and "other."	4/10/2013 – 3/31/2021	*Unhoused* is coded as 1 = unhoused and 0 = housed.
Veteran Status	Identifies whether the admitted client has military involvement.	4/10/2013 – 3/31/2021	*Veteran* is coded as 1 = veteran and 0 = non-veteran.
Employment Status	Identifies whether the admitted client is currently employed (yes, no, or refused).	8/15/2017 – 3/31/2021	*Unemployed* is coded as 1 = no employment and 0 = employed. Refused was coded as missing.
Low-Income Status	Collected by HRC. Indicates low income status at the time of admission based on family size and annual income.	8/6/2014 – 3/31/2021	*Low income* is coded where 1 = low income and 0 = not low income.
Age	Age of the client at the time of the admission is collected as the number of years.	4/10/2013 – 3/31/2021	*Age* is a continuously measured in years.
Substance	Identifies the substances (more than one could be identified) used by the client at the time of admission. Examples of original HRC substances include alcohol, methamphetamine, heroin, opioids, crack, cocaine, marijuana, synthetic marijuana, benzodiazepines, and barbiturates.	4/10/2013 – 3/31/2021	Individual variables were created for substances listed in the database. These substances included any alcohol, any marijuana/synthetic, any methamphetamine, any heroin/opioids, any crack/cocaine, , any MDMA, any PCP, any benzodiazepines, any barbiturates, and any other. For analyses a binary variable (*alcohol*) is used where 1 = any alcohol use and 0 = no alcohol use.
Multiple Substance User	All substances used by the client were listed in the database.	4/10/2013 – 3/31/2021	Clients with more than one substance listed were recoded as a *multiple substance user* (1 = yes; 0 = no).
BAC	All clients receive a blood alcohol concentration (BAC) test at intake and the results are entered into the HRC admissions database.	8/15/2017 – 3/31/2021	*BAC* is a continuous measure. For regression analyses, the original BAC is multiplied by 100 for interpretational purposes.
Educational Attainment	Indicates the self-reported highest level of education completed. Levels include less than high school, high school, associate's degree, bachelor's degree, professional or advanced degree, and "other" education.	2/20/2019 – 3/31/2021	Variable *No High School Completion* identified the clients who had a highest level of education that was less than completion of high school or high school equivalency. Coded where 1 = No High School

			Completion and 0 = High School Completion or more.
Mental Health Issues	Indicates whether the client identified any mental health issues during the intake process for admission to the HRC (yes or no)	4/10/2013 – 3/31/2021	*Mental Health Issue* is coded as 1 = self-reported mental health issues and 0 = no reported mental health issues.
Arrest History	Indicates whether the client self-reported ever being arrested in their lifetime (yes or no).	4/10/2013 – 3/31/2021	*Ever Arrested* is coded as 1 = arrest history and 0 = no arrest history.
Treatment History	Indicates whether the client reported receiving treatment for substance use or mental health issues within the last 12 months.	8/15/2017 – 3/31/2021	*Treatment in Last Year* is coded as 1 = received treatment and 0 = no treatment received.
Treatment Readiness	Readiness Ruler tool used to measure readiness to quit substance use. Outcomes include ready to quit, unsure, and not ready.	4/10/2013 – 3/31/2021	*Ready for Treatment* is coded as 1 = ready to quit and 0 = unsure or not ready to quit.
Admissions Count	Identifies the total number of times each individual client has been admitted to the HRC.	4/10/2013 – 3/31/2021	The *admissions count* is a continuous measure.
Repeat Client	Identifies whether an individual client has been admitted to the HRC on more than one occasion.	4/10/2013 – 3/31/2021	Admissions counts variable was recoded into binary variable *repeat client*, where 1 = repeat client (two or more admissions) and 0 = one-admission client.
Admission Number	Identified the admission number of a specific admission is for an individual.	4/10/2013 – 3/31/2021	Used to create two measures. *First HRC admission* identifies whether the admission is the first for an individual (1= first admission and 0 = repeat). *Second admission* identifies whether the admission is a second admission (=1) or third or more (=0). One-admission clients are coded missing.
Time to Re-Admission	The time to re-admission was measured by calculating the days between one admission and the next using unique identifiers.	4/10/2013 – 3/31/2021	*Days between admissions* is measured continuously, reflecting the number of days between subsequent HRC admissions for repeat clients.
Stay Duration	The HRC calculates the number of days a client stayed within the HRC from intake to discharge.	4/10/2013 – 3/31/2021	*Length of stay* was transformed from days to hours by multiplying the original value by 60. Results in a variable that is measured continuously and reflects the number of hours (with decimals) the client stayed within the HRC.
HRC Recovery Program	Indicates whether the client was enrolled within an HRC Recovery Program after discharge.	4/1/2014 – 3/31/2021	A binary variable was created that reflects whether the client

	Programs options included PART, PRS, and Reach.		was enrolled in an HRC program (=1) or not (=0).

Bivariate Association Between Client Characteristics and Trends in Admissions

Day vs. Night

Table 2 shows the significant associations that were observed between characteristics of the individual admitted to the HRC and whether the admission occurred during the day (between 7:00 AM and 6:59 PM) or at night (7:00 PM to 6:59 AM). All observed characteristics were statistically significantly associated with the time of day of the HRC admission at $p < .001$ and these differences are detailed below.

Clients brought to the HRC during the daytime were older on average (41.7 years) than those who were brought in during the night (37.4 years). A larger proportion of African American clients were admitted during the day compared to nighttime admissions. Conversely, a larger proportion of nighttime admissions were White or Hispanic/Latino compared to daytime admissions. Just over half of daytime admissions were referred to the HRC by law enforcement, while nearly all nighttime admissions to the HRC came from law enforcement officers.

Unhoused individuals were more likely to be brought to the HRC during the day (57.9%) compared to admissions at night (27.4%). A similar trend was observed for clients who are veterans, clients who had an educational attainment that was less than high school completion, clients who were unemployed, low-income clients, clients who had mental health issues, clients who received substance use or mental health treatment in the past year, clients who were ever arrested, and one-time HRC clients compared to repeat clients. In all cases, these clients made up a larger proportion of daytime admissions compared to admissions at night.

For the relationship between substance used and time of day, it was observed that a greater proportion than expected of daytime admissions involved substances other than alcohol. During the night, admissions were predominately alcohol-related. Additionally, a greater than expected proportion of daytime admissions involved clients who were using multiple substances. Nighttime admissions were predominantly clients who were only identified as using a single substance. The average BAC at intake reflects the increase in non-alcohol-related admissions during daytime hours. Specifically, the average BAC was approximately 64% higher during the night compared to the average BAC during the day.

Table 2. Differences in Characteristics of Daytime and Nighttime Admissions

	Day	Night
Male (*n* = 47,158)	84.2%	80.3%
White (*n* = 41,354)	39.6%	43.7%
African American (*n* = 41,354)	41.5%	32.0%
Hispanic/Latino (*n* = 41,354)	18.9%	24.3%
Unhoused (*n* = 45,821)	57.9%	27.4%
Veteran (*n* = 46,234)	9.7%	7.4%
No High School Completion (*n* = 6,191)	28.5%	20.2%
Unemployed (*n* = 14,854)	72.0%	48.7%
Low Income (*n* = 27,700)	91.9%	75.6%
Mental Health Issue (*n* = 36,996)	43.2%	26.0%
Treatment in Last Year (*n* = 14,680)	23.4%	13.2%
Ever Arrested (*n* = 37,255)	77.9%	56.5%
Alcohol User (*n* = 42,168)	66.0%	91.0%
Multiple Substance User (*n* = 42,168)	18.6%	7.8%
Police Referral (*n* = 47,182)	65.9%	94.2%
Repeat Client (*n* = 47,182)	63.1%	37.2%
Age (*n* = 47,167)	41.7	37.4
BAC (*n* = 17,491)	.095	.156

Work Week vs. Weekend

Table 3 displays the significant associations observed between characteristics of clients admitted to the HRC and whether the admission occurred during the work week or over the weekend. Once again, all observed characteristics were statistically significantly associated with whether the HRC admission occurred during the work week or the weekend at $p < .001$, except for gender ($\chi^2 = 3.879$; $df = 1$; $p = .049$).

The average age of clients admitted during the work week was 40.8 years, which was significantly greater than the average age of those admitted to the HRC during the weekend (37.8 years). A larger proportion of African American clients were admitted during the work week compared to weekend admissions. Conversely, a larger proportion of weekend admissions were White or Hispanic/Latino compared to work week admissions. Approximately three-quarters of work week admissions were referred to the HRC by law enforcement, compared to 90.6% of weekend admissions that came from law enforcement.

Unhoused individuals were more likely to be brought to the HRC during the work week, while an increased number of individuals who are housed were brought to the HRC during the weekend. A similar trend was observed for clients who are veterans, clients who had an educational attainment that was less than high school completion, clients who were unemployed, low-income clients, clients who had mental health issues, clients who received treatment during the past year, clients who were ever arrested, and one-time

HRC clients compared to repeat clients. In all cases, these clients made up a larger proportion of work week admissions compared to weekend admissions.

A greater proportion than expected of work week admissions involved substances other than alcohol. During the weekend, admissions were mostly alcohol related. Additionally, a greater than expected proportion of work week admissions involved clients who were using multiple substances. Weekend admissions were predominantly clients who were only identified as using a single substance. The average BAC at intake reflects the increase in non-alcohol-related admissions during work week hours. Specifically, the average BAC was approximately 27% higher during the weekend compared to the average BAC during the work week.

Table 3. Differences in Clients Admitted during the Work Week Compared to Weekend

	Work Week	Weekend
Male (n = 47,158)	81.8%	82.5%
White (n = 41,354)	40.9%	42.6%
African American (n = 41,354)	39.6%	33.1%
Hispanic/Latino (n = 41,354)	19.5%	24.3%
Unhoused (n = 45,821)	49.0%	33.4%
Veteran (n = 46,234)	9.1%	7.7%
Non-High School Graduate (n = 6,191)	26.9%	20.6%
Unemployed (n = 14,854)	67.3%	51.9%
Low Income (n = 27,700)	88.7%	77.6%
Mental Health Issue (n = 36,996)	39.5%	27.9%
Treatment in Last Year (n = 14,680)	21.8%	14.0%
Ever Arrested (n = 37,255)	72.7%	59.5%
Alcohol User (n = 42,168)	73.6%	86.6%
Multiple Substance User (n = 42,168)	16.9%	7.9%
Police Referral (n = 47,182)	72.6%	90.6%
Repeat Client (n = 47,182)	55.8%	41.9%
Age (n = 47,167)	40.8	37.8
BAC (n = 17,491)	.113	.144

Season of the Year

Trends regarding characteristics of the HRC clients were also observed across seasons of the year. Significant associations were observed for **age** (F = 3.89; p = .009), **gender** (χ^2 = 9.273; df = 3; p = .026), **housing status** (χ^2 = 91.734; df = 3; p < .001), **veteran status** (χ^2 = 21.919; df = 3; p < .001), **educational attainment** (χ^2 = 8.609; df = 3; p = .035), **arrest history** (χ^2 = 52.817; df = 3; p < .001), **alcohol use** (χ^2 = 58.056; df = 3; p < .001), **multiple substance use** (χ^2 = 37.505; df = 3; p < .001), **repeat client** (χ^2 = 66.567; df = 3; p < .001), **source of HRC referral** (χ^2 = 30.984; df = 3; p < .001), and **BAC** (F = 11.71; p < .001). No associations were observed across seasons for race/ethnicity, employment status, low-income status, mental health issues, and receiving treatment in the past year.

Table 4 displays all the statistically significant associations. Many of these associations are driven by the large sample size of the data. As such, only the associations that have been deemed to be substantively significant are discussed. While slight, variation in the average age of clients was observed across seasons. The oldest average age was observed in the spring (39.8 year), followed by the summer (39.4 years), winter (39.3 years), and fall (39.2 years). When considering pairwise comparisons, only the average age in the spring was deemed to be significantly greater than the average age in the winter and fall.

A larger proportion of clients during the summer and spring—and a smaller proportion of admissions in the winter and fall—were identified as being unhoused compared to not being unhoused than would be expected by chance if no such relationship existed. A greater proportion of clients who completed less than a high school degree were admitted to the HRC in the summer than would be expected. The proportion of admissions in the winter, spring, and fall did not substantively differ from what would be expected. A greater proportion of clients who have ever been arrested were admitted to the HRC during the summer, while a smaller proportion were admitted during the fall and winter. A greater proportion than expected of repeat clients were admitted to the HRC during the summer, while a smaller proportion of repeat admissions occurred during the winter and fall.

The substances used at admission varied across season. Specifically, a greater proportion of admissions during the fall were of alcohol users than would be expected by chance. Conversely, a smaller proportion than expected of admissions during the summer were alcohol using. Multiple substance users made up a greater proportion of admissions during the winter and fall, but a smaller proportion than would be expected in the spring and summer. Interestingly, the patterns of alcohol use did not necessarily match the average BAC at intake per season. The spring was the season with the highest average BAC (.134), followed by winter (.131), fall (.126), and summer (.120). Thus, while the greatest proportion of admissions for alcohol users was found in the fall, this season had the second lowest average BAC. However, summer was the season with the smallest proportion of alcohol users and this corresponds with summer also being the season with the lowest average BAC. Looking at pairwise comparisons of average BAC across season, the average BAC during the summer was significantly lower than the average BAC in the winter, spring, and fall. Additionally, the average BAC during the fall was significantly lower than the average in the spring. No meaningful differences were observed in the average BAC between the winter and the spring or fall.

Table 4. Differences in Clients Admitted by Season of the Year

	Winter	Spring	Summer	Fall
Male (*n* = 47,158)	81.4%	82.4%	82.8%	81.9%
Unhoused (*n* = 45,821)	39.8%	42.6%	45.0%	39.7%
Veteran (*n* = 46,234)	7.6%	9.3%	8.5%	8.3%
Non-High School Graduate (*n* = 6,191)	23.2%	23.9%	27.1%	23.3%
Ever Arrested (*n* = 37,255)	65.6%	67.3%	69.0%	64.3%

Alcohol User (*n* = 42,168)	80.5%	78.6%	77.9%	81.6%
Multiple Substance User (*n* = 42,168)	14.2%	12.2%	11.6%	13.4%
Police Referral (*n* = 47,182)	79.5%	81.8%	79.8%	81.6%
Repeat Client (*n* = 47,182)	47.5%	50.1%	52.1%	47.9%
Age (*n* = 47,167)	39.3	39.8	39.4	39.3
BAC (*n* = 17,491)	.131	.134	.120	.126

Bivariate Associations Between Client Characteristics and Repeat Admission

First, we analyzed bivariate associations between client characteristics and single-time or repeat clients. All observed characteristics were statistically significantly related to being either a single or repeat admit to the HRC. These associations are shown in Table 5.

A greater proportion of repeat clients were male compared to one-admission clients. A greater proportion than expected of African American clients were repeat clients compared to one-admission clients, while a smaller proportion than expected of White and Hispanic/Latino clients were repeats compared to one-admission clients. The average age of repeat clients was five years older than one-admission clients. Over half of repeat clients were identified as unhoused individuals, while one-fifths of one-admission clients were unhoused. Additionally, veterans made up a larger proportion of repeat clients compared to single-time admits.

A greater proportion of repeat clients, compared to single-time admits, had obtained an education that was less than high school completion, were unemployed, had low income status, self-reported a mental health issue, received treatment in the last year, and had a history of ever being arrested. Alcohol users make up a greater proportion of single-time clients compared to repeat clients, while a greater proportion of repeat clients are users of multiple substances. This is also reflected when observing the differences in average BAC at intake. Repeat clients have an average BAC that is approximately 25% lower compared to the BAC of single-admission clients. Finally, police are the source of HRC referral at a greater proportion for single-time clients compared to repeat clients. Repeat clients are more likely to be referred to the HRC by sources other than law enforcement compared to single-time clients.

Table 5. Differences in Characteristics of Single-time and Repeat Clients

	Single-time Client	Repeat Client
Male (*n* = 29,349)	77.6%	83.3%
White (*n* = 24,734)	44.0%	38.5%
African American (*n* = 24,734)	32.4%	41.7%
Hispanic/Latino (*n* = 24,734)	23.6%	19.8%
Unhoused (*n* = 28,588)	20.1%	52.3%
Veteran (*n* = 28,547)	5.5%	9.1%
Non-High School Graduate (*n* = 4,975)	18.9%	30.2%
Unemployed (*n* = 10,896)	46.6%	72.5%
Low Income (*n* = 19,105)	75.2%	90.8%

Mental Health Issue (n = 24,584)	29.4%	41.8%
Treatment in Last Year (n = 10,781)	13.2%	22.0%
Ever Arrested (n = 24,725)	56.7%	74.6%
Alcohol User (n = 27,155)	85.4%	71.0%
Multiple Substance User (n = 27,155)	12.9%	15.6%
Police Referral (n = 29,373)	84.3%	74.7%
Age (n = 29,363)	36.3	41.3
BAC (n = 11,615)	.143	.107

Bivariate Associations Between Client Characteristics and Admission Counts

Aside from receiving treatment within the last year, all observed client characteristics were significantly associated with number of HRC admissions. Table 6 shows the significant bivariate associations.

The average number of HRC admissions was greater for males compared to females and transgender clients. Compared to African American clients, White and Hispanic/Latino clients had fewer HRC admissions, on average. No significant difference was observed for the number of HRC admissions between White and Hispanic/Latino clients. Age and admissions counts were positively correlated, which suggests the number of admissions counts increases with age (r = .10). On average, unhoused clients and veteran clients had more HRC admissions than their non-unhoused and non-veteran counterparts. Similarly, clients who had not completed high school, were unemployed, and were of low-income status had more admissions, on average, than clients who had completed high school, were employed, and were not of low-income status. Similarly, clients with a self-reported mental health issue and with a history of being arrested had more HRC admissions, on average, than those without a mental health issue and those who had never been arrested. Alcohol users had fewer HRC admissions, on average, compared to non-alcohol users and multiple substance users had fewer HRC admissions, on average, compared to single substance users. BAC was negatively associated with number of admissions (r = –.04), which is to say that clients with lower average BACs tended to have more HRC admissions. Finally, clients whose source of admission was police had more admissions, on average, than clients with a source of admission other than police.

Table 6. Average Number of HRC Admissions by Client Characteristics

		Admissions Counts
Gender (n = 29,349)	Male	1.68
	Female or Transgender	1.35
Race/Ethnicity (n = 24,734)	White	1.62
	African American	1.79
	Hispanic/Latino	1.58
Housing Status (n = 26,371)	Unhoused	1.73
	Housed	1.11
Veteran Status (n = 28,547)	Veteran	2.22
	Not Veteran	1.58

Educational Attainment (*n* = 4,841)	Completed High School	2.13
	No High School Completion	2.68
Employment Status (*n* = 10,420)	Employed	1.25
	Not Employed	2.36
Low-Income Status (*n* = 18,668)	Low Income	1.91
	Not Low Income	1.10
Mental Health (*n* = 23,252)	Mental Health Issue	1.52
	No Mental Health Issue	1.34
Arrest History (*n* = 23,058)	Prior Arrest	1.49
	Never Arrested	1.10
Alcohol Use (*n* = 26,054)	Alcohol User	1.43
	Non-Alcohol User	1.55
Multiple Substance Use (*n* = 25,821)	Multiple Substance User	1.13
	Single Substance User	1.44
Source of Admission (*n* = 27,801)	Police Referral	1.31
	Non-Police Referral	1.26

Bivariate Associations between Client Characteristics and Length of Stay

We analyzed bivariate associations between client characteristics and length of stay per admission in the HRC. All client characteristics other than multiple substance use were statistically significantly associated with length of stay at the HRC. These associations are shown in Table 7.

Male clients had a length of stay at the HRC that was 43 minutes shorter, on average, compared to female and transgender clients. White clients (5.06 hours) had a length of stay that was significantly longer than African American (4.78 hours) and Hispanic/Latino (4.91 hours) clients. Additionally, the average length of stay for African American clients was significantly shorter than the average length of stay for Hispanic/Latino clients. Age was positively associated with length of stay. Older clients tended to stay longer than younger clients. Unhoused clients stayed at HRC nearly 51 minutes longer, on average, than clients who were housed. Veterans had a length of stay that was approximately 11 minutes longer than non-veteran clients. Overall, the average length of stay tended to be longer for clients who had not completed high school, who were not employed, and who had low-income status. Clients with a self-reported mental health issue and clients with a history of arrest both had lengths of stay within the HRC that were longer, on average, compared to clients without mental health issues or prior arrests.

Clients who used alcohol tended to stay at the HRC for longer durations than those who were not users of alcohol. Similarly, clients with higher BACs tended to stay for longer durations than those with lower BACs. Clients who had received treatment in the past year for either a substance use or mental health issue also had a longer average length of stay than clients who had not been to treatment. Similarly, those who identified that they were ready for treatment and wanted to quit their substance use had an average length of stay that was nearly 50 minutes longer than those who were either not ready or unsure if they were ready for treatment. Compared to first-time admissions to the HRC, repeat admissions had a longer length of stay. Clients whose admission source was not police stayed longer than clients who were referred to HRC by police.

Length of stay at the HRC varied across time of day, day of the week, and seasons. The length of stay was significantly longer for admissions that occurred during the night than admissions during the day. Though not substantively meaningful, admissions during the work week stayed an average of 5 minutes longer than clients admitted during the weekend. Finally, the average length of stay in winter was significantly longer than the average length of stay in the spring. No other seasonal differences were observed.

Table 7. Average Length of Stay at the HRC by Client Characteristics

		Average Length of Stay (hours)
Gender (*n* = 43,245)	Male	4.79
	Female or Transgender	5.54
Race/Ethnicity (*n* = 37,604)	White	5.06
	African American	4.78
	Hispanic/Latino	4.91
Housing Status (*n* = 42,283)	Unhoused	5.40
	Housed	4.56
Veteran Status (*n* = 42,581)	Veteran	5.07
	Not Veteran	4.89
Educational Attainment (*n* = 4,688)	Completed High School	5.82
	No High School Completion	6.16
Employment Status (*n* = 11,739)	Employed	4.60
	Not Employed	6.04
Low-Income Status (*n* = 24,633)	Low Income	5.17
	Not Low Income	4.27
Mental Health (*n* = 33,661)	Mental Health Issue	5.60
	No Mental Health Issue	4.90
Treatment History (*n* = 11,579)	Treatment in Last Year	6.96
	No Treatment in Last Year	5.17
Arrest History (*n* = 33,912)	Prior Arrest	5.29
	Never Arrested	4.81
Treatment Readiness (*n* = 32,505)	Ready for Treatment	5.57
	Not Ready or Unsure	4.75
Alcohol Use (*n* = 38,574)	Alcohol User	5.03
	Non-Alcohol User	4.64
Visit Number (*n* = 43,250)	First Visit	4.59
	Repeat Visit	5.41
Source of Admission (*n* = 43,250)	Police Referral	4.85
	Non-Police Referral	5.30
Time of Day (*n* = 43,250)	Day	4.50
	Night	5.25
Day of the Week (*n* = 43,250)	Work Week	4.95
	Weekend	4.87

Season of Admission (n = 43,250)	Winter	5.01
	Spring	4.85
	Summer	4.88
	Fall	4.92

Bivariate Associations Between Client Characteristics and Enrollment in Treatment

When considering bivariate relationships, aside from educational attainment, all observed characteristics were significantly associated with enrollment in an HRC recovery program after discharge. As shown in Table 8, a lower proportion than expected of male clients were enrolled in an HRC recovery program. A greater proportion of White and African American clients were enrolled in a recovery program, while a greater proportion of Hispanic/Latino clients were not enrolled in such programming. The average age of clients who went to recovery programming was nearly 4 years older than clients who did not enroll.

A greater proportion of unhoused clients, veteran clients, clients who were unemployed, and clients who were of low-income status enrolled in recovery programs. Similarly, more clients with a self-reported mental health issue, had been to treatment within the past year, and had a history of arrest were enrolled in an HRC program. Alcohol users made up a smaller proportion of clients who enrolled in a recovery program than would be expected. Yet, the proportion was greater for those who were users of multiple substances. These findings are further demonstrated when considering the average BAC of clients who were enrolled in a recovery program versus those who were not. Specifically, the BAC for clients who enrolled in an HRC recovery program was 40% lower than those who did not enroll in such programs. As would be expected, clients who expressed they were ready for treatment and clients who have previously been to the HRC made up a greater proportion of clients enrolled in an HRC recovery program than clients not enrolled in such programs.

Compared to what would be expected by chance, a smaller proportion of clients who enrolled in an HRC recovery program were referred to the HRC by the police. Clients enrolled during the daytime hours and clients admitted during the work week made up a greater proportion of those enrolled in a program. Furthermore, while the differences were minor, a greater proportion of clients who were enrolled in an HRC recovery program were admitted to the HRC during the winter and spring. Conversely, a smaller proportion of clients who were enrolled in an HRC recovery program were admitted to the HRC during the summer and fall.

Table 8. Client Enrollment in HRC Recovery Program after Discharge

	Percent of Admissions (N = 47,182)
HRC Recovery Program after Discharge	14.9%
No Recovery Program after Discharge	85.1%

	No Program	Program
Male (*n* = 47,158)	83.7%	73.3%
White (*n* = 41,354)	40.9%	45.7%
African American (*n* = 41,354)	36.0%	40.7%
Hispanic/Latino (*n* = 41,354)	23.1%	13.7%
Age (*n* = 47,167)	38.9	42.8
Unhoused (*n* = 45,821)	39.4%	56.6%
Veteran (*n* = 46,234)	8.0%	11.3%
Unemployed (*n* = 14,854)	56.2%	77.9%
Low Income (*n* = 27,700)	81.4%	95.8%
Mental Health Issue (*n* = 36,996)	30.6%	54.4%
Treatment in Last Year (*n* = 14,680)	14.6%	33.1%
Ever Arrested (*n* = 37,255)	63.0%	87.1%
Ready for Treatment (*n* = 34,508)	54.1%	85.4%
Alcohol User (*n* = 42,168)	82.9%	60.3%
Multiple Substance User (*n* = 42,168)	9.2%	33.4%
BAC (*n* = 17,491)	.134	.081
Repeat HRC Visit (*n* = 47,182)	34.2%	58.0%
Police Referral (*n* = 47,182)	88.0%	38.8%
Daytime Admission (*n* = 47,182)	43.7%	70.5%
Weekend Admission (*n* = 47,182)	48.1%	26.9%
Winter Admission (*n* = 47,182)	22.8%	23.7%
Spring Admission (*n* = 47,182)	25.4%	26.3%
Summer Admission (*n* = 47,182)	27.2%	26.7%
Fall Admission (*n* = 47,182)	24.5%	23.3%

Appendix F. Feasibility Assessment

Table 1. Recommended Measures for All Sobering Centers to Collect

Measure Name	Definition	Database Operationalization
Date of Admission	The date for when the client was brought to the sobering center. Helpful in tracking trends in admissions and for calculating other measures such as length of stay and time between admissions for repeat clients.	Date should be collected in an easily recognizable format that is easily read by any database and statistical program, such as 23Jan2023 or January 23 2023.
Time of Admission	Time of intake for all client admissions. Useful for tracking trends in admissions and for calculating other measures such as length of stay.	Time should be collected using the 24-hour clock to avoid confusion between AM and PM.
Unique ID	Everyone who enters the sobering center should be given a unique identifier in the database to allow for tracking individual clients across repeat admissions.	Should not be overly complicated and should not be comprised of sensitive or confidential information such as birthdates or social security numbers.
Gender	The gender of the client.	At minimum, sobering centers should identify the client's gender using the male/female dichotomy. Some locations may be interested in collecting broader categories of gender, such as non-binary or transgender.
Race	The race of the client.	Data collection of races should be sensitive to the prevalence of different racial groups within the local area. Sobering centers follow the operationalization of race used by the U.S. Census Bureau and set by the U.S. Office of Management and Budget (OMB). These racial categories include: White, Black or African American, Asian, American Indian or Alaska Native, Native Hawaiian or Other Pacific Islander, and Some Other Race.
Ethnicity	Identifies whether the client is of Hispanic/Latino origins.	For ethnicity, sobering centers should follow the standard classification set by the OMB. This classification includes: "Hispanic or Latino" or "Not Hispanic or Latino." Importantly, race and ethnicity can be combined if the overlap between race and ethnicity is of interest to the sobering center and local management.
Age at Intake	Identifies the age of the client at the time of their admission to the sobering center.	Age can be measured in two different ways: 1) by asking the client to self-report their age, or 2) by computing age using the day of the admission and either a self-reported birth date or actual birth date obtained from identification.
Housing Status	Individuals utilizing sobering centers vary dramatically in their living	At minimum, sobering centers should collect information on housing status (0 = Housed; 1 = Unhoused). If it is of interest to collect broader

	arrangements. As such, it is necessary to efficiently collect this information.	categories of living status, some options to consider could be: 0 = unhoused, 1 = single-family home, 2 = apartment/condo, 3 = shelter or temporary housing.
Employment	Identifies whether the admitted client is currently employed.	Employment should be coded as 1 = Employed and 0 = Unemployed. Some sobering centers might be interested in further information. Secondary information regarding employment could include status of employment (0 = part-time; 1 = full-time).
Educational Attainment	We recommend information be collected on the highest level of education achieved by the individual.	Categories of educational attainment may include: 0 = Has not Graduated High School, 1 = High School or GED, 2 = Some college, 3 = Associates degree, 4 = Bachelor's degree, 5 = Master's degree, 6 = Professional degree (e.g., law, medicine) or Doctorate degree (e.g., PhD, EdD).
Substance(s)	In our review of sobering centers, we found substantial inefficiencies in the collection of substance use data. Some sites, for example, attempted to include every possible substance an individual could use. We recommend substantially consolidating this information to ease data interpretation.	To consolidate substance use information, we recommend having clients identify their preferred substance. Responses should be recorded in a systematic format that categorizes like substances together. For example, options could include: alcohol, methamphetamine, crack/cocaine, heroin/opiates/opioids/narcotics, marijuana/synthetic marijuana, benzodiazepines, barbiturates, hallucinogens. In addition to information on primary substance, sobering centers should consider collecting data on additional substances used by clients. These responses should be stored separately from the primary substance use and can be used to identify clients who are utilizers of multiple substances.
BAC	We recommend that all individuals receive a blood alcohol concentration (BAC) test upon admission to document the incoming BAC levels of clients. If possible, we also think it would be of interest to gauge BAC levels upon discharge. This would help gain an understanding of whether alcohol using clients are being released while still intoxicated.	BAC should be recorded as indicated from the breathalyzer, out to three decimal places.
Date of Discharge	Reflects the date for when the client departed the sobering center.	Date of discharge should be collected in the exact same format as the date of admission.
Time of Discharge	Reflects the time of day in which the client departed the sobering center.	Time of discharge should be collected using the 24-hour clock, just like the time of admission measure.
Length of Stay	Sobering centers will want to document the length of stay within the facility for each individual. If the	Since the vast majority of clients spend mere hours in the facility, it is most useful to store length of stay in hours using decimals. For

	suggested data entry format for date and time are followed, the length of stay can be calculated by subtracting the intake time from the discharge time. Dates will need to be considered if the length of stay is longer than 24 hours.	example, a client who stays 8 hours and 30 minutes should be recorded as 8.5 hours.
Reason for Non-Admission	Not all clients brought to the sobering center are formally admitted. In some cases, the client is rejected from admission or transferred elsewhere. This information should be collected to better understand potential differences between those admitted and those not admitted to the sobering center.	Reasons for non-admission are likely to be unique to the sobering center given their unique policies and practices. Potential reasons may include: Not intoxicated, non-responsive/non-ambulatory, non-compliant, aggressive/violent, currently on a 'refuse entry' list due to prior inappropriate behavior, and refused services/walked out.

Table 2. Ancillary Measures for Sobering Centers to Consider

Measure Name	Definition	Database Operationalization
Source of Referral to Center	This measure can be used to capture who referred the client to the sobering center. The source of referral and transportation to the sobering center will likely differ across locations, depending on the policies and practices of the center. Potential sources may include law enforcement, EMS, walk-in, or sobering center van.	Sources should be categorized into discrete groups. If there are many different sources, these sources should be collapsed into groups of similar sources to ease data interpretation. Example coding: 1 = Police, 2 = EMS, 3 = sobering center van, 4 = walk-in.
Additional Information on Referral Source	Some sobering centers accept referrals from a variety of sources, centers should collect supplemental information as needed. For example, if more than one law enforcement agency uses the sobering center, the specific agency should be documented. If more than one agency and/or facility type refers clients, consider collecting officer information such as their badge number.	This information will need to be catered to the specific characteristics of the sobering center and their referral source. It is pertinent, however, that this information be entered into the database in a consistent and accurate manner.
Location of Pick-Up	To understand where clients are being brought to the sobering center from, information on the pick-up location should be considered. This information could include the physical address of the location, or if police are the main referral sources, a location indicator such as the police beat could also be used.	If collecting the physical address, procedures need to be put in place to encourage accuracy of data entry. Address should likely be collected with separate variables from number and street, city, and zip code to easily allow for mapping procedures. Regardless of location information used, it needs to be entered into the database in a consistent manner.
Arrest and Incarceration History	Some centers may be interested in collected more detailed background information about the clients who are brought into the facility. To help	This information could simply be collected by asking the client, "Have you ever been arrested?" Similarly, incarceration history could be collected by asking the client,

	understand the potential impact of the sobering center on client diversion from jail, arrest history and incarceration history may be of interest.	“Have you ever been incarcerated in either a jail or a prison?” With both questions, the response options could be coded where 0 = No, 1 = Yes.
Mental Health Diagnosis	An additional measure for client background information that me be of interest is the client’s history of mental health issues. Like other measures of background information, these measures will allow a sobering center to thoroughly describe the clients they cater to.	The first step in collecting mental health information may be to simply ask the client, “Have you ever received a diagnosis of a mental health disorder?” (coded where 0 = No; 1 = Yes). To learn even more information, follow-up questions could be considered, such as, “What disorder was the diagnosis for?” The individual entering the data could then enter the specific diagnoses. Centers should consider possible solutions to ease data entry and accuracy by collapsing similar disorders into larger disorder groups. Finally, for those with a mental health diagnosis, centers may consider also asking a client, “Are you currently taking medication for your diagnosis?” (coded where 0 = No; 1 = Yes).
Veteran Status	Identifies whether the admitted client has served in the Armed Forces of the United States, including the National Guard and Reserves.	Veteran should be collected as 1 = veteran and 0 = non-veteran.
Student Status	If the sobering center is in an area that has a large university or college, centers may be interested in collecting information on how often students are brought to the sobering center.	To measure student status, clients could be asked, “Are you currently enrolled as a student at a university or college? Responses would include 0 = No and 1 = Yes.
Client Address	While more cumbersome to collect and potentially prone to data entry errors, some sobering centers may consider collecting information on the actual address of the individual. This measure would allow centers to learn where their clientele is from and how far away their pick-up is from home. For example, in popular tourist locations, centers can glean an understanding of how often people from out of town are being brought to the sobering center.	When collecting the physical residential address, procedures need to be put in place to encourage the accuracy of data entry. Address should likely be collected with separate variables for number with street, city, and zip code. It is extremely important for this information to be entered into the database in a consistent manner.
Additional Substance Abuse	Some centers may be interested in collecting substance abuse information, such as substance abuse disorder diagnosis, history of substance abuse treatment, frequency of use, or client’s readiness to quit and/or attend treatment.	For substance abuse disorder, a client could be asked, “Have you ever been diagnosed with a substance abuse disorder” (coded 0 = No; 1 = Yes). For history of treatment, clients could be asked, “Have you ever received treatment for your substance abuse, including Alcoholics/Narcotics Anonymous?” (coded 0 = No; 1 = Yes). If timing of treatment is of interest, a follow-up question could be presented, with the client being asked if they

		are currently in treatment and, if not, when they last received treatment. For frequency of use, clients could be asked, “How often do you use your preferred substance or other substance?” Response options could include, daily (=1), nearly every day (=2), 3-4 times a week (=3), 2 times a week (=4), once a week (=5), 2-3 times a month (=6), once a month (=7), less frequent than monthly (=8). Finally, if a center is interested in understanding a client’s willingness to change, clients could be asked, “Would you consider attending drug/alcohol treatment?” (coded 0 = No; 1 = Yes”) or “Are you interested in working towards stopping your substance abuse?” (response options: ready (=1), unsure (=2), not ready (=3).
Departure from Sobering Center	Items capturing the circumstances under which the client departed the sobering center might be of interest for sobering centers to collect. Centers could consider a wide range details, including transportation of discharge, services to receive upon departure, and discharging location. Like all ancillary measures, the data collected will likely be tailored to what a sobering center is interested in knowing.	This information will need to be catered to the specific characteristics of the sobering center and characteristics of their discharge procedures. It is pertinent, however, that this information be entered into the database in a consistent and accurate manner. An example for one simple measure to document is, “Did the individual leave the sobering center with a treatment recommendation.” (coded where 0 = No; 1 = Yes).
Client Discharge Information	Sobering centers may want to document information on whether the client completed their stay at the sobering center and/or the circumstances under which the client was discharged.	The simplest way to document discharge information is to identify whether the client left the center against the advice from the staff (0 = No; 1 = Yes). If more detailed measures are of interest, centers could document whether the client completed their sobering center stay. If the answer is “No,” additional data could be collected for why the client did not complete their stay. Response options will likely be unique to the sobering center, but may include: walked out, transferred to jail, or transferred to hospital.