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RESEARCH REPORTS

POTENTIAL BIAS IN USE OF "SMELL OF ALCOHOL" AND OTHER SUBSTANCE USE DESCRIPTORS AS DIAGNOSTIC CRITERIA IN PREHOSPITAL CARE

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ABSTRACT

"Smell of alcohol" (SoA) is widely used as a diagnostic tool. However, assigning SoA to a patient is entirely provider dependent and may be associated with negative social connotations.

This paper aims to identify differences in the diagnostic application of SoA among patients in the prehospital setting. We further investigate whether SoA impacts patient care by evaluating transport times. To accomplish these aims, we performed a cross-sectional study of the National Emergency Medical Services Information Service (NEMSIS) databases for 2017-2023. SoA was established using NEMSIS's standardized substance use evaluation metric.

In part one of our study, we analyzed the use of SoA across multiple demographic factors including race and ethnicity, age, and gender. We found statistically significant differences in the application of the SoA metric to non-White patients (*OR* 1.056, 95% CI 1.052-1.060 to 1.266, 95% CI 1.248-1.283). Similar patterns were observed in the application of 'Other Substance Use Suspected' to Black or African American (*OR* 1.217, 95% CI 1.213-1.221) and female (*OR* 1.133, 95% CI 1.130-1.136) patients.

In part two of our study, we observed increased transport times for patients with a confirmed alcohol level. No increase was observed in patients with a positive SoA. These results suggest that SoA is applied in a biased manner across demographics, but its application does not influence patient transportation time in the prehospital setting.

INTRODUCTION

The smell of alcohol (SoA) is an unique odor that humans are able to distinguish (Commetto-Muniz & Abraham, 2008), and the presence of alcohol and its metabolites is detectable on the breath and body in 66-86% of cases of alcohol consumption (Moskowitz, Burns, & Furguson 1999; Malhotra et al. 2013). This distinctive odor is also widely accepted as a diagnostic tool in hospital medicine (Walsh & Macleod, 1983; Moskowitz, Burns, & Ferguson 1999; Shibayama & Ino, 2012; Liberatti et al, 2003), prehospital medicine (Maine Prehospital Care Protocols, 2024), policing (van Boekel et al, 2013), and other public service work.

However, the sense of smell and one's ability to distinguish odors is not routinely standardized or assessed, leaving room for error and inconsistency (Moskowitz, Burns, & Ferguson 1999; Shibayama & Ino, 2012). Furthermore, previous studies found SoA may cause implicit bias (Delker, Brown, & Hasin, 2016). This bias in turn may result in negative patient outcomes.

It is important that we analyze and discuss implicit bias in healthcare as it may impact patient care and outcomes. Implicit bias is often a result of fast, unconscious heuristic-based evaluations (Gopal et al. 2021; Marcelin et al. 2019). These evaluations in turn are shaped by external factors, including learned experiences (Gopal et al. 2021). However, the sum of these evaluations create preferential action, which when unconsciously applied, creates implicit bias. When the perceptions of the provider are negative toward the patient, this implicit bias can manifest in disparate patient care decisions and quality (Marcelin et al. 2019). Mitigating implicit bias requires intent and a multi-modal approach, but the first step is uncovering and identifying unconscious biases (Marcelin et al. 2019). This paper aims to establish whether implicit bias exists in the EMS community through examining the application of SoA to patients, where biased application could lead to differences in treatment (e.g. delaying or omitting a stroke assessment on a patient suspected of alcohol intoxication).

This study first evaluated patterns in the application of SoA across various demographic factors, including race, age, and gender. Differences observed across patient subpopulations represent underlying biases in the use of SoA. This study then investigated if SoA or other indications of alcohol use may impact patient care, utilizing transportation time as a proxy for patient management.

METHODS

Our study used the National EMS Database (NEMSIS) with data element definitions and collection standards as established by the National Highway Traffic Safety Administration (NEMSIS v3.4, 2024). Data collected included the years 2017-2023 as these years are in concordance with Version 3 of the National Emergency Medical Services Information System (NEMSIS) Database with improved data metrics and quality standards. Packages and functions used for data extraction and analysis are included in the supplemental section of this report (see Appendix A).

Our team designed this study to answer two research questions: (1) Is SoA applied equitably across different patient demographics? and (2) Does SoA or other alcohol or drug use indicators impact patient management? Our team accessed the National EMS Information System (NEMSIS) to study these questions. Each variable of the NEMSIS 3.4.0. Data Dictionary was reviewed. The following variables were selected: ePatient.13 [patient gender], ePatient.14 [patient race], ePatient.15 & ePatient.16 [patient age], eDisposition.20 [reason for choosing destination], and eHistory.17 [alcohol/drug use indicators]. All fields are required for EMS clinicians to complete, and they involve either a text-box answer (patient age) or checking a box related to the descriptors (patient gender, race, age, reason for choosing a destination, and alcohol/drug use indicators) as expressed by the patient and/or as determined by the clinician. A glossary of terms as well as definitions for select terms may be found in Appendix B.

NEMSIS data files were extracted to produce .sas7bdat files, which were read using the R software system (R Core Team, 2024). The relevant variables were extracted and matched according to the deidentified patient identification number (PcrKey). We then categorized our data to facilitate our model development as follows.

Race and ethnicity groups created include: (1) White; (2) Asian; (3) Black or African American; (4) Hispanic or Latino; or (5) American Indian, Alaska Native, Native Hawaiian, or other Pacific Islander. Patient gender, as reported by EMS providers, was recorded as (1) female, (2) male, or (3) unknown. Patient age was categorized by this study as: 0-20, 21-44, 45-54, 55-64, 65-74, 75-84, and 85+ years old in accordance with age categories established by the Centers for Medicare and Medicaid Services (White, 2020), with a slight modification account for the legal age of alcohol consumption in the United States of 21 years old. Disposition reason and EMS transport time (minutes) were extracted directly from NEMSIS.

Two subsets of data were extracted. To address our first research question regarding the use of the SoA metric across various demographics, data subset one - the Demographics Subset - was created including patients with a confirmed alcohol or drug use indicator. This indicator was recorded in standardized NEMSIS data element eHistory.17 [Alcohol/Drug Use Indicator].

Our second data subset - designated Altered Mental Status Subset - was designed to address our next research question: does a patient's response to element eHistory.17 impact their care? Because patient emergency department records were not linked in the NEMSIS database, our selection of patient outcomes was significantly limited. Our team identified patient transportation time as an outcome variable that could strongly reflect a responder's feelings towards the patient (e.g. for patients with life-threatening status, transport times were assumed to be shorter). To account for variation in transportation time across potential chief complaints (i.e. penetrating trauma vs. generalized weakness), our team also selected a common chief complaint of ICD-10 code R41.82 or "Change in Mental Status, NOS [Not Otherwise Specified]". Both emergent and non-emergent call types were included in the analysis because the emergent vs non-emergent return decision is based on the clinician impression of the patient: that is, whether the patient meets criteria for an emergent return based on clinical factors including SoA. It is for this reason that both 911 responses and interfacility transport calls were included in the analysis as well.

Please refer to Figure 1 for a visual representation of this data extraction process. An ANOVA analysis was performed for the final stage of our data extraction process to identify underlying differences in each data subset, (1) completed records with alcohol/drug use indicator and (2) completed records with altered mental status, relative to the overall NEMSIS dataset with completed records.

We then conducted a statistical analysis. For the Demographics Subset, we implemented a multinomial logistic regression model to determine if any patient demographics (age, race, or gender) were correlated with use of eHistory.17 [Alcohol or Drug Use Indicators]. Any statistically significant differences in utilization patterns could suggest bias in provider usage. For the Altered Mental Status Subset, we implemented a generalized linear model to identify statistically significant differences in patient transportation time

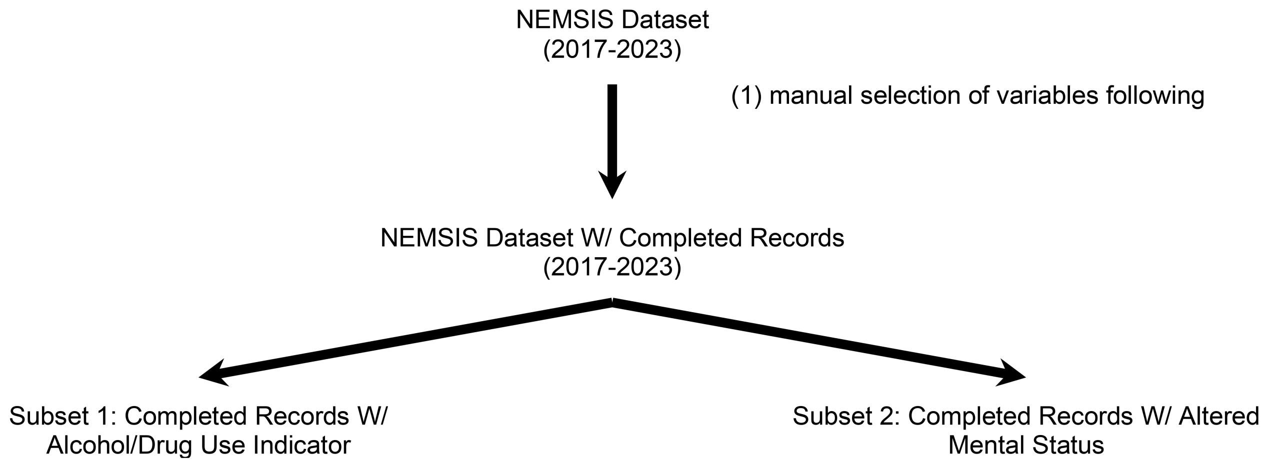

Figure 1. Visual representation of the data selection process.

across alcohol or drug use indicators when controlling for patient age, race or ethnicity, and gender. We chose to use a generalized linear model with a Quasipoisson family and a log link given that the distribution of EMS transportation times was a continuous numeric outcome with a strong rightward skew (shorter transportation times were more common than longer transportation times). Variations in these patterns by demographic or alcohol use indicator could reflect bias on the part of the responder.

This project met the local policy requirements for ethical review by meeting exemption criteria: NEMSIS data are de-identified to be HIPAA-compliant, and the dataset is publicly available. EMS providers are assumed to have entered the data factually in accordance with their respective documentation procedures for the purposes of providing care to their patients. The authors declare no conflicts of interest or disclosures.

RESULTS

General

262,685,635 unique EMS reports were filed with NEMSIS over the period of 2017-2023. Application of our inclusion and exclusion criteria significantly reduced the eligible population for our study. For example, in 2017, approximately 3.9 million unique calls were completed. Of these, nearly 50% were excluded on the grounds of incompletion.

Demographics Subset

For the Demographics Subset, approximately 11 million unique patient encounters with an alcohol or drug use indicator were recorded from 2017-2023. An ANOVA analysis and distribution plot was generated for each year (see Appendix C for results from 2017 analysis). A multinomial logistic regression model was then implemented, with results summarized in Figure 2 and in Appendix D and Appendix E. Each odds ratio compares demographic categories relative to our established reference group of white males aged 21-44 years who disclose using alcohol (“alcohol use disclosed by patient”). This reference group was chosen as it is the most populous patient group studied in terms of alcohol use descriptors. As such, other groups are considered “minority groups”.

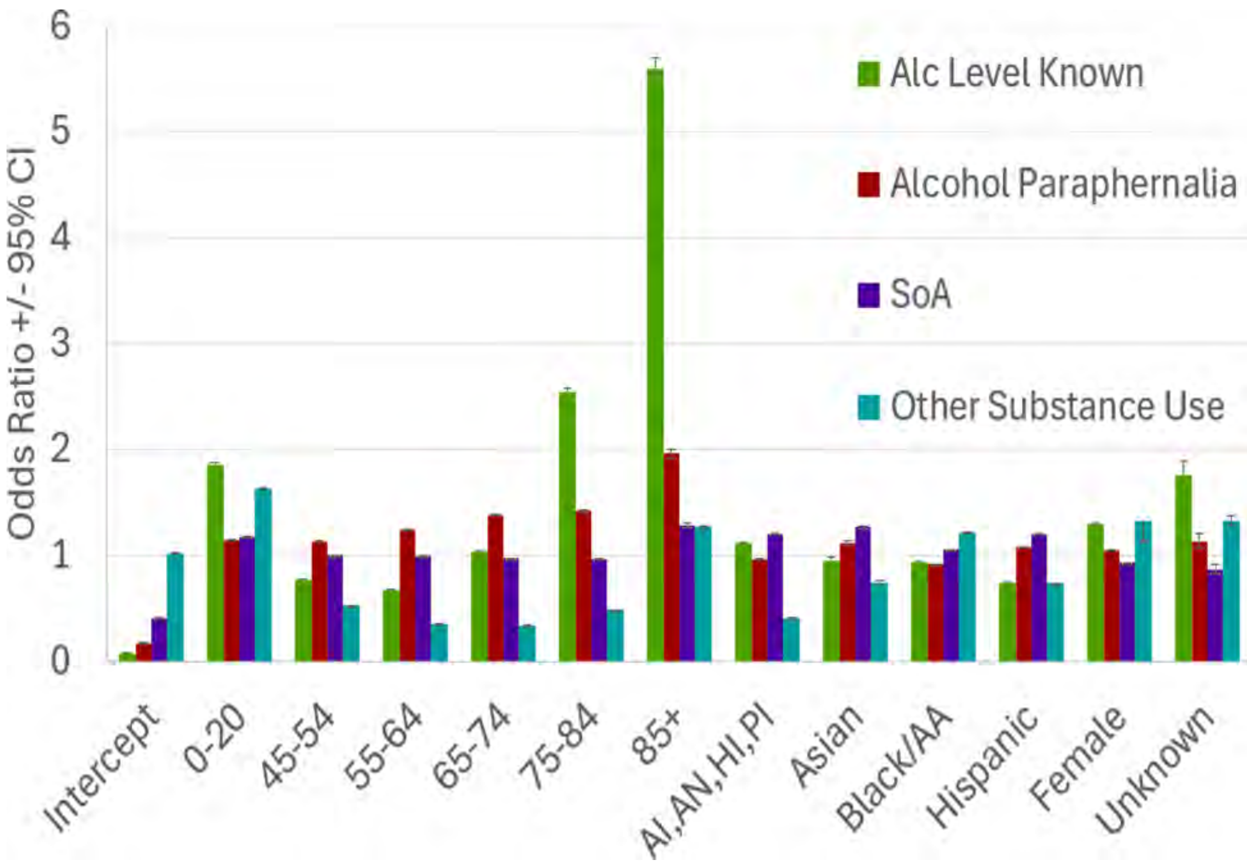

Figure 2: Logistic regression model data for NEMSIS 2017-2023.

Notable results include the fact that non-White patients had statistically significantly higher odds of being reported with SoA (*OR* 1.056±0.004 to 1.266±0.018, all 95% CI and $p<0.0001$). Additionally, the ‘Other Substance Use’ indicator was applied more frequently to Black or African American patients (*OR* 1.217±0.004 95%CI, $p<0.0001$) and female patients (*OR* 1.133±0.003 95%CI, $p<0.0001$).

Altered Mental Status Subset

For the Altered Mental Status Subset, approximately 7 million unique patient encounters were recorded from 2017-2023. A summary of the characteristics for each subset population are summarized in Appendix D. We then applied a generalized logistic regression model to predict EMS transportation times, controlling for patient demographic factors including age, race, and gender. Results can be found in Appendix F (below). Odds ratios reported estimate relative differences in EMS transportation time amongst altered mental status patients on the basis of alcohol or drug use when controlling for demographic factors, with higher odds ratios denote relatively longer EMS transportation times. Results indicate that, when compared to the control group of 21-44 year old males with reported alcohol usage, transport times were not statistically longer for minority groups.

DISCUSSION

ANOVA Analysis

Our team found statistically significant differences across key demographics, including patient age, race or ethnicity, and gender for each data subset. When considering these results in clinical context, however, such findings are expected.

Considering the Demographics Subset, age-related differences may be attributed to alcohol consumption patterns in the US population, with younger patients ages 21-44 more likely to engage with binge drinking or other high-risk consumption practices. Heterogeneity also exists between races/ethnicities, with higher rates of alcohol consumption among Hispanic patients. Existing literature has identified Hispanic White males are most likely to develop liver cirrhosis and to be involved in motor vehicle collisions associated with alcohol, two conditions which may lead to altered mental status (Delker, Brown, & Hasin, 2016; White, 2020; Rahimi, Elliott, & Rockey, 2013). Finally, with regard to variation by gender, existing literature has demonstrated that on average females consume approximately one third of the alcohol that men consume in a year (White, 2020). Therefore, the presence of a difference in gender between our study population and the general population was expected.

Considering the Altered Mental Status Subset, age differences may be attributable to increased susceptibility for sepsis or dementia in older populations. With regards to heterogeneity between races and ethnicities, lower rates of altered mental status were seen amongst Asian, American Indian, Alaskan Native, Hawaiian, and Pacific Islander populations relative to the general population. This may be a result of cultural differences in family and children involvement in elderly care. Finally, when considering gender, higher rates of altered mental status were noted among males. This may be a result of increased comorbidities and higher incidence of cerebrovascular accidents amongst males relative to females.

These differences may affect the validity or generalizability of our study’s outcomes. However, they reflect reasonable and expected patterns of substance use and altered mental status in the United States.

Demographics Subset - The Logistic Regression Model

The results generated by the Logistic Regression Model for NEMSIS data 2017-2023 demonstrate that there are disparities between different demographics when it comes to the application of alcohol use modifiers compared to a control group of 21-44 year old white males who self-reported alcohol use.

Alcohol Level Known: All age groups 0-20, 65-74, 75-84 and 85+ years old have a higher likelihood of alcohol level known than 21-44 year old patients (p<0.0001). The age groups 45-54 and 55-64 years old show a lower likelihood of having a known alcohol level than that anticipated for the control group. This is logical from the perspective that alcohol use by anyone in the age group 0-20 is considered illegal in the United States, and the presence of police with the ability to test for alcohol level in the field is more likely for these patients (Goldenberg, 2016). Additionally, alcohol intoxication is a differential diagnosis for patients with stroke, which is more likely in the 65+ year old age range. These patients may have undergone a toxicology screen prior to interfacility transport.

For race and ethnicity, AI, AN, HI, PI (p<0.0001) are more likely than the control group to have an alcohol level known, whereas Asian (p<0.01), Hispanic (p<0.0001), and Black/African American (p<0.0001) patients have a lower likelihood for having a known alcohol level than white patients. This is consistent with the literature in that people of AI, AN, HI, PI racial and ethnic background have a higher incidence of violent crime and motor vehicle collision associated with alcohol use than other races/ethnicities (Delker, Brown, & Hasin, 2016). Given that this population has an alcohol poisoning rate eight times that of White controls and that it also has the highest rate of alcohol use disorder of any of the subpopulations studied (Kerr et al 2022), it is more likely that drivers of the AI, AN, HI, PI racial and ethnic background involved in a motor vehicle accident or violent crime would display probable cause for a preliminary breathalyzer analysis to establish a known alcohol level (NHTSA 2025).

For gender, females (p<0.0001) and unknown gendered individuals (p<0.0001) are more likely to have an alcohol level known than males. This is contrary to the literature, which states that females have a lower overall use rate and binge rate that might lead to a police encounter than males (White, 2010). Further investigation of this phenomenon is not possible given lack of case-specific information within the NEMSIS database.

Alcohol Paraphernalia on Scene: All age groups (p<0.0001) have a higher likelihood of alcohol paraphernalia on scene than the control group. The increased presence of alcohol paraphernalia with increasing age, as seen in the odds ratio, is contrary to alcohol use patterns for age, which have been shown to decrease with age (Delker, Brown, & Hasin, 2016). A possible explanation for this is that alcohol clearance decreases with age, increasing its toxicity. (Vestal et al, 1977). This might result in higher incidence of medical emergencies during which paramedics would encounter the alcohol paraphernalia.

For race and ethnicity, Asian and Hispanic patients (p<0.0001) are statistically more likely to have alcohol paraphernalia on scene than White patients, and AI, AN, HI and PI (p<0.0001) and Black or African American (p<0.0001) patients are less likely. This is not explained by the literature, and further investigation is not possible given NEMSIS database lack of case-specific information.

For gender, females (p<0.0001) and unknown gendered patients (p<0.0001) are more likely to have alcohol paraphernalia on scene than males. As above, this is contrary to the literature (Delker, Brown, & Hasin, 2016) and further investigation is limited due to NEMSIS case-specific de-identification within the dataset.

Smell of Alcohol: All groups except for 0-20 (p<0.0001) and 85+ (p<0.0001) year olds have an equal or lower likelihood of SoA than the control group. This is expected as overall alcohol use and frequency declines with age. The group 0-20 years old have a higher likelihood of smelling like alcohol, which is supported through higher incidence of binge drinking and overall alcohol use among college-aged individuals (Delker, Brown, & Hasin, 2016). The spike for 85+ year old individuals is unexplained and requires additional research.

Racial and ethnic patterns identified by our analysis are not supported by the literature. While weekly drinking is reported to be highest among Hispanic patients, White patients are more likely to binge drink than individuals from other ethnicities (Delker, Brown, & Hasin, 2016). Our study found that all non-white race/ethnicity patients (all $p<0.0001$) have higher odds of being applied the Smell of Alcohol descriptor than white patients, which does not align with recorded alcohol use patterns (Delker, Brown, & Hasin, 2016) and is not explained otherwise. Therefore, it is likely that these discrepancies are due to provider bias.

Finally, female and unknown gendered patients are less likely to smell like alcohol as male patients. This matches the trends highlighted in the literature.

Other Substance Use Suspected: All age groups except for 0-20 year olds ($p<0.0001$) have a decreasing likelihood of suspicion of other substance use with age, and the 0-20 year old group has a higher likelihood of suspicion. This fits with published literature, which states that younger populations under age 26 have a higher likelihood of developing substance use disorder compared to older populations (Lu, Lopez-Castro, & Vu, 2023), which are reported to be at or below the same likelihood for the control group. Again, 85+ year old patients also show a higher likelihood ($p<0.0001$) than the control 21-44 year old demographic, which cannot be accounted for in the literature. Further research is warranted

What is not corroborated by the literature is the higher likelihood of Black or African American patients ($p<0.0001$) to be assigned the descriptor “Other Substance Use Suspected”; Black or African American patients have lower substance use disorders than White patients (Lu, Lopez-Castro, & Vu, 2023). This would presumably result in fewer emergency calls related to substance use requiring an ambulance for these populations. This finding may represent a provider bias.

Another potential bias may be found in the unequal assignment of “Other Substance Use Suspected” to female patients and unknown gendered patients, who per our results are more likely to incur this designation ($p<0.0001$). Females are less likely to develop substance use disorders than males, making this discrepancy likely due to provider judgment.

Altered Mental Status Subset - The Generalized Linear Model

Intercept: Perhaps the most interesting finding is that 21-44 year old white male patients who self-disclose alcohol use have a 10-times longer transport time than other demographics (*OR* 11.386, 95% CI 11.347-11.425, $p < 0.05$). It is possible that this metric is largely influenced by patient self-disclosure of alcohol use, as this implies a patient is (1) protecting their airway, (2) breathing spontaneously, (3) speaking coherently, and (4) oriented to the situation. However, a limitation of our study is that we do not have case-by-case data to understand why such delays occurred.

Age demographic: It is surprising that transport times are higher in other age groups except the 85+ demographic when compared to the 21-44 year old group. Elderly patients tend to be less healthy than patients in the age range 21-44 years, which means that there could be a higher number of true medical emergencies in this group when compared to the control (Vestal et al, 1977). Additionally, pediatric patients in the age group 0-20 may require transportation to a dedicated pediatrics emergency room, which may prolong transportation times. Further investigation is required.

Race and ethnicity demographic: A similar effect may also be the cause for prolonged transport times for AN, AI, HI, PI population members, many of whom live in rural areas without immediate access to a hospital (American Indians, 2014). Statistically shortened transport times for other races and ethnicities may be a function of increased urban safety-net hospital usage amongst these groups (Yearby, Clark, and Figueroa, 2022).

Gender demographic: With regards to the gender demographics, increased transport time for female and unknown gender patients is unexpected and not easily explained; men have a higher morbidity and mortality associated with injuries and accidents related to alcohol consumption (Delker, Brown, & Hasin, 2016). Further research is required.

Disposition reason: Disposition reason was included in our model to adjust for alternative causes of transportation delays among patients. Intuitively, any disposition reason other than “closest facility” would inherently have a longer expected transportation time. Interestingly, destinations “Regional Specialty Center” and “Physician Choice” were approximately 30% higher than other destination selections. This may be attributed to the fact that many municipalities do not possess tertiary and quaternary services. Further research incorporating patient zip code data is needed.

Alcohol use descriptors: Controlling for all patient demographics and disposition reasons, SoA did not seem to affect transport times with any statistical significance. The

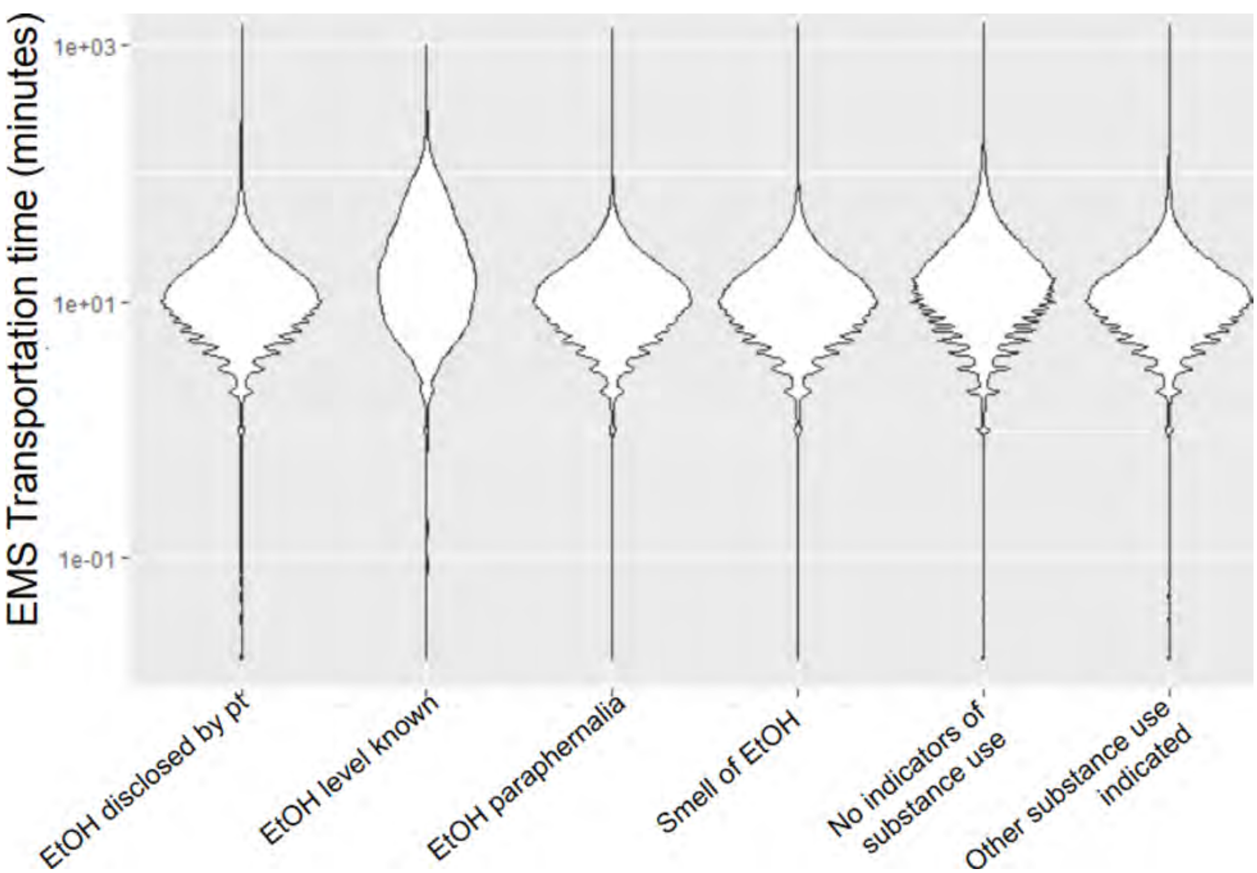

Figure 3. Violin plot of EMS transport time (minutes) vs. alcohol use indicators.

"alcohol level known" indicator had statistically longer transport times. This is to be expected as patients must be protecting their airway and breathing adequately to complete a portable breathalyzer test or be transported from one hospital to another, which would indicate lack of medical emergency. Interestingly, altered mental status patients without any indications of alcohol or drug use had increased transportation times. However, the transport times for all alcohol use descriptors were similar, as shown in Figure 3.

CONCLUSION

General Interpretation Summary

Our results serve to establish that provider assignment of subjective substance use descriptors to patients may be influenced by bias. While there was a statistically significant increase in the use of the SoA indicator among non-white patients relative to white patients, the clinical significance of this is unclear given the small magnitude of the absolute difference. Additional analysis of the clinical impact of these findings, as measured by patient transportation time, demonstrated such potential bias did not affect patient care.

Applicability to Existing Literature

Our results indicating a potential assessment bias aligns with existing literature. Indeed, numerous sources report that people of color were less likely to experience pain assessment or be treated with pain medications for traumatic injuries when compared to white patients (Brunsen et al, 2023; Kennel et al, 2019; Crowe et al, 2023). Also, Hanchate et al. (2016) and Pack et al. (2023) found that people of color were more likely to be transported to a safety net hospital vs white patients who were living in the same zip code. Respectively, Brunson et al. (2023) reinforce a well-documented bias that is widespread in medicine, namely that people of color are under-assessed and undertreated for pain in all environments, not just in the prehospital sphere. (Brunsen et al, 2023; Dickason et al, 2015).

Our results indicating an assessment bias on the part of prehospital providers regarding SoA and patient age add new perspective regarding prehospital provider bias, which is less well-studied. Our findings support the idea that bias regarding SoA and patient age does not impact patient outcomes, as measured by patient transportation time.

Our results indicating a treatment bias regarding patient gender add to existing studies examining this phenomenon. Rothrock et al (2001) describe gender disparities in the assessment and treatment of patients with chest pain, stating that elderly women are statistically less likely to receive aspirin or a 12-lead EKG in the field vs male controls. Additionally, when comparing female patients to males, EMS clinicians are less likely to correctly diagnose stroke, give epinephrine for anaphylaxis, or transport fall patients to trauma centers (Farcas et al., 2023). Therefore, our identification of potential gender bias in the prehospital setting adds to the greater conversation regarding gender-related bias in provider heuristics and patient care.

Limitations

This study has several limitations. First, a large number of patients were excluded from our study. Approximately 50% of patients had incomplete demographic variables recorded. These patients were excluded as incomplete demographic variables likely indicate incomplete or erroneous patient records. However, such incomplete data could be due to inconsistent coding or inaccurate charting. Exclusion of these patients may also introduce selection bias. Despite this limitation, millions of patients met our inclusion criteria for altered mental status and alcohol/drug use. We felt this sample size was sufficient for the purposes of our analysis.

A second limitation of our study is that some patient encounters could have resulted in multiple resource activation, such as in regions where fire and ambulance resources are dispatched simultaneously. This would lead to duplication in reporting patient status if both agencies are recorded by NEMSIS. Our analysis did not include specifying for the transporting agency as this data element was not available for all years of the 2017-2023 time period. However, in applicable systems, duplicate calls are a result of dispatch protocols and would likely be duplicated equally across all patients.

A third limitation of this study is that patient race and ethnicity are recorded based on provider judgment rather than patient's self-reported identity. NEMSIS could consider adding a data element regarding if patient race/ethnicity is self-reported or reported by EMS provider.

A fourth limitation is the fact that the equation of transport time to patient management has no precedent in the literature. Indeed, Elkbuli et al (2021) contend that longer transport times with aerial EMS had better outcomes for trauma patients when compared to ground EMS, and McCoy et al (2012) showed that transport times were not associated with increased mortality odds with penetrating traumas in ground EMS. We further acknowledge that there are numerous confounding factors that could influence transport time. Some confounding factors we consider include ZIP code, time of day, and other response data. However, these are omitted from the NEMSIS database to maintain patient confidentiality. Additionally, traditional outcomes such as patient morbidity or mortality measures were not available as patient outcomes after ED visit or hospital admission are not currently included in the NEMSIS database. Despite these limitations, NEMSIS database remains the best source of large-scale EMS data necessary for this caliber of analysis. Therefore, we feel that using transport time as a proxy for patient management quality is appropriate for the purposes of this study, but that this outcome variable may have significant limitations.

Our study focuses on the perceived feelings of the clinician towards the patient - clinical or otherwise per Hanchate et al (2016) - which results in a transport decision. We are aware that this decision may be influenced by numerous factors, including the patient's wishes, system status, hospital capability, etc, but ultimately the transport decision rests with the clinician. We account for some of this variability by including the transportation disposition reason. As such, looking at transport time is indicative of how the clinician perceives the patient, which affects patient management. We can speculate as to how management is affected, but ultimately we set out to investigate whether the feelings of the clinician as influenced by their record of substance use modifiers caused differences in transport times. We do not believe that the confounding factors listed influence our results to a great extent: the sheer number of calls that we analyze negates these confounders as we establish a value for response time (see Figure 3) that corresponds to the average for the US that is reported in the literature (Mell et al, 2017). Therefore, we assert that proxy association between transport time and patient management is appropriate for the purposes of this study.

A final limitation of this study is the cross-sectional, ecological nature of its design, which does not have patient-specific or quality control metrics in place. Therefore, it is not possible to ensure the data we include in our models is 100% accurate. We recognize steps NEMSIS has taken to review and standardize data and appreciate the data standards implemented by this national organization. In addition, our study lacks case-specific data, preventing our team from using conclusions of this study to guide patient care. However, our team believes this is a reasonable weakness that commonly impacts studies of this cross-sectional design.

Future Recommendations

Building on the foundation established by this study, we find it would be of interest to investigate if variation in use of alcohol or drug use indicators also exist in the prehospital settings of other countries. Additionally, more detailed EMS datasets should be created to allow for case-by-case analysis of patient care, allowing us to further analyze unusual patterns in patient care discussed in this paper.

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APPENDIX A. PACKAGES AND FUNCTIONS USED FOR DATA EXTRACTION AND ANALYSIS

Data processing:

1) Individual race variable

```
# Importing dataset from NEMSIS
Race <- read_sas("C:/Users/PC/Documents/DataScience/2023/pcrpatientracegroup.sas7bdat")
head(Race)
# Recoding variable by race/ethnicity categories
# provided by NEMSIS
Race$Race_Recoded <- "None"
Race$Race_Recoded <- if_else(Race$ePatient_14 == "2514001",
    "AI_AN_HI_or_PI", Race$Race_Recoded)
Race$Race_Recoded <- if_else(Race$ePatient_14 == "2514003",
    "Asian", Race$Race_Recoded)
Race$Race_Recoded <- if_else(Race$ePatient_14 == "2514005",
    "Black", Race$Race_Recoded)
Race$Race_Recoded <- if_else(Race$ePatient_14 == "2514007",
    "Hispanic", Race$Race_Recoded)
Race$Race_Recoded <- if_else(Race$ePatient_14 == "2514009",
    "AI_AN_HI_or_PI", Race$Race_Recoded)
Race$Race_Recoded <- if_else(Race$ePatient_14 == "2514011",
    "White", Race$Race_Recoded)
# Plotting recoded variable distribution
# ggplot(Race,aes(x=Race_Recoded))+ geom_bar()
# Clean up race dataset
Race_Final <- Race[, c("PcrKey", "Race_Recoded")]
Race_Final <- Race_Final %>%
    filter(Race_Recoded != "None")
rm(Race)
```

2) Individual age variable

```
Demographics <- read_sas("C:/Users/PC/Documents/DataScience/2023/pub_pcrevents.sas7bdat",
    col_select = c(PcrKey, ePatient_13, ePatient_15,
        ePatient_16))
# Utilizing health care age categories as
# estbalished by Medicare/Medicaid, adjusted for
# minimum legal drinking age in the US (age 21):
# 0-20, 21-44, 45-54, 55-64, 65-74, 75-84, and
# 85+
head(Demographics)
Demographics$Age_Cat <- "None"
Demographics$Age_Cat <- if_else(Demographics$ePatient_16 ==
```

```
    "2516001", "0-20", Demographics$Age_Cat)
Demographics$Age_Cat <- if_else(Demographics$ePatient_16 ==
    "2516003", "0-20", Demographics$Age_Cat)
Demographics$Age_Cat <- if_else(Demographics$ePatient_16 ==
    "2516005", "0-20", Demographics$Age_Cat)
Demographics$Age_Cat <- if_else(Demographics$ePatient_16 ==
    "2516007", "0-20", Demographics$Age_Cat)
Demographics$Age_Cat <- if_else(Demographics$ePatient_16 ==
    "2516009" & Demographics$ePatient_15 < 21, "0-20",
    Demographics$Age_Cat)
Demographics$Age_Cat <- if_else(Demographics$ePatient_16 ==
    "2516009" & Demographics$ePatient_15 >= 21 & Demographics$ePatient_15 <
    45, "21-44", Demographics$Age_Cat)
Demographics$Age_Cat <- if_else(Demographics$ePatient_16 ==
    "2516009" & Demographics$ePatient_15 >= 45 & Demographics$ePatient_15 <
    55, "45-54", Demographics$Age_Cat)
Demographics$Age_Cat <- if_else(Demographics$ePatient_16 ==
    "2516009" & Demographics$ePatient_15 >= 55 & Demographics$ePatient_15 <
    65, "55-64", Demographics$Age_Cat)
Demographics$Age_Cat <- if_else(Demographics$ePatient_16 ==
    "2516009" & Demographics$ePatient_15 >= 65 & Demographics$ePatient_15 <
    75, "65-74", Demographics$Age_Cat)
Demographics$Age_Cat <- if_else(Demographics$ePatient_16 ==
    "2516009" & Demographics$ePatient_15 >= 75 & Demographics$ePatient_15 <
    85, "75-84", Demographics$Age_Cat)
Demographics$Age_Cat <- if_else(Demographics$ePatient_16 ==
    "2516009" & Demographics$ePatient_15 >= 85, "85+",
    Demographics$Age_Cat)

# Plot Age category
# ggplot(Demographics,aes(x=Age_Cat))+ geom_bar()

# Clean up Age dataset
Age_Final <- Demographics[, c("PcrKey", "Age_Cat")]
Age_Final <- Age_Final %>%
    filter(Age_Cat != "None")
```

3) Individual gender

```
head(Demographics)
Demographics$Gender_Cat <- "None"
Demographics$Gender_Cat <- if_else(Demographics$ePatient_13 ==
    "9906001", "Female", Demographics$Gender_Cat)

Demographics$Gender_Cat <- if_else(Demographics$ePatient_13 ==
    "9906003", "Male", Demographics$Gender_Cat)

Demographics$Gender_Cat <- if_else(Demographics$ePatient_13 ==
    "9906005", "Unknown", Demographics$Gender_Cat)

# Plot Gender category
# ggplot(Demographics,aes(x=Gender_Cat))+
# geom_bar()
```

```
# Clean up Gender Data
Gender_Final <- Demographics[, c("PcrKey", "Gender_Cat")]
Gender_Final <- Gender_Final %>%
    filter(Gender_Cat != "None")
rm(Demographics)
```

4) Disposition reason

```
Dispo_Reason <- read_sas("C:/Users/PC/Documents/DataScience/2023/factpcrdestinationreason.sas7bdat")

Dispo_Reason$Dispo_Reason_Recoded <- "None"
Dispo_Reason$Dispo_Reason_Recoded <- if_else(Dispo_Reason$eDisposition_20 ==
    "4220001", "Closest_Facility", Dispo_Reason$Dispo_Reason_Recoded)
Dispo_Reason$Dispo_Reason_Recoded <- if_else(Dispo_Reason$eDisposition_20 ==
    "4220003", "Diversion", Dispo_Reason$Dispo_Reason_Recoded)
Dispo_Reason$Dispo_Reason_Recoded <- if_else(Dispo_Reason$eDisposition_20 ==
    "4220005", "Family Choice", Dispo_Reason$Dispo_Reason_Recoded)
Dispo_Reason$Dispo_Reason_Recoded <- if_else(Dispo_Reason$eDisposition_20 ==
    "4220007", "Insurance", Dispo_Reason$Dispo_Reason_Recoded)
Dispo_Reason$Dispo_Reason_Recoded <- if_else(Dispo_Reason$eDisposition_20 ==
    "4220009", "Law Enforcement", Dispo_Reason$Dispo_Reason_Recoded)
Dispo_Reason$Dispo_Reason_Recoded <- if_else(Dispo_Reason$eDisposition_20 ==
    "4220011", "Medical Direction", Dispo_Reason$Dispo_Reason_Recoded)
Dispo_Reason$Dispo_Reason_Recoded <- if_else(Dispo_Reason$eDisposition_20 ==
    "4220013", "Other", Dispo_Reason$Dispo_Reason_Recoded)
Dispo_Reason$Dispo_Reason_Recoded <- if_else(Dispo_Reason$eDisposition_20 ==
    "4220015", "Patient choice", Dispo_Reason$Dispo_Reason_Recoded)
Dispo_Reason$Dispo_Reason_Recoded <- if_else(Dispo_Reason$eDisposition_20 ==
    "4220017", "Physician choice", Dispo_Reason$Dispo_Reason_Recoded)
Dispo_Reason$Dispo_Reason_Recoded <- if_else(Dispo_Reason$eDisposition_20 ==
    "4220019", "Protocol", Dispo_Reason$Dispo_Reason_Recoded)
Dispo_Reason$Dispo_Reason_Recoded <- if_else(Dispo_Reason$eDisposition_20 ==
    "4220021", "Regional Specialty Center", Dispo_Reason$Dispo_Reason_Recoded)

# Plot Dispo Reason category
# ggplot(Dispo_Reason,aes(x=Dispo_Reason_Recoded))+
# geom_bar()+ theme(axis.text.x =
# element_text(angle = 90, vjust = 0.5, hjust =
# 1))

# Clean Up Dispo Reason
Dispo_Final <- Dispo_Reason[, c("PcrKey", "Dispo_Reason_Recoded")]
Dispo_Final <- Dispo_Final %>%
    filter(Dispo_Reason_Recoded != "None")
rm(Dispo_Reason)
```

5) Alcohol use indicator

```
EtOH_Indicator <- read_sas("C:/Users/PC/Documents/DataScience/2023/factpcralcoholdruguseindicator.sas7b
EtOH_Indicator$Alcohol_Cat <- "None"
EtOH_Indicator$Alcohol_Cat <- if_else(EtOH_Indicator$eHistory_17 ==
    "3117001", "Alc_Paraphernalia", EtOH_Indicator$Alcohol_Cat)
```

```
EtOH_Indicator$Alcohol_Cat <- if_else(EtOH_Indicator$eHistory_17 ==
    "3117005", "Alc_Disclosed_By_Pt", EtOH_Indicator$Alcohol_Cat)
EtOH_Indicator$Alcohol_Cat <- if_else(EtOH_Indicator$eHistory_17 ==
    "3117009", "Alc_Level_Known", EtOH_Indicator$Alcohol_Cat)
EtOH_Indicator$Alcohol_Cat <- if_else(EtOH_Indicator$eHistory_17 ==
    "3117011", "Alc_Smell_on_Breath", EtOH_Indicator$Alcohol_Cat)
EtOH_Indicator$Alcohol_Cat <- if_else(EtOH_Indicator$eHistory_17 ==
    "3117003", "Other_Substance_Use_Suspected", EtOH_Indicator$Alcohol_Cat)
EtOH_Indicator$Alcohol_Cat <- if_else(EtOH_Indicator$eHistory_17 ==
    "3117007", "Other_Substance_Use_Suspected", EtOH_Indicator$Alcohol_Cat)

# Plot Alcohol Use Indicator
# ggplot(EtOH_Indicator,aes(x=Alcohol_Cat))+
# geom_bar()+ theme(axis.text.x =
# element_text(angle = 90, vjust = 0.5, hjust =
# 1))

# Clean up Alcohol Use Indicator
EtOH_Indicator_Final = EtOH_Indicator[, c("PcrKey",
    "Alcohol_Cat")]
# EtOH_Indicator_Final=
# EtOH_Indicator_Final%>%filter(Alcohol_Cat!='None')
rm(EtOH_Indicator)
```

6) Alcohol and altered mental status primary symptom code

```
Primary_Symptoms <- read_sas("C:/Users/PC/Documents/DataScience/2023/factpcrprimarysymptom.sas7bdat")
Primary_Symptoms$Diagnosis_Cat <- "Other/None"
Primary_Symptoms$Diagnosis_Cat <- if_else(Primary_Symptoms$eSituation_09 ==
    "F10.1", "Alc_Abuse_not_intox", Primary_Symptoms$Diagnosis_Cat)
Primary_Symptoms$Diagnosis_Cat <- if_else(Primary_Symptoms$eSituation_09 ==
    "F10.10", "Alc_Abuse_not_intox", Primary_Symptoms$Diagnosis_Cat)
Primary_Symptoms$Diagnosis_Cat <- if_else(Primary_Symptoms$eSituation_09 ==
    "F10.12", "Alc_Abuse_with_intox", Primary_Symptoms$Diagnosis_Cat)
Primary_Symptoms$Diagnosis_Cat <- if_else(Primary_Symptoms$eSituation_09 ==
    "F10.120", "Alc_Abuse_with_intox", Primary_Symptoms$Diagnosis_Cat)
Primary_Symptoms$Diagnosis_Cat <- if_else(Primary_Symptoms$eSituation_09 ==
    "F10.129", "Alc_Abuse_with_intox", Primary_Symptoms$Diagnosis_Cat)

Primary_Symptoms$Diagnosis_Cat <- if_else(Primary_Symptoms$eSituation_09 ==
    "F10.229", "Alc_Dep_with_intox", Primary_Symptoms$Diagnosis_Cat)
Primary_Symptoms$Diagnosis_Cat <- if_else(Primary_Symptoms$eSituation_09 ==
    "F10.23", "Alc_Dep_with_withdrawal", Primary_Symptoms$Diagnosis_Cat)
Primary_Symptoms$Diagnosis_Cat <- if_else(Primary_Symptoms$eSituation_09 ==
    "F10.230", "Alc_Dep_with_withdrawal", Primary_Symptoms$Diagnosis_Cat)
Primary_Symptoms$Diagnosis_Cat <- if_else(Primary_Symptoms$eSituation_09 ==
    "F10.231", "Alc_Dep_with_withdrawal", Primary_Symptoms$Diagnosis_Cat)
Primary_Symptoms$Diagnosis_Cat <- if_else(Primary_Symptoms$eSituation_09 ==
    "F10.239", "Alc_Dep_with_withdrawal", Primary_Symptoms$Diagnosis_Cat)

Primary_Symptoms$Diagnosis_Cat <- if_else(Primary_Symptoms$eSituation_09 ==
    "F10.9", "Alc_Use", Primary_Symptoms$Diagnosis_Cat)
Primary_Symptoms$Diagnosis_Cat <- if_else(Primary_Symptoms$eSituation_09 ==
```

```
    "F10.92", "Alc_Use_with_intox", Primary_Symptoms$Diagnosis_Cat)
Primary_Symptoms$Diagnosis_Cat <- if_else(Primary_Symptoms$eSituation_09 ==
    "F10.920", "Alc_Use_with_intox", Primary_Symptoms$Diagnosis_Cat)
Primary_Symptoms$Diagnosis_Cat <- if_else(Primary_Symptoms$eSituation_09 ==
    "F10.929", "Alc_Use_with_intox", Primary_Symptoms$Diagnosis_Cat)
Primary_Symptoms$Diagnosis_Cat <- if_else(Primary_Symptoms$eSituation_09 ==
    "F10.92", "Alc_Use", Primary_Symptoms$Diagnosis_Cat)
Primary_Symptoms$Diagnosis_Cat <- if_else(Primary_Symptoms$eSituation_09 ==
    "R41.82", "AltMentalStatus", Primary_Symptoms$Diagnosis_Cat)

# Plot Primary Symptoms
# ggplot(Primary_Symptoms,aes(x=Diagnosis_Cat))+
# geom_bar()

# Clean Up Primary Symptoms
Primary_Sx_Final <- Primary_Symptoms[, c("PcrKey",
    "Diagnosis_Cat")]
rm(Primary_Symptoms)
```

7) Secondary symptoms

```
Secondary_Symptoms <- read_sas("C:/Users/PC/Documents/DataScience/2023/factpcradditionalsymptom.sas7bda
Secondary_Symptoms$Diagnosis_Cat <- "Other/None"
Secondary_Symptoms$Diagnosis_Cat <- if_else(Secondary_Symptoms$eSituation_10 ==
    "F10.1", "Alc_Abuse_not_intox", Secondary_Symptoms$Diagnosis_Cat)
Secondary_Symptoms$Diagnosis_Cat <- if_else(Secondary_Symptoms$eSituation_10 ==
    "F10.10", "Alc_Abuse_not_intox", Secondary_Symptoms$Diagnosis_Cat)
Secondary_Symptoms$Diagnosis_Cat <- if_else(Secondary_Symptoms$eSituation_10 ==
    "F10.12", "Alc_Abuse_with_intox", Secondary_Symptoms$Diagnosis_Cat)
Secondary_Symptoms$Diagnosis_Cat <- if_else(Secondary_Symptoms$eSituation_10 ==
    "F10.120", "Alc_Abuse_with_intox", Secondary_Symptoms$Diagnosis_Cat)
Secondary_Symptoms$Diagnosis_Cat <- if_else(Secondary_Symptoms$eSituation_10 ==
    "F10.129", "Alc_Abuse_with_intox", Secondary_Symptoms$Diagnosis_Cat)

Secondary_Symptoms$Diagnosis_Cat <- if_else(Secondary_Symptoms$eSituation_10 ==
    "F10.229", "Alc_Dep_with_intox", Secondary_Symptoms$Diagnosis_Cat)
Secondary_Symptoms$Diagnosis_Cat <- if_else(Secondary_Symptoms$eSituation_10 ==
    "F10.23", "Alc_Dep_with_withdrawal", Secondary_Symptoms$Diagnosis_Cat)
Secondary_Symptoms$Diagnosis_Cat <- if_else(Secondary_Symptoms$eSituation_10 ==
    "F10.230", "Alc_Dep_with_withdrawal", Secondary_Symptoms$Diagnosis_Cat)
Secondary_Symptoms$Diagnosis_Cat <- if_else(Secondary_Symptoms$eSituation_10 ==
    "F10.231", "Alc_Dep_with_withdrawal", Secondary_Symptoms$Diagnosis_Cat)
Secondary_Symptoms$Diagnosis_Cat <- if_else(Secondary_Symptoms$eSituation_10 ==
    "F10.239", "Alc_Dep_with_withdrawal", Secondary_Symptoms$Diagnosis_Cat)

Secondary_Symptoms$Diagnosis_Cat <- if_else(Secondary_Symptoms$eSituation_10 ==
    "F10.9", "Alc_Use", Secondary_Symptoms$Diagnosis_Cat)
Secondary_Symptoms$Diagnosis_Cat <- if_else(Secondary_Symptoms$eSituation_10 ==
    "F10.92", "Alc_Use_with_intox", Secondary_Symptoms$Diagnosis_Cat)
Secondary_Symptoms$Diagnosis_Cat <- if_else(Secondary_Symptoms$eSituation_10 ==
    "F10.920", "Alc_Use_with_intox", Secondary_Symptoms$Diagnosis_Cat)
Secondary_Symptoms$Diagnosis_Cat <- if_else(Secondary_Symptoms$eSituation_10 ==
    "F10.929", "Alc_Use_with_intox", Secondary_Symptoms$Diagnosis_Cat)
```

```
Secondary_Symptoms$Diagnosis_Cat <- if_else(Secondary_Symptoms$eSituation_10 ==
    "F10.92", "Alc_Use", Secondary_Symptoms$Diagnosis_Cat)
Secondary_Symptoms$Diagnosis_Cat <- if_else(Secondary_Symptoms$eSituation_10 ==
    "R41.82", "AltMentalStatus", Secondary_Symptoms$Diagnosis_Cat)

# Plot Primary Symptoms
# ggplot(Secondary_Symptoms,aes(x=Diagnosis_Cat))+
# geom_bar()

# Clean Up Primary Symptoms
Secondary_Sx_Final <- Secondary_Symptoms[, c("PcrKey",
    "Diagnosis_Cat")]
rm(Secondary_Symptoms)
```

8) Outcome: transport times

```
Comp_Elements <- read_sas("C:/Users/PC/Documents/DataScience/2023/computedelements.sas7bdat",
    col_select = c(PcrKey, EMSTransportTimeMin))
head(Comp_Elements)
Comp_Elements %>%
    drop_na(EMSTransportTimeMin)

# Plot EMS Transport times
# ggplot(Comp_Elements,aes(x=EMSTransportTimeMin))+
# geom_histogram()

# Clean up Transport times
Trans_Time_Final <- Comp_Elements[, c("PcrKey", "EMSTransportTimeMin")]
rm(Comp_Elements)
```

9) Final dataset merge

```
Final_Dataset <- merge(Age_Final, Race_Final, by = "PcrKey")
Final_Dataset <- merge(Final_Dataset, Gender_Final,
    by = "PcrKey")
Final_Dataset <- merge(Final_Dataset, Dispo_Final,
    by = "PcrKey")
Final_Dataset <- merge(Final_Dataset, EtOH_Indicator_Final,
    by = "PcrKey")
Final_Dataset <- merge(Final_Dataset, Primary_Sx_Final,
    by = "PcrKey")
Final_Dataset <- merge(Final_Dataset, Secondary_Sx_Final,
    by = "PcrKey")
Final_Dataset <- merge(Final_Dataset, Trans_Time_Final,
    by = "PcrKey")

Altered_Mental_Status <- Final_Dataset %>%
    filter(Diagnosis_Cat.x == "AltMentalStatus" | Diagnosis_Cat.y ==
        "AltMentalStatus")

Alcohol_Status <- Final_Dataset %>%
    filter(Alcohol_Cat != "None")
```

```r
# ggplot(Altered_Mental_Status,aes(x=Diagnosis_Cat.x,
# fill=Alcohol_Cat))+ geom_bar(stat='count',
# position=position_dodge())+ theme(axis.text.x =
# element_text(angle = 90, vjust = 0.5, hjust=1))

# Anova analysis to see if there is any
# difference in patient demographics among all
# NEMSIS patients who 1) have altered mental
# status as a chief complaint or 2) have a
# different chief complaint (not AMS).
Final_Dataset$Altered_Mental_Status_binary <- if_else(Final_Dataset$Diagnosis_Cat.x ==
    "AltMentalStatus", 1, 0)
Final_Dataset$Altered_Mental_Status_binary <- if_else(Final_Dataset$Diagnosis_Cat.y ==
    "AltMentalStatus", 1, Final_Dataset$Altered_Mental_Status_binary)
one_way_AOV_AMS_age <- aov(Altered_Mental_Status_binary ~
    Age_Cat, data = Final_Dataset)
summary(one_way_AOV_AMS_age)
one_way_AOV_AMS_race <- aov(Altered_Mental_Status_binary ~
    Race_Recoded, data = Final_Dataset)
summary(one_way_AOV_AMS_race)
one_way_AOV_AMS_gender <- aov(Altered_Mental_Status_binary ~
    Gender_Cat, data = Final_Dataset)
summary(one_way_AOV_AMS_gender)

# Anova analysis to see if there is any
# difference in patient demographics among
# altered mental status patients who 1) have an
# alcohol or drug use indicator and 2) have no
# alcohol or drug use indicator.
Final_Dataset$Alcohol_Cat_binary <- if_else(Final_Dataset$Alcohol_Cat ==
    "None", 0, 1)
one_way_Alc_age <- aov(Alcohol_Cat_binary ~ Age_Cat,
    data = Final_Dataset)
summary(one_way_Alc_age)
one_way_Alc_race <- aov(Alcohol_Cat_binary ~ Race_Recoded,
    data = Final_Dataset)
summary(one_way_Alc_race)
one_way_Alc_gender <- aov(Alcohol_Cat_binary ~ Gender_Cat,
    data = Final_Dataset)
summary(one_way_Alc_gender)

# Sanity test
Final_Dataset$Alcohol_Cat_binary <- Final_Dataset$Alcohol_Cat_binary ==
    1
ggplot(Final_Dataset, aes(Age_Cat)) + geom_bar(aes(fill = Alcohol_Cat_binary))
ggplot(Final_Dataset, aes(Race_Recoded)) + geom_bar(aes(fill = Alcohol_Cat_binary))
ggplot(Final_Dataset, aes(Gender_Cat)) + geom_bar(aes(fill = Alcohol_Cat_binary))
# The p-value shows how likely it is that the F
# value calculated from the test would have
# occurred if the null hypothesis of no
# difference among group means were true. A low
# p-value therefore indicates that there is a
# statistically significant difference between
```

```r
# the two populations on the basis of the
# alcohol/drug use indicator variables.

# File rewritten for each year of data
write_csv(Final_Dataset, "2023_General.csv")
write_csv(Altered_Mental_Status, "2023_AMSSubset.csv")
write_csv(Alcohol_Status, "2023_AlcSubset.csv")

# Load in cleaned datasets:
data_2017_Alc <- read_csv("2017_AlcSubset.csv", col_names = TRUE)
data_2017_AMS <- read_csv("2017_AMSSubset.csv", col_names = TRUE)
data_2017_Alc$year <- "2017"
data_2017_AMS$year <- "2017"
data_2018_Alc <- read_csv("2018_AlcSubset.csv", col_names = TRUE)
data_2018_AMS <- read_csv("2018_AMSSubset.csv", col_names = TRUE)
data_2018_Alc$year <- "2018"
data_2018_AMS$year <- "2018"
data_2019_Alc <- read_csv("2019_AlcSubset.csv", col_names = TRUE)
data_2019_AMS <- read_csv("2019_AMSSubset.csv", col_names = TRUE)
data_2019_Alc$year <- "2019"
data_2019_AMS$year <- "2019"
data_2020_Alc <- read_csv("2020_AlcSubset.csv", col_names = TRUE)
data_2020_AMS <- read_csv("2020_AMSSubset.csv", col_names = TRUE)
data_2020_Alc$year <- "2020"
data_2020_AMS$year <- "2020"
data_2021_Alc <- read_csv("2021_AlcSubset.csv", col_names = TRUE)
data_2021_AMS <- read_csv("2021_AMSSubset.csv", col_names = TRUE)
data_2021_Alc$year <- "2021"
data_2021_AMS$year <- "2021"
data_2022_Alc <- read_csv("2022_AlcSubset.csv", col_names = TRUE)
data_2022_AMS <- read_csv("2022_AMSSubset.csv", col_names = TRUE)
data_2022_Alc$year <- "2022"
data_2022_AMS$year <- "2022"
data_2023_Alc <- read_csv("2023_AlcSubset.csv", col_names = TRUE)
data_2023_AMS <- read_csv("2023_AMSSubset.csv", col_names = TRUE)
data_2023_Alc$year <- "2023"
data_2023_AMS$year <- "2023"

data_combined_Alc <- rbind(data_2017_Alc, data_2018_Alc,
    data_2019_Alc, data_2020_Alc, data_2021_Alc, data_2022_Alc,
    data_2023_Alc)
write_csv(data_combined_Alc, "2017_to_2023_Combined_Alc.csv")
data_combined_AMS <- rbind(data_2017_AMS, data_2018_AMS,
    data_2019_AMS, data_2020_AMS, data_2021_AMS, data_2022_AMS,
    data_2023_AMS)
write_csv(data_combined_AMS, "2017_to_2023_Combined_AMS.csv")

# Models for the year Combined Alcohol data
# subset Data Setup with reference ranges
data_combined_Alc <- read.csv("2017_to_2023_Combined_Alc.csv")
data_combined_AMS <- read.csv("2017_to_2023_Combined_AMS.csv")
```

```
names <- c("Age_Cat","Race_Recoded","Gender_Cat","Dispo_Reason_Recoded","Alcohol_Cat")
data_combined_Alc[,names] <- lapply(data_combined_Alc[,names] , factor)
data_combined_Alc$Age_Cat<- relevel(data_combined_Alc$Age_Cat, ref= "21-44")
data_combined_Alc$Race_Recoded<-al relevel(data_combined_Alc$Race_Recoded, ref= "White")
data_combined_Alc$Gender_Cat<- relevel(data_combined_Alc$Gender_Cat, ref= "Male")
data_combined_Alc$Dispo_Reason_Recoded<- relevel(data_combined_Alc$Dispo_Reason_Recoded, ref = "Closest
data_combined_Alc$Alcohol_Cat<- relevel(data_combined_Alc$Alcohol_Cat, ref="Alc_Disclosed_By_Pt")

##Model 1: are demographics associated with certain alcohol use label
Alcohol_Label_Bias_Model<- multinom(Alcohol_Cat ~ Age_Cat + Race_Recoded + Gender_Cat, data=data_combin
betas.Alcohol<- coef(Alcohol_Label_Bias_Model)
OR.Alcohol<- round(exp(betas.Alcohol),3)
OR.Alcohol
CI.OR.Alcohol<- round(exp(confint(Alcohol_Label_Bias_Model)),3)
CI.OR.Alcohol

#Models for the year 2017 AMS data subset
##Data Setup with reference ranges
data_combined_AMS[,names] <- lapply(data_combined_AMS[,names] , factor)
data_combined_AMS$Age_Cat<- relevel(data_combined_AMS$Age_Cat, ref= "21-44")
data_combined_AMS$Race_Recoded<- relevel(data_combined_AMS$Race_Recoded, ref= "White")
data_combined_AMS$Gender_Cat<- relevel(data_combined_AMS$Gender_Cat, ref= "Male")
data_combined_AMS$Dispo_Reason_Recoded<- relevel(data_combined_AMS$Dispo_Reason_Recoded, ref = "Closest
data_combined_AMS$Alcohol_Cat<- relevel(data_combined_AMS$Alcohol_Cat, ref="Alc_Disclosed_By_Pt")
##Model 2: is alcohol use label associated with different outcome (EMS transport time) controlling for

Transport_Time_Model <- glm(EMSTransportTimeMin ~ Age_Cat +
    Race_Recoded + Gender_Cat + Dispo_Reason_Recoded +
    Alcohol_Cat, data = data_combined_AMS, family = quasipoisson(link = "log"))
# Poisson family used as transport time is a
# 'count' variable
Betas.Transport <- coef(Transport_Time_Model)
OR.Transport <- round(exp(Betas.Transport), 3)
CI.Transport <- round(exp(confint.default(Transport_Time_Model)),
    3)
Output.Transport <- cbind(OR.Transport, CI.Transport)
Output.Transport

myVars <- c("Age_Cat", "Race_Recoded", "Gender_Cat",
    "Dispo_Reason_Recoded", "EMSTransportTimeMin",
    "Alcohol_Cat")
catVars <- c("Age_Cat", "Race_Recoded", "Gender_Cat",
    "Dispo_Reason_Recoded", "Alcohol_Cat")

table1.overall <- CreateTableOne(vars = myVars, data = data_combined_Alc,
    factorVars = catVars)
print(table1.overall)

table2.alcohol_strat <- CreateTableOne(vars = myVars,
    strata = "Alcohol_Cat", data = data_combined_Alc,
    factorVars = catVars)
print(table2.alcohol_strat)
```

```
z_Combined <- summary(Alcohol_Label_Bias_Model)$coefficients/summary(Alcohol_Label_Bias_Model)$standard
p_Combined <- (1 - pnorm(abs(z_Combined), 0, 1)) *
    2
p_Combined

z_Combined <- summary(Transport_Time_Model)$coefficients/summary(Transport_Time_Model)$standard.errors
p_Combined <- (1 - pnorm(abs(z_Combined), 0, 1)) *
    2
p_Combined

summary(Transport_Time_Model)

# ggplot for SOA - Age and Gender
data_subset_SOA_AG <- subset(data_combined_Alc, Alcohol_Cat ==
    "Alc_Smell_on_Breath")
data_subset_SOA_AG <- subset(data_subset_SOA_AG, Gender_Cat ==
    "Male" | Gender_Cat == "Female")
p1 <- ggplot(data_subset_SOA_AG, aes(x = as.factor(Age_Cat)),
    fill = as.factor(Age_Cat)) + geom_bar() + facet_wrap(~Gender_Cat) +
    scale_color_brewer(palette = "RdBu") + scale_fill_brewer(palette = "RdBu") +
    theme(legend.position = "none")
p1

# ggplot for SOA - Gender and Race
data_subset_SOA_GR <- subset(data_combined_Alc, Alcohol_Cat ==
    "Alc_Smell_on_Breath")
data_subset_SOA_GR <- subset(data_subset_SOA_GR, Gender_Cat ==
    "Male" | Gender_Cat == "Female")
p4 <- ggplot(data_subset_SOA_GR, aes(x = as.factor(Race_Recoded)),
p4  fill = as.factor(Race_Recoded)) + geom_bar() +
    facet_wrap(~Gender_Cat) + scale_color_brewer(palette = "RdBu") +
    scale_fill_brewer(palette = "RdBu") + theme(legend.position = "none")

# ggplot for OSUS
data_subset_OSUS_AG <- subset(data_combined_Alc, Alcohol_Cat ==
    "Other_Substance_Use_Suspected")
data_subset_OSUS_AG <- subset(data_subset_SOA, Gender_Cat ==
    "Male" | Gender_Cat == "Female")
p3 <- ggplot(data_subset_OSUS_AG, aes(x = as.factor(Age_Cat)),
    fill = as.factor(Age_Cat)) + geom_bar() + facet_wrap(~Gender_Cat) +
    scale_color_brewer(palette = "RdBu") + scale_fill_brewer(palette = "RdBu") +
    theme(legend.position = "none")
p3

# ggplot for OSUS
data_subset_OSUS_AG <- subset(data_combined_Alc, Alcohol_Cat ==
    "Other_Substance_Use_Suspected")
data_subset_OSUS_AG <- subset(data_subset_SOA, Age_Cat ==
    "0-20" | Age_Cat == "21-44" | Age_Cat == "45-54" |
    Age_Cat == "55-64" | Age_Cat == "65-74" | Age_Cat ==
    "75-84" | Age_Cat == "85+")
```

```r
p5 <- ggplot(data_subset_OSUS_AG, aes(x = as.factor(Race_Recoded)),
    fill = as.factor(Race_Recoded)) + geom_bar() +
    facet_wrap(~Age_Cat) + scale_color_brewer(palette = "RdBu") +
    scale_fill_brewer(palette = "RdBu") + theme(legend.position = "none") +
    scale_y_continuous(trans = "log10")
p5
```

```r
# ggplot for transport time
p2 <- ggplot(data_combined_AMS, aes(x = Alcohol_Cat,
    y = EMSTransportTimeMin)) + geom_violinplot(outlier.colour = "red") +
    theme(legend.position = "none") + scale_y_continuous(trans = "log10")
p2
```

APPENDIX B. GLOSSARY AND DICTIONARY OF TERMS

Grouping	Descriptor	Definition (Based on Definitions Listed in Extended Data Definitions NEMSIS v3.5.0)
eHistory.17	N/A	Alcohol & Drug Use Indicators
eHistory.17	None Reported	Situations where this option is applicable: The patient (or the EMS crew) identified that the use of drugs or alcohol were unrelated to the patient's condition; There was no apparent alcohol or drug use; or, Patient denied the use/misuse of drugs or alcohol.
eHistory.17	Unable to Complete	Patient was unable to confirm or deny drug or alcohol use for any reason (e.g., unconsciousness, language barrier, or other physical impairment/barrier). This value would also be appropriate if there was not enough patient contact or no other indicators are present to determine.
eHistory.17	Alcohol Containers/Paraphernalia at scene	Refers to any material/object used in the intake of alcohol into the human body.
eHistory.17	Drug Paraphernalia at Scene	Any material/object used in manufacturing, producing, processing, preparing, injecting, ingesting, inhaling, or otherwise introducing into the human body or misuse of a substance.
eHistory.17	Patient Admits to Alcohol Use	By written, verbal, or motor action (e.g., head nod), patient admitted to consuming alcohol or being under the influence of alcohol. Patient does not have to meet any legal standard of intoxication for this purpose.
eHistory.17	Patient Admits to Drug Use	By written, verbal, or motor action (e.g., head nod), patient admitted to injecting, ingesting, inhaling, or being under the influence of drugs. Patient does not have to meet any legal standard of intoxication for this purpose.
eHistory.17	Positive Level Known from Hospital or Law Enforcement	Third-party report of drug or alcohol use based on a diagnostic source (e.g., breathalyzer, blood, urine, field narcotic test, field sobriety test, or other patient record).
eHistory.17	Smell of Alcohol on Breath	EMS clinician observation of an alcohol-like odor coming from the patient
eHistory.17	Other Drug Use Suspected	EMS clinician observation of signs or symptoms of suspected drug use. This value would also be appropriate if the patient's condition improved after administration of an opioid antagonist.
ePatient.13	N/A	Patient Gender
ePatient.13	Female	Patient Gender recorded as female.
ePatient.13	Male	Patient Gender recorded as male.
ePatient.13	Unknown	Patient Gender not identified by EMS clinician
ePatient.14	N/A	Patient Race
ePatient.14	American Indian, Alaska Native, Hawaiian Islander, Pacific Islander (AI, AN, HI, PI)	A person having origins in any of the original peoples of North, Central, and South America and who maintains tribal affiliation or community attachment.
ePatient.14	Asian	A person having origins in any of the original peoples of the Far East, Southeast Asia, or the Indian subcontinent including Cambodia, China, India, Japan, Korea, Malaysia, Pakistan, the Philippine Islands, Thailand, and Vietnam.
ePatient.14	Black or African American	A person having origins in any of the black racial groups of Africa. Terms such as "Haitian" or "Negro" can be used in addition to "Black or African American."
ePatient.14	Hispanic or Latino	A person of Cuban, Mexican, Puerto Rican, South or Central American, or other Spanish culture or origin, regardless of race. The term "Spanish origin" can be used in addition to "Hispanic or Latino."
ePatient.14	White	A person having origins in any of the original peoples of Europe, the Middle East, or North Africa.
ePatient.15	N/A	Patient Age (value)
ePatient.16	N/A	Patient Age (units)

APPENDIX C. 2017 ANOVA SUBSET COMPARISON AND SUMMARY STATISTICS

Variable	*F*-Value	Degrees of Freedom	*p*-value
Subset 1: Alcohol or Drug Use Indicator			
Age	14345	6	<2e-16
Race and ethnicity	1422	4	<2e-16
Gender	11068	2	<2e-16
Subset 2: Altered Mental Status			
Age	246.3	6	<2e-16
Race and ethnicity	161.2	4	<2e-16
Gender	826.9	2	<2e-16

Note: Similar patterns observed for 2018-2023 populations.

APPENDIX D. STUDY POPULATION CHARACTERISTICS (2017-2023)

	Categorical Count	Percentage	Categorical Count	Percentage
	Subset 1: Alcohol or Drug Use Indicator		Subset 2: Altered Mental Status	
Total	14,459,186	100	9,396,991	100
Age (years)				
0-20	797,935	5.5	479,641	5.1
21-44	6,552,786	45.3	1,901,035	20.2
45-54	2,559,280	17.7	911,592	9.7
55-64	2,748,599	19.0	1,399,276	14.9
65-74	1,240,249	8.6	1,682,331	17.9
75-84	396,363	2.7	1,696,399	18.1
85+	163,974	1.1	1,326,717	14.1
Race & Ethnicity				
American Indian, Alaskan Native, Hawaiian, or Pacific Islander	560,083	3.9	214,792	2.3
Asian	152,626	1.1	163,365	1.7
Black or African American	3,035,693	21.0	1,792,571	19.1
Hispanic	1,715,586	11.9	836,517	8.9
White	8,995,198	62.2	6,389,746	68.0
Gender				
Female	4,826,610	33.4	4,996,180	53.2
Male	9,615,847	66.5	4,387,143	46.7
Unknown	16,729	0.1	13,668	0.1
Disposition Reason				
Closest Facility	7,051,664	48.8	4,116,069	53.2
Patient Choice	4,363,249	30.2	1,783,771	19.0
Protocol	1,074,700	7.4	687,042	7.3
Regional Specialty Center	569,640	3.9	590,449	6.3
Family Choice	397,908	2.8	937,792	10.0
Other	154,508	1.1	246,762	2.6
EMS Transport Time in Minutes				
Transport Time in Mins (SD)	14.66	16.06	16.88	19.01
Alcohol Categorization				
Alcohol Disclosed by Patient	5,944,108	41.1	541,437	5.8
Alcohol Level Known	478,465	3.3	66,648	0.7
Alcohol Paraphernalia on Scene	1,168,535	8.1	221,994	2.4
Smell of Alcohol	2,503,663	17.3	385,886	4.1
No Alcohol Disclosed	-	-	7,604,556	80.9
Other substance Use Suspected	4,364,415	30.2	576,470	6.1

Table D-1: Study population characteristics for demographic and altered mental status subsets.

	Alcohol Use Descriptors				
	Alcohol Disclosed by Patient	Alcohol Level Known	Alcohol Paraphernalia On Scene	Smell of Alcohol	Other Substance Use Suspected
Total	5,944,108	478,465	1,168,535	2,503,663	4,364,415
Age (years), *n* (%)					
0-20	226,268 (3.8)	34,355 (7.2)	45,329 (3.9)	112,682 (4.5)	379,301 (8.7)
21-44	2,423,094 (40.8)	194,326 (40.6)	418,850 (35.8)	1,025,944 (41.0)	2,490,572 (57.1)
45-54	1,150,208 (19.4)	70,540 (14.7)	223,082 (19.1)	483,243 (19.3)	632,207 (14.5)
55-64	1,338,139 (22.5)	71,923 (15.0)	284,116 (24.3)	555,805 (22.2)	498,616 (11.4)
65-74	595,634 (10.0)	49,920 (10.4)	141,014 (12.1)	238,535 (9.5)	215,146 (4.9)
75-84	166,844 2.8)	35,888 (7.5)	41,077 (3.5)	64,764 (2.6)	87,790 (2.0)
85+	43,921 (0.7)	21,513 (4.5)	15,067 (1.3)	22,690 (0.9)	60,783 (1.4)
Race & Ethnicity, *n* (%)					
American Indian, Alaskan Native, Hawaiian, or Pacific Islander	267,520 (4.5)	23,743 (5.0)	49,054 (4.2)	129,914 (5.2)	89,852 (2.1)
Asian	61,595 (1.0)	5,269 (1.1)	13,238 (1.1)	31,617 (1.3)	40,907 (0.9)
Black or African American	1,178,008 (19.8)	86,263 (18.0)	212,886 (18.2)	500,724 (20.0)	1,057,812 (24.2)
Hispanic	715,730 (12.0)	43,636 (9.1)	145,073 (12.4)	348,654 (13.9)	462,493 (10.6)
White	3,721,255 (62.6)	319,554 (66.8)	748,284 (64.0)	1,492,754 (59.6)	2,713,351 (62.2)
Gender, *n* (%)					
Female	1,893,710 (31.9)	193,378 (40.4)	383,063 (32.8)	756,042 (30.2)	1,600,417 (36.7)
Male	4,044,416 (68.0)	284,287 (59.4)	784,192 (67.1)	1,745,337 (69.7)	2,757,615 (63.2)
Unknown	5,982 (0.1)	800 (0.2)	1,280 (0.1)	2,284 (0.1)	6,383 (0.1)
Disposition Reason, *n* (%)					
Closest Facility	2,843,450 (47.8)	179,512 (37.5)	612,063 (52.4)	1,250,603 (50.0)	2,166,036 (49.5)
Patient Choice	1,956,101 (32.9)	69,790 (14.6)	322,571 (27.6)	733,540 (29.3)	1,281,257 (29.4)
Protocol	441,115 (7.4)	24,373 (5.1)	87,873 (7.5)	209,286 (8.4)	312,053 (7.1)
Regional Specialty Center	224,294 (3.8)	56,937 (11.9)	38,144 (3.3)	109,999 (4.4)	140,266 (3.2)
Family Choice	132,191 (2.2)	8,703 (1.8)	46,362 (4.0)	68,745 (2.7)	141,907 (3.3)
Other	350,702 (5.9)	139,233 (29.1)	60,764 (5.2)	139,191 (5.2)	327,331 (7.5)
EMS Transportation Time, Mean (*SD*)					
EMS Transportation Time	14.48 (15.51)	28.33 (33.25)	13.16 (12.14)	13.37 (13.25)	14.53 (15.54)

Table D-2. Study population characteristics, stratified by descriptor of alcohol use.

APPENDIX E. LOGISTIC REGRESSION MODEL DATA FOR NEMSIS 2017-2023 BY ALCOHOL USE DESCRIPTOR

	Alcohol Use Descriptors (Relative to Alcohol Disclosed by Patient)			
	Alcohol Level Known	Alcohol Paraphernalia On Scene	Smell of Alcohol	Other Substance Use Suspected
Intercept	0.076 [0.076,0.077]***	0.171 [0.170, 0.172]***	0.410 [0.409, 0.411]***	1.022 [1.019, 1.024]***
Age, years (*OR* [95%CI]) - Relative to 21-44 years-old population				
0-20	1.854 [1.831, 1.877]***	1.145 [1.133, 1.157]***	1.177 [1.169, 1.186]***	1.630 [1.621,1.639]***
45-54	0.763 [0.756, 0.770]***	1.128 [1.122, 1.135]***	1.000 [0.996, 1.004]	0.527 [0.526, 0.529]***
55-64	0.670 [0.664, 0.676]***	1.243 [1.237, 1.250]***	0.998 [0.994, 1.002]***	0.349 [0.348, 0.351]***
65-74	1.031 [1.020,1.041]***	1.382 [1.373, 1.391]***	0.971 [0.966, 0.976]***	0.335 [0.334 ,0.337]***
75-84	2.537 [2.506, 2.569]***	1.420 [1.404, 1.436]***	0.959 [0.950, 0.968]***	0.485 [0.481, 0.489]***
85+	5.597 [5.502, 5.694]***	1.963 [1.926, 2.000]***	1.287 [1.266, 1.308]***	1.267 [1.251,1.283]***
Race & Ethnicity (*OR* [95%CI]) - Relative to White race and ethnicity				
American Indian, Alaskan Native, Hawaiian, or Pacific Islander	1.115 [1.100, 1.131]***	0.964 [0.955, 0.974]***	1.205 [1.196, 1.213]***	0.403 [0.400,0.406]***
Asian	0.955 [0.928, 0.983]*	1.118 [1.097, 1.140]***	1.266 [1.248, 1.283]***	0.745 [0.736, 0.755]***
Black or African American	0.931 [0.924, 0.939]***	0.916 [0.911, 0.921]***	1.056 [1.052,1.060]***	1.217 [1.213, 1.221]***
Hispanic	0.745 [0.737, 0.753]***	1.075 [1.068, 1.081]***	1.196 [1.191,1.202]***	0.737 [0.734, 0.740]***
Gender (*OR* [95%CI]) - Relative to male gender				
Female	1.304 [1.296, 1.312]***	1.046 [1.041, 1.050]***	0.929 [0.926, 0.932]***	1.133 [1.130, 1.136]***
Unknown	1.757 [1.631, 1.892]***	1.131 [1.064, 1.201]***	0.869 [0.828, 0.912]***	1.325 [1.278, 1.374]***

* p <0.01, ** $p < 0.001$, *** $p < 0.0001$

APPENDIX F. GENERALIZED LINEAR MODEL FOR EMS TRANSPORT TIME OF ALTERED MENTAL STATUS PATIENTS FOR NEMSIS 2017-2023

	Odds Ratio	95% Confidence Interval
(Intercept)	11.386	[11.347,11.425]*
Patient age - Relative to 21-44 years-old population		
Age 0-20	1.217	[1.213,1.220]*
Age 45-54	1.032	[1.029,1.034]*
Age 55-64	1.052	[1.049,1.054]*
Age 65-74	1.042	[1.039,1.044]*
Age 75-84	1.004	[1.002,1.007]*
Age 85+	0.913	[0.911,0.916]*
Patient Race & Ethnicity - Relative to White race and ethnicity		
American Indian, Alaskan Native, Hawaiian, or Pacific Islander	1.034	[1.029,1.038]*
Asian	0.832	[0.827,0.836]*
Black or African American	0.853	[0.851,0.854]*
Hispanic	0.881	[0.878,0.883]*
Gender - Relative to Male gender		
Female	0.991	[0.990,0.992]*
Unknown	1.118	[1.101,1.134]*
Disposition - Relative to Closest Facility		
Diversion	1.629	[1.616,1.642]*
Family Choice	1.432	[1.428,1.435]*
Insurance	1.932	[1.909,1.937]*
Law Enforcement	1.323	[1.311,1.335]*
Medical Direction	1.589	[1.579,1.599]*
Other	1.829	[1.822,1.835]*
Patient choice	1.257	[1.255,1.260]*
Physician choice	2.158	[2.153,2.163]*
Protocol	1.199	[1.195,1.202]*
Regional Specialty	2.122	[2.117,2.127]*
Alcohol Use Descriptor - Relative to Alcohol Disclosed by Patient		
Alcohol Level Known	1.552	[1.541,1.562]*
Alcohol Paraphernalia	0.968	[0.962,0.974]*
Smell of Alcohol	0.936	[0.931,0.940]*
None	1.194	[1.190,1.198]*
Substance Use Suspected	1.001	[0.996,1.005]

* $p < 2e\text{-}16$