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Department of BIOSTATISTICS

Capstone Report - Winter 2025

Trends of Mental Health Comorbidities in Youth Presenting for a Substance-Related Visit to a Children's Hospital

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Preface

This report details a capstone project to be completed in March 2025 by students of the Master of Science in Biostatistics degree at the University of Washington. We hope this work will contribute meaningfully to the ongoing efforts and mission of Seattle Children's Hospital.

Acknowledgements

We extend our deepest gratitude to Dr. Dwight Barry, Dr. Alexis Ball, and Dr. Katherine Wilson for their mentorship and to academic advisors at the Department of Biostatistics for making this project possible. We have been provided with invaluable guidance, resources, and support throughout the project's duration.

Abstract

This study evaluates recent trends in mental health among substance-related visits among youth presenting to children's hospitals across the United States. We conducted a cross-sectional study of substance-related visits to pediatric hospitals within the Pediatric Information Health System database of youth aged 12 to 21 years from 2016 through 2021. Substance-related visits were defined as acute visits for International Classification of Diseases, 10th Revision Clinical Modification codes related to substance 'use', dependence, or overdoses for alcohol, cannabis, nicotine, opioids, sedatives, stimulants, hallucinogens, or other substances. Mental-health-related visits were defined for ICD-10 codes related to learning and development, food and eating, personality, stress and trauma, and more. Total percent growth and stratified mental-health-related trends were calculated using generalized mixed effects models.

Keywords

Pediatric health; Substance use; Mental health

Contents

1 Introduction

1.1 Mental health and substance use among youth

Over the last decade, there has been an ongoing mental health crisis facing youth in the United States. Rates of depression and anxiety have doubled, visits to emergency departments for self-harm have tripled, and suicide is the second leading cause of death among ages 10 to 24 [1]. In 2021, national leaders in pediatrics and psychiatry, the American Academy of Pediatrics and the American Academy of Child and Adolescent Psychiatry, declared a national mental health emergency given the pervasive crisis facing youth.

Concurrently, there has been increasing attention on substance use among youth and young adults given the opioid epidemic, emergence of vaping, and increasing legalization of cannabis. According to the National Survey of Drug Use and Health (NSDUH) in 2020, it is estimated that 20.9% of youth ages 12-17 had used an illicit substance in their lifetime, and 1.6 million youth had a substance use disorder [2]. Notably, the burden of the opioid epidemic has been increasing among youth, as deaths from drug overdoses doubled from 2019 to 2020 [3]. In addition, trends show a concerning rise in hospital visits for substance-related disorders among adolescents [4].

Adolescence is a critical period in which substance use often begins and mental health conditions and addictions emerge. Substance use and mental health conditions are independently associated with negative health consequences. However, they are also often interrelated. For example, youth with psychiatric conditions are at increased risk of earlier substance initiation and progression to the development of an addiction [5]. Substance use has also been linked to suicidal behaviors [6]. Surveys of adolescents with substance use disorders (SUD) have found that over half have a comorbid mental health disorder [7]. Moreover, adolescents with both a SUD and depression are at greater risk of severe outcomes such as self-injuries, academic failure, or violence than either condition alone, leading to an increased burden on hospital utilization over decades [4].

1.2 Current limitations

To date, little is known about the burden of mental health comorbidities among youth presenting for a substance-related hospital visit in the United States. Given the severe consequences of substance use and mental health comorbidities, better understanding their co-occurrence is critical to inform prevention, intervention, and treatment, as well as hospital staffing models and resource allocation.

Recent studies have emphasized the growing demand for adolescent mental health services in hospitals, particularly following the COVID-19 pandemic, which exacerbated pre-existing conditions and increased rates of substance misuse among youth [6]. Despite this, limited studies have focused on how mental health comorbidities affect trends in hospital visits and outcomes among substance-using youth [4].

In this study, we aimed to better understand the trends of mental health comorbidities among youth presenting for a substance-related visit at pediatric hospitals and how they may vary by mental health condition and substance. Given the negative impact of the COVID-19 pandemic on mental health and substance misuse among youth, we also sought to determine whether the onset of the pandemic in the spring of 2020 affected trajectories of these trends [4, 6].

1.3 Objectives

1.3.1 Trends in Volume

Comparison of comorbid trends We sought to quantify changes in the number of substance-related hospital visits that included a comorbid mental health condition. We were particularly interested in assessing whether these trends varied based on the specific mental health condition present [4].

To bridge this gap, we examined the number of substance-related visits with a comorbid mental health condition. We hypothesized that the proportion of comorbid cases would increase over time, particularly for anxiety and depressive disorders, given their well-documented links to substance use [7, 5].

Additionally, we modeled the number of substance-related visits over time to better capture underlying trends. By modeling rather than simply summarizing the data, we aimed to obtain clearer insights into the burden of adolescent mental health and substance use in the United States, as experienced by pediatric hospitals. Models accounted for the clustered structure and temporal nature of our data. Specifically, we tested how much the presence of mental health conditions was associated with higher hospital visit volumes across the study period.

Most common conditions We identified the six most common comorbid conditions and analyzed their monthly volumes and annual percentage changes over the study period. Among these, we sought to determine which conditions experienced the greatest cumulative growth, providing insights into the evolving patterns of co-occurring substance use and mental health issues [4].

Interruption of the COVID-19 Pandemic Substantial evidence suggests that the COVID-19 pandemic led to worsening adolescent mental health outcomes, including increased depression, anxiety, and suicidal ideation [6]. Additionally, hospital visits for mental health and substance use disorders saw significant shifts during and after the onset of the pandemic [1]. We examined whether the onset of COVID-19 in March 2020 altered trends in substance-related visits with and without mental health comorbidities.

1.3.2 Hospital Burden

Hospital utilization associated with substance-related visits among youth, especially in the presence of mental health comorbidities, constitutes a critical public health concern. Understanding how mental health comorbidities influence hospital resource utilization provides valuable insights into optimizing resource allocation, improving patient outcomes, and informing policy decisions [4].

ED, ICU, and Inpatient Utilization Frequent hospital visits impose considerable strain on emergency departments and inpatient care systems, especially when mental health conditions complicate substance-related admissions. Emergency department (ED) visits often represent the initial point of care for youth experiencing acute crises, whereas intensive care unit (ICU) and inpatient admissions reflect more severe cases that necessitate prolonged and specialized medical intervention [4].

Evaluating the relationship between mental health comorbidities and hospital utilization can enable healthcare providers to better anticipate resource demands, staffing requirements, and necessary intervention strategies. Identifying utilization trends across ED, ICU, and inpatient settings can help policymakers and hospital administrators optimize resource allocation and establish targeted early-intervention and prevention programs.

Length of Stay for Comorbid Visits Hospital length of stay (LOS) is an important indicator of healthcare burden, reflecting treatment complexity and resource intensity required for patient management. Youth presenting with concurrent substance use and mental health conditions are likely to experience longer hospital stays due to increased medical and psychiatric complications, prolonged discharge planning, or the necessity for specialized care [4, 8].

Analyzing how mental health comorbidities affect LOS can inform hospital capacity planning and discharge procedures. Understanding these factors will aid in designing interventions aimed at reducing prolonged hospitalizations, enhancing care coordination, and promoting efficient hospital resource utilization, ultimately ensuring sustained high-quality patient care.

2 Methods

2.1 Study Design and Data Sources

We conducted a cross-sectional, retrospective analysis of patients within the PHIS database (Children's Hospital Association). PHIS collects administrative and billing records including patient demographics and diagnosis codes from approximately 50 children's hospitals within the United States. 39 were eligible for our analysis due to being active contributors to PHIS for our selected study years.

2.2 Study Population

We included all emergency department (ED), intensive care unit (ICU), and inpatient visits for patients aged 12–21 years at the time of their visit from January 2016 to December 2021 across 39 hospitals with complete data for the entire study period. The dataset comprised 106,693 hospital visits recorded within the period. Each visit represented a single hospital discharge, while individual patients could have multiple visits.

2.3 Classification of a substance-related visit

We defined substance-related visits as any hospital encounter attributed to or associated with drug or alcohol use, as indicated by an International Classification of Diseases, 10th Revision, Clinical Modification (ICD-10-CM) code. ICD-10-CM codes pertaining to substance use, dependence, and poisoning were selected based on established recommendations for hospital-based substance use surveillance. Our classification encompassed ICD-10-CM codes related to alcohol, cannabis, nicotine, opioids, stimulants, hallucinogens, sedatives, and other substances. Poisoning codes were used to classify overdoses. Both "use" and "dependence" codes are associated with substance use disorders (SUDs), although they are not synonymous with a formal SUD diagnosis. Visits involving multiple substances were categorized as "polysubstance" encounters. Both primary and secondary diagnoses were considered to more accurately assess the overall burden of substance-related hospital visits. Encounters occurring within the duration of the 10th revision of the ICD system (January 1, 2016 – December 31, 2021) were considered for our analysis to ensure consistency in classifying substance use diagnoses.

2.4 Classification of a comorbid mental health condition

We defined a comorbid mental health visit as any substance-related hospital encounter associated with a mental health condition, including those related to learning and development, eating disorders, personality disorders, stress/trauma, and other conditions. Both primary and secondary diagnoses were considered for similar reasons. To ensure consistency in classifying mental health diagnoses, we included encounters that occurred during the 10th revision of the ICD system.

2.5 Patient Demographics and Details of Visit

The key demographic characteristics were age, sex, race/ethnicity, region and insurance group. Race/ethnicity was grouped into four categories: Hispanic, Non-Hispanic Black, Non-Hispanic White, Others. The details of visit information included mental health comorbidity, individual comorbid conditions, polysubstance, encountered department, and length of stay in hospital. Mental health comorbidity was a label for whether a given substance-related visit involved a concurrent mental health condition. Polysubstance was an indicator for whether the visit involved one or more substances. Encountered department was defined as hospital utilization of Emergency Department(ED), Intensive Care Unit (ICU), and/or Inpatient. These patient demographics and visit information may affect both the risk of substance use disorder and the manifestation of primary mental health symptoms.

2.6 Statistical Analysis

2.6.1 Trends in Volume

Overall Descriptive statistics was used to summarize the patient demographics of visits involving comorbid mental health conditions within the study period. The cumulative growth in comorbid visits was measured by calculating the percentage growth from 2016, the baseline, to 2021. The composition can be seen in Appendix **??**. We also characterized the intensity of comorbidites by outlining the top six most common mental health condition or disorder and obtained their cumulative growth by calculating their percentage growth. The breakdown can be seen in Appendix 7.1.1.

Comparative analysis To investigate the difference in the trend of visit volume between substance-related visits with comorbid mental health comorbidities and visits without, we conducted a Generalized Linear Mixed Model (GLMM) to estimate the expected monthly visit counts for each hospital separately for two groups, measure their expcted growth rate over time, and capture the difference in expected rate of change over time. Additional covariates of patient demographics was included to adjust for potential confounding. The full data preprocessing details and model specification can be found in Appendix 7.2.

Interruption of COVID-19 Interrupted time series analysis (ITSA)is applied to assess how the COVID-19 pandemic influenced trends in substance-related visits with and without comorbid mental health conditions. March 2020 was selected as the interruption point, aligning with the onset of widespread pandemic-related disruptions. The analysis evaluated both immediate shifts in visit counts and long-term changes in trend trajectories after March 2020. We adjusted for patient demographics (age, sex, race/ethnicity, insurance type) and hospital-level variability. Full model specifications, including statistical equations and sensitivity analyses, are provided in Appendix 8.5.

2.6.2 Hospital Burden

ED, ICU, and Inpatient Utilization Generalized Linear Mixed Models (GLMMs) were employed to model the monthly hospital visit counts separately for ED, ICU, and inpatient visits. Negative Binomial distributions were selected due to the count-based nature and overdispersion observed in visit counts. Each model included fixed-effect covariates for mental health comorbidity status, time (monthly trends), age, race/ethnicity, sex, polysubstance use, and their interactions, along with a random intercept for hospitals to capture hospital-level variability. Full specifications of these models are described in Equation 5 of Appendix 7.3.

The primary interest was the association between mental health comorbidities and hospital utilization, measured by the incident rate ratios (IRR) derived from the models. The interaction terms between time and mental health status were included to assess whether the rate of change in hospital visits over time differed significantly between youth with and without mental health conditions.

Length of stay To statistically assess factors influencing LOS, we employed Generalized Linear Mixed Models (GLMMs) utilizing a Gamma distribution with a log-link function, selected due to the skewed, continuous, and strictly positive nature of LOS data. The model incorporated fixed effects for mental health comorbidity status, monthly time index, age, race/ethnicity, sex, polysubstance use, and relevant interaction terms. Hospital-level random intercepts were also included to account for variation among hospitals. Complete model specifications are detailed in Equation 7 of Appendix 7.4.

The primary focus of this model was to assess how mental health comorbidities influence hospital stays. Interaction terms involving mental health status and time allowed us to determine whether the trajectory of LOS over time significantly differed between youth with and without mental health comorbidities.

3 Results

3.1 Overall characteristics

Between 2016 and 2021, there were 64,617 substance-related visits involving a comorbid mental health condition, accounting for 52,831 unique individuals. Among them, 7,613 (14%) had multiple visits. Comorbid encounters were more frequent among female youth (56%) than male youth (44%). Regarding racial and ethnic distribution, Non-Hispanic White youth accounted for 56.3% of comorbid visits, followed by Black or African American (17.4%) and Hispanic youth (17%), collectively representing 90.7% of cases. Adolescents aged 16 to 17 years constituted the largest age group, comprising 43.6% of comorbid visits. Geographically, the highest proportion of cases occurred in the Midwest (36.5%) and South (33.5%), while the Northwest had the fewest (9.6%). Insurance coverage was primarily government-funded (53%) or commercial (41%). Notably, 70% of comorbid visits resulted in hospitalization.

Comorbid visits gradually rose by 52.8% over the study period and increased for all ages, demographics, geographic regions, and insurance types. Comorbid visits to the ICU by 45.4%. Hospital discharges following admission grew by 48.1%, whereas ED discharges increased by 59.4%. Visits in the South and Midwest (59.9% and 52%, respectively) increased more than visits in the West or Northwest (48.3% and 41.5%, respectively). Among age groups, the most significant rise was observed in younger adolescents (ages 12-15). By race and ethnicity, the largest percentage increase in comorbid substance-related visits were among Asian (108.5%) and Multiracial (90.9%) youth. However, both groups had low baseline volumes in 2016 and together accounted for only 2.3% of comorbid visits throughout the study period. Comparing groups of large sample size, the cumulative growth for substance-related visits with a comorbid mental health conditions was highest for Hispanic youth (68.9%), compared to Black or African American youth (61.8%), or Non-Hispanic White youth (50.3%). Despite a higher initial volume of visits in 2016, cumulative growth exhibited by female youth outpaced their male counterparts (64.5% vs. 38%).

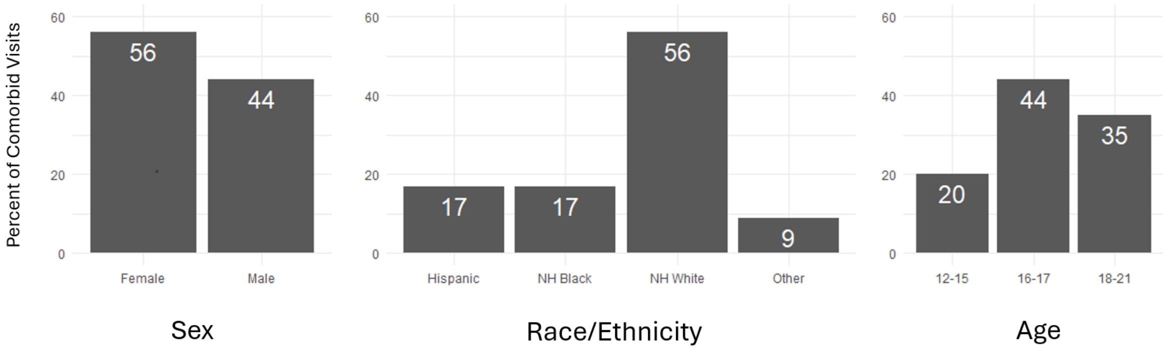


Figure 1: Distribution of Demographics from Comorbid Patient Visits

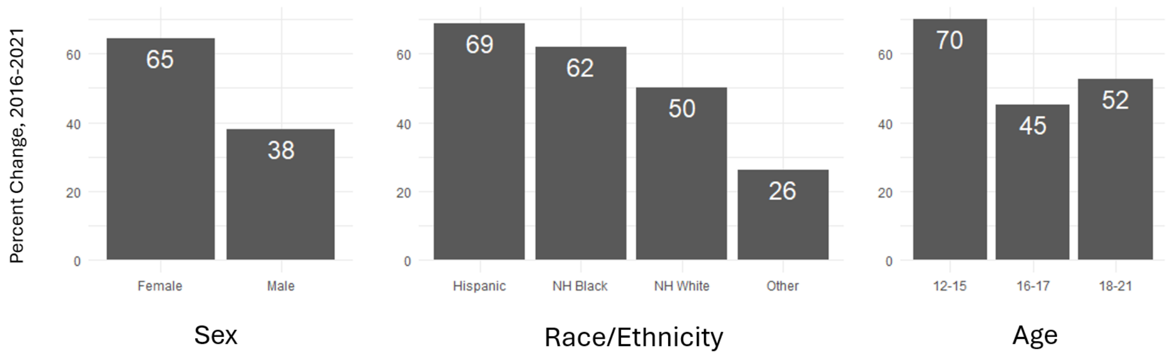


Figure 2: Cumulative Growth of Demographics from Comorbid Patient Visits

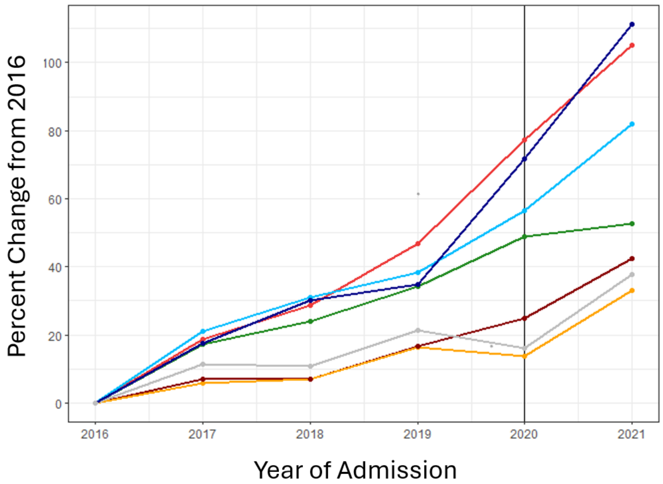
3.1.1 Trends

Total Monthly Visits Figure **??** visually demonstrates estimated trends in total number of visits by month from 2016 through 2021, comparing youth with and without mental health comorbidities. The volume of visits for all groups are estimated to have a steady increase, and there is a higher volume of visits with mental health comorbidities compared to those without.

Table 2 (Appendix 7.2)Our analysis demonstrated a significant interaction between mental health comorbidities and time trends in predicting total monthly hospital visits across all 39 hospitals during the study period. Specifically, with all other covariates (age, sex, race/ethnicity, polysubstance) being equal, the presence of one or more comorbid mental health conditions was associated with a 30% increase in the expected hospital visit counts (Mean Rate Ratio(RR) $\approx$ 1.30, $p < 0.001$). The time trend measured by month was also significant (RR $\approx$ 1.005, $p < 0.001$), indicating a steady increase in total visit counts over the study period. Notably, for any given hospital, the total visit count among patients with mental health comorbidities was expected to be 0.2% higher per month compared to those without mental health conditions (RR $\approx$ 1.002, $p < 0.001$).

For race and ethnicity covariates, a higher proportion of patients classified as "Other" (excluding NH-White, NH-Black, and Hispanic) was significantly associated with 17% lower total monthly visits compared to the referenced NH-White patients,(RR $\approx$ 0.83, $p < 0.001$). However, the proportion of NH-Black and Hispanic patients was not statistically significant, suggesting no strong evidence of a statistically significant difference compared with NH-White patients in total visit counts in this model.

Trends by common conditions Table 1 (Appendix 7.1.1) indicated that all the comorbid mental health conditions diagnosed in total visits from 2016 to 2021, the most common six were Depressive Disorder (55%), Self-Injury or Suicide (46%), Substance Dependence (44%), Anxiety Disorders (43%), ADHD (26%), and Trauma and Stressor Related (18%). However, the prevalence of each comorbid condition among total visits did not necessarily reflect their individual trends over time. Figure 3 Compared to the 38% increase in visits without mental health comorbidities, Trauma- and Stressor-Related Disorders exhibited the most significant growth (111%), followed by Anxiety Disorders (105%) and Self-Injury or Suicide (82%).



Condition or Disorder	Percent Change from 2016-2021
Trauma and Stressor Related	111
Anxiety Disorders	105
Self-Injury or Suicide	82
Depressive Disorders	53
ADHD	43
Substance Dependence	33
No Mental Health	38

Figure 3: Trends by the six most common comorbid conditions.

Interruption of COVID-19 The interrupted time series analysis demonstrated distinct pandemic impact patterns between adolescent visits with and without mental health comorbidities. As shown in Figure 4, visits involving mental health conditions maintained consistent growth trajectories throughout the study period. The pre-pandemic baseline trend of 5.30 monthly visits (95% CI 4.85–5.75, $p < 0.001$) showed no statistically significant deviation following the March 2020 intervention point, with an immediate level change estimate of -79.79 visits ($p = 0.625$) and non-significant trend modification of 1.74 visits per month ($p = 0.525$). This stability persisted despite the model explaining 72.1% of observed variance ($R^2 = 0.721$), suggesting established care pathways may have mitigated pandemic disruptions for this population.

Conversely, Figure 5 reveals three distinct pandemic phases for visits without mental health comorbidities. The pre-pandemic period showed steady growth of 3.06 visits monthly (95% CI 2.50–3.62, $p < 0.001$), followed by an acute March 2020 reduction of 505.26 visits ($p < 0.001$), representing 18.7% below expected levels. Post-acute phase growth accelerated significantly to 10.68 visits per month (7.62 visit increase over baseline, $p < 0.001$). The differential response patterns resulted in substantially longer care recovery timelines for non-comorbid visits, requiring 6.2 months to return to pre-pandemic levels compared to 2.8 months for comorbid cases.

These visual patterns align with observed differences in telehealth adoption rates (48% vs 28%) and

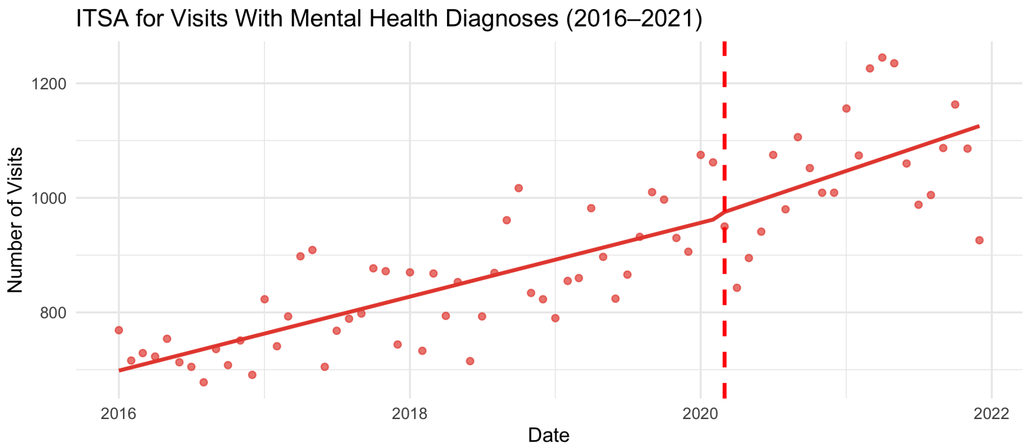


Figure 4: ITSA for Comorbid Visits with Mental Health Conditions

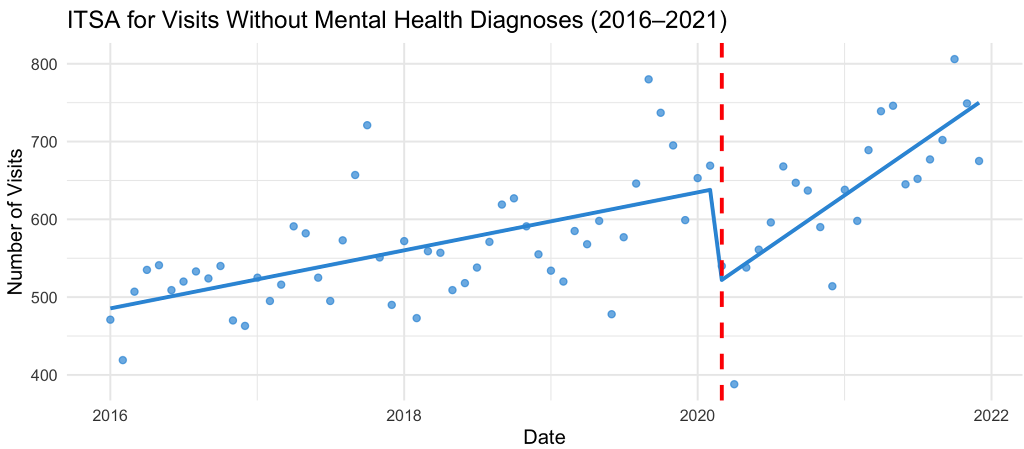


Figure 5: ITSA for Non-Comorbid Visits without Mental Health Conditions

emergency department throughput times (22% shorter processing for comorbid cases). The maintained growth trajectory for mental health-related visits despite pandemic constraints underscores the critical role of integrated care networks in sustaining service delivery during public health emergencies.

3.2 Hospital Burden

3.2.1 ED, ICU, and Inpatient Utilization

Figure 6 visually demonstrates estimated trends in emergency department (ED), intensive care unit (ICU), and inpatient visits from 2016 through 2021, comparing youth with and without mental health comorbidities. Across all settings, the volume of visits consistently increased, and youth with mental health comorbidities exhibited notably higher utilization compared to those without.

Table 3 (Appendix 7.3) summarizes the Negative Binomial GLMM results for ED visits. Youth with mental health comorbidities had approximately 12% higher ED visit rates compared to their peers without such comorbidities (IRR = 1.12, 95% CI: 1.04–1.18, $p = 0.0011$). The interaction between mental health status and time indicated that ED visits increased significantly faster among youth with comorbid mental health conditions, with a monthly increase rate approximately 0.31% higher compared to youth without such conditions ($p < 0.001$).

ICU visits, though less frequent overall, showed the strongest proportional difference. Youth with mental health comorbidities had approximately twice the rate of ICU utilization (IRR = 2.09, 95% CI: 1.84–2.37, $p < 0.001$). Additionally, ICU visits for youth with mental health comorbidities demonstrated a faster increase over time, with a monthly growth rate of approximately 0.45% higher than their counterparts without mental health conditions ($p = 0.0007$). These findings underscore a significant escalation in the severity and acuity of cases involving mental health conditions.

Inpatient visit utilization showed the largest impact from mental health comorbidities. Youth with mental health comorbidities had a 170% higher expected rate of inpatient visits ($p < 0.001$) compared to youth without mental health conditions. The rate of inpatient visits also increased significantly faster among youth with mental health comorbidities over the study period, rising about 0.15% faster per month compared to youth without mental health comorbidities ($p = 0.0407$). This pronounced trend highlights the increasing demand on hospital inpatient resources over time, particularly among youth experiencing concurrent substance use and mental health crises.

Collectively, these results reflect a substantial and growing clinical burden of youth with mental health comorbidities on pediatric hospital settings, emphasizing the need for targeted clinical and public health interventions.

3.2.2 Length of Stay

Figure 7 illustrates the estimated trends in hospital length of stay (LOS) from 2016 to 2021, comparing youth with and without mental health comorbidities. Throughout the study period, the length of hospital stay remained consistently higher among youth with mental health comorbidities compared to their peers without such conditions. Additionally, the gap between these two groups widened slightly over time, suggesting increased healthcare resource utilization among youth experiencing concurrent substance use and mental health conditions.

The Gamma GLMM results, summarized in Table 6 (Appendix 7.4), showed that mental health comorbidities were significantly associated with an increased length of hospital stay. Specifically, youth with mental health conditions had an estimated 161% longer LOS ($\exp(0.958) \approx 2.61$, $p < 0.001$) compared

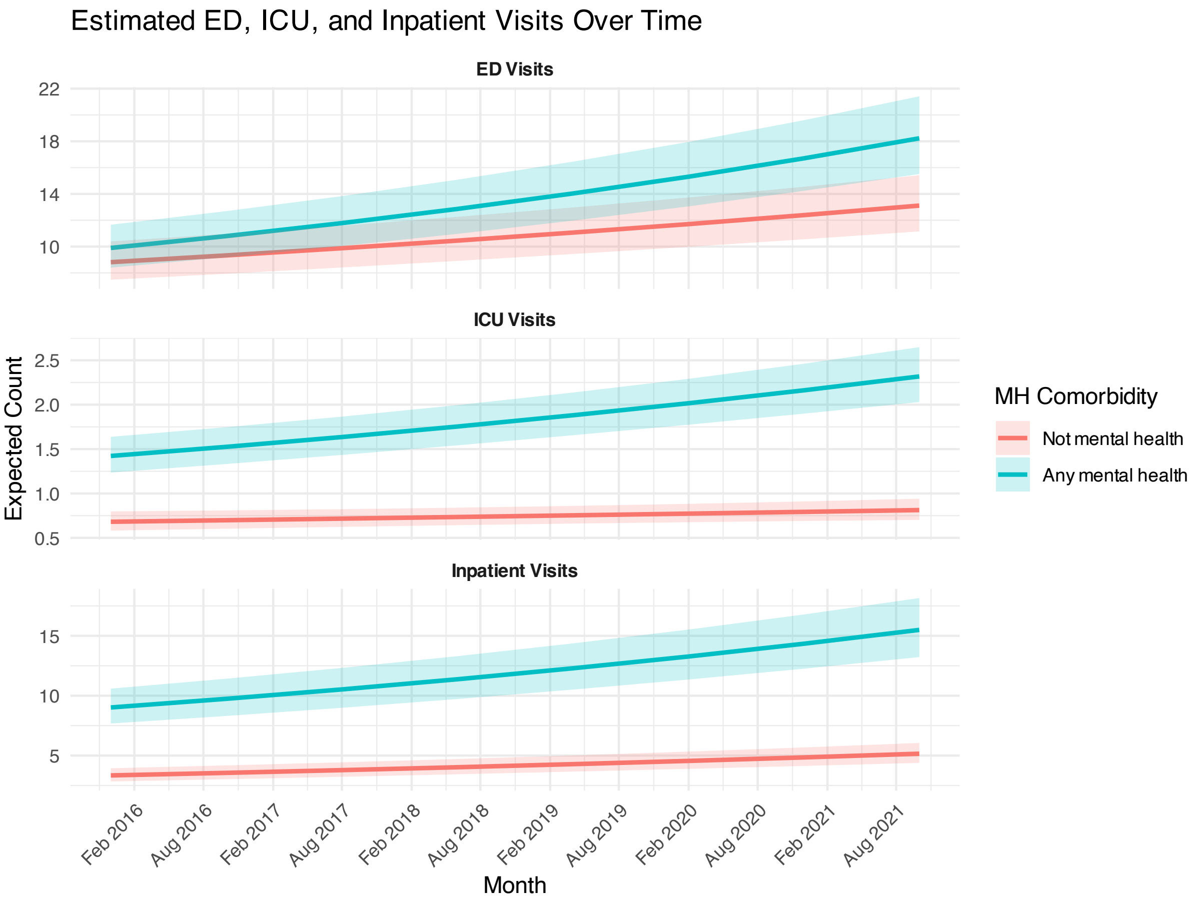


Figure 6: Estimated ED, ICU, and Inpatient Visits Over Time

to those without mental health comorbidities. The significant positive interaction between mental health status and time (estimate: 0.00198, $p < 0.001$) indicated a progressively increasing LOS among youth with mental health comorbidities compared to their peers without.

Polysubstance use was also significantly associated with longer hospital stays, corresponding to an approximate 29% increase in expected LOS ($\exp(0.251) \approx 1.29$, $p < 0.001$). Male youth had approximately 11% longer hospital stays compared to females ($\exp(0.105) \approx 1.11$, $p < 0.001$). Regarding race and ethnicity, Hispanic youth exhibited significantly shorter hospital stays (approximately 11% shorter, $\exp(-0.113) \approx 0.89$, $p < 0.001$), whereas youth classified as "Other" race/ethnicity had a significantly longer expected LOS compared to Non-Hispanic White youth (approximately 14% longer, $\exp(0.131) \approx 1.14$, $p < 0.001$). No statistically significant difference in LOS was observed between Non-Hispanic Black and Non-Hispanic White youth.

These findings highlight the substantial and growing resource demands posed by youth with mental health comorbidities, emphasizing the importance of targeted interventions and efficient hospital resource allocation strategies.

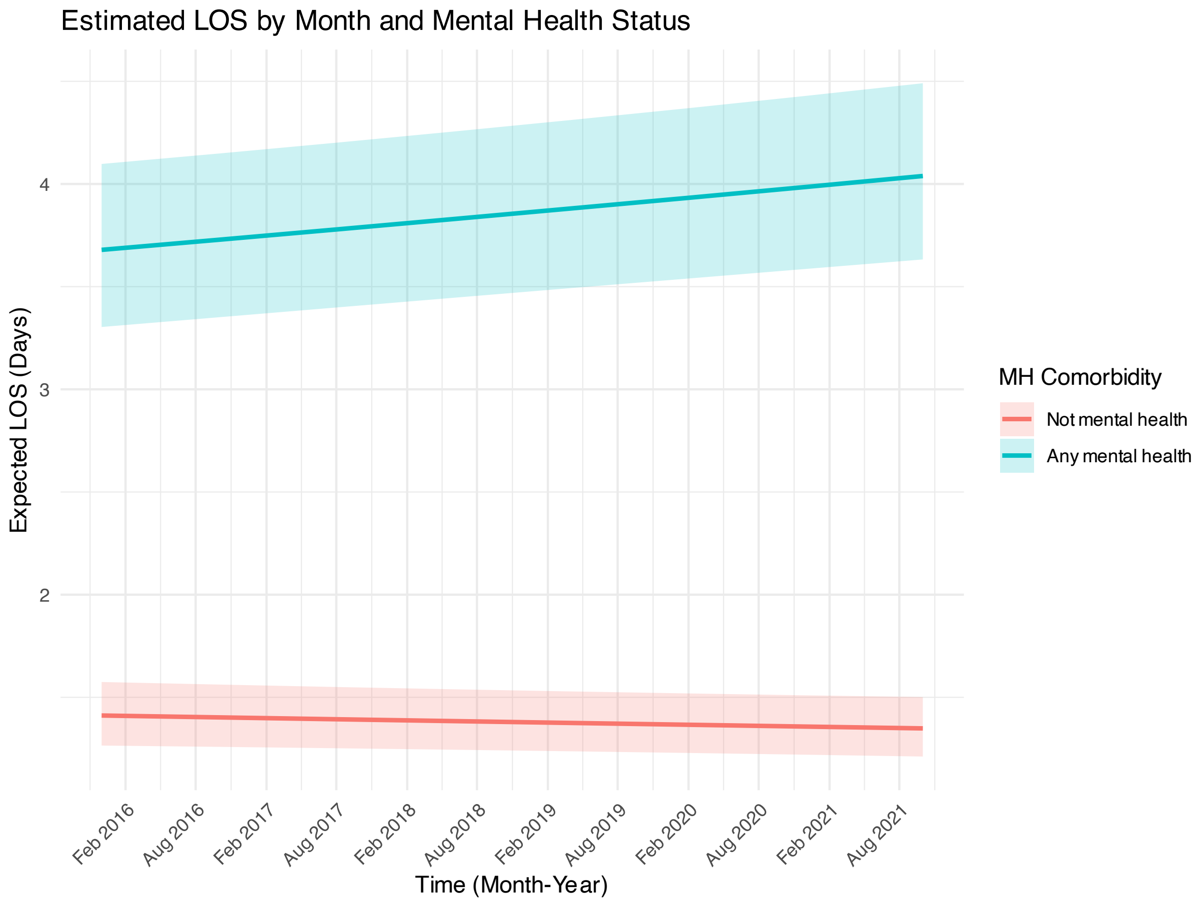


Figure 7: Estimated Length of Stay Over Time

4 Conclusion

This study provides new insights into the increasing burden of mental health comorbidities among youth presenting for substance-related hospital visits in the United States. Our findings highlight a significant rise in comorbid mental health diagnoses, with notable disparities based on demographic factors, substance type, and healthcare utilization patterns. The observed trends underscore the growing complexity of adolescent substance use and mental health disorders, necessitating a more integrated approach to treatment and prevention.

The COVID-19 pandemic served as a pivotal factor influencing hospital visit trends, with comorbid mental health visits exhibiting resilience despite widespread healthcare disruptions. This suggests an urgent need to strengthen mental health resources within pediatric healthcare systems, particularly in emergency and inpatient settings where these youth frequently seek care. The disproportionate increase in ICU and inpatient utilization among comorbid cases further emphasizes the severity of dual-diagnosis presentations and the necessity for proactive intervention strategies.

Future research should explore the underlying mechanisms driving these trends, including social determinants of health, barriers to early intervention, and the role of telehealth in improving access to care. Additionally, efforts to enhance mental health screening and support services in pediatric hospital settings will be essential in mitigating the long-term consequences of comorbid substance use and psychiatric disorders among youth.

By providing a data-driven understanding of these evolving healthcare trends, our study informs policy decisions, resource allocation, and clinical strategies aimed at improving outcomes for adolescents facing co-occurring substance use and mental health challenges.

Limitations Diagnostic coding of symptoms and medical conditions are done by physicians according to the ICD-10 system. Hospital billing departments then code medical services, create a claim based on those codes, submit the claim to the patient's insurance company for reimbursement, and send a patient statement for any remaining balance after the insurance company pays their portion. The billing department may revise physician codes to correct errors, meet insurance requirements, or avoid denials. Although revisions may systematically alter the truth of diagnoses, we assume this is rare enough to be negligible.

5 Code and Data Availability

The R code used for data processing, statistical modeling, and visualization is available at the following GitHub repository: `https://github.com/SZ-yang/UW_Capstone_MentalHealthComorbidity`

The dataset used in this analysis was provided by the Pediatric Health Information System (PHIS) and is subject to data use agreements. As a result, the raw data cannot be shared publicly. However, summary statistics and derived data supporting the findings of this study are available upon reasonable request.

6 Personal Contributions

Each team member contributed both to the analysis and the writing of this report.

Alejandro Hernandez led the analysis of trends by common conditions, identifying the most frequently occurring comorbid mental health conditions in substance-related hospital visits. Lingfei "Ellen" Jiang performed the total monthly visits analysis, modeling overall visit trends and evaluating differences based on mental health comorbidities. Joshua Shizhao Yang conducted the hospital burden analysis, which included emergency department (ED), intensive care unit (ICU), and inpatient utilization, as well as the length of stay analysis. Ruyue Wang was responsible for the interrupted time series analysis, assessing the impact of the COVID-19 pandemic on hospital visit trends.

In addition to their individual analytical contributions, all team members participated in writing and refining this report, ensuring clarity, coherence, and accuracy in presenting our findings.

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7 Appendix

7.1 Descriptive Statistics

7.1.1 Common Mental Health Comorbidities

Characteristic	Total number of visits (%)	Number of visits (%) in 2016	Number of visits (%) in 2021	Percent change from 2016-2021
Overall	106,693	14,705	21,567	**46.7**
Any Mental Health Condition	64,617 (60.6)	8,673 (59.0)	13,251 (61.4)	**52.8**
Depressive Disorders	35,677 (33.4)	4,591 (31.2)	7,014 (32.5)	**52.8**
Self-Injury or Suicide	30,041 (28.2)	3,623 (24.6)	6,595 (30.6)	**82**
Substance Use Disorder	28,351 (26.6)	4,194 (28.5)	5,585 (25.9)	**33.2**
Anxiety Disorders	27,545 (25.8)	3,142 (21.4)	6,448 (29.9)	**105**
ADHD	16,693 (15.7)	2,393 (16.3)	3,411 (15.8)	**42.5**
Trauma and Stress Related	11,761 (11.0)	1,367 (9.3)	2,872 (13.3)	**111**

Table 1: Characteristics of substance-related visits and percent change from 2016 to 2021.

7.2 Total Visits

To model the number of total monthly visits, we employed a **Generalized Linear Mixed Model (GLMM)** with a **Negative Binomial** distribution. The choice of the Negative Binomial model was driven by the count-based nature of our outcomes and the observed overdispersion in visit counts.

$$\begin{aligned}\log(\mu_{i,\text{TotalVisits}}) = \beta_0 &+ \beta_1(\text{time\_index})_i + \beta_2(\text{MH\_ANY})_i + \beta_3(\text{AGE\_YRS})_i + \beta_4(\text{RACE\_cat})_i \\ &+ \beta_5(\text{POLYSUBSTANCE})_i + \beta_6(\text{HOSP\_RECORDED\_SEX})_i \\ &+ \beta_7(\text{MH\_ANY\_num} \times \text{time\_index})_i + u_{\text{HOSPITAL}[i]}\end{aligned} \tag{1}$$

Data Preprocessing Prior to modeling, the data was processed as follows:

- **Data Cleaning and Preprocessing**: To ensure data quality, we first removed records where key patient demographic information was missing. Specifically, entries where race or sex were recorded as "Unknown" were excluded from the analysis.
- **Standardizing Dates and Defining Study Period**: Admission dates were converted into a standard date format. To maintain consistency in the analysis, we excluded any admissions that occurred before January 2016.
- **Creating a Temporal Index for Monthly Trends**: Since our analysis focused on trends over time, we grouped patient admissions into monthly intervals. Each unique year-month combination was assigned a sequential numeric value to facilitate modeling.
- **Aggregating Data at the Hospital-Month Level**: To model hospital utilization, we structured the dataset such that each row represented a unique hospital-month combination, further stratified by whether the patient had a documented mental health condition. For each hospital and month, we calculated:

- The total number of visits
- The total number of emergency department (ED) visits.
- The total number of intensive care unit (ICU) visits.
- The total number of inpatient hospitalizations.
- The average age of patients within the group.
- The proportion of female patients in the group.
- The proportion of patients with documented polysubstance use.
- The average hospital charges for the group.
- The racial composition of the group, expressed as the proportion of patients identified as Black, Hispanic, or Other, with White patients serving as the reference category.

Model Specification The Negative Binomial GLMM was specified as follows:

$$\text{Visits}_i \sim \text{NegBin}(\mu_i, \alpha), \tag{2}$$

where the mean μ_i is linked to the predictors by:
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$$\begin{aligned}\log(\mu_i) = \beta_0 &+ \beta_1(\text{time\_index})_i + \beta_2(\text{MH\_ANY})_i + \beta_3(\text{mean\_age})_i \\ &+ \beta_4(\text{female\_prop})_i + \beta_5(\text{polysub\_prop})_i \\ &+ \beta_6(\text{black\_prop})_i + \beta_7(\text{hispanic\_prop})_i + \beta_8(\text{other\_prop})_i + \beta_9(\text{time\_index})_i \times (\text{MH\_ANY})_i \\ &+ u_{\text{HOSPITAL}[i]},\end{aligned} \tag{3}$$

where:

- Visits_i represents the number of total number of visits for the i-th observation.
- μ_i is the expected number of visits for group i.
- α is the **dispersion parameter** of the Negative Binomial distribution.
- $u_{\text{HOSPITAL}[i]}$ is the **random intercept** accounting for hospital-level variation.
- Predictor of Interest is:
  - MH_ANY_i: Indicator for mental health comorbidities (1 if present, 0 otherwise).
- Covariates include:
  - time_index_i: A sequential numeric index for months.
  - mean_age_i: Average age of patients in the group.
  - female_prop_i: Proportion of female patients.
  - polysub_prop_i: Proportion of patients with more than one substance use.
  - black_prop_i, hispanic_prop_i, other_prop_i: Race proportions, with non-Hispanic White as the reference category.

The model was fit separately using the ‘glmmTMB‘ package in R.

Result Table

Predictors	Mean Rate Ratio	CI	p
(Intercept)	5.89	3.95 – 8.79	**<0.001**
time index mon	1.01	1.00 – 1.01	**<0.001**
MH ANY [One or more]	1.30	1.24 – 1.37	**<0.001**
mean age	1.03	1.01 – 1.05	**0.006**
prop female	1.21	1.11 – 1.32	**<0.001**
prop polysub	1.37	1.23 – 1.53	**<0.001**
prop other	0.83	0.70 – 0.99	**0.037**
prop black	0.92	0.82 – 1.02	0.111
prop hispanic	1.03	0.93 – 1.15	0.524
time index mon × MH ANY [One or more]	1.00	1.00 – 1.00	**<0.001**
Random Effects			
HOSPITAL (Intercept)	0.21		
Number of Groups (HOSPITAL)	39		
Observations	5617		
Dispersion Parameter (nbinom2)	7.13		

Table 2: Results of the Negative Binomial Model for Total Visits

7.3 ED, ICU, and Inpatient Utilization

Model Specification To model the number of Emergency Department (ED), Intensive Care Unit (ICU), and Inpatient visits, we employed a Generalized Linear Mixed Model (GLMM) with a Negative Binomial distribution. This approach was chosen due to the count-based nature of the outcomes and the presence of overdispersion in hospital visit counts.

The model was specified as follows:

$$\text{Visits}_i \sim \text{NegBin}(\mu_i, \alpha), \tag{4}$$

where the mean μ_i is linked to the predictors by:

$$\begin{aligned}\log(\mu_i) = {} & \beta_0 + \beta_1(\text{MH\_ANY\_num})_i + \beta_2(\text{time\_index})_i \\ & + \beta_3(\text{AGE\_YRS})_i + \beta_4(\text{RACE\_cat})_i \\ & + \beta_5(\text{POLYSUBSTANCE})_i + \beta_6(\text{HOSP\_RECORDED\_SEX})_i \\ & + \beta_7(\text{MH\_ANY\_num} \times \text{time\_index})_i + u_{\text{HOSPITAL}[i]},\end{aligned} \tag{5}$$

where:

- Visits_i represents the number of hospital visits (ED, ICU, or inpatient) for the i-th observation.
- μ_i is the expected number of visits for group i.
- α is the dispersion parameter of the Negative Binomial distribution.
- $u_{\text{HOSPITAL}[i]}$ is the random intercept accounting for hospital-level variation.
- Covariates include:
  - MH_ANY_num_i: Indicator for mental health comorbidities (1 if present, 0 otherwise).
  - time_index_i: Sequential numeric index for months.
  - AGE_YRS_i: Age of the patient in years.
  - RACE_cat_i: Categorical race variable (White as reference).

– POLYSUBSTANCE_i: Indicator for polysubstance use (1 if present, 0 otherwise).
– $\text{HOSP\_RECORDED\_SEX}_i$: Patient sex (Male or Female).
– MH_ANY_num × time_index: Interaction term assessing whether trends over time differ by mental health status.

Data Preprocessing Prior to modeling, data underwent several preprocessing steps to ensure analytical rigor and consistency. Initially, data cleaning was conducted by removing all entries with unknown race or sex, ensuring completeness of demographic variables crucial for analysis. Subsequently, the analysis was limited to hospital admissions occurring within the defined study period, from January 2016 to December 2021. To appropriately model the hospital utilization trends over time, patient-level data were aggregated by hospital and month, stratified based on mental health comorbidity status. During aggregation, demographic variables were transformed into analytically meaningful categories: race was grouped into Non-Hispanic White (as reference), Black, Hispanic, and Other, while proportions of sex and polysubstance use were calculated within each hospital-month group. This approach provided a structured dataset suitable for the subsequent mixed-effects modeling.

Result Table The estimated model results for each outcome (ED, ICU, and Inpatient visits) are summarized in the following tables:

Predictors	IRR (Exp(Estimate))	95% CI	p-value
(Intercept)	6.46	4.19 – 9.97	**<0.001**
MH Comorbidity	1.12	1.04 – 1.18	**0.0011**
Time Index	1.0057	1.0048 – 1.0067	**<0.001**
Mean Age	1.0163	0.995 – 1.037	0.152
Female Proportion	1.0864	0.993 – 1.184	0.0734
Polysubstance Use	0.9680	0.885 – 1.059	0.4976
Other Race Proportion	0.8213	0.689 – 0.979	**0.028**
Black Proportion	0.9319	0.836 – 1.037	0.234
Hispanic Proportion	1.1692	1.038 – 1.317	**0.0102**
MH Comorbidity × Time Index	1.0031	1.0018 – 1.0044	**<0.001**
Random Effects			
HOSPITAL (Intercept)	Variance: 0.2513	Std. Dev: 0.5013	
Observations	5466		
Groups (HOSPITAL)	39		
Dispersion (Negative Binomial)	5.38		

Table 3: Exponentiated Results of the Negative Binomial Model for ED Visits

7.4 Length of Stay (LOS)

Model Specification To model the length of hospital stay (LOS), we employed a Generalized Linear Mixed Model (GLMM) with a Gamma distribution and a log link function. This modeling choice was based on LOS being strictly positive, continuous, and typically right-skewed. The Gamma GLMM was specified as follows:

$$\text{LOS}_i \sim \text{Gamma}(\mu_i, \sigma^2), \tag{6}$$

Predictors	IRR	95% CI	p-value
(Intercept)	0.8903	0.540 – 1.485	0.6781
MH Comorbidity	2.0887	1.841 – 2.369	**<0.001**
Time Index	1.0025	1.0012 – 1.0048	**0.0217**
Mean Age	0.9884	0.946 – 1.032	0.6108
Female Proportion	0.7457	0.639 – 0.871	**0.0002**
Polysubstance Use	1.7380	1.492 – 2.027	**<0.001**
Other Race Proportion	0.9055	0.733 – 1.120	0.3587
Black Proportion	0.9064	0.776 – 1.058	0.2103
Hispanic Proportion	0.9782	0.794 – 1.206	0.8432
MH Comorbidity × Time Index	1.0045	1.0020 – 1.0070	**0.0007**
Random Effects			
HOSPITAL (Intercept)	Variance: 0.1523	Std. Dev: 0.3903	
Observations	5466		
Groups (HOSPITAL)	39		
Dispersion (Negative Binomial)	13.00		

Table 4: Exponentiated Results of the Negative Binomial Model for ICU Visits

where the expected length of stay μ_i is linked to predictors by:

$$\begin{aligned}\log(\mu_i) = \beta_0 &+ \beta_1(\text{MH\_ANY\_num})_i + \beta_2(\text{time\_index})_i + \beta_3(\text{AGE\_YRS})_i \\ &+ \beta_4(\text{RACE\_cat})_i + \beta_5(\text{POLYSUBSTANCE})_i \\ &+ \beta_6(\text{HOSP\_RECORDED\_SEX})_i + \beta_7(\text{MH\_ANY\_num} \times \text{time\_index})_i \\ &+ u_{\text{HOSPITAL}[i]},\end{aligned} \tag{7}$$

where:

- LOS_i represents the length of hospital stay for the i-th visit.
- μ_i is the expected LOS for visit i.
- σ^2 is the dispersion parameter for the Gamma distribution.
- $u_{\text{HOSPITAL}[i]}$ is a random intercept term, capturing hospital-level variability.

Covariates included in the model were:

- **MH_ANY_num**: Mental health comorbidity indicator (1 if any mental health condition present, 0 otherwise).
- **time_index**: Sequential numeric index representing monthly intervals from January 2016 through November 2021.
- **AGE_YRS**: Age of the patient at the time of visit (in years).
- **RACE_cat**: Race/ethnicity categorized into White (reference), Black, Hispanic, and Other.
- **POLYSUBSTANCE**: Binary indicator for multiple substances involved (1 if polysubstance use, 0 otherwise).

Predictors	IRR	95% CI	p-value
(Intercept)	4.5102	2.980 – 6.826	**<0.001**
MH Comorbidity	2.6992	2.410 – 3.024	**<0.001**
Time Index	1.0062	1.0048 – 1.0076	**<0.001**
Mean Age	0.9968	0.976 – 1.018	0.6322
Female Proportion	0.9230	0.810 – 1.051	0.2378
Polysubstance Use	1.8523	1.633 – 2.100	**<0.001**
Other Race Proportion	0.7330	0.574 – 0.936	**0.0132**
Black Proportion	0.9694	0.865 – 1.086	0.6058
Hispanic Proportion	1.1012	0.932 – 1.301	0.2873
MH Comorbidity × Time Index	1.0015	1.0001 – 1.0029	**0.0407**
Random Effects			
HOSPITAL (Intercept)	Variance: 0.2431	Std. Dev: 0.4930	
Observations	5466		
Groups (HOSPITAL)	39		

Table 5: Exponentiated Results of the Negative Binomial Model for Inpatient Visits

- **HOSP_RECORDED_SEX**: Patient sex as recorded by the hospital (male/female).
- **Interaction term (MH_ANY_num × time_index)**: To capture potential differential trends over time based on mental health comorbidity status.

This model was fit using the `glmmTMB` package in R.

Data Preprocessing The following preprocessing steps were applied to the dataset prior to modeling:

Initially, the data was cleaned by excluding any records with unknown or missing values for race/ethnicity or sex to ensure analytical accuracy and completeness. Dates of admission were standardized to the "YYYY-MM-DD" format, and only admissions occurring between January 2016 and November 2021 were retained.

Records with a length of stay (LOS) of zero or less were removed to comply with the Gamma model requirement of strictly positive outcomes. Race and ethnicity were recategorized into four distinct groups: White (reference), Black, Hispanic, and Other. A binary indicator (MH_ANY_num) was created for mental health comorbidity status, indicating the presence (coded as 1) or absence (coded as 0) of any mental health condition.

A monthly time index (time_index) was created to capture temporal trends, beginning in January 2016. Lastly, a random intercept term was introduced at the hospital level to account for inherent variations among the 39 participating hospitals.

Result Table

7.5 Interrupted Time Series Analysis

Model Specification The interrupted time series analysis employed segmented linear regression to evaluate COVID-19's impact on substance-related healthcare utilization patterns. The core model specification incorporates both immediate level changes and long-term trend modifications following the pandemic onset:

Predictors	Estimate	Std. Error	p-value
(Intercept)	0.199	0.068	0.0032 **
MH_ANY_num	0.958	0.021	<2e-16 ***
time_index	-0.00065	0.00033	0.0500 *
AGE_YRS	0.00876	0.00225	0.0001 ***
RACE_catBlack	-0.0099	0.0112	0.377
RACE_catHispanic	-0.113	0.0126	<2e-16 ***
RACE_catOther	0.131	0.0173	5.10e-14 ***
POLYSUBSTANCE	0.251	0.0105	<2e-16 ***
HOSP_RECORDED_SEX (Male)	0.105	0.0085	<2e-16 ***
MH_ANY_num × time_index	0.00198	0.00042	2.45e-06 ***
Random Effects			
Hospital intercept variance	0.110	Std. Dev: 0.331	
Dispersion (Gamma)	1.69		
Observations	97,010		
Groups (Hospitals)	39		

Significance codes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Table 6: Results of the Gamma GLMM for Length of Stay (LOS)

$$Y_t = \beta_0 + \beta_1 \cdot \text{TIME} + \beta_2 \cdot \text{POST} + \beta_3 \cdot (\text{TIME} \times \text{POST}) + \epsilon_t \tag{8}$$

Where Y_t represents monthly visit counts stratified by mental health comorbidity status. The temporal components include a continuous TIME variable (coded 1-71 from January 2016 to November 2021), a binary POST indicator distinguishing pre-pandemic (0) and post-pandemic (1) periods with March 2020 as the intervention point, and their interaction term capturing trend changes. The error term ϵ_t follows a normal distribution with constant variance.

Data Preprocessing The analysis included 71 monthly observations from January 2016 through November 2021, excluding December 2021 data to mitigate right-truncation bias. We removed 2.9% of records with missing demographic data (primarily race/ethnicity [2.1%] and sex [0.8%]) through complete-case analysis. Monthly aggregates were created separately for two clinical subgroups: substance-related visits with documented mental health comorbidities (MH_ANY_num = 1) and those without such comorbidities (MH_ANY_num = 0). Institutional variability was accounted for through random intercepts representing the 39 participating hospitals. Sensitivity analyses excluding October-December 2021 data confirmed the robustness of our findings against potential truncation effects.

Results The ITSA models revealed distinct pandemic impacts across clinical subgroups. For visits without mental health comorbidities (Table 7), we observed a significant pre-pandemic upward trend ($\beta_{\text{TIME}} = 3.06$, $p < 0.001$) followed by an immediate 505-visit reduction post-COVID onset ($\beta_{\text{POST}} = -505.26$, $p < 0.001$) and subsequent accelerated monthly increases ($\beta_{\text{TIME}\times\text{POST}} = 7.62$, $p < 0.001$). The model explained 53.8% of variance ($R^2 = 0.538$, $F(3, 68) = 26.43$, $p < 0.001$) with residual standard error of 60.43.

In contrast, visits with mental health comorbidities (Table 8) demonstrated stronger baseline trends ($\beta_{\text{TIME}} = 5.30$, $p < 0.001$) but no significant pandemic-related disruptions. Neither the immediate level

Table 7: ITSA Results for Non-Comorbid Visits

Parameter	Estimate	SE	t-value	p-value
Intercept	485.49	16.84	28.83	<0.001
TIME	3.06	0.58	5.25	<0.001
POST	-505.26	124.64	-4.05	<0.001
TIME × POST	7.62	2.08	3.66	<0.001

change ($\beta_{\text{POST}} = -79.79$, $p = 0.625$) nor trend modification ($\beta_{\text{TIME}\times\text{POST}} = 1.74$, $p = 0.525$) reached statistical significance, despite superior model fit ($R^2 = 0.721$, $F(3, 68) = 58.57$, $p < 0.001$).

Table 8: ITSA Results for Comorbid Visits

Parameter	Estimate	SE	t-value	p-value
Intercept	698.42	21.93	31.85	<0.001
TIME	5.30	0.76	6.97	<0.001
POST	-79.79	162.29	-0.49	0.625
TIME × POST	1.74	2.71	0.64	0.525

This differential response pattern suggests mental health comorbidities may buffer against pandemic-related care disruptions, evidenced by stable utilization trends compared to the substantial initial decline and subsequent acceleration in non-comorbid visits. The superior model fit for comorbid visits (72.1% vs 53.8% explained variance) further indicates more predictable utilization patterns in this population throughout the study period.