Assessing the Impact of Homelessness on COVID-19 Hospitalization Rates in Patients with Underlying Medical Conditions Through Explainable AI

J. M. Imtinan Uddin[1], Hayden Hall[2], Jessica Long[3], Connor Kimbrell[2], Isabel Obrien[2], Sudave Mendiratta[2], Patrick Koo[2], Yingfeng Wang[1], and Hong Qin[1,4](✉)

[1] Department of Computer Science and Engineering, The University of Tennessee at Chattanooga, Chattanooga, USA
cbj988@mocs.utc.edu, yingfeng-wang@utc.edu

[2] The University of Tennessee Health Science Center, Chattanooga, USA
{hhall27,pkoo}@uthsc.edu

[3] Erlanger Health System, Chattanooga, USA
Jessica.Long@erlanger.org

[4] Department of Computer Science, Old Dominion University, Norfolk, USA
hqin@odu.edu

Abstract. Preexisting comorbidities like COPD and smoking history increase SARS-CoV-2 risk, but the impact of homelessness and mental health remains underexplored. This study investigates the correlation between homelessness and COVID-19 hospitalizations in patients with COPD, mental illness, smoking habit, and age using national EHR data from All of Us, including 129,524 patients, 3,547 of whom were homeless. A statistical examination using logistic regression confirmed that homelessness increases hospitalization odds, with 19.83% of homeless COVID-19 patients hospitalized, compared to 15.08% in the general population. SHAP plots, an explainable AI method highlighted significant interactions between homelessness, COPD, smoking, gender, and mental disorders on COVID-19 hospitalizations.

Keywords: Homeless · COVID-19 · Hospitalizations · COPD · Mental Disorder · Explainable AI

1 Introduction

Homelessness is a burgeoning social obstacle in the United States of America. A report from 2023 shows that 653,100 people were experiencing homelessness in the United States of America, which is a 12% increase from 2022 [1]. Homelessness is associated with a wide range of factors such as domestic violence, poverty, inadequate access to resources, and unaffordable housing [2–6]. This problem has a connection with mental disorders, drug abuse, and the criminal justice system [7,8]. Homeless people experience different kinds of chronic diseases as they have limited access to proper medical care and health insurance,

R. Stahlbock and H. R. Arabnia (Eds.): CSCE 2024, CCIS 2253, pp. 1–15, 2025.
https://doi.org/10.1007/978-3-031-85856-7_9

making the homeless population have higher vulnerability and morbidity than the general population. Often, homeless people have many underlying conditions that remain unaddressed because of their unwillingness to express their healthcare needs, thus putting homeless people at risk [9,10]. Homeless people are more prone to chronic obstructive pulmonary disease (COPD), asthma and other pulmonary diseases. The outbreak of COVID-19 has shown an unprecedented challenge to the public health systems worldwide. Unfortunately, since then, homeless people have had a tough time, making them more susceptible to the COVID-19 pandemic. The virus responsible for COVID-19 can transmit quickly, spreading infections with a heightened risk of infecting people who live in homeless shelters. Elderly individuals and those with pre-existing diseases are at a higher risk of experiencing severe symptoms from COVID-19 [15]. The homeless population often have illnesses similar to older adults and develop the conditions at an earlier stage of life than the general population [16]. In addition, chronic illnesses like hypertension, diabetes mellitus, pulmonary diseases, and cardiovascular disease are more frequent among the homeless than in the general population and are often left uncured [17,18]. Data also indicates a higher rate of infection with COVID-19 among persons experiencing homelessness [14]. Also, it has been observed that a previous history of Chronic Obstructive Pulmonary diseases and asthma increases the severity of COVID-19-related illness among homeless [11,12], thus increasing the risk of COVID-19-related hospitalization.

Many researchers have investigated the impact of COVID-19 on the homeless population. In [22], the authors focused exclusively on determining the COVID-19 infection rate among the homeless in the Greater Boston area. Similarly, authors in [23] examined COVID-19 positive rates among the homeless, but their study was limited to major cities, neglecting the fact that homeless individuals also reside in smaller cities and rural areas. Although, authors in [24] attempted to analyze the impact of various factors on COVID-19 hospitalization among the homeless, their study had several limitations. Furthermore, the method used to identify recent homelessness may have overlooked individuals not utilizing health or shelter services. The study also failed to differentiate between various subgroups within the homeless population and did not investigate factors associated with acute care utilization during the COVID-19 pandemic.

So, health disparity is prevalent among homeless, which affects their health. Moreover, the COVID-19 outbreak added additional severity to homeless health, such as the increased risk of COVID-19 hospitalization. However, little is known about how the pandemic and what factors have impacted hospitalizations among this vulnerable population. This research aims to determine which variables affect clinical severity most, like COVID-19 hospitalization, focusing on a statistical analysis and explainable AI to find the prevalence of Chronic obstructive pulmonary disease (COPD), COVID-19, and other associated factors in COVID-19 hospitalizations among the homeless population.

The rest of the paper is organized as follows. Section 2 contains the research methodology. Section 3 contains results and discussion of our proposed method. Section 4 contains the conclusion.

2 Research Methodology

In this study, a pairwise method is initially used, employing Eq. 1, 2, 3, 4, 5 to determine the prevalence of Chronic Obstructive Pulmonary disease (COPD), COVID-19 and their comorbidity among the homeless population in comparison to the non-homeless population, facilitating understanding of the effect of preexisting disease history in the COVID-19. Later, a statistical method using logistic regression is used to identify and quantify the factors contributing to COVID-19-related hospitalization among the homeless population, which was corroborated by SHapley Additive exPlanations (SHAP), an explainable AI method [13]. Figure 1 illustrates our proposed methodology for this research.

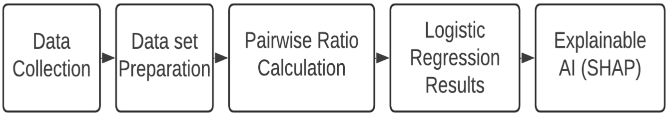


Fig. 1. Flowchart of the proposed method

In the following subsections, more detail about the methodology is discussed.

2.1 Data Collection

The dataset utilized in this study was gathered from the All of Us Research Platform's [26] Survey Domain and Observation Domain, spanning the period from February 1, 2020, to July 1, 2022, from the USA. In the Survey Domain, participants were asked various questions about their living conditions and place of residence. Observation Domain stores clinical data about a patient obtained in the context of an examination, questioning, or procedure, and data not represented by another domain, such as medical history, social and lifestyle facts, and family history, recorded here.

Homeless Participant Selection Criteria. The criteria used to identify and filter homeless participants for this study involved a combination of survey responses and direct observation spread across two primary domains. In the Survey Domain, participants were classified as homeless based on their responses to specific questions. Those who reported living outside or self-identified as homeless were included. This was determined using questions such as "Where are you currently living?" with an answer option of "Outside," and "What type of household do you live in?" with an option for "Homeless." In the Observation Domain, participants were directly labeled as "Homeless" based on observational data.

Initially, these methods combined to identify a total of 7,010 homeless participants. Additional filtering criteria were then applied to refine this group. Participants who did not provide gender information, either by skipping the question or preferring not to answer, were excluded. The study then focused on participants aged between 40 to 95 years old. After applying these filters, the final count of participants identified as homeless and fitting the age and gender criteria was 3,547. This rigorous process ensured a focused and relevant participant group for the study.

Non-homeless Participant Selection Criteria. The survey domain and observation domain were used to determine the non-homeless population, where participants were asked questions about their living place and the type of it. Participants who responded affirmatively about having a living place were marked as non-homeless. Initially, 357,499 non-homeless were identified based on their answer. Then, additional filtering was applied to exclude participants who skipped gender information and include participants aged between 40 and 95 years, yielding a total number of participants of 125,977.

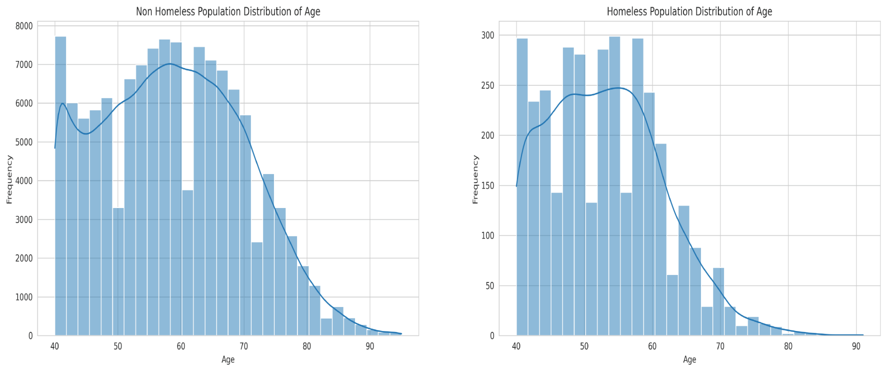
2.2 Dataset Description

This dataset contains 3,547 homeless participants and 125,977 non-homeless participants aged between 40 to 95 years containing the participant's unique identification number, gender, age, smoking history, COPD history, COVID-19-history, mental illness history, COVID-19-related hospitalization history. The following Table 1 describes the features of the dataset used in this study.

Table 1. Features description

Variable	Type	Categories/Range
Smoker	Categorical	Yes/No
Homeless	Categorical	Yes/No
Mental Disorder	Categorical	Yes/No
Age	Categorical	40 to 95 years
Gender	Categorical	Male/Female
COPD	Categorical	Yes/No
Covid-19 Hospitalization	Categorical	Yes/No

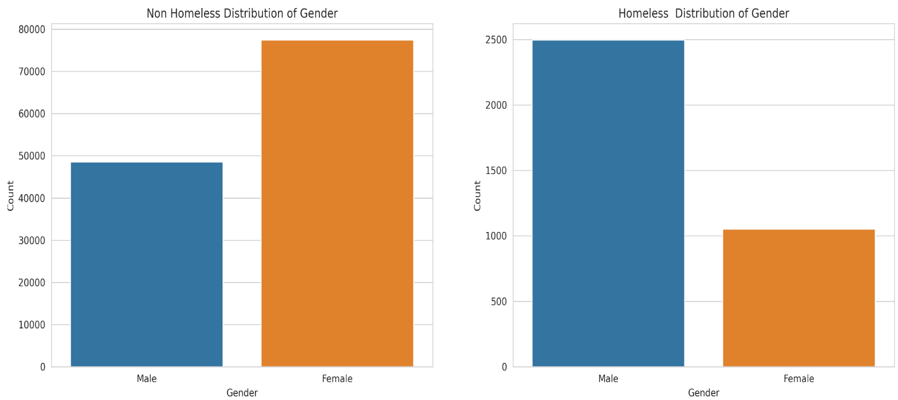
Comparing both Figs. 2a and 2b, it appears that the non-homeless population has a higher frequency of individuals in younger age groups, which could be due



(a) Non Homeless age distribution (b) Homeless age distribution

Fig. 2. Age distribution comparison between non-homeless and homeless populations

to a larger overall population size or a different age structure in the general population. The homeless population shows a more even distribution across middle ages but a sharp decline in older ages, which could reflect various socioeconomic factors or access to resources affecting lifespan and the likelihood of becoming homeless at different ages.



(a) Non Homeless gender distribution (b) Homeless gender distribution

Fig. 3. Gender distribution comparison between non-homeless and homeless populations

Comparing the gender distributions using Fig. 3a and 3b, it's apparent that within the homeless population, males are disproportionately represented. This could be due to a variety of social, economic, and health-related factors. On the other hand, the gender distribution in the non-homeless population is more balanced, which is typical in many societies where the numbers of males and females are fairly equal.

The participants include COVID-19-positive patients who required hospitalization. The following Table 2 describes the participant count for different types of COVID-19 patients among people experiencing homelessness. Among the 474 COVID-19-positive homeless patients, 94 (19.83%) were hospitalized.

Table 2. Case Group/Homeless Participant Count

Description	Count
Total Homeless Patients	3,547
COVID-19 Positive Hospitalized Patients	94
COVID-19 Positive Homeless Patients	474
COVID-19 "Non-Determined Homeless"	3,073

The following Table 3 describes the participant count for different types of COVID patients among non-homeless.

Table 3. Control Group/Non Homeless Participant Count

Description	Count
Total Non-Homeless Patients	125,977
COVID-19 Positive Hospitalized Patients	1,882
COVID-19 Positive Patients	12,480
COVID-19 "Non-Determined" Non-Homeless	111,615

The control group includes 12,480 COVID-19-positive non-homeless patients; among them, 1,882 (15.08%) were hospitalized, making it evident that COVID-19 hospitalization is more prevalent in homeless population.

The data presented in Table 4 outlines various health conditions and statuses among homeless and non-homeless populations, with a focus on smoking, COVID-19 hospitalizations, mental disorders, and Chronic Obstructive Pulmonary Disease (COPD). Among the non-homeless, smokers constituted 18.46% of the population, while a higher proportion of homeless individuals, at 32.79%, were smokers. COVID-19 hospitalization rates for smokers showed a significant disparity; 54.26% of homeless smokers required hospitalization compared to 24.65% of non-homeless smokers. A striking 95.74% of homeless individuals hospitalized for COVID-19 had mental disorders, compared to 73.70% in the non-homeless hospitalized group. The prevalence of mental disorders was also high among the homeless population at 90.89%, compared to 60.82% among

Table 4. Summary of Cases

Category	Positive Cases	Total Cases	%
S, NH	23,259	125,977	18.46
S, H	1,163	3,547	32.79
Hosp., S, H	51	94	54.26
Hosp., S, NH	464	1,882	24.65
MD, Hosp., H	90	94	95.74
MD, Hosp., NH	1,387	1,882	73.70
MD, H	3,224	3,547	90.89
MD, NH	76,614	125,977	60.82
COPD, Hosp., H	40	94	42.55
COPD, Hosp., NH	571	1,882	30.34
COPD, H	1,226	3,547	34.56
COPD, NH	18,878	125,977	14.99

NH = Non-Homeless, H = Homeless, Hosp. = Covid-19 Hospitalization, S = Smoker, MD = Mental Disorder, COPD = Chronic Obstructive Pulmonary Disease.

the non-homeless. For those with COPD, the hospitalization requirement due to COVID-19 was 42.55 % for the homeless and 30.34 % for the non-homeless. The overall COPD prevalence was 34.56% among homeless individuals and significantly lower at 14.99% in the non-homeless population. This data highlights the disproportionate impact of these health conditions on homeless individuals, especially regarding hospitalization rates and the prevalence of mental disorders and COPD.

Figure 4 also provides graphic visualization of the Table 4.

2.3 Dataset Preparation

Each participant's documented history of certain diseases is examined against their COVID-19 hospitalization status. To analyze the impact of specific diseases, gender or habits on the hospitalization rates among homeless people due to COVID-19, the dataset was organized by assigning a unique ID to each participant. The medical history of the participants was grouped under these IDs. If a participant had a documented history of a particular disease, such as Chronic Obstructive Pulmonary Disease (COPD), the corresponding column for that disease was marked as "YES." Conversely, if there was no history of the disease, the column was marked as "NO" . This approach enabled the examination of how different features, including the presence of specific diseases or habits, might influence the hospitalization rates among homeless people who contracted COVID-19. This structured data is essential for identifying correlations and potentially

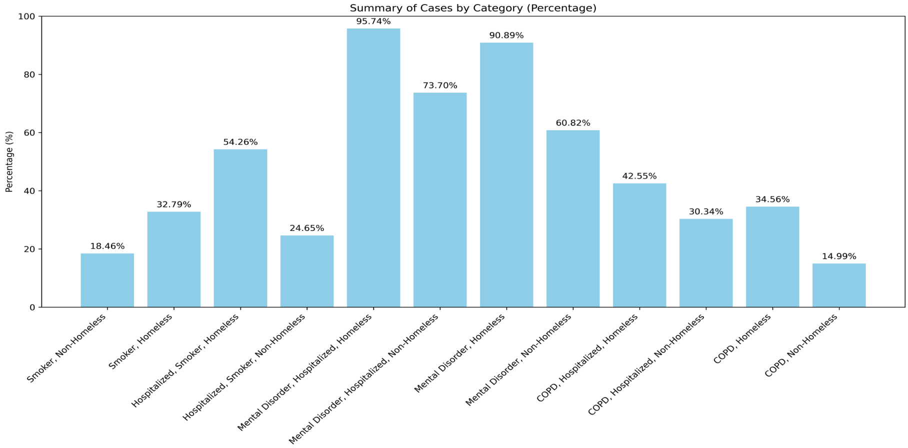


Fig. 4. Summary of cases by category

causative factors affecting health outcomes in this vulnerable population. Later, a label encoder was used to code "YES" and "Male" as "1" and "0" otherwise.

2.4 Pairwise Ratio Calculation of COPD and COVID-19

A matrix representing COPD and COVID-19 interactions among a population is constructed and normalized. For two diseases D_1 as COPD and D_2 as COVID-19, the interaction count $count(D_1, D_2)$ is calculated, which represents the number of individuals diagnosed with both D_1 and D_2 together, yielding comorbidity of D_1 and D_2. The resulting counts are then normalized to represent the proportion of the population exhibiting each disease combination. Let T denote the total count of participants in the study. The normalized interaction for each disease pair is computed as $Normalized\ Interaction = \frac{count(D_1,D_2)}{T} \times 100$. This normalization process converts the raw interaction counts into percentages, indicating the prevalence of each disease combination relative to the total population. Equations 3, 4 were used to calculate the interaction for homeless and non-homeless populations.

$$\text{Interaction Count}_{D_1,D_2} = count(D_1, D_2) \tag{1}$$

$$T = \text{Total number of individuals} \tag{2}$$

$$\text{Interaction of Homeless}_{D_1,D_2} = \frac{\text{Interaction Count}_{D_1,D_2}}{T_{\text{Homeless}}} \tag{3}$$

$$\text{Interaction of Non-homeless}_{D_1,D_2} = \frac{\text{Interaction Count}_{D_1,D_2}}{T_{\text{Non-homeless}}} \tag{4}$$

$$\text{Comparison of Interactions} = \frac{\text{Interaction of Homeless}_{D_1,D_2}}{\text{Interaction of Non-homeless}_{D_1,D_2}} \quad (5)$$

These final ratios of interactions obtained by Eq. 5 is used to understand the prevalence of COPD and COVID-19 in the homeless population compared to the non-homeless population. This approach allows us to gain insights into potential differences in COPD and COVID-19 patterns and pervasiveness between these two distinct groups of people. The provided visualization in Fig. 5 in the result section visually represents these findings, shedding light on the widespread presence of the disease among homeless and non-homeless individuals.

2.5 Statistical Analysis

Statistical analyses, such as P-value, 95% Confidence Interval (95% CI), and Odds Ratios, were determined for variables like age, COPD, smoking history, and mental disorder, which may increase the risk of COVID-19 hospitalization in homeless. Pairwise logistic regression is used between predictor variables like age, gender, COPD history, smoking history, and mental disorder history with the target variable, COVID-19 hospitalization, to determine the P-value, 95% confidence interval, and odd ratio. The significance of logistic regression in statistical analysis is underscored by its ability to handle binary and categorical outcomes, provide interpretable results, model complex relationships. The results in the logistic regression model indicate how the relationship between homelessness and COVID-19 hospitalization odds (Odd Ratio) changes when considering the effect of another variable compared to the reference group, which consists of individuals who are not homeless and do not have the condition specified above (e.g., age, smoking history, mental disorder, gender, COPD). The analysis determines the p-value, indicating the statistical significance of the results rejecting the null hypothesis where it states that the specific disease condition has no contribution on covid-19 hospitalization. A p-value of less than 0.001 suggests that the result provides enough confidence that the result observed is not due to random chance.

2.6 Explainable AI (SHAP Values)

AI or Machine learning is being used everywhere in this modern technological world, from the healthcare sector to space technologies [19–21,25]. Previously, the AI model was a black box, making it difficult to understand its inner operations. However, Explainable AI or interpretable AI is a system that can understand the underlying reasoning of an AI model's decision-making process. It provides an overall insight into a predictor variable's range of affecting capability on an AI model's decision, unlike the black box idea of the AI model. This research employs an explainable AI-based method, namely SHapley Additive exPlanations (SHAP) [13] on the logistic regression method that was used for statistical analysis, to identify the predictor variables that necessitate COVID-19 hospitalization, further justifying the corroboration of the results of the above-mentioned statistical analysis.

3 Result Analysis and Discussion

This section, revisiting the primary objective of this research, focuses on the prevalence of COPD, COVID-19, and factors that increase hospitalization among homeless COVID-19 patients. The following subsections discuss the detailed results obtained by the proposed methodology.

3.1 Result of Pairwise Ratio of COPD and COVID-19

The pairwise ratio helps to understand the prevalence of COPD, COVID-19, and their interaction among people experiencing homelessness compared to non-homeless. In the following results, the heat map shows the ratios of COPD and COVID-19 prevalence among the homeless compared to non-homeless. This heat map is generated using the Eq. 5.

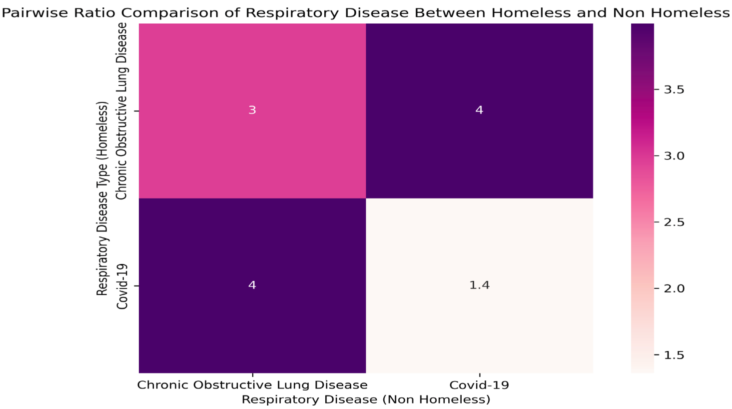


Fig. 5. Respiratory Disease Prevalence on the homeless population

To understand the heat map, it is important to read from column vs row, which shows the ratio of disease among the homeless denoted by column value against ratio value of disease among the non-homeless denoted by row value.

Figure 5 demonstrates that the incidence of COVID-19 is significantly higher among the homeless population, being 1.4 times greater than that of the non-homeless population. Furthermore, the prevalence of Chronic Obstructive Pulmonary Disease (COPD) is notably higher in the homeless population, occurring at a rate three times greater than in those who are not homeless. Most strikingly, the comorbidity of COVID-19 and COPD is observed four times more frequently in the homeless population compared to those with stable housing. This data underscores the heightened health risks faced by individuals experiencing homelessness, adding more severity to COVID-19 patients with COPD history, yielding four more times prevalent.

3.2 Interpretation of the Statistical Analysis

The statistical analysis finds the contribution of each variable (Odd Ratios) independently on COVID-19 hospitalizations. It confirms that the results are not due to a random chance by a hypothesis testing with a p-value less than 0.001. In this research null hypothesis is that predictor variables mentioned in the Table 5 has no contribution on covid-19 hospitalization. The following table shows the statistical results obtained by the proposed methodology.

Table 5. Statistical Results

Variable	p-value	Odds Ratio	95% CI
Age	<0.001	1.01	1.01–1.02
Smoker	<0.001	3.02	2.27–4.01
Mental disorder Patient	<0.001	1.90	1.53–2.35
Male	<0.001	2.10	1.66–2.64
COPD Patient	<0.001	2.20	1.60–3.03
Homeless	<0.001	1.80	1.46–2.41

The pairwise statistical results between predictor variables and target variables from the logistic regression model show how the relationship between homelessness and the odds of COVID-19 hospitalization varies when considering the effects of additional variables. Specifically, the age indicates that with each additional year, the odds of COVID-19 hospitalization for homeless individuals increase by a factor of 1.01, 95% CI (1.01–1.02), assuming other variables are constant. This suggests that aging gradually increases the risk of COVID-19 for the homeless population compared to those who are not homeless. In the case of smoking, it is found that homeless individuals who are smokers have 3.02 times greater odds of being hospitalized with 95% CI (2.27–4.01) due to COVID-19 than non-homeless without smoking habit, considering other factors remain the same. This highlights the significant risk increase due to smoking among people experiencing homelessness. Furthermore, the result shows that homeless individuals with a mental disorder are 1.90 times (95% CI (1.53–2.35)) more likely to be hospitalized for COVID-19 compared to non-homeless individuals without a mental disorder, controlling for other factors. This indicates a substantial increase in risk associated with mental disorders in the homeless population. Additionally, the result suggests that gender influences the effect of homelessness on COVID-19 hospitalization risk. Male homeless individuals have 2.10 times the odds of hospitalization with 95% CI (1.66–2.64) compared to non-homeless female. The COPD reveals that homeless individuals with Chronic Obstructive Pulmonary Disease (COPD) have more than double the odds (2.20 times) with 95% CI (1.60–3.03) of COVID-19 hospitalization compared to non-homeless individuals without COPD pointing to a significantly heightened risk for this subgroup of the homeless population. Lastly, Homeless population itself without any previous history of diseases have 1.80 times with 95% CI (1.46–2.41) odds of being hospitalized compared to non-homeless population. All the statistical results obtained by the proposed method are accompanied by a p-value of less than 0.001, indicating that results are not due to a random chance rejecting the null hypothesis.

3.3 Explainable AI (SHAP) Results

Fig. 6. SHAP Summary Plot

In this section, SHAP (SHapley Additive exPlanations) was applied on the logistic regression model that was used for statistical analysis for further verification of the result. SHAP (SHapley Additive exPlanations) values explain feature importance in logistic regression models by decomposing predictions into contributions from each feature. This method provides a consistent and interpretable measure of feature importance, considering all possible subsets of features (Fig. 6). AQ1

This SHAP (SHapley Additive exPlanations) summary plots-based logistic regression analysis identifies key predictors for COVID-19-related hospitalization that bolsters the results obtained by statistical analysis. These predictors, represented by red dots on the positive side of the x-axis in the plots, correlate with an increased likelihood of hospitalization. The y-axis in these plots ranks the importance of each feature, further emphasizing their significance in the predictive model. A notable finding is the high impact of Chronic Obstructive Pulmonary Disease (COPD) on the model's predictions, where positive SHAP values indicate an increased risk of hospitalization. Similarly, patients with mental disorders show a significant number of positive SHAP values, suggesting a higher likelihood of hospitalization. Age also contributes as a crucial factor; as age increases, the SHAP values show that older age groups may face a higher risk of hospitalization. Another contributing predictor is homelessness, which positively influences the model's prediction for hospitalization. Smoking history is equally significant, with being a smoker associated with positive SHAP values, indicating a greater chance of hospitalization. Gender difference plays a role as well, with the data showing that homeless males are more likely to be hospitalized due to COVID-19 indicated by the red dots on the positive side of the x axis. In conclusion, the SHAP summary plots underscore the contribution of factors such as age, smoking status, homelessness, history of COPD, and the presence of a mental disorder in determining the risk of COVID-19-related hospitalization.

4 Conclusion

This study presents a comprehensive analysis on identifying factors that contributes to COVID-19 hospitalization among homeless population in United States of America as a initiative to tackle COVID-19 crisis as well as future pandemic. This can offer recommendations to policy maker and public health officials where to focus on. This research will also assess the current preventive measure for pandemic helping to reform public health strategies and health provision models. To further expand this research, more data of countries and continents can be included thus facilitating the process of understanding how varying policy approaches and healthcare systems influence COVID-19 outcomes among the homeless.

Acknowledgment. We thank the support of USA NSF PIPP 2200138 and BD Spoke 1761839 and internal support at the University of Tennessee at Chattanooga, and an internal BRIC grant at the College of Medicine Chattanooga.

References

1. National Low Income Housing Coalition: HUD releases 2023 annual homeless assessment report. National Low Income Housing Coalition (2023). https://nlihc.org/resource/hud-releases-2023-annual-homeless-assessment-report
2. Cronley, C.: Unraveling the social construction of homelessness. J. Hum. Behav. Soc. Environ. **20**(2), 319–333 (2010). https://doi.org/10.1080/10911350903269955
3. O'Connell, J.J.: Stories from the Shadows: Reflections of a Street Doctor. Boston Health Care for the Homeless Program (2015)
4. Jencks, C.: The Homeless. Harvard University Press, Cambridge (1994)
5. Carter, G.R.: From exclusion to destitution: race, affordable housing, and homelessness. SSRN J. (2011). https://doi.org/10.2139/ssrn.1808950

6. Jones, M.M.: Does race matter in addressing homelessness? A review of the literature: race and homelessness. World Med. Health Policy **8**(2), 139–156 (2016). https://doi.org/10.1002/wmh3.189
7. Funk, A.M., Greene, R.N., Dill, K., Valvassori, P.: The impact of homelessness on mortality of individuals living in the United States: a systematic review of the literature. J. Health Care Poor Underserved **33**(1), 457–477 (2022). https://doi.org/10.1353/hpu.2022.0035
8. Aldridge, R.W., et al.: Morbidity and mortality in homeless individuals, prisoners, sex workers, and individuals with substance use disorders in high-income countries: a systematic review and meta-analysis. The Lancet **391**(10117), 241–250 (2018). https://doi.org/10.1016/S0140-6736(17)31869-X
9. Omerov, P., Craftman, Å.G., Mattsson, E., Klarare, A.: Homeless persons' experiences of health- and social care: a systematic integrative review. Health Soc. Care Community **28**(1), 1–11 (2020). https://doi.org/10.1111/hsc.12857
10. Liu, M., Hwang, S.W.: Health care for homeless people. Nat. Rev. Dis. Primers. **7**(1), 5 (2021). https://doi.org/10.1038/s41572-020-00241-2
11. Zhu, A., et al.: Respiratory infectious disease outbreaks among people experiencing homelessness: a systematic review of prevention and mitigation strategies. Ann. Epidemiol. **77**, 127–135 (2023). https://doi.org/10.1016/j.annepidem.2022.03.004
12. Individuals Experiencing Homelessness are Likely to have Medical Conditions Associated with Severe Illness from COVID-19 Issue Brief. U.S. Department of Health and Human Services, Office of the Assistant Secretary for Planning and Evaluation (2020). https://aspe.hhs.gov/reports/individuals-experiencing-homelessness-are-likely-have-medical-conditions-associated-severe-illness. Accessed 20 Jan 2024
13. Lundberg, S., Lee, S.-I.: A unified approach to interpreting model predictions (2017). https://doi.org/10.48550/ARXIV.1705.07874
14. Hsu, H.E., et al.: Race/ethnicity, underlying medical conditions, homelessness, and hospitalization status of adult patients with COVID-19 at an urban safety-net medical center – Boston, Massachusetts 2020. MMWR Morbidity and Mortality Weekly Report, vol. 69, no. 27, pp. 864–869 (2020). https://doi.org/10.15585/mmwr.mm6927a3
15. Cha, S., et al.: Morbidity and mortality among adults experiencing homelessness hospitalized with COVID-19. J. Infect. Dis. **224**(3), 425–430 (2021). https://doi.org/10.1093/infdis/jiab261
16. Brown, R.T., Kiely, D.K., Bharel, M., Mitchell, S.L.: Geriatric syndromes in older homeless adults. J. Gen. Intern. Med. **27**(1), 16–22 (2012). https://doi.org/10.1007/s11606-011-1848-9
17. Pribish, A., Khalil, N., Mhaskar, R., Woodard, L., Mirza, A.-S.: Chronic disease burden of the homeless: a descriptive study of student-run free clinics in Tampa, Florida. J. Community Health **44**(2), 249–255 (2018). https://doi.org/10.1007/s10900-018-0580-3
18. Baggett, T.P., Liauw, S.S., Hwang, S.W.: Cardiovascular disease and homelessness. J. Am. Coll. Cardiol. **71**(22), 2585–2597 (2018). https://doi.org/10.1016/j.jacc.2018.02.077
19. Wahl, B., Cossy-Gantner, A., Germann, S., Schwalbe, N.R.: Artificial intelligence (AI) and global health: how can AI contribute to health in resource-poor settings? BMJ Glob. Health **3**(4), e000798 (2018). https://doi.org/10.1136/bmjgh-2018-000798

20. Ulnicane, I.: Against the new space race: global AI competition and cooperation for people. AI Soc. **38**(2), 681–683 (2023). https://doi.org/10.1007/s00146-022-01423-0
21. Hasan, M., Al Mamun, M., Das, M.C., Hasan, M.M., Islam, A.M.: The application and comparison of deep learning models for the prediction of chest cancer prognosis. In: 2023 International Conference on Smart Applications, Communications and Networking (SmartNets), Istanbul, Turkiye, pp. 1–5. IEEE (2023). https://doi.org/10.1109/SmartNets58706.2023.10216201
22. Baggett, T.P., Keyes, H., Sporn, N., Gaeta, J.M.: Prevalence of SARS-CoV-2 infection in residents of a large homeless shelter in Boston. JAMA **323**(21), 2191 (2020). https://doi.org/10.1001/jama.2020.6887
23. Mosites, E., et al.: Assessment of SARS-CoV-2 infection prevalence in homeless shelters – four U.S. cities, March 27–April 15, 2020. MMWR morbidity and mortality weekly report, vol. 69, no. 17, pp. 521–522 (2020). https://doi.org/10.15585/mmwr.mm6917e1
24. Liu, M., et al.: Hospitalizations during the COVID-19 pandemic among recently homeless individuals: a retrospective population-based matched cohort study. J. Gen. Intern. Med. **37**(8), 2016–2025 (2022). https://doi.org/10.1007/s11606-022-07506-4
25. Uddin, J.I., Fatema, K., Dhar, P.K.: Depression risk prediction among tech employees in Bangladesh using adaboosted decision tree. In: 2020 IEEE International Women in Engineering (WIE) Conference on Electrical and Computer Engineering (WIECON-ECE), pp. 135–138 (2020)
26. All of Us Research Hub. https://researchallofus.org/. Accessed 20 Mar 2023