

Article

Economic and Social Factors That Predict Readmission for Mental Health and Drug Abuse Patients

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Abstract: According to the United Nations, curtailing the rise of mental illness and drug abuse has been an important goal for sustainable development of member states. In the United States, reducing readmission rates for mental health and drug abuse patients is critical, given the rising health care costs and a strained health care system. This study aims to examine economic and social factors that predict readmission likelihood for mental health and drug abuse patients in the state of New York. Patient admission data of 25,846 mental health patients and 32,702 drug abuse patients with multiple visits in New York hospitals in 2015 were examined. Findings show that economic factors like income level and payment type impact readmission rates differently: The poorest patients were less likely to get readmitted while patients with higher incomes were likely to experience drug relapse. Regarding social factors, mental health patients who lived in neighborhoods with high social capital were less likely to be readmitted, but drug abuse patients in similar areas were more likely to be readmitted. The findings show that policy-makers and hospital administrators need to approach readmission rates differently for each group of patients.

Keywords: readmission; social capital; economics; mental health; drug abuse



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“The inclusion of noncommunicable diseases under the health goal is a historical turning point. Finally, these diseases are getting the attention they deserve. Through their 169 interactive and synergistic targets, the Sustainable Development Goals (SDGs) seek to move the world towards greater fairness that leaves no one behind.”

Dr Chan, 2013 WHO Director-General

1. Introduction

In 2013, the 66th World Health Assembly adopted a comprehensive plan to curtail the rise of mental illness and drug abuse worldwide [1]. The then World Health Organization (WHO) director, Dr. Chan, called this a “historical turning point” that moved the world toward a more sustainable future. Since then, treating mental health and drug abuse has always been integrated into the United Nations (UN) platform to promote sustainable development among member states [2]. Responding to this, various studies have focused on factors that can predict and curtail mental illness and drug abuse in various contexts [3–7].

In the United States (US), mental health and drug abuse patients have steadily increased in recent years. According to the 2017 National Survey on Drug Use and Health, nearly one in five US adults suffered from a mental health condition, and one in eight US adults struggled with both alcohol and drug use disorders [8]. The Mental Health America institute estimated that youth mental health is worsening with an increase of 4.3% over five years for youth age 12–17 [9]. The opioid crisis, which has killed 128 people every day due to overdose [10], is an example of severe drug abuse issues in the US. In addition, with the Covid-19 pandemic in 2020, it is estimated that there will be even more

people suffering from the psychological impacts of lock-downs due to emotional stress and financial distress [3].

In addition, there is a sustainability crisis in the US public health care system [11]. It has a declining tax base and diminishing social values that are encouraging more private sector choices, and there are two views on addressing the sustainability of the US public health care system [12,13]. First, while there may be economies in more efficient administration of the public health care system that will address sustainability concerns, more scrutiny is needed of how funding is provided. Those who maintain that the system is unsustainable would argue that public funding and administration is part of the problem. The solution may be that Americans have to accept less-comprehensive public health insurance, with more services being paid for out-of-pocket or by private insurance. In this situation, supporters of this view would believe that the private-for-profit insurance companies are the source of the health expenditure increase. A second view is based on the rising cost of health care, which is threatening to overwhelm the public health care system. Thus, a major structural reform of the system is required to encourage better public management as it has the opportunity to provide greater efficiency in the form of faster service and greater choice for Americans [14]. Furthermore, the use of public funds to provide health care suggests that when the expenditure for health care increases, either taxes must be increased or public services reduced. Thus, to avoid such negative effects, public health care needs to maintain quality while addressing the individual's health needs accurately (e.g., differentiating illness accurately).

Against this backdrop, this study seeks to identify economic and social factors that predict readmission rates of mental health and drug abuse patients in the state of New York. Understanding these factors will help policy-makers and health administrators pursue high-quality health care and improve public health in a sustainable manner without exhausting limited resources.

This study's focus on the state of New York is motivated by the state's high readmission rates, with 93% of hospitals estimated to be penalized for such high rates [15]. In 2008, it is estimated that 15% of all hospital stays in NY result in readmission, costing \$3.7 billion per year [16]. Reducing readmission rates has become a priority for state public health officials. In addition, the state has a high growth of mental health and drug abuse patients, ranking fifth in the nation [17]. This makes it more critical to understand the factors that impact readmission rates for mental health and drug abuse patients in the state of New York.

2. Conceptual Foundation

2.1. Readmission Rates in the US Health System

Compared to other developed countries, hospitals in the United States have higher readmission rates [18]. Given the rapid rise of health care costs and rampant inefficiencies in the health care system, reducing readmission rates has been a crucial goal for quality health care and sustainable development in the US [19]. To combat this issue, in the US, since 2013, Medicare reimbursement has been linked to hospital 30-day readmission rates for acute myocardial infarction (AMI), heart failure (HF), and pneumonia (PN). Subsequently, reducing readmission rates has become an important indicator of hospital performance in the US, and a growing number of studies have examined factors that contribute to reduced readmissions. To date, prior studies have suggested a plethora of factors, ranging from hospital and treatment characteristics [20–22] to patient-level social and economic factors [23–25]. These studies make it clear that readmission is a complex issue dependent not only on hospital-related factors but also on out-of-hospital factors such as social support [25], economic means [20,26], community factors [24], or even county-level characteristics [23].

Because readmission rates historically grow out of the concern from the Centers for Medicare and Medicaid Services (CMS) for AMI, HF, and PN patients, most readmission rate research has focused on patients with chronic conditions [20,22,25]. Recent studies have investigated readmission rates for all medical care services [23,24], for insured pa-

tients [21,26], or for patients with recent surgery or with pneumonia [27]. However, hospital readmissions for other different types of patients, including mental health and drug abuse patients, are still understudied. Studies have found that mental health and drug abuse patients indeed have a higher risk of readmission compared to other groups [28,29]. Thus, the objective of this study is to examine factors that contribute to readmission rates among mental health and drug abuse patients in the state of New York.

In addition, while some studies have looked at readmission rates for mental health and drug abuse patients [5,27,30,31], they often aggregate findings for both types of patients as one category. This study argues that such analyses can be incomplete as mental health patients possibly differ from drug abuse patients in terms of demographic factors, service utilization patterns, and diagnostic services [4]. Thus, this study aims to compare results for each type of patient to understand specific influential factors for their readmission rates.

2.2. Conceptual Model

Building on prior research, it is hypothesized that the likelihood of readmission for a patient will be explained by three groups of factors: Hospital treatments, economic factors, and social factors. First, the nature of treatments that patients receive can determine how likely they are to relapse and be readmitted. This is especially important for mental health and drug abuse patients [32], and prior studies have pointed out that those two types of patients utilize treatments and service hours differently [4]. Specifically, drug abuse patients had more treatments and longer stays than mental health patients [4], while prior diagnostic history was a strong predictor for readmission rates among mental health patients [30,33]. Thus, this study hypothesizes that these differences in hospital treatments will explain the readmission rate for mental health versus drug abuse patients.

Second, various studies have attributed readmission rates to economic factors, especially whether patients have access to economic means to afford hospital visits [20,21,25,26]. For mental health and drug abuse patients, economic factors can also reflect their neighborhood living conditions as low-income patients often cluster in poor areas and are more prone to mental health problems or entrenched drug usage. For instance, several studies have associated homelessness with a higher risk of readmission for mental health patients [30,34,35]. Thus, it is hypothesized that economic factors can help explain the readmission rates for mental health and drug abuse patients.

Finally, recent studies have posited that social factors also predict patient readmission rates [23,24]. Instead of relying on economic factors as a proxy for social impacts, these studies explored the supporting characteristics of patient living environment or community health system factors. For example, several researchers have suggested that follow-up in community hospitals can reduce readmission rates for mental health patients [30,31]. Others have identified stronger community support can reduce readmission rates in general [24,33,36]. Compared to hospital treatment factors (hospital-controllable) and economic factors (patient-controllable), these community factors are uncontrollable for hospitals and patients. Thus, they can provide a complete understanding of readmission rates. In this paper, it is hypothesized that social factors play a critical role in readmission rates of mental health and drug abuse patients because those patients need a wide range of social support to overcome their issues.

In sum, this study's conceptual model (Figure 1) uses hospital treatments, economic factors, and community factors to explain readmission rates for mental health and drug abuse patients. One model is built for each type of patient, and the findings are compared and contrasted to unveil insights that can inform policy-makers on how to reduce readmission rates for those patients. Next, data sources and variables used in the analysis are discussed.

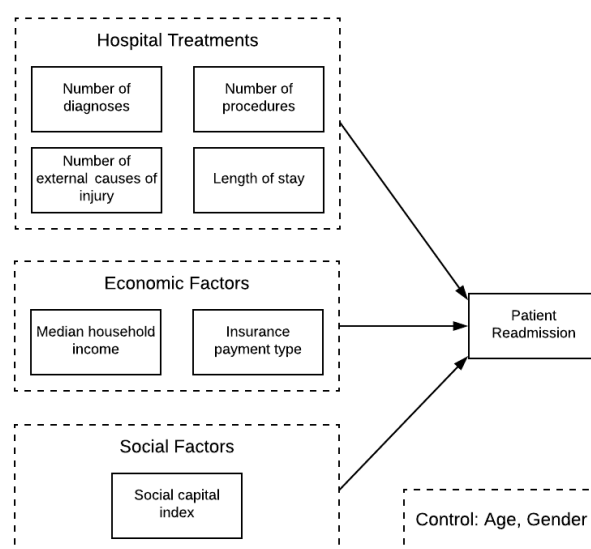


Figure 1. Conceptual model.

3. Materials and Methods

3.1. Data Sources and Variables

The study used 2015 discharge data from the New York State Inpatient Databases (SID) by the Healthcare Cost and Utilization Project (HCUP), and Agency for Healthcare Research and Quality [37]. The original dataset contained 2.29 million records. The unique patient identifier was used in the dataset to filter out patients with multiple hospital visits in 2015, and patients who received services classified as mental health and drug abuse services. This left 120,140 patients.

To distinguish mental health versus drug abuse patients, the ICD-10 Procedure Coding System (ICD-10-PCS) was used to identify specific services received by patients during their hospital visits. Specifically, mental health patients were those who received service coded 218 (psychological and psychiatric evaluation and theory) while drug abuse patients were those who received service coded 219 (alcohol and drug rehabilitation/detoxification). Excluding patients with missing data, the final datasets contained 25,846 mental health patients and 32,702 drug abuse patients.

From the patient's visit date and length of stay, a calculation was made as to whether the visit was readmission within 30 days of last visit discharge. This gave a primary outcome variable for hospital readmission (1/0 indicator). The independent variables come from three groups: Hospital treatments, economic factors, and social factors, with demographics as control variables.

Hospital treatments included the number of diagnoses received during a visit, the number of procedures received during a visit, the number of external causes of injury, and length of stay [5,30,31,38]. Following prior studies [5,21], economic factors, such as the median household income for a patient's zip code, and insurance type of primary payer were used. Insurance payment method includes private (self-pay, group insurance) and public (Medicare, Medicaid). Income was determined based on New York State's income categories (e.g., 1 = under poverty <\$12,760 for an individual, <\$24,600 for a family of four). Demographics included sex and age [30].

Social factors came from the social capital index for a patient's county [39]. The social capital index is developed by the Northeast Regional Center for Rural Development (<http://aese.psu.edu/nercrd>), and it is calculated using an array of individual and community factors to measure the socio-economic growth of a community. Prior studies have suggested that social capital within a community will impact patient readmission rates [23,24,40]. For this study, the social capital index is particularly relevant as supporting communities are likely to help reduce readmission rates for mental health and drug abuse patients [24,36].

3.2. Statistical Analysis

To estimate the likelihood of readmission for patients, a multinomial logistic regression was used. This type of regression uses maximum likelihood estimation to predict the probability of category membership on a dependent variable based on multiple independent variables. Goodness of fit analyses were conducted to accurately specify the model, in which a gamma distribution and log link were selected.

The sample size was split into two groups: Mental health patients with a total of 25,846 cases, and drug abuse patients with a total of 32,702 cases. The assumption of multinomial logistic regression in this study was that readmission due to a diagnosed illness is not related to the readmission for another diagnosed illness. In our mental health patient sample, a majority of the patients were hospitalized based on the occurrence of an emergency (82.1%), and 61.1% identified as male. The average age was 42 years old, and the average length of stay was 14 days. On the other hand, 52.4% of drug abuse patients were hospitalized due to an emergency, and 75.4% identified as male. The mean age was 43 years old. The average length of stay was 6.5 days.

Our model is as follows. The dependent variable $Y = 0$ if not readmitted, $Y = 1$ if readmitted.

$$y_i = (y_{i1}, y_{i2}, \dots, y_{ir})^T$$

Readmission = length of stay + number of diagnoses + number of procedures + number of external causes + median household income + payment type + social capital + sex + age.

4. Results

4.1. Mental Health Patients

A multinomial logistic regression was performed to model the relationship between the predictors and type of illness in the two groups (mental health issues and drug abuse). The traditional 0.05 criterion of statistical significance was employed for all tests. For mental health patients, the final model showed a good fit between model and data, $\chi^2(14, N = 25,846) = 199.70$, Nagelkerke $R^2 = 0.01$, $p < 0.001$. Goodness-of-fit results showed that Pearson Chi-square was insignificant ($p = 0.41$), which indicated that the model fit the data well. Table 1 shows that for mental health patients, their readmission rates are significantly predicted by length of stay, number of diagnoses, number of procedures, median income, payment type, social capital, gender, and age.

Consistent with prior studies [22], our results showed that for mental health patients, their readmission likelihood was predicted by hospital treatments: Specifically, by the number of diagnoses and the number of procedures, but not the number of external causes. While the more diagnoses a patient had, the lower the readmission odds (negative coefficient), the more procedures a patient had, the higher the readmission odds (positive coefficient). A one-unit increase in the number of diagnoses will lead to a 0.02 decrease in the relative log odds of being readmitted as a mental patient, while a one-unit increase in the number of procedures will result in a 0.025 increase in the readmission odds. Length of stay appears as a significant predictor, but its beta was small, indicating its low impact.

Economic factors showed positive impacts on readmission likelihood, but the effects varied. Specifically, median income level as a whole showed a negative significant impact ($p < 0.05$) on readmission, and for every unit increase in the income level, there was a 0.08 unit decrease in readmission odds. However, among different income categories, patients who fell under the poverty line tended not to be readmitted ($\beta = -0.79$, $p < 0.05$), while the effects of income were negated for other income levels. On the other hand, the payment method (i.e., insurance coverage) also had an impact on readmission odds, but only among patients who used Medicare or Medicaid ($\beta = -0.30$, $p < 0.05$; $\beta = -0.39$, $p < 0.01$, respectively).

Table 1. Findings from Multinomial Logistic Regression for Mental Health vs. Drug Abuse Patients.

Independent Variables (IV)	Descriptive	Mental Health (SE)	Descriptive	Drug Abuse (SE)
<i>Hospital Treatments</i>				
Length of Stay		−0.00 ** (0.00)		0.04 ** (0.00)
Number of Diagnoses		−0.02 ** (0.00)		−0.017 ** (0.00)
Number of Procedures		0.025 * (0.01)		0.005 n.s. (0.02)
Number of External Causes		0.035 n.s. (0.03)		−0.046 n.s. (0.03)
<i>Economic Factors</i>				
Median Income		−0.05 ** (0.01)		−0.06 ** (0.01)
\$0–\$25,000	39.0%	−0.079 * (0.04)	35.9%	−0.073 * (0.03)
\$25,001–\$30,000	18.4%	−0.045 n.s. (0.04)	17.5%	0.103 ** (0.04)
\$30,001–\$35,000	16.6%	0.030 n.s. (0.05)	18.2%	0.087 * (0.04)
\$35,001+	25.9%	0 (0)	28.4%	0 (0)
Payment Type		−0.08 ** (0.02)		−0.13 ** (0.01)
Medicare	30.0%	−0.297 * (0.13)	12.4%	−0.240 ** (0.08)
Medicaid	54.3%	−0.391 ** (0.13)	66.3%	−0.093 n.s. (0.07)
Private Insurance	12.4%	−0.089 n.s. (0.13)	15.9%	0.280 ** (0.08)
Self-pay	2.0%	−0.084 n.s. (0.16)	2.6%	0.360 ** (0.11)
No Charge	1.3%		0.1%	−0.689 n.s. (0.40)
Other			2.8%	
<i>Social Factor</i>				
Social Capital		−0.04 * (0.01)		0.04 ** (0.01)
<i>Demographic</i>				
Proportion of Male	58.6%	−0.27 ** (0.02)	75.6%	−0.36 ** (0.03)
Age		0.00 * (0.00)		−0.01 ** (0.00)

* $p < 0.05$, ** $p < 0.01$.

Additionally, the results showed that a one-unit increase in the social capital status is associated with a 0.04 decrease in the relative log odds of being readmitted to the hospital as a mental health patient. The beta shows a negative result, which suggests that patients who have higher social capital (which reflects the social environment of their neighborhood) will have lower readmission odds. This finding is aligned with prior studies that have suggested the positive impacts of social influences on readmission rates [24,25].

Age was also found to have a significant positive impact on readmission odds ($p < 0.05$). Income level showed a negative significant impact ($p < 0.05$) on readmission. For every unit increase in the income level, there is a 0.08 unit decrease in readmission odds.

4.2. Drug Abuse Patients

Table 1 shows that for drug abuse patients, significant predictors for their readmission were length of stay, number of diagnoses, income level, payment method, social capital, gender, and age. The model has a good fit, $\chi^2(15, N = 32,702) = 791.54$, Nagelkerke $R^2 = 0.04$, $p < 0.001$. Goodness-of-fit results also show that Pearson Chi-square was insignificant ($p = 0.28$), which indicates that the model fits the data well.

Among hospital treatment factors, only length of stay and number of diagnoses were significant predictors for readmission odds among drug abuse patients. Interestingly, every day remaining hospitalized was associated with a 0.04 increase in the readmission odds ($\beta = 0.04$). On the other hand, a one-unit increase in the number of diagnoses was associated with a 0.017 decrease in relative log odds of being readmitted ($\beta = -0.017$, $p < 0.01$).

As with mental health patients, economic factors also had a significant impact on readmission odds for drug abuse patients. At the aggregate level, income level had a significant negative impact on readmission odds. A one-level increase in the variable income level is associated with a decrease in the relative odds of being readmitted. While only income below the poverty line impacted readmission odds for mental health patients, higher income brackets also impacted drug abuse patients (below the poverty line, between \$24,000–\$35,000, and above \$35,000). More interestingly, patients below the poverty line saw reduced readmission odds while patients with higher income levels saw a higher chance of being readmitted as a drug abuse patient.

Payment through Medicare, self-pay, and private insurance, but not through Medicaid, had a positive impact on readmissions. Specifically, every one-unit increase in the use of Medicare is associated with a decrease of 0.24 units in readmissions odds ($\text{Exp}(\beta) = 0.79$).

On the other hand, every one-unit increase in self-pay is associated with a 0.28-unit increase in readmission and a 0.36-unit increase for private insurance payer.

Social capital had an opposite effect on drug abuse patients compared to mental health patients. The results showed that a one-unit increase in social capital is associated with a 0.05 increase in being readmitted as an opioid patient ($\beta = 0.05$, $p < 0.01$). Combined with the findings related to the income level above, this further confirms that drug abuse patients who have more disposable income and live in good neighborhoods are more likely to relapse.

For demographics, every year increase in age is associated with a 0.01 decrease in the relative log odds ($\text{Exp}(\beta) = 1.01$) of being readmitted. Moreover, males were more likely to be readmitted than females.

4.3. Patients with Both Mental Health and Drug Abuse Issues

The number of patients who have been diagnosed to have two types of illness (drug abuse and mental health) is 4226. Similar to the two models above, a multinomial logistic regression was performed to model the relationship between the predictors and their readmission likelihood. The traditional 0.05 criterion of statistical significance was employed. The final model showed a good fit between model and data, $\chi^2(15, N = 4226) = 1021.23$, Nagelkerke $R^2 = 0.01$, $p < 0.001$. Goodness-of-fit results showed that Pearson Chi-square was insignificant ($p = 0.54$), which indicated that the model fit the data well. Table 2 shows that significant unique contributions were made by all the factors except the number of external causes and age.

Table 2. Findings from Multinomial Logistic Regression for Patients with both Mental Health and Drug Abuse.

Independent Variables (IV)	Descriptive	Mental Health and Drug Abuse (SE)
<i>Hospital Treatments</i>		
Length of Stay		0.00 ** (0.01)
Number of Diagnoses		−0.02 ** (0.01)
Number of Procedures		0.14 ** (0.04)
Number of External Causes		−0.01 n.s. (0.10)
<i>Economic Factors</i>		
Median Income		−0.04 ** (0.01)
\$0–\$25,000	33.0%	−0.04 ** (0.02)
\$25,001–\$30,000	20.1%	0.07 ** (0.02)
\$30,001–\$35,000	18.6%	0.07 ** (0.02)
\$35,001+	28.2%	0
Payment Type		−0.08 ** (0.01)
Medicare	25.0%	−0.08 n.s. (0.05)
Medicaid	55.6%	−0.12 ** (0.05)
Private Insurance	14.9%	0.23 ** (0.05)
Self-pay	2.3%	0.27 ** (0.07)
No Charge	0.0%	−0.53 n.s. (0.30)
Other	2.2%	0
<i>Social Factor</i>		
Social Capital		0.05 ** (0.01)
<i>Demographic</i>		
Proportion of Male	63.1%	−0.26 ** (0.01)
Age		−0.00 n.s. (0.00)

* $p < 0.05$, ** $p < 0.01$.

When the data were analyzed based on a patient who has been diagnosed with two types of illness, length of stay had a positive significant impact on readmission odds. For every day in the hospital, there is an increase of 0.01 units in relative log odds of being readmitted as a patient. The number of procedures had a positive significant impact on readmission odds. For every increase in the number of procedures done on the patient, there is an increase of 0.12 units in the odds of being readmitted as a patient. Being a patient

who fell under the poverty line had a significant negative impact on being readmitted. For every increase in income bracket, there is a decrease of 0.22 units of being readmitted as a patient. The odds ratio is $\text{Exp}(\beta) = 0.81$. For dual illness patients, the results showed that payment method did have an impact on their readmission odds. Additionally, social capital did not have an impact on patients' readmission odds. The results showed that males were more likely to be readmitted than females.

5. Discussion

This study examines contributing factors that predict readmission likelihood for mental health and drug abuse patients. Readmission rates in the United States have been high for many years [8,18], and many institutions have been faced with financial penalties for high readmission rates [27]. To address these concerns, hospitals are seeking a new path forward to reduce readmissions. Several studies have reported different ways of reducing the readmissions rate. These include improving patient safety at hospital discharge [41], enhancing medication reconciliation [42], and improving the transition from inpatient to outpatient setting [43]. However, these prior studies often focus on chronic diseases [20,22,25] or combine mental health and drug abuse patients into one group [5,27,32]. This study separates these two groups of patients to discern differences in factors that impact their respective readmission odds. The findings showed some similarities and differences. For both groups, hospital treatments, economic factors, and social factors played significant roles in predicting readmissions. However, their effects varied across the two groups. Specifically, the number of procedures was a significant predictor for mental health patients' readmissions, but not for drug abuse patients, while length of stay was a significant predictor for drug abuse patients' readmissions but not for mental health patients. This is a contrasting finding with prior studies as researchers have associated lower length of stay with lower readmission rates for mental health patients [31,32]. Interestingly, for mental health patients, the number of procedures had a positive impact, and the number of diagnoses had a negative impact. Prior research has often associated the number of procedures with lower readmission rates [22,38], but has not scrutinized the number of diagnoses. Future study is needed to explain the underlying reason.

In terms of economic factors, the findings confirm prior studies that economic factors matter [5,34], however, prominent differences between the two types of patients were found. Patients in higher income levels were likely readmitted for drug abuse issues but not mental health issues, and private insurance and self-pay significantly predicted readmissions of drug abuse patients but not mental health patients. Relating back to the Affordable Care Act, mental health is covered by Medicare and Medicaid, so this finding that only Medicare and Medicaid patients are frequently readmitted makes sense. This finding also suggests that healthcare accessibility through economic means has different effects on different types of patients. This seems to indicate that patients with more disposable income are likely to relapse to drug abuse. This finding is also related to social capital impact when an opposite effect is observed: High social capital locations were associated with a higher chance of readmission for drug abuse, but lower readmission odds for mental health patients. This is a surprising finding given prior studies have often associated well-off communities with lower admission rates overall [23,24,31,36,43]. Thus, the findings indicate that community-based support should be strategically allocated for each type of disease, as found in this current study.

The findings have several implications for societal sustainability. First, this study illustrates the importance of healthcare accessibility to the reduction of readmission rates for mental health and drug abuse patients. It echoes prior studies and suggests policy-makers pay greater attention to economic inequality as a direct influencer on community well-being [23,24]. For instance, given patients with high income levels who live in neighborhoods with high social capital actually have higher readmission odds for drug abuse issues, community leaders in well-off areas can consider incorporating rehabilitation facili-

ties to address the issue. Second, the findings inform hospital administrators of various factors that can be used as an indicator of potential readmission among mental health and drug abuse patients. By identifying potential relapse, hospitals can reduce inefficiencies and get closer to a more sustainable healthcare system [19]. Finally, the findings show differences between mental health and drug abuse patients, which suggests the need for different policies to reduce readmission rates for each group of patients. For instance, patients with lower socio-economic means are likely to suffer from mental illness, thus governmental-level support is needed to help this population (e.g., extending coverage for mental illness).

The study is not without limitations. The data focused solely on New York State, thus, the findings are generalizable only to states that have similar demographics and populations. However, nation-wide data would be more comprehensive in addressing the shortfall for this study. A second limitation is that this data set is focused only on one year of readmission data. A longitudinal data set would benefit the study of these readmission rates in a time series manner. In other words, other determinants, such as a change in public policy due to a change in political parties, could be used to compare the difference in insurance cost and how that will impact readmission rates.

6. Conclusions

Hospitals in the United States are financially penalized for having a higher than expected thirty-day readmission rate among patients who have comorbid mental health diagnoses or other symptoms. Traditionally, hospitals have been categorizing readmission rates between drug abuse patients with mental health patients [5,27,31,32]. It is also unknown what the effect of distinguishing the readmission data into its respective disease could have on readmission rates. While many patients are comorbid patients, this study found that although the effects vary in each group, it is important to have different and separate policies to reduce readmission rates for patients with different types of diseases. Prior studies argued that providing support to mental health patients after their discharge helps with reducing physical health readmissions [36]. In addition, prior studies found that alcohol dependence and other mental disorders are associated with inpatient admission or emergency department (ED) visits [5]. In that same study, the authors found that insurance types were predictors of readmission. This study contributes to the existing literature by utilizing hospital discharge data from the state of New York to understand predictors for readmission rates of mental health and drug abuse patients. This study investigated not only the hospital-controllable and patient-controllable factors (i.e., hospital treatments and economic factors) but also uncontrollable factors, such as social determinants, to predict the readmission odds of mental health and drug abuse patients. Considering the high rate of readmissions and ED use in the United States [18], and the concomitant spending by patients, such efforts to address these knowledge gaps could improve patient outcomes and reduce readmission rates, which leads to a reduction of health care costs in a sustainable manner.

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