Hepatitis C Screening Disparities in America's Opioid Capital: What Do We Have to Learn?

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Abstract

Background: Hepatitis C (HCV) disproportionately affects minority populations(1). In order to identify other health disparity gaps and improve testing guidelines, we examined the Wilmington, NC area - ranking #1 nationally in opioid abuse with greater than 11.6% of its population misusing prescription opioids(2). Coinciding with this is an impressive rate of HCV making it a magnified model for the rest of America(3). Our goal for this study was to identify disparities in HCV screening based on patient demographics, and to create a model predicting who are most likely to test positive.

Methods: This was a retrospective observational study of randomly selected patients in a rural community hospital system. Patients were categorized by sex, age, primary language, access to a primary care provider (PCP), history of intravenous (IV) drug use, insurance payor, 2017 adjusted gross income for their zip code, and HCV infection status. An optimal model was created using a forward-selection approach to provide the minimum Akaike information criterion. Predictive capabilities of each formulated equation were tested through five-fold cross validation.

Results: 10,000 patients were included, half were screened for HCV, and 601 were HCV positive. Negative predictors for HCV screening were being male (log odds - 0.426, $p < 0.01$) and age 25-44 (log odds - 0.379, $p < 0.01$). The strongest positive predictors for screening, besides IV drug use, were English as primary language (log odds 0.818, $p < 0.01$) and access to a PCP (log odds 0.778, $p < 0.01$). Lack of health insurance/self-pay was not a predictor. For the HCV infection model (sensitivity 43.48%, specificity 94.07%), the prototype most likely to be HCV positive was an age 25-44 (log odds 1.394, $p < 0.01$), male (log odds 0.922, $p < 0.01$), English speaker (log odds 1.627, $p < 0.01$), with a history of IV drug use (log odds 2.106, $p < 0.01$), and government insurance (log odds 2.108, $p < 0.01$). Increases in adjusted gross income were associated with decreases in the log-odds of HCV infection ($p < 0.01$).

Conclusions: Males age 25-44 were the least likely to be screened for HCV and most likely to test positive. Attention should also be brought to non-English speakers and those without a PCP to close health disparity gaps. Lack of health insurance was not a screening barrier, but socioeconomic inequalities were seen by lower infection rates in higher income areas and increased likelihood of infection in those without private insurance. Despite the high specificity of these models, other factors need to be explored for better sensitivity.

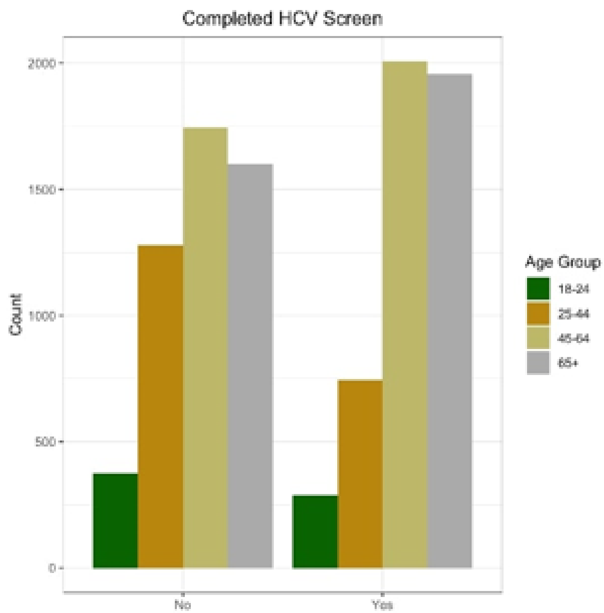
References:

1. Vutien P, Hoang J, Brooks L, Nguyen NH, Nguyen MH. Racial Disparities in Treatment Rates for Chronic Hepatitis C. Medicine. 2016;95(22). doi:10.1097/md.0000000000003719
2. The opioid crisis in America’s workforce. Wilmingtonnc.gov. https://www.wilmingtonnc.gov/home/showdocument?id=5561. Published 2016. Accessed July 15, 2020.
3. State of the County Health (SOTCH) Report 2017. Brunswickcountync.gov. https://www.brunswickcountync.gov/wp-content/uploads/2018/04/SOTCH-2017.pdf. Published 2017. Accessed July 15, 2020.

Learning Objectives

1. Discuss current healthcare disparities in hepatitis C screening.
2. Cite current USPSTF hepatitis C screening guidelines.

Tables and/or Figures



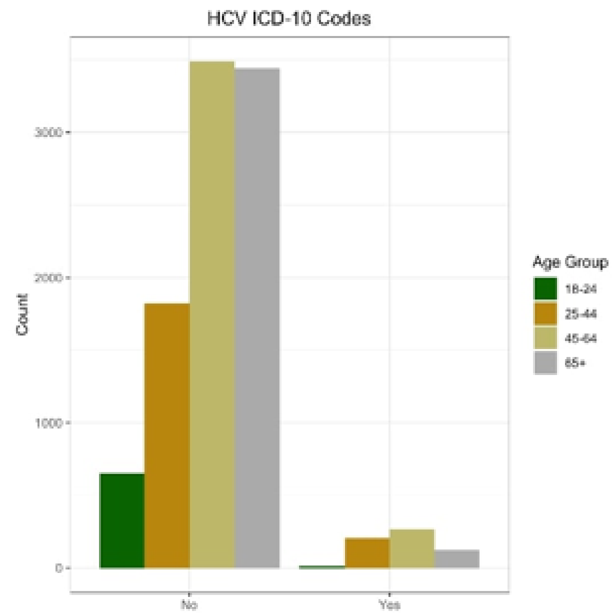


Figure 1 (left): Distribution of HCV screens by age group. Figure 2 (right): Distribution of HCV infections by age group.

Table 3. Logistic Regression Results – Screening.

	Dependent Variable: HCV Screen Completed							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age_25-44	-0.446***	-0.422***	-0.415***	-0.418***	-0.421***	-0.366***	-0.404***	-0.379***
	(0.092)	(0.093)	(0.093)	(0.093)	(0.093)	(0.093)	(0.094)	(0.095)
Age_45-64	0.333***	0.424***	0.422***	0.415***	0.415***	0.449***	0.394***	0.431***
	(0.087)	(0.087)	(0.088)	(0.088)	(0.088)	(0.088)	(0.089)	(0.090)
Age_65+	0.382***	0.486***	0.481***	0.464***	0.464***	0.456***	0.448***	0.456***
	(0.087)	(0.088)	(0.088)	(0.088)	(0.088)	(0.088)	(0.091)	(0.092)
Gender		-0.430***	-0.430***	-0.429***	-0.429***	-0.405***	-0.429***	-0.426***
		(0.042)	(0.042)	(0.042)	(0.042)	(0.043)	(0.043)	(0.044)
Language			-0.607***	0.604***	0.602***	0.660***	0.789***	0.818***
			(0.187)	(0.188)	(0.188)	(0.187)	(0.189)	(0.191)
Access to PCP				0.707***	0.708***	0.737***	0.778***	0.778***
				(0.105)	(0.105)	(0.107)	(0.107)	(0.108)
Hist IV Drug Use					0.486	1.254**	1.264**	1.286**
					(0.522)	(0.576)	(0.574)	(0.577)
HCV w/o Coma						-1.885***	-1.845***	-1.828***
						(0.168)	(0.170)	(0.170)
Ins. Government							0.205**	0.265***
							(0.096)	(0.097)
Ins. Other							0.590***	0.693***
							(0.199)	(0.201)
Ins. Private							0.358***	0.373***
							(0.092)	(0.093)
Ins. Self-Pay							0.681***	0.716***
							(0.089)	(0.091)
AGI								0.000***
								(0.000)
Constant	-0.169**	-0.073	-0.672***	-0.689***	-0.688***	-0.730***	-1.247***	-1.752***
	(0.080)	(0.081)	(0.202)	(0.202)	(0.202)	(0.202)	(0.218)	(0.225)
Observations	10,000	10,000	10,000	10,000	10,000	10,000	10,000	9,931
Log-Likelihood	-6,801.65	-6,749.35	-6,743.79	-6,719.84	-6,719.42	-6,628.35	-6,568.16	-6,454.31
AIC	13,611.30	13,508.70	13,499.60	13,453.70	13,454.80	13,274.70	13,162.30	12,936.60

Note: Standard errors are in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. We include one additional variable in each subsequent model to determine the marginal improvements to the AIC that each variable provides. Through unreported analyses, we find the variables *Race*, *Chronic Viral Hepatis*, and *Unspecified HCV with Coma* do not consistently increase model strength. It should be noted the coefficient for AGI (i.e., 0.000003) is small because the data for the variable includes very large numbers.

Table 4. Logistic Regression Results – Infection.

	Dependent Variable: Positive HCV Infection					
	(1)	(2)	(3)	(4)	(5)	(6)
Age_25-44	1.550***	1.495***	1.511***	1.473***	1.421***	1.394***
	(0.280)	(0.281)	(0.281)	(0.281)	(0.285)	(0.286)
Age_45-64	1.219***	1.024***	1.018***	1.017***	0.983***	0.956***
	(0.278)	(0.279)	(0.279)	(0.279)	(0.283)	(0.283)
Age_65+	0.418	0.189	0.178	0.176	-0.348	-0.325
	(0.286)	(0.287)	(0.287)	(0.287)	(0.293)	(0.294)
Gender		0.921***	0.925***	0.932***	0.935***	0.922***
		(0.088)	(0.088)	(0.088)	(0.091)	(0.091)
Language			2.473**	2.451**	2.683***	1.627***
			(1.006)	(1.006)	(1.018)	(1.016)
Hist IV Drug Use				2.484***	2.099***	2.106***
				(0.0534)	(0.540)	(0.545)
Ins_Government					2.171***	2.108***
					(0.274)	(0.275)
Ins_Other					2.876***	2.815***
					(0.323)	(0.325)
Ins_Private					0.685**	0.671**
					(0.282)	(0.283)
Ins_Self-Pay					0.844***	0.820***
					(0.274)	(0.275)
AGI						-0.000***
						(0.000)
Constant	- 3.783***	-4.073***	-6.532***	-6.512***	-7.863***	-7.398***
	(0.270)	(0.273)	(1.041)	(1.041)	(1.086)	(1.086)
Observations	10,000	10,000	10,000	10,000	10,000	9,931
Log-Likelihood	-2,209.87	-2153.30	-2,145.57	-2,136.16	-1,990.34	-1,964.79
AIC	4,427.74	4,316.59	4,303.13	4,286.31	4,002.67	3,953.57

Note: Standard errors are in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. We include one additional variable in each subsequent model to determine the marginal improvements to the AIC that each variable provides. Through unreported analyses, we find the variables *Race, Chronic Viral Hepatis C, Access to Primary Care Provider, Unspecified HCV without Coma,* and *Unspecified HCV with Coma* do not consistently increase model strength. It should be noted the coefficient for AGI (i.e., -0.000003) is small because the data for the variable includes very large numbers.