Hepatitis C screening disparities in the Advent of Broadened American Screening Guidelines: a perspective from the United States opioid capital

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Background: Hepatitis C is known to disproportionately affect minority populations. However, screening disparities for Hepatitis C have not been thoroughly studied since the United States Preventive Services Task Force updated their recommendations in 2020 to include adults age 18–79. The goals of this study were to better understand current Hepatitis C screening disparities and develop a model predicting what patients are at highest risk to test positive when screened.

Methods: This is a retrospective observational study of 10,000 patients within a southeastern North Carolina healthcare system, centered in America's opioid capital with 11.6% of its population abusing prescription opioids and some of the highest Hepatitis C rates in the state.

Results: The strongest negative predictors for screening were being male (log odds −0.426, standard error 0.044, P<0.01) and age 25–44 (log odds −0.379, standard error 0.095, P<0.01). The strongest positive predictors for screening were history of intravenous drug use (log odds 1.286, standard error 0.577, P<0.01), English as primary language (log odds 0.818, standard error 0.191, P<0.01), and access to a primary care provider (log odds 0.778, standard error 0.108, P<0.01). Health insurance and race were non-factors. A model was also developed to predict Hepatitis C infection likelihood (sensitivity 43.48%, specificity 94.07%).

Conclusions: Males age 25–44 were least likely to be screened for Hepatitis C and at higher risk of testing positive. Better understanding of current screening disparities can potentially lead to better health outcomes.

Keywords: Hepatitis C; health disparities; diagnostic screening; hepatology

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Introduction

History and prevalence of health disparities

The history of healthcare in America is wrought with racial and social injustice at nearly every level. Most are familiar with the nearly unspeakable wrongdoings of the "Tuskegee Study of Untreated Syphilis in the African American Male", the unconsented sterilization of Native American and African American women in the 1900s by eugenic boards and tuberculin-based experiments performed on orphans at St. Vincent's House orphanage in Philadelphia (1-4). Despite the advances in technology and medical knowledge in the decades since, there are still marked racist, ageist, sexist, and socioeconomic health

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disparities affecting millions of Americans that are not grabbing headlines because of their more insidious nature and the role of implicit bias on their existence. Included in this are not just disparities in treatment, but also testing, screening, and diagnosis. An unfortunate example of this is hepatitis C (HCV), which disproportionately affects minority populations (5). In order to further explore this phenomenon, we designed a study to evaluate HCV screening disparities and the bias that may be present in the use of this screening test.

Current screening guidelines

Current guidelines per the United States Preventive Services Task Force (USPSTF) recommend HCV screening for asymptomatic adults ages 18–79, without a history of liver disease, via anti-HCV antibody testing, pregnant women included. This is a grade B recommendation that was updated from the former suggestion that only adults born within the years of 1945 and 1965 along with those participating in high-risk behaviors be screened. Such change was prompted by recognition that Baby Boomers only accounted for approximately three-quarters of Americans infected with HCV, given the increasing prevalence of disease among the young using intravenous (IV) drugs as well as improved treatment options since the prior recommendations were published in 2013 (6).

Study goals

In pursuing this inquiry, we chose to examine our local population of the Wilmington, North Carolina area (located in the southeastern/coastal region of NC)—ranking #1 nationally in opioid abuse with an estimated 11.6% of its population misusing prescription opioids (7). Coinciding with this is the disproportionately high rate of HCV making it a magnified model for the rest of America (8). Our goal was to identify disparities in HCV screening based on patient demographics and socioeconomic variables, and to create a model predicting individuals who are at the highest risk to test positive when screened.

Methods

Study design, patient selection, exclusion criteria

This was a retrospective, observational study of 10,000 randomly selected patients (5,000 who had been screened for HCV and 5,000 who had not) in a rural community hospital system located in the Wilmington, NC area, who qualify for HCV screening per 2020 USPSTF guidelines. Patient selection was completed by the hospital's data analytics department via the healthcare system's patient database. Patients were categorized by sex, age, race, primary language, access to a primary care provider, history of IV drug use, insurance payor, 2017 adjusted gross income for their home zip code, and HCV infection status. Patients were further grouped into four age groups (18–24, 25–44, 45–64, and 65+) to facilitate further analysis. The above sample size was chosen to allow for adequate statistical power and with the aim to represent a more even distribution of the selected geographic community and to minimize potential selection bias.

The study was conducted in accordance with the Declaration of Helsinki (as revised in 2013). The study was approved by institutional review board of New Hanover Regional Medical Center (No. FWA00004714) and individual consent for this retrospective analysis was waived.

Statistical analysis

An optimal model was created using a forward-selection approach to provide the minimum Akaike information criterion (AIC). Predictive capabilities of each formulated equation were tested through five-fold cross validation.

We started our forward-selection approach by categorizing patients within our pre-determined age ranges (18–24, 25–44, 45–64, and 65+) and used this as a dummy variable, serving as a way to include age as both a categorical and explanatory variable within our regression. We then sequentially tested the addition of each of the demographic or socioeconomic characteristics listed in *Tables 1,2*. If the characteristic was statistically significant and strengthened the model, then it was kept, added to the regression, and the next characteristic was tested. If a characteristic was not statistically significant then it was not added to the model. The stepwise building of this model can be seen in both in *Tables 3,4* with each column listed 1–8 representing a step in the building of the model by characteristic, finally represented by the equations seen in the results section below. Each model in this process was compared to others developed in this stepwise development to ensure the final equation had the minimum Akaike information criterion, including as many relevant criteria as possible, creating the truest achievable model for our data.

Table 1 Patient demographics

Characteristic	Patients (N=10,000)
Gender, n (%)	
Female	6,010 (60.1)
Male	3,990 (39.9)
Age group, n (%)	
18–24	629 (6.3)
25–44	2,106 (21.1)
45–64	3,676 (36.8)
65+	3,589 (35.9)
Race, n (%)	
Native American	27 (0.3)
Asian	41 (0.4)
Bi-racial	25 (0.2)
African American	1,262 (12.6)
Pacific islander	6 (0.1)
Other	214 (2.1)
Unknown	535 (5.3)
Caucasian	7,890 (78.9)
Primary language, n (%)	
Not English	140 (1.4)
English	9,860 (98.6)
Access to primary care provider, n (%)	
No	9,559 (95.6)
Yes	441 (4.4)
History of IV drug use, n (%)	
No	9,985 (99.9)
Yes	15 (0.1)
Chronic viral Hep C, n (%)	
No	9,737 (97.4)
Yes	263 (2.6)
Insurance type, n (%)	
Commercial	661 (6.6)
Government	2,605 (26.1)
Other	150 (1.5)
Private	2,525 (25.2)
Self-pay	4,059 (40.6)
2017 adjusted gross income	165,980.8 [48,717.7, 188,196.8]
HCV screen completed, n (%)	
No	5,000 (50.0)
Yes	5,000 (50.0)
HCV ICD-10 codes, n (%)	
No	9,399 (94.0)
Yes	601 (6.0)

Numeric data are presented by median [IQR], and categorical data are presented by count (%, excluding NAs). Commercial insurance includes payors denoted as "Commercial", "Institutional/Corporate Client", "Third Party Liability", and "Worker's Comp". Government insurance includes payors denoted as "Government/Veterans Administration", "Medicaid", "Medicaid Pending", "Medicare", and "Tricare". Private insurance includes payors denoted as "Blue Cross", "Medicare Replacement", and "United Healthcare". HCV, hepatitis C.

There is inherent risk of absence of some data in all retrospective analyses, however via utilizing a matched case-control style approach including date-based sampling, the two groups (screen versus unscreened) were paired as best as possible to minimize selection bias and the variation of extrinsic factors differently affecting them. Information regarding the completion of a negative screening test was not taken from verbally reported patient history, but only obtained from negative results from laboratory HCV antibody testing performed within the healthcare system where this study was performed. Reported history of HCV infection was accepted as a positive diagnosis in addition to positive laboratory testing, so there is potential for some information bias to a portion of 295 patients per *Table 2*, though the percentage of individuals with recall bias falsely reporting a history of HCV infection is thought to likely be low. Other information bias includes potential history not obtained from patients or not included in the electronic medical record; however, this was minimized as best as possible by using the same strict criteria for gathering of all measured demographic and social factors in the study and requiring a "yes" or "no" response to be recorded in a field, with no assumptions made for null fields. Such fields may include including primary language, access to a primary care provider, history of IV drug use, insurance status, and race.

Table 2 Demographics by dependent variable of interest

Characteristic	HCV screen completed		HCV ICD-10 codes	
	No	Yes	No	Yes
Gender				
Female	2,815	3,195	5,763	247
Male	2,185	1,805	3,636	354
Age group				
18–24	341	288	615	14
25–44	1,367	739	1,902	204
45–64	1,688	1,988	3,413	263
65+	1,604	1,985	3,469	120
Primary language				
Not English	96	44	139	1
English	4,904	4,956	9,260	600
Access to PCP				
No	4,856	4,703	8,987	572
Yes	144	297	412	29
History IV drug use				
No	4,992	4,993	9,392	593
Yes	8	7	7	8
Chronic HCV				
No	4,750	4,987	9,399	338
Yes	250	13	0	263
Unspecified HCV w/o coma				
No	4,705	4,957	9,399	263
Yes	295	43	0	338
Insurance type				
Commercial	410	251	646	15
Government	1,400	1,205	2,341	264
Other	87	63	104	46
Private	1,314	1,211	2,425	100
Self-pay	1,789	2,270	3,883	176

This table presents the counts of the main covariates in relation to the dependent variables of interest. It is clearly seen that some variables (e.g., "History IV drug use" and "Chronic HCV") include rare events which may influence logistic regression's results. Further, there are only 601 counts of positive HCV infections out of 10,000 observations, which we believe will confound logistic regression's ability to properly predict the likelihood of infection. HCV, hepatitis C; PCP, primary care provider.

A healthcare system-based sampling method was deemed appropriate, as opposed to a general population sampling, as the variable being primarily examined was whether or not a patient was screened for HCV when eligible when seen at a medical visit, though likelihood to test positive when screened was examined as a secondary point. Also, healthcare system-based sampling was important for this study as to provide a baseline to potentially later build upon for quality improvement measures, which may also later positively contribute to the field of knowledge of hepatitis screening disparities

Results

Of the 10,000 patients in this study 6,010 (60.1%) were female and 3,990 (39.9%) were male. 601 (6%) had been diagnosed with HCV. Baseline patient characteristics are displayed in *Tables 1,2* as well as *Figure 1*.

HCV screens

We first sought to predict whether or not a patient was screened for HCV given his or her demographics. We established an optimal model using a forward-selection approach and found that Equation [1] provides both the minimum AIC and includes all statistically significant variables:

$$\mathrm{P}(HCV\mathrm{Screen}=1)=\frac{\left[e^{\beta 0+\beta 1 AgeGroup+\beta 2 Gender+\beta 3 Language+\beta 4\mathrm{PCPAccess}+\beta 5 InsuranceType+\beta 6 AGI}\right]}{\left[1+e^{\beta 0+\beta 1 AgeGroup+\beta 2 Gender+\beta 3\mathrm{PCPAccess}+\beta 4 HistIVDrug+\beta 5 InsuranceType+\beta 6 AGI}\right]} \quad [1]$$

where AgeGroup becomes one of the dummy variables Age_25-44, Age_45-64, or Age_65+, depending upon the patient's age group; Gender equals 1 if a patient is a male; Language equals 1 if a patient's primary language is English; PCPAccess equals 1 if a patient has access to a primary care provider; HistIVDrug equals 1 if a patient has a history of illicit IV drug use; and HCVwoComa equals 1 if a patient has experienced an unspecified viral Hepatitis C infection without a coma. Further, InsuranceType becomes one of the dummy variables Ins_Government, Ins_Other, Ins_Private, or Ins_Self-Pay, depending upon the patient's healthcare payor. AGI is the 2017 adjusted gross income for the ZIP code a patient provided to the hospital system. Lastly, β0 is the constant term and may be considered the log-odds our "Control" group is screened when all other variables are equal to 0. The baseline group reflects females who are between the ages of 18 and 24, do not speak English as their primary language,

Table 3 Logistic regression results—screening

Patient characteristic	Dependent variable: HCV screen completed							
	1	2	3	4	5	6	7	8
Age_25–44	−0.446*** (0.092)	−0.422*** (0.093)	−0.415*** (0.093)	−0.418*** (0.093)	−0.421*** (0.093)	−0.366*** (0.093)	−0.404*** (0.094)	−0.379*** (0.095)
Age_45–64	0.333*** (0.087)	0.424*** (0.087)	0.422*** (0.088)	0.415*** (0.088)	0.415*** (0.088)	0.449*** (0.088)	0.394*** (0.089)	0.431*** (0.090)
Age_65+	0.382*** (0.087)	0.486*** (0.088)	0.481*** (0.088)	0.464*** (0.088)	0.464*** (0.088)	0.456*** (0.088)	0.448*** (0.091)	0.456*** (0.092)
Gender	–	−0.430*** (0.042)	−0.430*** (0.042)	−0.429*** (0.042)	−0.429*** (0.042)	−0.405*** (0.043)	−0.429*** (0.043)	−0.426*** (0.044)
Language	–	–	−0.607*** (0.187)	0.604*** (0.188)	0.602*** (0.188)	0.660*** (0.187)	0.789*** (0.189)	0.818*** (0.191)
Access to PCP	–	–	–	0.707*** (0.105)	0.708*** (0.105)	0.737*** (0.107)	0.778*** (0.107)	0.778*** (0.108)
Hist IV Drug Use	–	–	–	–	0.486 (0.522)	1.254** (0.576)	1.264** (0.574)	1.286** (0.577)
HCV w/o Coma	–	–	–	–	–	−1.885*** (0.168)	−1.845*** (0.170)	−1.828*** (0.170)
Ins_Government	–	–	–	–	–	–	0.205** (0.096)	0.265*** (0.097)
Ins_Other	–	–	–	–	–	–	0.590*** (0.199)	0.693*** (0.201)
Ins_Private	–	–	–	–	–	–	0.358*** (0.092)	0.373*** (0.093)
Ins_Self-Pay	–	–	–	–	–	–	0.681*** (0.089)	0.716*** (0.091)
AGI	–	–	–	–	–	–	–	0.000*** (0.000)
Constant	−0.169** (0.080)	−0.073 (0.081)	−0.672*** (0.202)	−0.689*** (0.202)	−0.688*** (0.202)	−0.730*** (0.202)	−1.247*** (0.218)	−1.752*** (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

Statistical significance is represented respectively by the asterisks ***, **, and * corresponding to the 1%, 5%, and 10% levels. Standard errors can be found in the parenthesis. The stepwise addition of each variable from left to right in the creation of the final model is included to demonstrate improvements to the AIC provided by each characteristic. Neither "Unspecified HCV with coma", "Chronic viral hepatitis", nor "Race" consistently increased the strength of the model, as determined via unreported analyses. The AGI variable included data with comparatively very large numbers which is the reason that its coefficient is noted to be markedly small (i.e., 0.000003). HCV, hepatitis C; PCP, primary care provider; AGI, adjusted gross income; AIC, Akaike information criterion.

are without access to a primary care provider or a history of illicit drug use, have not experienced an unspecified HCV infection, and have commercial insurance. It should be noted the estimated coefficients ($\beta 1, \cdots, \beta 8$) of Equation [1] are the marginal increases in the log-odds when the associated variables are included into the model.

We present the estimated results of Equation [1] in *Table 3* and find all but one of the estimated coefficients are statistically significant at a minimum, by the 5% level in any model. Only the coefficient associated with HistIVDrug in Model 5 is not found to be statistically significant at any level, but the coefficient for the variable becomes significant in subsequent models. We find Model 8 provides the minimum AIC and maximum log-likelihood of any of the models implemented and conclude it is the optimal model for predicting whether or not a patient is screened for HCV. From the results via Model 8, we find the log-odds that a patient from our baseline group is screened for HCV is −1.752. By adding the coefficients associated with the demographics of interest, we can easily find the log-odds of

Table 4 Logistic regression results—infection

Patient characteristic	Dependent variable: positive HCV infection					
	1	2	3	4	5	6
Age_25–44	1.550*** (0.280)	1.495*** (0.281)	1.511*** (0.281)	1.473*** (0.281)	1.421*** (0.285)	1.394*** (0.286)
Age_45–64	1.219*** (0.278)	1.024*** (0.279)	1.018*** (0.279)	1.017*** (0.279)	0.983*** (0.283)	0.956*** (0.283)
Age_65+	0.418 (0.286)	0.189 (0.287)	0.178 (0.287)	0.176 (0.287)	−0.348 (0.293)	−0.325 (0.294)
Gender	–	0.921*** (0.088)	0.925*** (0.088)	0.932*** (0.088)	0.935*** (0.091)	0.922*** (0.091)
Language	–	–	2.473** (1.006)	2.451** (1.006)	2.683*** (1.018)	1.627*** (1.016)
Hist IV drug use	–	–	–	2.484*** (0.0534)	2.099*** (0.540)	2.106*** (0.545)
Ins_Government	–	–	–	–	2.171*** (0.274)	2.108*** (0.275)
Ins_Other	–	–	–	–	2.876*** (0.323)	2.815*** (0.325)
Ins_Private	–	–	–	–	0.685** (0.282)	0.671** (0.283)
Ins_Self-Pay	–	–	–	–	0.844*** (0.274)	0.820*** (0.275)
AGI	–	–	–	–	–	−0.000*** (0.000)
Constant	− 3.783*** (0.270)	−4.073*** (0.273)	−6.532*** (1.041)	−6.512*** (1.041)	−7.863*** (1.086)	−7.398*** (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

Statistical significance is represented respectively by the asterisks ***, **, and * corresponding to the 1%, 5%, and 10% levels. Standard errors can be found in the parenthesis. The stepwise addition of each variable from left to right in the creation of the final model is included to demonstrate improvements to the AIC provided by each characteristic. Neither “Unspecified HCV with coma”, “Unspecified HCV without coma”, “Chronic viral hepatitis C”, “Access to primary care provider”, nor “Race” consistently increased the strength of the model, as determined via unreported analyses. The AGI variable included data with comparatively very large numbers which is the reason that its coefficient is noted to be markedly small (i.e., −0.000003). HCV, hepatitis C; AGI, adjusted gross income; AIC, Akaike information criterion.

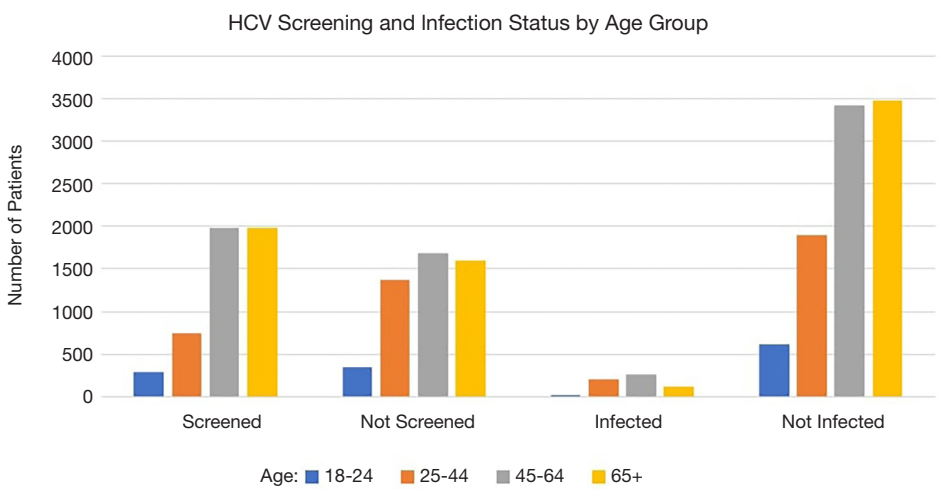

Figure 1 Distribution of HCV screens and infection status by age group. HCV, hepatitis C.

any particular demographic. For example, the log-odds that a male patient is screened for HCV is −2.178 (from adding the estimated coefficients: −1.752 to 0.426), indicating males are less likely to be screened for HCV than females. We further find the log-odds a patient is screened for HCV decrease if a patient is between the ages of 25 and 44, or has experienced an unspecified HCV infection without a coma. The log-odds a patient is screened for HCV increase for those who are over the age of 45, speak English as their primary language, have access to a primary care provider, have a history of IV drug use, and have any type of non-commercial insurance, or self-pay for treatment. Increases in AGI increase the log-odds a patient is screened.

Overall, the strongest negative predictors for screening included being male (log odds −0.426, standard error 0.044, P<0.01) and age 25–44 (log odds −0.379, standard error 0.095, P<0.01). The strongest positive predictors for being screened included history of IV drug use (log odds 1.286, standard error 0.577, P<0.01), English as primary language (log odds 0.818, standard error 0.191, P<0.01), and access to a primary care provider (PCP) (log odds 0.778, standard error 0.108, P<0.01). Type of health insurance and race did not consistently increase model strength.

HCV infections

We sought to predict whether or not a patient will test positive for HCV given his or her demographics. We established an optimal model using a forward-selection approach and find that Equation [2] provides both the minimum AIC and includes all statistically significant variables:

$$\mathrm{P}(HCVICD\text{-}10Codes=1)=\frac{\left[e^{\beta 0+\beta 1 AgeGroup+\beta 2 Gender+\beta 3 Language+\beta 4 HistIVDrug+\beta 5 InsuranceType+\beta 6 AGI}\right]}{\left[1+e^{\beta 0+\beta 1 AgeGroup+\beta 2 Gender+\beta 3 Language+\beta 4 HistIVDrug+\beta 5 InsuranceType+\beta 6 AGI}\right]} \quad [2]$$

where AgeGroup becomes one of the dummy variables Age_25-44, Age_45-64, or Age_65+, depending upon the patient's age group; Gender equals 1 if a patient is a male; Language equals 1 if a patient's primary language is English; and HistIVDrug equals 1 if a patient has a history of illicit IV drug use. As before, InsuranceType becomes one of the dummy variables Ins_Government, Ins_Other, Ins_Private, or Ins_Self-Pay, depending upon the patient's healthcare payor. AGI is the 2017 adjusted gross income for the patient's home ZIP code. The baseline group now reflects females who are between the ages of 18 and 24, do not speak English as their primary language, do not have a history of illicit drug use, and have commercial insurance. The term β0 is the log-odds our "Control" group tests positive for HCV, and the other estimated coefficients (β1,⋯, β6) of Equation [2] are the marginal increases in the log-odds when the associated variables are included into the model.

We present the estimated hierarchical results of Equation [2] in *Table 4* and find all the coefficients, except the one associated with Age_65+, in any model statistically significant at the 1% level. We also find Model 8 provides the minimum AIC and maximum log-likelihood of any of the models and conclude it is the optimal model for predicting whether or not a patient will test positive for HCV. It should be noted the probability a patient in the baseline group tests positive for HCV is 0.06%. We find being between the ages of 25 and 64, being a male, English as their primary language, having a history of illicit IV drug use, having any form of insurance, and self-paying for healthcare are all associated with increases in the log-odds of a positive HCV infection. Increases in AGI are associated with decreases in the log-odds of positive HCV infection.

Consequently, we can apply the marginal increases in the log-odds to find the probability a patient will test positive. For example, if a male patient is between the ages of 25 and 44, English is their primary language, does have a history of IV drug abuse, has government insurance, and has a $0 AGI, the probability he is infected with HCV is calculated as 20.64%. Conversely, if the aforementioned male patient lived in an area with an average AGI of just $50,000, his calculated probability of positive infection drops to only 18.44%.

Because the log-odds of the control group are negative with a large magnitude (−7.398), we expect few patients will be assigned probabilities large enough to be classified as positive HCV infections in the cross-validation predictions. Nonetheless, we test Equation [2]'s predictive capabilities with five-fold cross validation. We apply three optimization methods (baseline, equating sensitivity to specificity, and maximizing Youden's Index) to identify various probability thresholds and present the associated prediction results in *Table 5*. Each optimization method produces low sensitivities and high specificities. The Baseline method yields the greatest sensitivity, but severely underpredicts the number of positive infections. As such, we find the baseline method is not the proper probability threshold to classify records. The other two methods produce nearly

Table 5 Positive HCV infection prediction results

Method	Threshold	Sensitivity	Specificity
Baseline	0.5000	43.48%	94.07%
Spec = Sens	0.0620	13.32%	97.36%
Max Youden's Index	0.0670	14.36%	97.27%

This table compares sensitivity and specificity rates for Eqn. [2]'s ability to predict positive HCV infections. Each method finds a different threshold value used to assign observations to a particular class. For example, under the Baseline method, an observation associated with a predicted probability of 0.52 would be classified as a positive infection; but an observation associated with a predicted probability of 0.35 would be classified as a negative infection. We suspect the Baseline Sensitivity is high because using threshold value predicts only 22 observations would be positively infected. Consequently, we argue that maximizing Youden's Index provides the best results for the model since sensitivity is appropriately maximized while only marginally dimensioning specificity. HCV, hepatitis C.

identical thresholds, sensitivities, and specificities, but the second method (equating sensitivity to specificity) fails to meet its objective because the prediction sensitivity and specificity are nowhere close to one another. Consequently, we find that maximizing Youden's Index when predicting HCV infections finds the optimal classification threshold. We believe the small proportion of patients in the overall sample who are HCV positive is driving the low sensitivity rates.

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), with English as his primary language (log odds 1.627, P<0.01), 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

Negative predictors for being screened for HCV included being male and age 25–44. Positive predictors for HCV screening were history of IV drug use, English as primary language, and access to a PCP. Type of health insurance and race were nonfactors. For our hepatitis C infection prediction model, the prototypical patient most likely to be HCV positive when screened was a male, age 25–44, English speaker, with a history of IV drug use, and government insurance. The higher this patient's adjusted gross income, the less likely they were to test positive for HCV. This brings to light the alarming disparity of a population most likely to be infected with HCV that was also least likely to be screened, namely males ages 25–44.

Are these disparities consistent with national standards?

There has not been a substantial amount of research regarding hepatitis C screening rates since the expansion of USPSTF screening guidelines in 2020; however, disparities that existed prior to this updated recommendation are better established. One 2016 study in southeastern Michigan reviewed over 40,000 patients eligible for screening within a healthcare system. Variables that were associated with a higher chance of screening were being male, African American, occurring at a residency teaching clinic, electronic health engagement, and having more than one clinic visit on file. They also found the higher a patient's Charlson Comorbidity Index, the less likely they were to be screened (9). The Charlson Comorbidity Index is a tool that calculates estimated 10-year mortality based upon numerous factors including one's age as well as presence of diabetes, liver disease, renal disease, cancer, and multiple other diseases (10).

Separately, a study reviewing the 2013–2016 National Health Interview Survey analyzing almost 42,000 individuals throughout the United States showed that people with lower income, lower education, and private health insurance were less likely to be screened. Additionally, Asians had 27% lower odds of being screened compared to Blacks, and people in the Midwest were less likely to be screened than those in the Northeast, South, or West (11). Another smaller study performed out of Tulane in 2017 found that within the New Orleans, Louisiana population less HCV screening tests were ordered on women than men, and less tests were ordered on Caucasians than African Americans (12).

In comparison to our results with the new ages 18 to 79 guidelines, we note some similarities and differences against the aforementioned studies. In the southeastern North Carolina region we studied, males were less likely to be screened for HCV than women, opposite the Tulane study. Those whose primary language was English and those with a primary care provider were more likely to be screened, a trend also noted in southeastern Michigan. Lastly, health insurance and race were not significant factors in a patient being screened for HCV, unlike any of the above findings.

It appears that in addition to the broadened age range

for screening there may be regional and local variations on screening likelihoods based upon the local population, the accessibility to healthcare, physician practice tendencies and bias, and numerous other socioeconomic and access to healthcare variables. In the future, it will be important to establish both national and additional regional trends to better understand the new populations at risk for HCV screening disparities. With additional research in this field, it may also be possible to create an improved HCV infectivity tool which may be utilized to identify higher risk groups so that they may receive appropriate focus for screening and eventual treatment, if indicated. Ideally, with these larger sampling sizes and better understanding of regional variance, the sensitivity of this model may be improved to serve as an additional screening tool in counseling patients on the importance of their being tested.

Areas for future research

In order to better address these healthcare gaps, a similar evaluation may be warranted in other areas of high HCV infection prevalence, opiate abuse, or potentially on a national level to see larger population trends. Such analysis may also allow for development of a more sensitive tool for prediction of HCV infectivity as well as better identification of those being lost in healthcare disparity gaps. At this same institution, a quality improvement project is currently being pursued to evaluate ways to improve screening rates within the described population and everyone else eligible.

We believe using this forward-selection approach to provide the minimum Akaike information criterion is a worthwhile approach for future studies of similar focus as it would allow direct comparison of numerous models to determine which individual characteristics significantly increase the strength of the model while minimizing data loss, and establishing the best overall fit. This way, only key characteristics are included in final predictive models, but also the singular contribution of each characteristic to a model can be evaluated in a step-wise fashion so that no data contribution from any particular subset is overlooked or unaccounted for.

Final thoughts

In review, with the latest 2020 USPSTF HCV screening guidelines including adults ages 18 to 79, we found a significant screening disparity in males ages 25–44. These individuals were also the most likely to be infected per our HCV infection prediction model. Other significant screening factors included history of IV drug use, English as primary language, and access to a PCP. With additional research into other populations across the country, a greater understanding of new screening disparities may be established, leading to improved focus on at-risk populations, higher screening rates, and a closure of this important health disparity gap.

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Footnote

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Conflicts of Interest: All authors have completed the ICMJE uniform disclosure form (available at https://amj.amegroups.com/article/view/10.21037/amj-21-15/coif). The authors have no conflicts of interest to declare.

Ethical Statement: The authors are accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved. The study was conducted in accordance with the Declaration of Helsinki (as revised in 2013). The study was approved by institutional review board of New Hanover Regional Medical Center (No. FWA00004714) and individual consent for this retrospective analysis was waived.

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