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Cost- Effectiveness of Routine Opt-Out Screening for Human Immunodeficiency Virus, Hepatitis C Virus, and Sexually Transmitted Infections in United States Jails within "Hotspots"

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ABSTRACT

Background: Incarcerated populations experience disproportionately high rates of human immunodeficiency virus (HIV), hepatitis C virus (HCV), and sexually transmitted infections (STIs), particularly in geographic "hotspot" areas. Despite Center of Disease Control (CDC) recommendations for routine opt-out screening, most U.S. jails rely on risk-based approaches that miss a substantial proportion of infections. Missing opportunities to treat for these infectious diseases in jails represents a significant issue; reducing the prevalence of communicable diseases on a national level requires addressing carceral hotspot areas.

Objective: To compare the cost-effectiveness of routine opt-out versus risk-based screening for HIV, HCV, chlamydia, syphilis, and gonorrhea in jails located within infection hotspots.

Methods: We created Markov state transition models using parameters derived from existing literature for five major infections – HIV, HCV, chlamydia, syphilis, and gonorrhea. With these models, we ran simulations that showcase the predicted number of infected incarcerated individuals who receive treatment with opt-out screening versus risk-based screening. Using health utility values and treatment costs, we calculated the Incremental Cost Effectiveness Ratio (ICER) for all infection models that we compared to a Willingness to Pay Threshold (WTP) to assess the relative cost effectiveness of opt-out screening and risk-based screening.

Results: For STI models, opt-out screening shows high cost-effectiveness relative to the WTP, with ICER values being far below the $100,000 WTP (ranging from $727 to $4,941 additional cost for opt-out screening per QALY gained). The HCV model showed moderate cost effectiveness with opt-out screening, with an ICER of $85,760 per QALY gained, whereas the HIV model was not cost-effective. Additionally, a higher proportion of infected individuals are estimated to be able to complete full treatment course while incarcerated with opt-out screening. Considerable gains were seen with the chlamydia and syphilis models with 20.5% and 22.8% more infection positive cases estimated to be fully treatable during incarceration respectively.

Conclusions: Routine opt-out screening for most infectious diseases examined is highly cost-effective in hotspot jails. Our findings support prioritizing opt-out screening implementation in high-burden correctional facilities as a strategy to improve individual health outcomes and reduce community transmission.

Introduction

Incarcerated populations experience disproportionately high rates of HIV, hepatitis C virus (HCV), and other sexually transmitted infections (STIs) compared with the general U.S population. At jail intake, infection rates for HIV, chlamydia, gonorrhea, and syphilis are consistently several times higher than those observed in surrounding communities.[1] These disparities reflect both individual risk behaviors and structural inequities, including limited access to preventive care and testing prior to incarceration. As a result, jails carry a disproportionate burden of disease while also presenting one of the few consistent points of healthcare contact for many high-risk individuals, which is an important opportunity for public health intervention.

The burden of HIV, HCV, and STIs is not evenly distributed across the United States. Geographic and epidemiologic analyses identify specific "hotspot" areas, defined here as areas with high prevalence for HIV, HCV, and/or STIs. In these hotspots, many people cycle through local jails each year, intensifying disease transmission and creating a setting where routine testing could have substantial benefits.[2] Because incarceration and STI prevalence cluster geographically, testing in hotspot jails represents a practical and impactful strategy to advance both individual and community health equity.

Despite longstanding Centers for Disease Control and Prevention (CDC) recommendations, most U.S. jails still lack consistent routine-opt out testing programs for HIV or other STIs.[3] Instead, many screening facilities rely on opt-in or risk-based screening, which depends on symptom recognition and self-disclosure. Because of this, a large proportion of infections remain undetected. For populations with limited access to healthcare, such as incarcerated individuals, opt-out testing normalizes screening as part of standard care, minimizes stigma, and increases detection. This persistent implementation gap continues to undermine both the health of incarcerated individuals and broader community prevention efforts.[3]

Evidence now supports the feasibility and public health value of implementing rapid, individual opt-out tests for multiple infections at jail intake. Rapid diagnostic technologies now permit same-day results for HIV, HCV, and syphilis, while nucleic acid amplification tests (NAATs) can process gonorrhea and chlamydia with high accuracy. [4] Newer same-day GC/CT platforms further expand the potential for comprehensive intake screening.[4] Previous economic analyses have suggested that routine opt-out screening in carceral settings can be cost-effective.[5] Expanding routine opt-out testing across these diseases in high-burden jails represents an efficient and ethically grounded public health approach.

Given constrained state and county budgets, identifying cost-effective strategies for screening in high-burden regions is a pressing public health priority. This analysis compares routine opt-out testing with risk-based screening for HIV, HCV, syphilis, gonorrhea, and chlamydia in jails located in hotspot areas. Using state-transition models - a commonly used tool to simulate a given population cohort's transition through various health states over time using probabilistic measures - and publicly available epidemiological data, we estimate the incremental health and economic benefits associated with implementing individual opt-out testing for each infection at jail intake. The findings underscore that routine testing in hotspot jails is both feasible and necessary to reduce disease burden, promote equity, and strengthen national treatment and prevention efforts.

Methods

OVERVIEW

We created state transition models to perform a cohort simulation of individuals incarcerated in jails that provides an estimate of the QALYs to be gained and costs to be accrued from risk-based vs. opt out screening. QALY (quality adjusted life years) and cost values derived from established

values in the literature were used to calculate an Incremental Cost-Effectiveness Ratio (ICER) for each screening intervention, allowing us to assess relative cost effectiveness between screening types.

Models used a standard cohort size of 100,000 which allows for simple interpretation and can represent multiple jails and a time horizon of ten years, which was utilized to show potential long term benefits of each screening intervention.

Five models were created in this study. We focus on risk-based vs. opt out screening within hotspots. These sites are based on the state level prevalence of human immunodeficiency virus (HIV), hepatitis C virus (HCV), and sexually transmitted infections (STIs). Using publicly available prevalence data from 2023, we calculated which states were in the top 75% percentile for prevalence. In the models, all state prevalence data was scaled up for carceral institutions (apart for the HIV and HCV models which use estimates directly from studies on state carceral prevalence).

PARAMETER DERIVATIONS

Some parameters needed for the model were not available in the literature. Thus, we used available data to derive estimates for these parameters (see Equation 1, Equation 2, and Equation 3). Cumulative risks were often available in the literature. With these numbers, we could derive annual risk as well as state transition probabilities where needed.

Equation 1 – Hazard to probability conversions

$$P = 1 - e^{-\lambda}$$

p = weekly (or monthly) state transition probability

λ = hazard rate (instantaneous incidence rate)

$$\lambda = -\ln(1 - c)/D$$

c = cumulative risk

D = estimate duration of health stage

Equation 2 – Annual risk derivation

$$r = 1 - (1 - c)^{\frac{1}{y}}$$

r = annual risk

c = cumulative risk (as found in literature)

y = number of years over which the risk is accumulated

Equation 3 – Survival probability to hazard rate

$$S = e^{-\lambda * t}$$

S = probability of survival at time, t

λ = constant hazard rate (annual)

t = time (year)

*Use to S from literature to solve for λ and then apply state transition probability equation above.

Cohort Parameters

For each infection, the relative proportions of each health state (e.g., for HIV, the proportion of AIDS vs. HIV) was determined based on data in the literature (Table 1a and Table 1b). The most prominent health states for each infection were included. For both gonorrhea and chlamydia this included pelvic inflammatory disease (PID) and epididymitis. Health states unique to a given infection were as follows – disseminated gonococcal infection (DGI) in the gonorrhea model, chronic pelvic pain (CPP) and tubal factor infertility (TFI) in the chlamydia model, primary, secondary, latent, and tertiary stages in the syphilis model, acquired immunodeficiency syndrome (AIDS) and sustained virological resistance (SVR) in the HIV model, and compensated cirrhosis (CC), decompensated cirrhosis (DC), and hepatocellular carcinoma (HCC) in the HCV model.

Similarly, the estimated proportion of those who would be already diagnosed upon carceral admission was based on estimates from the literature. It is worth noting that we included the assumption that only 10% of those who were previously diagnosed would self-identify, given barriers such as stigma and fear of lack of confidentiality in carceral settings. Health utility (a commonly used metric for health economic evaluations ranging from 0 to 1, with higher values denoting better health quality) for each health state and cost estimates for treatment and screening were found in the literature as well.

Table 1a: Cohort parameters for STI models

	Gonorrhea Model			Chlamydia Model			Syphilis Model		
Parameter		Value	Reference(s)		Value	Reference(s)		Value	Reference(s)
Hotspot carceral prevalence[a]		0.0639	(6, 7, 8)		0.115	(6, 16)		0.0221	(6)
Percentage diagnosed before screening[b]		0.0550	(9)		0.060	(9)		0.0224	(21)
Health state proportions	DGI	0.0175	(10)	PID[c]	0.0627	(6, 17)	Primary[i]	0.017	(21)
				CPP[c]	0.0113	(18)	Latent[i]	0.014	(21)
	PID[c]	0.110	(11, 12) (p. 259)[13]	TFF	0.000107	(19)	Secondary[i]	0.0015	(21)
				Epididymitis[g]	0.0010	(p. 260)[13]	Tertiary[i]	0.0013	(21)
	Epididymitis	0.0010	(p. 260)						
Health utility per state	Gon-[d]	1	N/A	Chl-[d]	1	N/A	Syph-[d]	1	N/A
	Gon+[e]	0.85	(p. 259)[13]	Chl+[h]	0.97	(20)	Syph+ Primary	0.88	(22)
	Gon+ DGI[f]	0.60	(p. 259)[13]					0.803	
	Gon+ PID	0.63	(p. 259)[13]	Chl+ PID	0.756	(20)	Syph+ Latent[j]	0.726	(22)
	Gon+ Epididymitis	0.46	(p. 259)[13]	Chl+ CPP	0.759	(20)	Syph+ Secondary[j]		(22)
				Chl+ TFI	0.905	(20)			

	Gonorrhea Model	Chlamydia Model	Syphilis Model
		Chl+ Epididymitis 0.665 (20)	Syph+ Tertiary 0.65 (22)
Screening cost	$50 (14)	$50 (14)	$50 (14)
Treatment cost	$85 (15)	$151 (15)	$1,000 (23)

Notes:

a. Calculated by taking the mean of the top 75th percentile prevalence state for the infection and scaling for carceral institutions
b. Used proportion of asymptomatic or latent cases as a proxy; assumed only 10% previously diagnosed would self-identify
c. Based on proportion of infection+ cases that are female and proportion of infection+ cases that develop into PID/CPP
d. Based on health utility of 1 representing perfect health
e. Estimate based on mild cases in men and women (average)
f. Estimate based on outpatient cases in men and women
g. No epididymitis proportion for chlamydia found, used epididymitis proportion for gonorrhea as proxy
h. Based on health utility of symptomatic chlamydia in men and women (average)
i. Normalized proportions to exclude proportion of congenital syphilis from study
j. Estimated using range of values found from primary and tertiary stages

Table 1b – Cohort parameters for HIV and HCV models

	HIV Model			HCV Model		
Parameter		Value	Reference(s)		Value	Reference(s)
Hotspot carceral prevalence[a]		0.0165	(24)		0.277	(33)
Percentage diagnosed before screening[b]		0.0938	(25)		0.025[c]	(34)
Health state proportions	AIDS+	0.216	(26)	Mild[e]	0.422	(34,35)
	SVR[d]	0.132	(27, 28)	Moderate[e]	0.434	(34,35)
				CC[e]	0.129	(34,35)
				DC[e]	0.012	(34,35)
				HCC[e]	0.03	(34,35)
Health utility per state	HIV-	1	N/A	HCV-	1	N/A
	HIV+	0.82	(29)	HCV+ Mild[g]	0.751	(36)
	HIV+ AIDS+	0.70	(29)	HCV+ Moderate[g]	0.751	(36)
	HIV+ SVR[f]	0.92	(29,30)	HCV+ CC[g]	0.671	(36)
				HCV+ DC[g]	0.602	(36)
				HCV+ HCC[g]	0.662	(36)
Screening cost		$50	(31)		$151	(37)
Monthly treatment cost[h]		$1,617	(32)		$6,458	(38)

Notes:

a. Calculated by taking the mean of the top 75th percentile prevalence state for the infection and scaling for carceral institutions; HCV values were not scaled as were taken from study examining carceral seroprevalence
b. Assumed only 10% previously diagnosed would self-identify in both models
c. Used estimate of what percentage of marginalized populations are not aware of HCV+ status

d. Scaled down according to estimated percentage of incarcerated individuals with health insurance in community
e. Used study estimating the proportion of fibrosis (F) stages and another study examining progression of fibrosis to DC and HCC (applied cumulative risk equation to get estimated proportion of cases)
f. Used meta regression utility values provided for each stage
g. Based on study that showed utility gain of 0.1 one year post treatment for HIV patients
h. For HCV, used average cost per inmate specifically, adjusted for inflation, and divided by two for two-month treatment course

State Transition Model Matrices

We created state transition matrices to represent the probabilities of transitioning between various health stages within each infection model. We treated each infection as independent regarding state transition probabilities to create individual infection models. Transition probabilities were derived from available data in the literature (Table 2). We treated the small risk of death from advanced health states within the gonorrhea and chlamydia models as negligible, apart from the risk of death for disseminated gonococcal infection (DGI) which is rare but fatal.

Within the model, cycles were applied representing a time step in which state transition probabilities are applied to move individuals between health states. The gonorrhea, chlamydia, and syphilis models used weekly cycles to best represent the treatments lengths of the infections (ranging between 1-3 weeks of treatment). The HIV and HCV models utilized monthly cycles given that treatment for these infections take multiple months to achieve – in our models, we examined three-month HIV treatment and two-month HCV treatment. We treated the risk of acquiring a given infection while incarcerated as negligible.

In all models, exit states (representing states in which the individual no longer accrues costs or benefits associated with carceral treatment) included death (which had low probabilities associated with certain health states), carceral release, and cured states (except for HIV which used the sustained virological resistance (SVR) state in place of cured). We treated the probability of entering treatment after diagnosis as 1.0, in other words, the individual was guaranteed to enter treatment unless carceral release occurred. Based on the average length of jail stay of 32 days, we found that the weekly probability of release is approximately 0.195 and the monthly probability of release is approximately 0.670.[39]

Table 2a: State transition probabilities for STI models

Gonorrhea Model			Chlamydia Model			Syphilis Model		
Transition	Weekly State Transition Probability	Reference(s)	Transition	Weekly State Transition Probabiliy	Reference(s)	Transition	Weekly State Transition Probability	Reference(s)
Gon+ -> Gon+ DGI[a]	0.0044	(10)	Chl+ -> Chl+ PID[c]	0.00127	(6,42)	Syph+ Primary -> Syph+ Secondary[d]	0.154	(45)
Gon+ -> Gon+ PID[a]	0.0257	(10)	Chl+ PID -> Chl+ CPP[c]	0.260	(43)	Syph+ Secondary -> Syph+ Latent[d]	0.118	(46)
Gon+ -> Gon+ Epididymitis[a]	0.000222	(10)	Chl+ PID -> Chl+ TFI[c]	0.170	(43)	Syph+ Latent -> Syph+ Tertiary[d,e]	0.000594	(47)
DGI -> Death[b]	0.0000424	(40)	Chl+ -> Chl+ Epididymitis[c]	0.170	(43)	Syph+ Tertiary -> Death[d,f]	0.00639	(47)
Gonorrhea treatment success rate	0.95	(41)	Chlamydia treatment success rate	0.95	(44)	Syphilis treatment success rate	0.95	(48)
Weekly probability of carceral release[a]	0.195	(39)	Weekly probability of carceral release[a]	0.195	(39)	Weekly probability of carceral release[a]	0.195	(39)

Notes:

a.) Applied equation 1 to derive – found cumulative probability of progression from literature, D = 4.5 weeks to represent average length of jail stay and find P weekly

b.) Applied equation 1 to derive, used D = 12 months to find lambda (assume same constant risk of death)

c.) Applied equation 1 to derive – found cumulative risk of incidence from literature, D = 52 weeks to find p weekly

d.) Applied equation 1 to derive – D depended on values in literature for typical time spent in each syph+ state

e.) Assumed tertiary occurs 10 years after primary infection

f.) Assumed 3 years until death after untreated tertiary infection begins

Table 2b: State transition probabilities for HIV and HCV models

HIV Model			HCV Model		
Transition	Monthly State Transition Probability	Reference(s)	Transition	Monthly State Transition Probability	Reference(s)
HIV+ -> AIDS+[a]	0.00576	(49)	HCV+ Mild -> HCV+ Mod[e]	0.0021	(52)
AIDS+ -> Death[b]	0.0301	(50)	HCV+ Mod -> HCV+ CC[e]	0.0031	(52)
HIV treatment success rate within 3 months (attain SVR)[c]	0.653	(51)	HCV+ CC -> HCV+ DC[e]	0.0032	(52)
Monthly carceral release probability[d]	0.670	(39)	HCV+ DC -> HCV+ HCC[e]	0.0012	(52)
			HCV+ DC -> HCV+ HCC[e]	0.0012	(52)
			HCV+ CC -> Death[f]	0.0008	(53)

HIV Model		HCV Model		
		HCV+ DC -> Death[g]	0.0170	(54)
		HCV+ HCC -> Death[f]	0.0226	(55)
		HCV treatment success rate (8 week treatment)[h]	0.991	(56)
		Monthly probability of carceral release[d]	0.670	(39)

Notes:

a.) Applied equation 1 to derive – D = 10 years and c = 0.5, estimated based on literature statistic that 50% of HIV patients develop AIDS in 10 years, converted to P monthly

b.) Applied equation 1 and equation 3 to derive – used AIDS+ untreated 2 year survival rate of 48%

c.) Based on three-month treatment success rate for obtaining SVR

d.) Applied equation 1 to derive = D = 1.1 months (based on average length of jail stay)

e.) Used state transitions provided from other study, converted from annual to monthly

f.) Applied equation 1 and equation 2 – converted 5 year survival and mortality rates to annual

g.) Applied equation 1 to derive - converted constant death rate probability to monthly

h.) Based on two months of ledipasvir-sofosbuvir treatment

RISK BASED VS. OPT-OUT SCREENING CASE DETECTION RATES

A comprehensive literature search was employed to find relevant studies from which risk based and opt-out screening case detection rates could be derived. Case detection rates were defined as the proportion of positive cases that were diagnosed through screening out of all estimated positive cases in the cohort. These rates are impacted by the number of people who meet the screening criteria for risk-based screening, the test uptake percentage in both screening methods, and test sensitivity.

We identified a study that assessed risk based vs. opt-out screening for HCV in an urban prison in Philadelphia.[57] Our sources for case detection rates in other studies, however, were based on different populations, such as young adults in an emergency department setting and women in a sexual health clinic. We would expect differences in screening implementation within the carceral environment – for instance, those in the carceral setting may not report as many symptoms as those in the outside community or may have different test uptake rates. Given this, we elected to scale the case detection rates for the other infections according to the HCV screening prison study (Table 3). This resulted in risk-based case detection rates being slightly lowered and opt out case detection rates being slightly higher.

Table 3: Case Detection Rates for Risk Based vs. Opt-Out Screening

	Risk Based Case Detection Rate (Scaled)*	Opt-Out Case Detection Rate (Scaled)*	% Difference	Reference(s)	Study Population	Calculation Notes
HIV	12.3%	43.3%	31.0%	(58)	Patients in urban, Midwest ED	P(Diagnosed | HIV+) = identified cases / estimated total cases
Gonorrhea	21.2%	43.8%	22.7%	(59, 60)	Young adult patients in urban ED	Eckman et. al study provided numbers for treated and detected, used McWhirter et al. estimate of young adults who will seek treatment after diagnosis to derive number detected Detected = Detected + Treated / Treated P(Diagnosed | Gon+) = detected cases / estimated total cases
Chlamydia	19.9%	58.3%	38.4%	(61)	High risk women in US	P(Diagnosed | Chl+) = screening coverage * test acceptance probability
Syphilis	43.4%	83.0%	39.5%	(62)	Female patients in sexual health clinic in Australia	P(Diagnosed | Syph+) = identified cases / estimated total cases Used 2/3 of positivity rate of high risk high risk group to find the estimated cases excluded in the low-risk group and then added to confirmed cases in high risk group Opt-out group used full positivity rate
HCV	24.2%	57.1%	32.9%	(57)	Incarcerated individuals, urban prison	P(Diagnosed | HCV+) = identified cases / estimated total cases Scaled down PDPH cohort (opt-out) with by percentage that would typically opt out in real world setting (40%)[66]

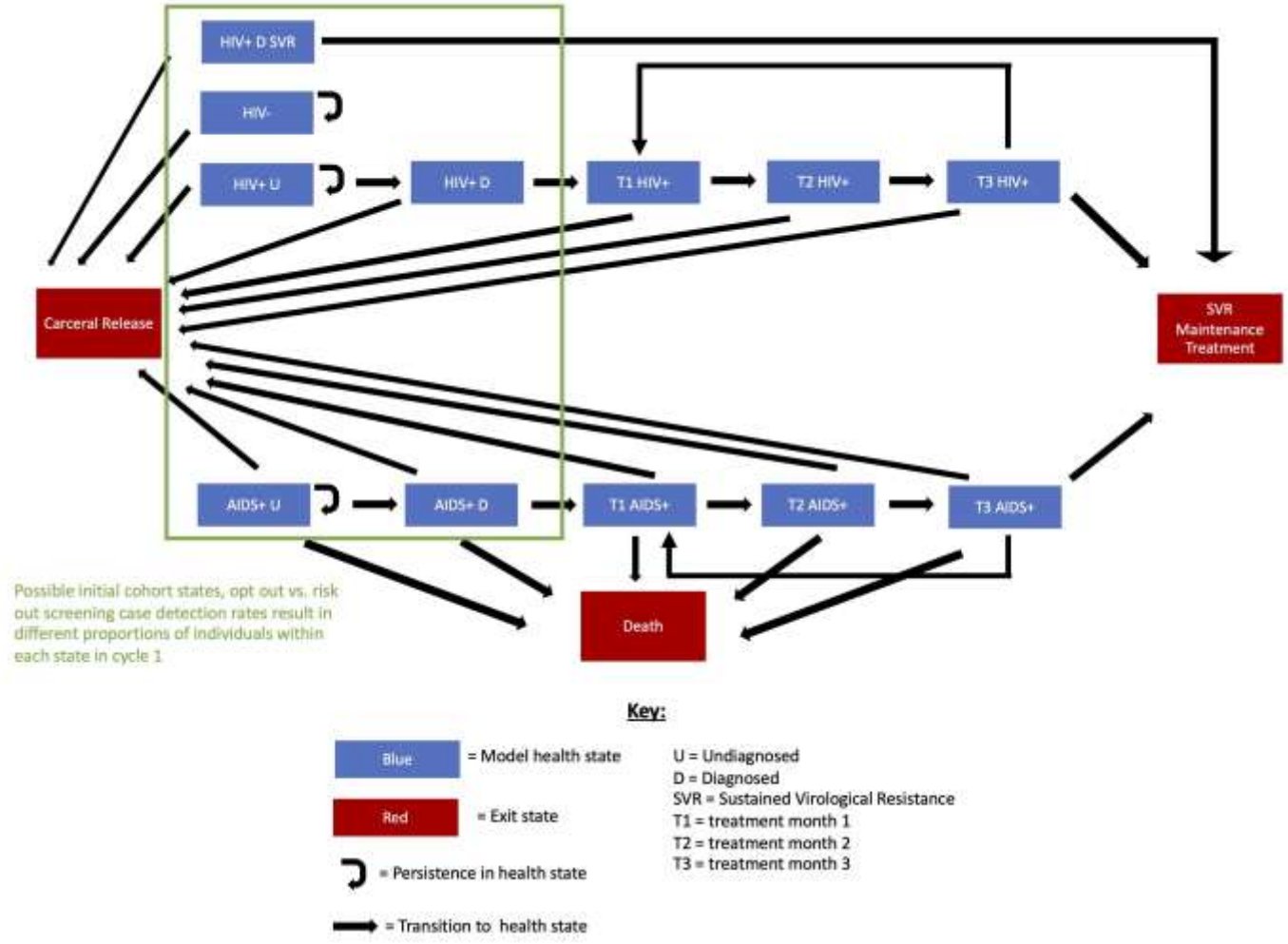
*To scale up according to the HCV calculated case detection rates (the only study using a prison population), the average of the original case detection rates for each screening type for each infection was divided by the

HCV case detection rates for each screening type. As a result, risk-based screening case detection rates were multiplied by a scaling factor of 0.7 and opt-out case detection rates were multiplied by a factor of 1.23.

Simulation

For the Markov simulation applied (in which transitions to the next state only depend on the current state i.e., the simulation does not have "memory"), we first took our initial cohort vectors - which included the number of people in each health state for a given infection for a cohort of 100,000 – and simulated a one-time risk based and opt-out screening upon jail admission using the calculated case detection rates. These rates changed the proportion of people in undiagnosed vs. diagnosed health states, which had downstream effects in the simulation; those who became diagnosed could enter carceral treatment (Figure 1).

Figure 1: HIV Example State Transition Model Conceptual Diagram



After adjusting the cohort vectors for each screening method, we performed the simulation. We utilized Python (version 3.11.5) to conduct the simulation. The general process was as follows. For each cycle (520 cycles for the weekly models and 120 cycles for monthly models), the number of people who moved from one health state to another was calculated, using the probabilities from the state transition matrix and current cohort numbers (this was performed via matrix multiplication).

The number of people who exited the model after each transition was calculated and used to add in a dynamic inflow of people meaning that in every cycle individuals were added in response to the

number of individuals that previously exited the model. We decided to keep the number of people in active states constant (100,000), so the number of people who exited in each cycle were replaced to replenish the cohort to 100,000. The inflow vector used the same proportions of health states defined in the initial cohort vector.

We calculated accumulated QALYs and costs by calculating the associated utility and costs for each stage per cycle (this involved multiplying the health state distribution in the current cohort by utility and cost vectors). Equations 4 and 5 below provide more detail on the calculation of accumulated QALYs and costs. The values from each cycle were summed to find total QALYs and costs for each simulation. We applied an annual discount factor of 0.03 (which was converted for weekly and monthly models respectively) to capture the time value of money (Equation 6 and Equation 7). Total costs included the costs of treatment accrued across the simulation and the cost of screening (Equation 7).

Equation 4: QALYs per cycle

$$\text{QALYs per cycle} = \sum_i \sum_j (utility_j * number\ of\ people\ in\ state_j * \frac{1}{t})$$

j = health state
i = cycle
t = number of cycles per year (52 for weekly models, 12 for monthly models)

Equation 5 – Treatment costs per cycle

$$\text{Treatment costs per cycle} = \sum_i \sum_k (treatment\ cost_k * number\ of\ people\ in\ state_k)$$

k = treatment health state
i = cycle

Equation 6: Total discounted QALYs

$$\text{Total discounted QALYS} = (\sum_i QALYs\ per\ cycle) * (\frac{1}{(1+0.03)^{\frac{i}{t}}})$$

i = cycle
t = number of cycles per year (52 for weekly models, 12 for monthly models)

Equation 7: Total discounted costs

$$\text{Total costs} = ((\sum_i Treatment\ cost\ per\ cycle) * (\frac{1}{(1+0.03)^{\frac{i}{t}}})) + (simulation\ cohort\ size * percentage\ of\ people\ screened * cost\ of\ screening\ test)$$

i = cycle
t = number of cycles per year (52 for weekly models, 12 for monthly models)

ICER Calculation

We used the total discounted QALY and treatment cost values from the state transition model simulation to calculate ICER values and compare cost effectiveness between risk based and opt-out screening for each model. For total discounted costs, we also added in the cost of screening. We used the same sources as used to derive case detection rates to estimate the number of people who were screened (regardless of if they were positive or not) in the cohort for each screening intervention (Table 4). Based on the number of people estimated to be screened, we estimated the total screening test cost. Our total costs did not include the personnel cost associated with administering the tests as these costs are highly variable, with different facilities, for instance, employing different medical professionals with different hourly rates to administer testing.

Table 4: Estimated population screening percentages according to literature

	Risk Based % Screened*	Opt-Out % Screened*	% Difference	Reference(s)	Study population	Calculation Notes
HIV	29.9%	40.8%	10.9%	(58)	Patients in urban, Midwest ED	% screened from stated screening coverage
Gonorrhea	52.0%	59.0%	7.0%	(59)	Young adult patients in urban ED	% screened based on proportion receiving STI testing among those at risk on STI survey and proportion agreeing to get STI testing under universally offered screening strategy
Chlamydia	30.0%	50.0%	20.0%	(61)	High risk women in US	% screened from stated screening coverage
Syphilis	43.4%	83.0%	39.6%	(62)	Female patients in sexual health clinic in Australia	% screened based on number of women who chose to be tested / all women identified high risk (risk based) or all women (opt out)
HCV	5.3%	40.0%	34.7%	(57)	Incarcerated individuals, urban prison	% screened for risk based derived from proportion of population noted as high risk % screened for opt-out scaled down[63] from 100% to 60% (for more realistic application than controlled study)

*Derived estimates for % screened among the entire population (i.e., for risk-based, % screened among both low and high-risk groups) such that could find estimates for number of people screened in the cohort and associated testing costs

ICER was calculated as follows (Equation 8):

Equation 8: ICER

$$\text{ICER} = \frac{(\text{Risk based discounted costs}) - (\text{Opt} - \text{out discounted costs})}{(\text{Risk based discounted QALYS}) - (\text{Opt} - \text{out discounted QALYS})}$$

We interpreted the ICER values in reference to a Willingness to Pay Threshold (WTP), representing the cost that a society is willing to pay for a health improvement. We used a WTP of $100,000 per QALY gained, which has been shown to be used in previous cost-effectiveness studies in carceral settings and also serves as largely common WTP threshold utilized within health economics studies with US populations. [64,65] With this WTP, if the ICER was below $100,000 per QALY gained, we determined opt-out screening to be cost-effective.

Results

ICER Values

Each individual infection model showed ICER values consistent with cost-effectiveness given our WTP of $100,000 except for the HIV model (Table 5). The gonorrhea model showed very high-cost effectiveness, with an ICER value suggesting that with opt-out screening, the additional cost is only $727 for 1 additional QALY gained. The chlamydia and syphilis models similarly showed high-cost effectiveness, with ICER values of $2,731 and $4,941 respectively. The HCV model also showed cost effectiveness, though its ICER value was relatively higher than the other models ($85,760), suggesting higher costs per QALY gained. The HIV model did not show cost-effectiveness, with an ICER much higher than the WTP of $100,000 (ICER: $211,024).

Table 5: Total discounted QALYs, total discounted costs, and ICER values

	Total Discounted QALY	Total Discounted Costs	ICER Value	Interpretation
Gonorrhea Model	Risk Based: 41,710,718 Opt-Out: 41,770,043 Difference: 59,325	Risk Based: $272,800,633 Opt-Out: $315,930,070 Difference: $43,129,437	$727	Opt-out screening is cost effective
Chlamydia Model	Risk Based: 41,969,728 Opt-Out: 42,023,246 Difference: 53,518	Risk Based: $182,836,380 Opt-Out: $328,981,942 Difference: $146,145,563	$2,731	Opt-out screening is cost effective
Syphilis Model	Risk Based: 42,008,171 Opt-Out: 42,074,835 Difference: 66,664	Risk Based: $361,210,636 Opt-Out: $690,619,660 Difference: $329,409,024	$4,941	Opt-out screening is cost effective
HCV Model	Risk Based: 31,703,140 Opt-Out: 31,745,228 Difference: 42,088	Risk Based: $2,426,936,290 Opt-Out: $6,036,407,214 Difference: $3,609,470,924	$85,760	Opt-out screening is cost effective
HIV Model	Risk Based: 33,950,481 Opt-Out: 33,950,762 Difference: 281	Risk Based: $138,632,288 Opt-Out: $197,913,801 Difference: $59,281,513	$211,024	Opt-out screening is not cost effective

Proportion of Cases Treated

Additionally, with opt-out screening, we see a higher percentage of cases treated (Table 6, Figure 2). The largest difference in the percentage of treated cases with opt-out vs. risk-based screening was seen with the chlamydia and syphilis models which showed 20.49% and 22.76% more cases respectively being treated with the opt-out screening intervention models. The HIV and HCV models show relatively low percentages of treated cases (between 0.14% and 3.37%) and little difference in the percentage treated between opt-out and risk-based screening interventions.

Table 6: Estimated screened and treated cases

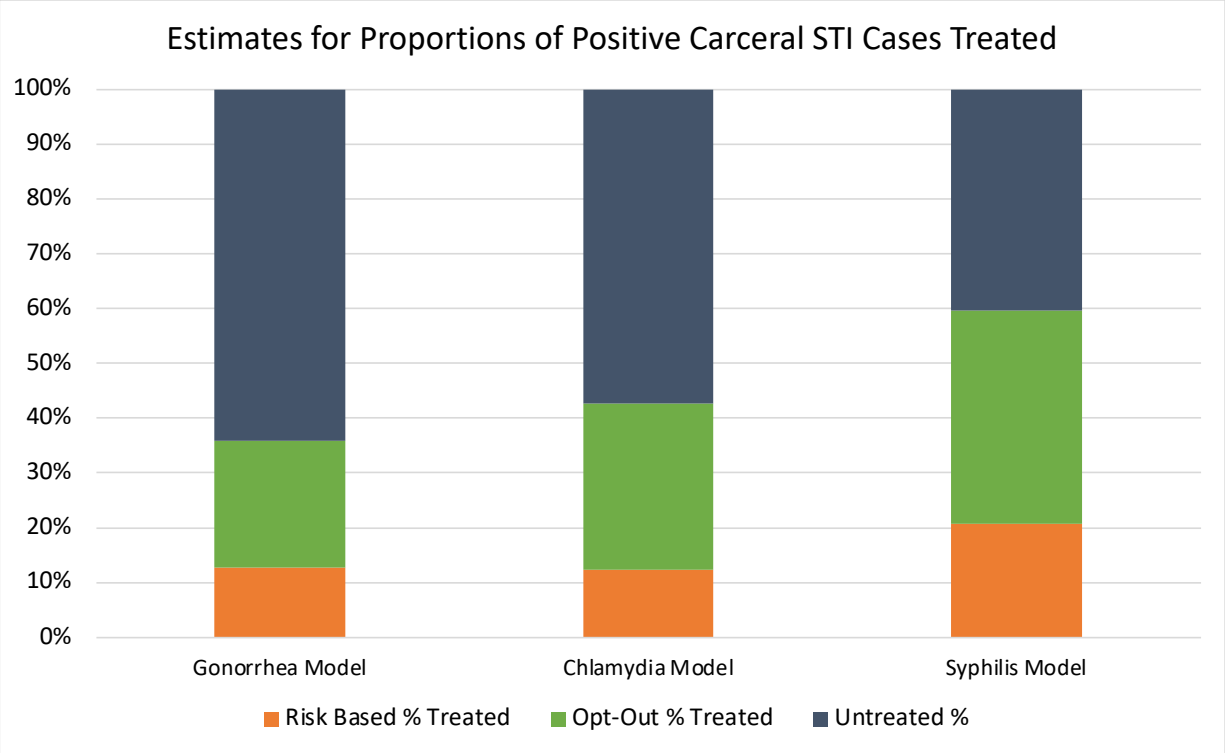
	Total Simulation Cohort Number (Initial + constant inflow over 10 years)	Estimated Number of Screened Cases*	Estimated Number of Treated Cases**	Estimated Number of Infection+ Cases in Cohort***	Treated / Total Infection+ Cases Estimated in Cohort (%)
Gonorrhea Model	10,240,003	Risk Based: 5,272,801 Opt-Out: 5,982,602 Difference: 709,880	Risk Based: 94,960 Opt-Out: 174,152 Difference: 79,192	654,336	Risk Based: 14.51% Opt-Out: 26.62% Difference: 12.10%
Chlamydia Model	10,240,036	Risk Based: 3,042,000 Opt-Out: 5,070,000 Difference: 2,028,000	Risk Based: 165,259 Opt-Out: 406,552 Difference: 241,293	1,177,600	Risk Based: 14.03% Opt-Out: 34.52% Difference: 20.49%
Syphilis Model	10,240,005	Risk Based: 4,400,762 Opt-Out: 8,499,204 Difference: 4,098,442	Risk Based: 59,374 Opt-Out: 110,878 Difference: 51,504	226,304	Risk Based: 26.24% Opt-Out: 49.00% Difference: 22.76%
HCV Model	8,140,731	Risk Based: 425,256 Opt-Out: 4,824,439 Difference: 4,399,182	Risk Based: 33,802 Opt-Out: 75,931 Difference: 42,129	2,254,982	Risk Based: 1.50% Opt-Out: 3.37% Difference: 1.87%
HIV Model	8,140,423	Risk Based: 2,401,031 Opt-Out: 3,280,492 Difference: 879,461	Risk Based: 193 Opt-Out: 361 Difference: 168	134,317	Risk Based: 0.14% Opt-Out: 0.27 % Difference: 0.13%

*Calculated using screening percentages from Table 4

**Found in simulation by counting the amount of times final treatment state transitioned into cured state

***Calculated by multiplying total simulation cohort number by hotspot carceral prevalence. Represents all estimated infection cases across 10 year timeframe

Figure 2: Treated / Total Infection+ Cases Estimated in Cohort (%) for STI models



Looking at the number of cases fully treated during incarceration relative to the number of cases present for each infection model over time (Figures 3a and 3b), we can also see how effective opt-out screening is at facilitating increased treatment. In the STI models, a clear difference between the cumulative number of cases treated between the two screening types is seen shortly after the simulation starts, with notable differences appearing around cycle 100 (roughly two years). Among all STI models, opt-out screening for syphilis shows the greater difference in cumulative number of cases treated. It is evident, however, that the cumulative number of cases treated with either screening type is much lower than the cumulative number of positive cases at any given time point.

Within the HIV and HCV models, we see very low cumulative numbers of cases treated with either screening type relative to the cumulative number of positive cases.

Figure 3a: Cumulative Number of New Cases Presenting to Jail for STIs Over Time

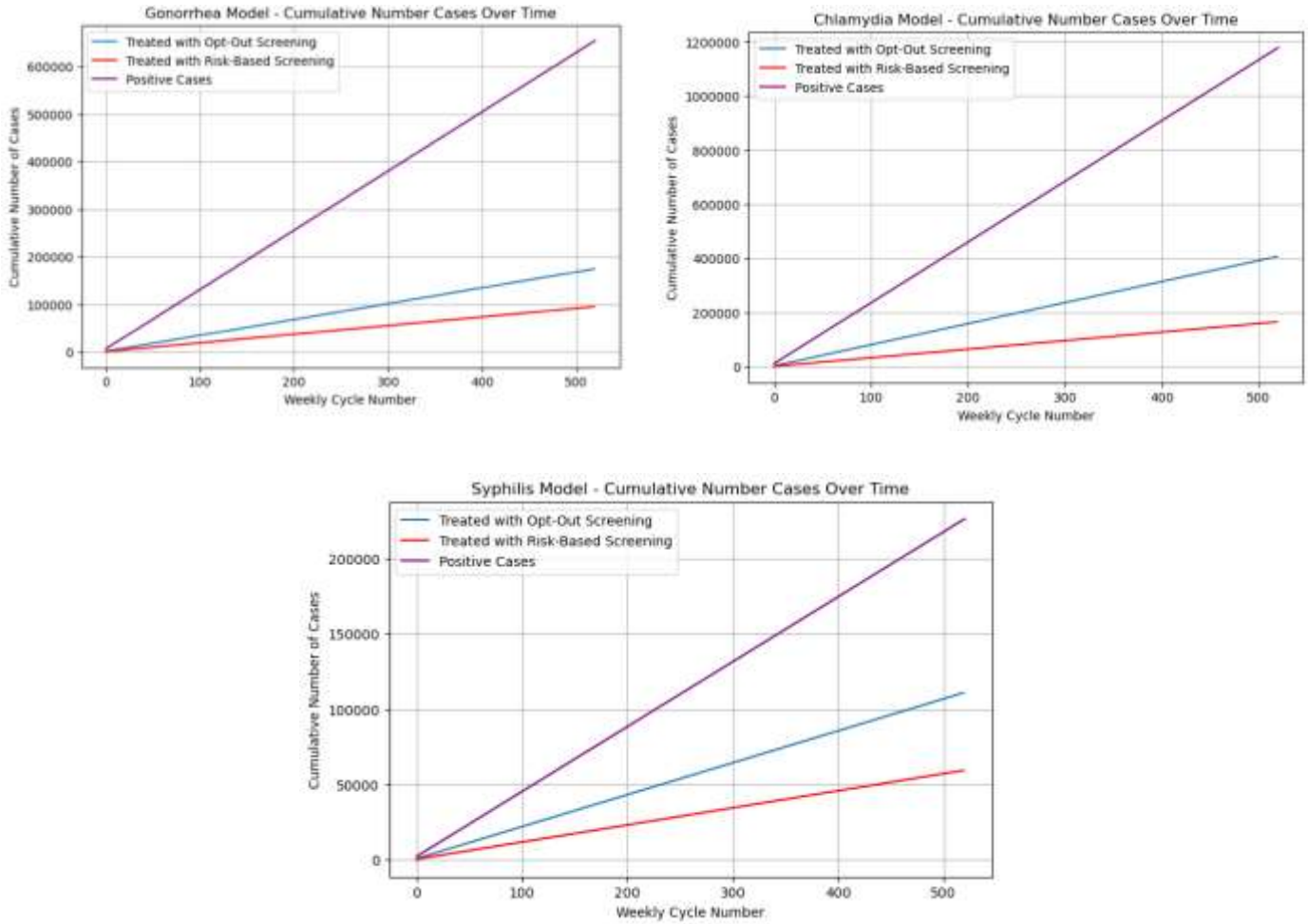
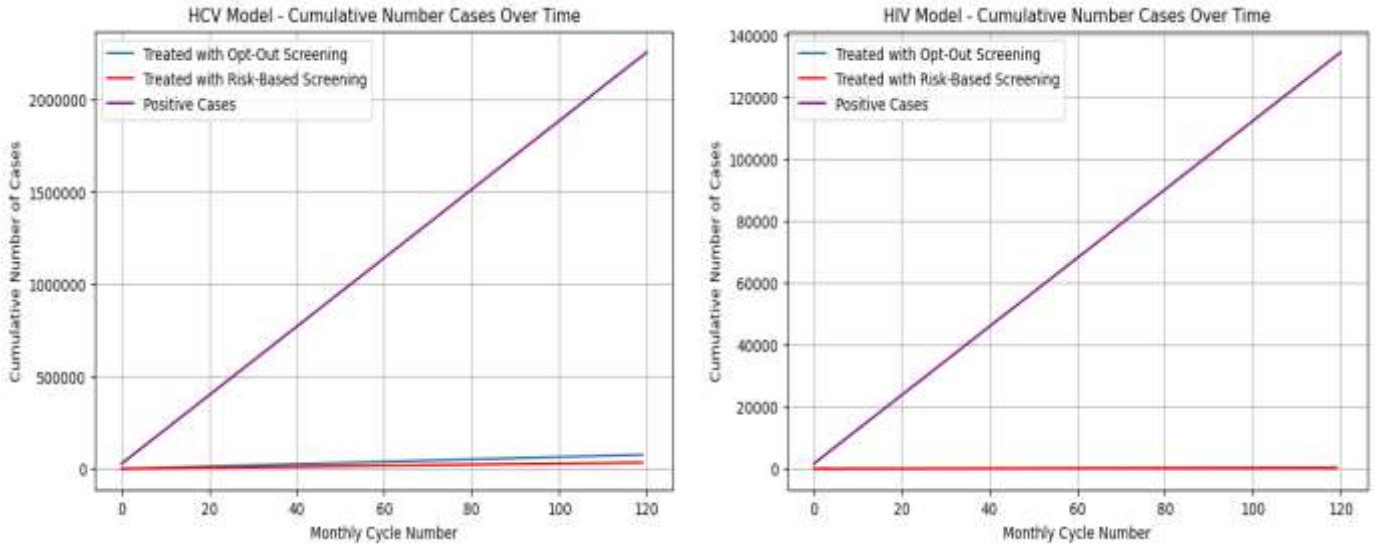


Figure 3b: Cumulative Number of New Cases Presenting to Jail for HCV and HIV Over Time



Discussion

KEY FINDINGS

Our analysis exhibits strong support for implementing routine opt-out screening in jails for four major infections within infection hotspots. All infection models, aside from the HIV model, showed cost-effectiveness with routine opt-out screening given the carceral specific WTP utilized. Based on literature derived values, we found much higher case detection rates with routine opt-out screening than risk-based screening, translating into an increase in quality-of-life health benefits with opt-out screening seen in all models. In addition to the higher case detection rates with opt-out screening, the very cost effective ICER values for the STI models are largely based upon lower treatment costs and short treatment durations. The moderate cost effective ICER value seen with the HCV model and the not cost effective ICER value seen with the HIV model, by contrast, are likely due to much higher treatment cost and longer treatment course.

Of note, the HCV model shows very high accumulated discounted costs across the simulation relative to other models. This is best explained by the expensive nature of HCV treatment (approximately $12,000 for a two-month treatment) combined with the relatively very high prevalence of HCV in carceral hotspots (we estimated a prevalence of 27.7% based on a previous study that established carceral HCV seroprevalence data). Additionally, in our model, we assume that everyone who is diagnosed will enter treatment while incarcerated. Due to the reality of high probability of jail release at any point in time, this resulted in a number of cases where HCV treatment was started but not finished, therefore increasing costs.

The ICER values for the STI models and HCV model being below the WTP threshold provides strong quantitative justification for widespread opt-out screening, which is largely already regarded as best practice; we show that the cost of opt out screening applied to a large carceral population is considered worthwhile in relation to societal willingness to pay for expected health gain.

Additionally, all models showed an increased percentage of estimated fully treated cases during incarceration with opt-out screening, explained by opt-out screening allowing for more infected patients to receive diagnosis and subsequently enter treatment. However, relative to the number of the total positive cases in the cohort, both screening types still only allow for full course of treatment while incarcerated for a relatively small portion of those who need it.

STRENGTHS

This study presents a novel examination of the cost benefit of opt-out screening within a key population disproportionately impacted by infectious disease – the incarcerated population. Our study considers an important reality of treatment within carceral settings, high probability of carceral release which limits the ability of patients to complete full treatment course in jails, thereby creating a model that is well generalizable. Additionally, through focusing on jails in infection hotspots, our results may help inform strategic public health interventions that aim to target these crucial facilities. The results of this study also support previous similar studies showing cost effectiveness with an opt-out screening approach.[52, 59, 61]

LIMITATIONS

This study has several methodological limitations. Many needed parameters for the cohort and state transition probabilities were not readily available in the literature, requiring derivation and using studies from varied populations that may show differences to the incarcerated population. One particularly consequential parameter we had to derive was case detection rates, which we based on available studies in the literature from varied populations and scaled for the incarcerated population. Other methodological limitations include the exclusion of personnel costs (which are

high but were excluded due to variability among jails in different regions) and not incorporating a dynamic adjustment to the inflow vector that would account for the anticipated decreased prevalence of the infections in the community over the long simulation timeframe. The lack of this dynamic inflow means that the cost benefit associated with prevention (i.e., decreased transmission in the community in response to individuals entering the community after treatment) is not captured in this study. The assumption that those who were diagnosed through carceral screening would certainly enter treatment if not released also serves as a limitation, with this being dependent on resource constraints in reality.

Lastly, other constraints of applying opt-out testing in a real jail setting include adjusting workflow and staffing to account for increased screening upon admission and security concerns related to moving a large cohort of inmates to testing settings regularly. Linkage to care post-release is another important consideration not included in this study's modeling. While it is possible to start treatment in jail and facilitate connection to a treatment center if the patient is released before completing treatment, we excluded this consideration from our model due to estimating continuity of treatment post-release being not feasible with discharge planning varying greatly between facilities. Additionally, the proportion of those released from a carceral institution who seek to finish treatment course is limited with patients facing many barriers such as lack of insurance, stigma, and poor health literacy.[66]

IMPLICATIONS

The results of this study highlight the strong cost benefit of implementing opt-out screening within jails within hotspots. The cost-effective nature of opt-out screening upon carceral admission in combination to its other known benefits, such as stigma reduction and decreased transmission, suggest the need for subsequent concerted initiatives aimed at making opt-out screening widespread in jails across the nation within hotspots.

While many jails may be located in hotspots for multiple infections, it is worth noting that screening for multiple infections upon admission may not be cost-effective, due to the accrual of high treatment costs. High treatment cost is a particularly impactful issue within HIV treatment efforts with antiviral therapy costing thousands of dollars annually and maintaining sustained virological resistance representing a recurring monthly cost. Other studies have shown cost-effectiveness with HIV opt-out screening, however, they only consider the cost of test administration and not treatment and are often not specific to carceral facilities.[67-69] One study examining HIV opt-out screening cost-effectiveness in a county jail in Georgia did find a cost effective result, though the model included the benefits and reduced costs associated with the number of secondary HIV transmissions averted and only analyzes one jail over a one year time horizon.[5] The high monthly probability of carceral release represented in our HIV model also influences cost-effectiveness considerably, with many who start the treatment leaving the facility before completion and therefore not receiving the full health quality benefits of the treatment.

Future efforts should focus on identifying avenues to decrease the cost of antiviral therapy within carceral facilities and linkage to post-release treatment access. State benefit programs such as Medicaid or 340 B programs can be utilized to pay for HIV treatment costs, representing an opportunity to decrease the cost of HIV treatment to the jail and make an opt out screening intervention possibly cost effective. Additionally, the Medicaid 1115 Waiver offers an avenue for states to pilot changes in regulations related to Medicaid coverage. In recent years, a number of states have applied for and received the Medicaid 115 Waiver to address the Medicaid Inmate Exclusion Policy (MIEP) which prevents the use of Medicaid funds for treating infectious diseases in jails.[70] Within these states, decreasing the cost of

medications to the facility, particularly for HCV and HIV treatment, can help facilitate the adoption of routine opt-out screening.

Conclusions

Overall, our study suggests that both national and state health organizations should prioritize the implementation of routine opt-out screening for major infections, particularly within hotspot areas. Executing this will require partnerships between programs such as the Ryan White HIV/AIDS program, the Center for Disease Control, and state departments of health.

Routine opt-out screening in jails can have a significant impact on prevalence and incidence of these infections within the larger community. Mobilizing the will of the community to implement pilot and implementation programs within jails serves as a promising avenue to improve population health.

Conflict of Interest:

The authors have no conflicts of interest to declare.

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