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Social network dynamics of tobacco smoking and alcohol use among persons involved with the criminal legal system (PCLS): A modeling study

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Abstract

Background: Tobacco smoking and alcohol use contribute to a synergy of epidemics (a "syndemic") that disproportionately affects persons involved with the criminal legal system (PCLS) and their social networks. An improved understanding of the complex interrelationships among the factors of the incarceration-tobacco-alcohol syndemic is essential to develop effective reform policies and interventions. However, collecting empirical data on these interrelationships is often hampered due to logistical and ethical challenges.

Methods: We developed an agent-based network model (ABNM) to simulate the effects of the incarceration-tobacco-alcohol syndemic in the state of Rhode Island, USA. The model was validated and calibrated using empirical survey and demographic data. Outcomes included current smoking and heavy alcohol use rates in the first year after release among previously incarcerated agents and in their social networks.

Results: The model successfully replicated demographic, substance use, and incarceration-related parameters. Simulation results suggest high rates of smoking (approximately 80% currently smoking persons in the first few weeks after release) and heavy alcohol use (approximately 40% current heavy alcohol use rate in the first few weeks after release) among PCLS, especially persons with multiple incarceration events. The model also estimated elevated rates of current smoking and current heavy alcohol use in the direct social contacts of PCLS.

Discussion: This ABNM integrates biobehavioral health processes relating to incarceration and substance use. This model can be used as a platform to evaluate the potential impacts of interventions provided to PCLS and their networks.

Introduction

The United States has one of the highest incarceration rates in the world (Fair & Walmsley, 2022). Persons involved with the criminal legal system (PCLS) often experience chronic stress which may exacerbate existing health disorders (Massoglia & Remster, 2019), and they are more likely to suffer from substance use disorders than the general population (Western, 2006). Specifically, tobacco smoking and alcohol use are substantially more prevalent among PCLS than the general population (Begun et al., 2011; Fazel et al., 2017; Springer et al., 2018). Unfortunately, interventions to address either behavior during incarceration have demonstrated limited efficacy (de Andrade & Kinner, 2017; Naik et al., 2014; Prendergast et al., 2017). These factors suggest a synergistic epidemic ("syndemic") of chronic stress, tobacco smoking and alcohol use among PCLS (Singer et al., 2017).

Although the investigation of the incarceration-tobacco-alcohol syndemic has received some attention in the scientific literature, far less attention has been paid to the fact that its adverse effects extend beyond PCLS. A substantial body of evidence in the general population has demonstrated that smoking (Christakis & Fowler, 2008) and alcohol use (Knox et al., 2019) cluster within social networks. Potential mechanisms underlying such clustering include network diffusion (i.e., the spread of behaviors through a social network; Granovetter, 1973) or social selection/homophily (i.e., individuals with similar traits connecting more readily;

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McPherson et al., 2001), or a combination of the two (Christakis & Fowler, 2008; Mercken et al., 2010; Rosenquist et al., 2010). The limited effectiveness of smoking cessation or alcohol interventions among individuals embedded in networks engaging in these behaviors underscores the potency of such clustering effects (Blok et al., 2017; Homish & Leonard, 2008). The increased stress experienced by PCLS may also affect their social network contacts (Lee et al., 2015). Reentry into the general population upon release is a particularly vulnerable time for PCLS and their communities, with both groups more likely to resort to smoking or alcohol as coping mechanisms (Dumont et al., 2013; Visher & Travis, 2003). There is, however, limited research on smoking and alcohol use in the social networks of PCLS.

Two significant obstacles to empirical research on the network effects of the incarceration-alcohol-tobacco syndemic are the ethical challenges of collecting data on the network communities of PCLS (Rosen et al., 2020), and the logistical difficulties of tracking syndemics connected to incarceration (Daza et al., 2020). Approaches that combine empirical data with complex systems modeling methods can help mitigate these research challenges (Tsai, 2018). Agent-based network models (ABNMs) simulate the behaviors and health profiles of incarcerated persons and their social network members, with each individual person represented as an "agent", and their social connections as "ties" or "links". Agent-based network models offer a complementary approach to empirical research, allowing for exploration of the effects of varying societal parameters (e.g., incarceration policies, interventions) through simulation. Complex system models have helped explore behavioral and policy interventions separately in assessing biobehavioral health impacts of tobacco smoking (Huang et al., 2021; Jeon et al., 2018; Levy et al., 2016), alcohol use (Braun et al., 2006; Buckley et al., 2022; Rehm et al., 2013), and criminal legal systems (Hawdon et al., 2017; Lofgren et al., 2022; Lum et al., 2014).

In this paper, we developed an ABNM that integrates incarceration, tobacco smoking, and alcohol use in social networks, biosocial health processes that have that have largely been investigated in separate research studies. We focussed on the incarceration-tobacco-alcohol syndemic in the networks of PCLS in the state of Rhode Island (RI), USA, where our team is based and maintains a strong collaborative partnership with the Department of Corrections (RIDOC), the Department of Health (RIDOH), and academic research units. We used the model to quantify tobacco smoking and alcohol use within PCLS networks and the projected course of smoking and alcohol use among recently released persons.

Methods

Overview

An ABNM consisting of 10,000 adult persons, between 18 and 84 years of age, was constructed. A high-level description of the major processes incorporated in the ABNM is provided in this section, followed by detailed descriptions in subsequent subsections.

One timestep in the model was defined as being equivalent to one day of calendar time. Each simulated individual agent was assigned a set of variables describing demographic characteristics (age, sex, and race). The agents experienced incarceration, release, and recidivism in concordance with empirical data published by RIDOC. Tobacco smoking of agents was classified per guidelines suggested by the US Centers for Disease Control and Prevention (CDC) in three states: "never" (fewer than 100 lifetime cigarettes smoked), "former" (at least 100 lifetime cigarettes smoked but none in the past month), and "current" (100 lifetime cigarettes and at least one in the past month; CDC, 2021). Alcohol use was classified in four states depending on the quantity of alcohol consumed in units of grams per day (GPD): a low-risk Category I (< 20 GPD for females, <40 GPD for males), a moderate risk Category II (21-40 GPD for females, 41-60 GPD for males), or a high-risk Category III (> 40 GPD for females, > 60 GPD for males), or a non-drinking category, as recommended by the World Health Organization (WHO; MacKillop et al., 2022). The distribution of these states was parameterized using a recently published analysis of data from the National Epidemiologic Survey on Alcohol and Related Conditions (NESARC-II; WHO, 2002; Puka et al., 2023). Each simulated agent was also embedded in a social network community determined by ties with close friends and kin based on population data from the Survey Center on American Life (Cox, 2021). These social networks provided the set of agents who might experience behavioral health stressors, such as incarceration, or smoking or heavy alcohol use. Further details on modeling the incarceration, tobacco smoking and alcohol use, and network processes are provided below. Detailed input parameters for the ABNM are provided in Table 1.

Tobacco Smoking and Alcohol Use

The proportion of agents in the Current, Former and Never smoking categories was parameterized based on race and sex, per data from the US National Health Interview Survey (NHIS; Integrated Public Use Microdata Series [IPUMS] NHIS, n.d.). Transitions between current and former smoking states were set numerically to ensure that the distribution of agents in each state remained consistent with population-level NHIS data over the course of the simulation. Derivation of these rates is described in the Supplementary Appendix. Alcohol use was modeled in the four states described above. The distribution of persons in each state was parameterized using published data from NESARC II (Puka et al., 2023). Transitions between states were modeled using recently published annual rates (Puka et al., 2023), that were converted into daily rates as shown in the Supplementary Appendix.

Incarceration and Underlying Disparities

Incarceration was modeled by defining two locations: a "correctional setting" (CS), representative of the unified prison-jail system in Rhode Island, and an "outside" setting. We set an incarceration probability for the modeled agents to match the approximated incarceration rate estimated at approximately 200-250 per 100,000 persons using 2019 data from RIDOC (National Institute of Corrections, n.d.; Rhode Island Department of Corrections, 2019), which estimated the incarcerated population has ranged from 2100-2700 in recent years, in a state of about 1.1 million people (Anderson, 2023; United States Census Bureau, n.d.-b). Additionally, sentence duration was probabilistically modeled in accordance with estimates published from secondary data analyses of RIDOC data (Macmadu et al., 2021).

The model included incarceration disparities stratified by race, sex, current smoking, heavy alcohol use (i.e., "Category III", as per the NIAAA categorization defined earlier), and persons with prior incarceration history. To model disproportionate representation of criminal legal involvement for agents by race, sex, smoking and heavy alcohol use, disparity metrics processes were modeled by the rate of incarceration experienced by a group relative to the size of that group in the general population. Since local Rhode Island data on disparity metrics were not available, national data from the Bureau of Justice Statistics informed the disproportionality in incarceration by race and sex (Custom Charts - 2016 SPI Data Analysis Tool, n.d.). To model disparities associated with substance use, recently published survey data informed the parameter on the over-representation of currently smoking persons among PCLS, noting that about 65% of persons are currently smoking at the time of incarceration (Ives et al., 2022). Data from a meta-analysis informed the disproportionate incarceration associated with high-risk alcohol use (Category III in our model); the meta analytic data suggested a 23% average rate of heavy drinking at the time of incarceration (Fazel et al., 2017). Agents suspended smoking and alcohol use during the time of incarceration, given the limited smoking and almost no alcohol use in the RIDOC setting (Personal Communication, Carole Dwyer, Warden, RIDOC). Increased probability of recidivism was set at a rate to match the overall incarceration rate in the population (Table 1).

Social Networks and Substance Use

Social network structures were modeled in accordance with data from the Survey Center on American Life, which suggest that a US adult has approximately four close friends in their network (Cox, 2021). Accordingly, the simulated agents are embedded in social networks of a mean size of four throughout their simulated life course. Clustering in the social networks of tobacco smoking and alcohol use were modeled in accordance with data published from the Framingham Heart Study, which suggest that smoking in networks of smoking persons increased by 61% in the first degree (i.e., persons who are directly linked through a social connection; Christakis & Fowler, 2008). With regard to alcohol use, Framingham Study data suggest that rates of heavy alcohol use increased by 50% in the first degree (Rosenquist et al., 2010). We modeled the first-degree dynamics of smoking and the onset of heavy alcohol use in accordance with these estimates, thus incorporating a "behavioral diffusion" mechanism in our model.

Post-Release Tobacco Smoking and Alcohol Use

As stated above, agents becoming incarcerated were more likely to be in the Current Smoking state or Category III alcohol use state, and use of both substances was suspended during incarceration. At the time of release from incarceration, agents resumed smoking and alcohol use in the same state that they had been in at the time that they became incarcerated. Upon release, the agents were able to transition between smoking states and alcohol use states at the same rates as the overall population.

Simulated Outcomes

The model simulated the rates of tobacco smoking and alcohol use in the social networks of PCLS over a 30-year period. This period was deemed to be sufficient given that the emergent outcome the validation and calibration parameters (Figures 1 to 3) were found to be adequately stable at the end of the simulation. Additionally, the rate of smoking and alcohol use was simulated in agents for a year after their release. Given that this is a stochastic model, it was simulated 30 times to account for the uncertainty in the simulations, as has been done in similar previous studies (Corlu et al., 2020; Khanna et al., 2019), and justified by the low variation seen across the input parameters specified.

Model Evaluation

The model was evaluated in two steps: "face validation" and "calibration" (Caro et al., 2012; Collins et al., 2024). Face validation here is defined as the process of verifying that the model accurately represents the specified relationships between input parameters and the corresponding simulated outputs, by comparing these outputs with the original empirical data from which the parameters were derived (Barlas, 1996; Oreskes et al., 1994; Sargent, 2013). This step ensures that the model is consistent with the input data. In contrast, calibration is the process of adjusting model parameters or structure to achieve a close agreement between the emergent properties of the model and independent empirical data not directly specified in the model (Thiele et al., 2014). These emergent properties arise from the complex interactions among the model components and are not directly controlled by the specified input parameters. Calibration allows the model to reproduce real-world phenomena more accurately and helps improve the generalizability of the model. Thus, validation focuses on the accurate representation of "first order" variables, which are directly specified in the model, while calibration aims to fine-tune the model to better replicate the emergent properties and downstream processes (second and greater order of interaction) that arise from the interactions among the model components (Sargent, 2013; Thiele et al., 2014).

The model was validated on Rhode Island demographic characteristics (race, sex, age distributions), social network size, and the prevalence of smoking and alcohol use in the population. Model calibration involved comparing the simulated net incarceration rate, which is interactively influenced by the mean population rate, and modeled disparities in incarceration due to race, sex, tobacco smoking and alcohol use, and sentence duration. The model was calibrated to reproduce a net incarceration rate that accounts for these interacting parameters and is consistent with the empirical rates for Rhode Island.

Computational Tools

The model was coded using the Repast4py (Collier & Ozik, 2022) library for agent-based modeling and the networkX (Hagberg et al., 2008) library for social network analysis in

Python 3 (Python Software Foundation, n.d.). The EMEWS (Ozik et al., 2018) software was used for parallel simulation for efficient calibration. Post-processing of the data was conducted using the “data.table” (Dowle & Srinivasan, 2023) library in R (version 4.4.0; R Core Team, 2022). The “DiagrammeR” package was used for network visualization (see Figure 5; Iannone, 2023). The model code is available in a public GitHub repository (Khanna et al., 2024).

Table 1

Input Parameters and Data Sources

Category	**Parameter**	**Value**		**Data Source**
Demographic parameters	Number of agents	10,000		Model Design
	Race/ethnicity distribution	White: 71.4% Black: 8.5% Hispanic: 16.3% Asian: 3.8%		US Census Reporter (Census profile: Rhode Island, n.d.)
	Sex distribution	Female: 51.3% Male: 48.7%		US Census Bureau (United States Census Bureau, n.d.-a)
	Adult age range	18–84 years		Model Design
Tobacco smoking[a]	Current	Females White: 12.1% Black: 9.5% Hispanic: 5.3% Asian: 1.8%	Males White: 13.7% Black: 14.4% Hispanic: 10.3% Asian: 9.4%	National Health and Interview Survey (IPUMS NHIS, n.d.)
	Former	Females White: 24.2% Black: 11.7% Hispanic: 9.6% Asian: 5.3%	Males White: 30.6% Black: 15.9% Hispanic: 23.1% Asian: 21.1%	As above
	Never	Females White: 63.7% Black: 78.8% Hispanic: 85.1% Asian: 92.9%	Males White: 55.6% Black: 69.6% Hispanic: 66.6% Asian: 69.4%	As above
	State transition matrix: Probabilities to transition between current and former smoking states for each race and sex per day	Set to maintain stationary distribution across the simulation time		Derivation in Appendix
Alcohol use behavior	Non-drinking	35%		NESARC II (Puka et al., 2023)
	Category I (low risk)	55%		As above
	Category II (moderate risk)	5%		As above
	Category III (moderate risk)	5%		As above
	State transition matrix: Probabilities to transition between states daily	Derived from NESARC II (Puka et al., 2023)		Supplementary Appendix

Table 1 (continued)

Input Parameters and Data Sources

Category	Parameter	Value				Data Source
Incarceration	Daily incarceration probability for never incarcerated persons	6.85e-6				Rhode Island Department of Corrections (Rhode Island Department of Corrections, 2019)
	Daily incarceration probability for previously incarcerated persons	0.00010275				Free parameter, value set to match overall incarceration rate
	Sentence duration[b]	Females		Males		Rhode Island Department of Corrections (Macmadu et al., 2021)
		2–4w	40.0%	2–4w	43.0%	
		5–26w	47.5%	5–26w	50.0%	
		27w–1y	6.5%	27w–1y	2%	
		1–3y	4.5%	1–3y	3%	
		3–6y	1.5%	3–6y	3%	
	Distribution by race and sex	Females White: 2.6% Black: 2.4% Hispanic: 1.6% Asian: 0.07%		Males White: 34.0% Black: 36.2% Hispanic: 21.1% Asian: 0.93%		Bureau of Justice Statistics (Custom Charts - 2016 SPI Data Analysis Tool, n.d.)
	Rate by current tobacco smoking	Mean 65% of persons Currently smoking at the time of incarceration				Survey data (Ives et al., 2022)
	Rate by heavy alcohol use	Mean 23% of persons in Category III alcohol use at the time of incarceration				Meta analysis (Fazel et al., 2017)
Social Network**	Mean number of friends reported	4				Survey Center on American Life (Cox, 2021)
Social Networks and Tobacco Smoking	Smoking onset	Probability increased by 61% in the first degrees of connection to a current smoking agent				Framingham Heart Study (Christakis & Fowler, 2008)
Social Networks and Alcohol Use	Alcohol use onset	Probabilities of heavy alcohol use increase by 50% in the first degree of connection to a heavily alcohol using agent				Framingham Heart Study (Rosenquist et al., 2010)

[a]Current, Former and Never smoking percentages for each race and sex sum to 100%.
[b]The unit “w” denotes weeks, “y” denotes years, and 52w = 1y.

Results

Model Validation

Demographic Parameters

The simulated distributions of race and sex demographics in Figures 1a and 1b show close agreement with their census-based sources presented in Table 1

Substance Use Parameters

The state distributions of smoking and alcohol use in the population over time are presented below. The simulated state distributions of smoking and alcohol use closely shown in Figures 2a and 2b closely align with the input targets specified in Table 1.

Model Calibration

The mean incarceration rate per 100,000 (Figure 3) is about 200 per 100,000 (relative to the empirical estimate of about 200 to 50 per 100,000; Rhode Island Department of Corrections, 2019) The mean duration of agent incarceration is approximately four months (close to the empirical data; Macmadu et al., 2021).

Figure 1a

Simulated Race Distribution

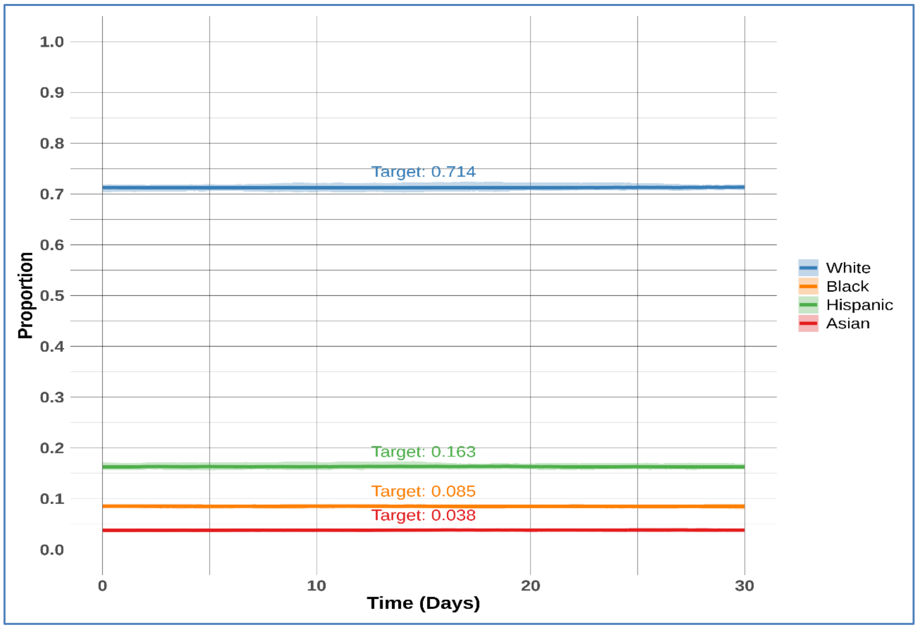
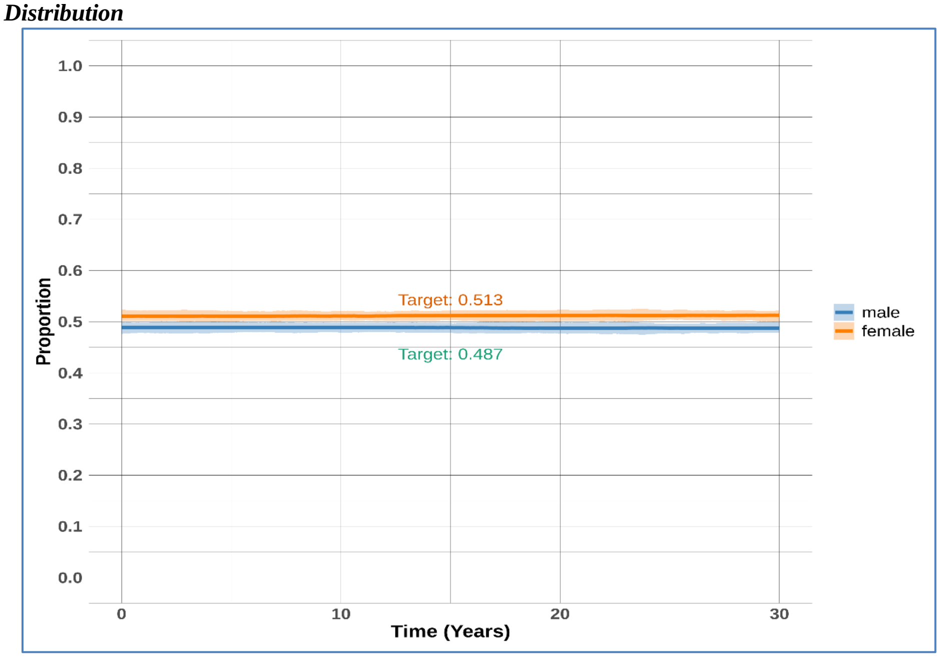


Figure 1b

Simulated Sex Distribution



Note: Solid lines and shaded regions represent the mean and standard deviation respectively across 30 model runs.

Simulation Results

Tobacco Smoking and Heavy Alcohol Use among Released Persons

The simulated data from the model shows an elevated rate of tobacco smoking and heavy alcohol use in the set of recently released agents (Figures 4a and 4b). Within a week of release, the current smoking rate is about 80%. Note that the base rate of current smoking at the time of incarceration is about 65%. However, agents who have experienced incarceration previously, and are currently smoking, have a greater probability of becoming incarcerated than either group alone. At any given time, the set of released agents includes agents who have been incarcerated multiple times, thus increasing the current smoking rate in the released agents. Similarly, the rate of heavy alcohol use within a week of release is approximately 40%, higher than the base rate of heavy alcohol use of 23% on average in the incarcerated population at the time of incarceration. Again, there is feedback between incarceration and heavy alcohol use, thus driving up the rate of current heavy alcohol using agents at the time of release.

Figure 2a

Simulated State Distribution of Tobacco Smoking

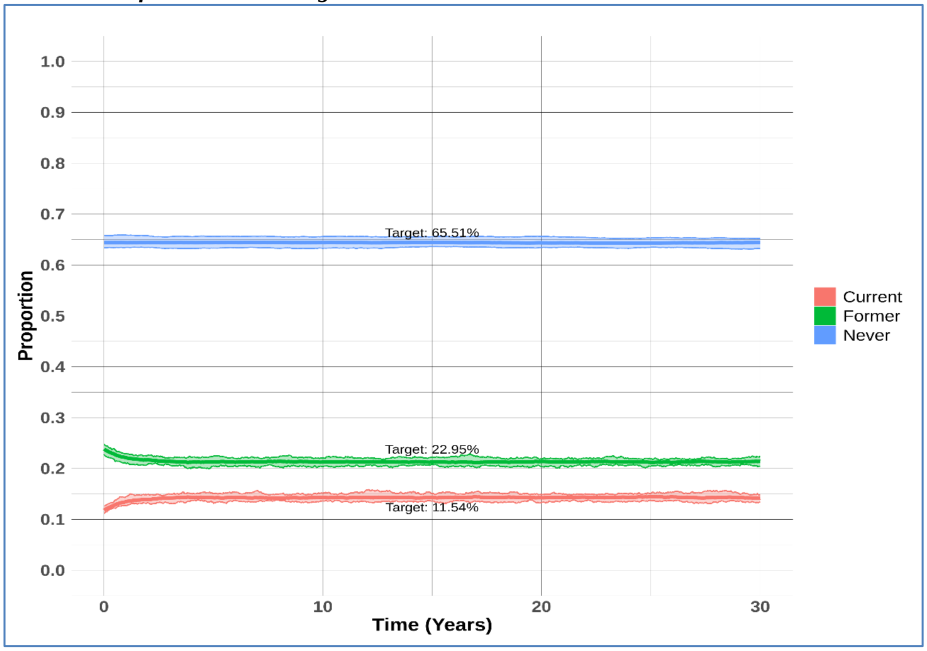
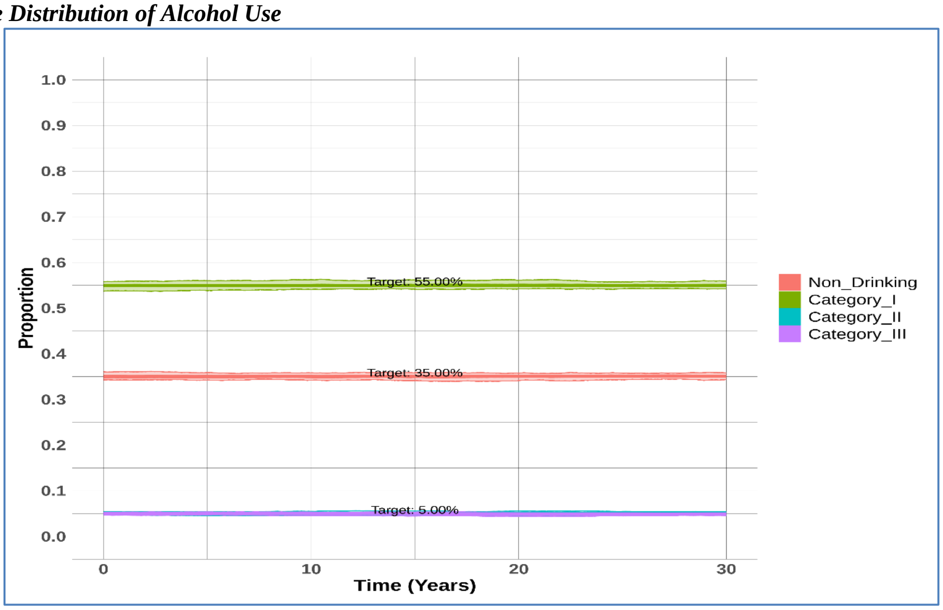


Figure 2b

Simulated State Distribution of Alcohol Use

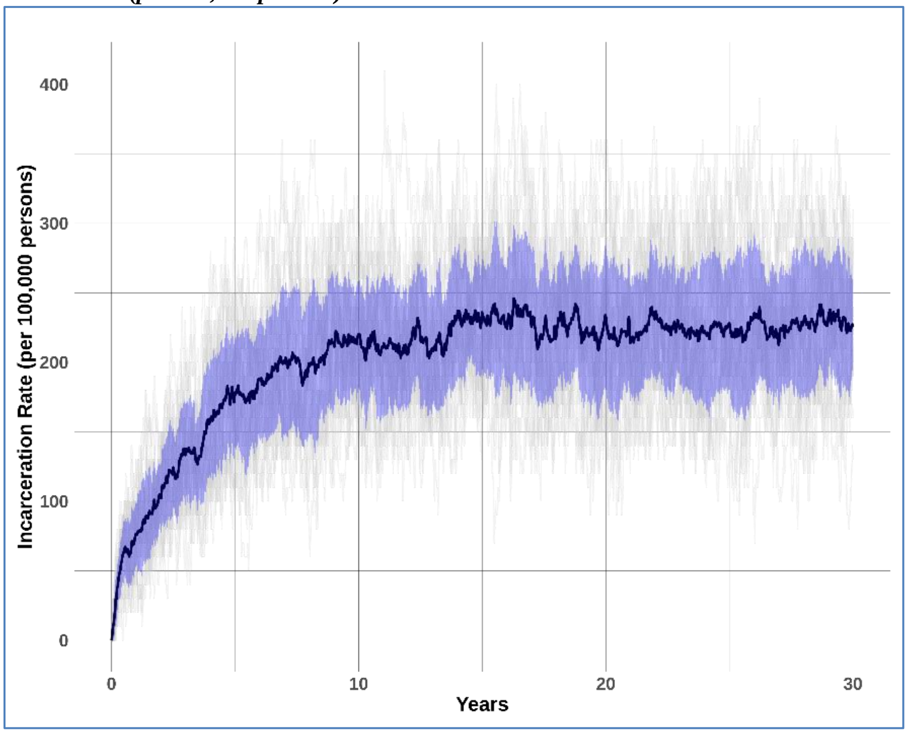


Note**:** Solid lines and shaded regions represent the mean and standard deviation respectively across 30 model runs**.**

Upon release, the simulated agents are exposed to the same transition rates as the general population, thus the rapid decline in current smoking and heavy alcohol use rates. In real life, the transition rates among recently released persons might be different than in the general population if they continue to experience incarceration-associated stressors. In the simulation, we are thus simulating a "best case" scenario, i.e., agents experience the same transition rates upon release as the general population, therefore potentially overestimating the decline in current smoking and heavy drinking over time.

Figure 3

Simulated Incarceration Rate (per 100,000 persons)



Note: The solid line and the dark blue regions represent the mean and standard deviation of the simulated incarceration rate across the 30 model runs. The light grey lines show the individual incarceration rate trajectories.

Figure 4a

Simulated Rate of Current Smoking as a Function of Time Since Release

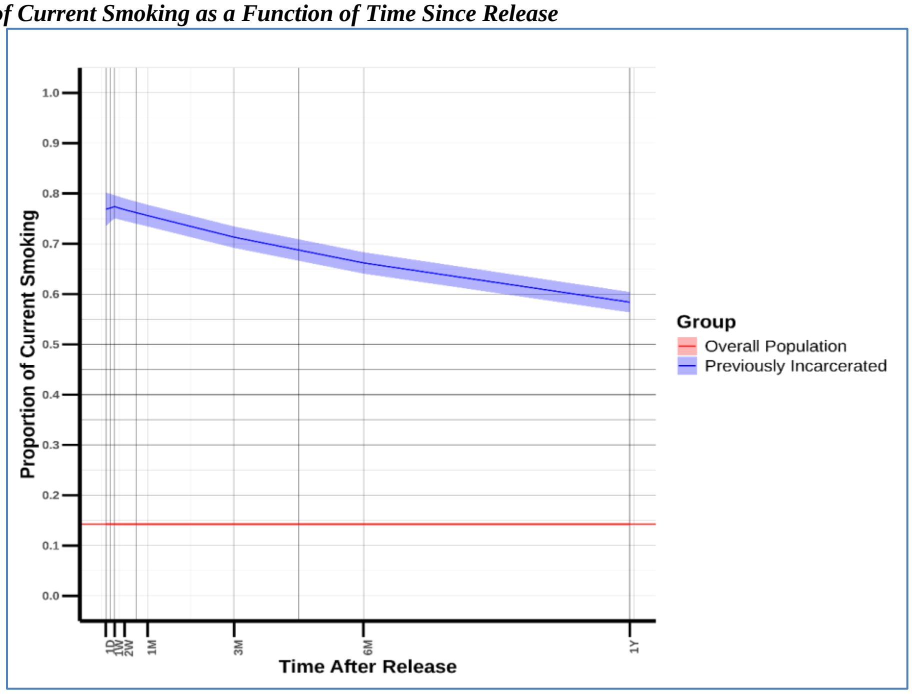
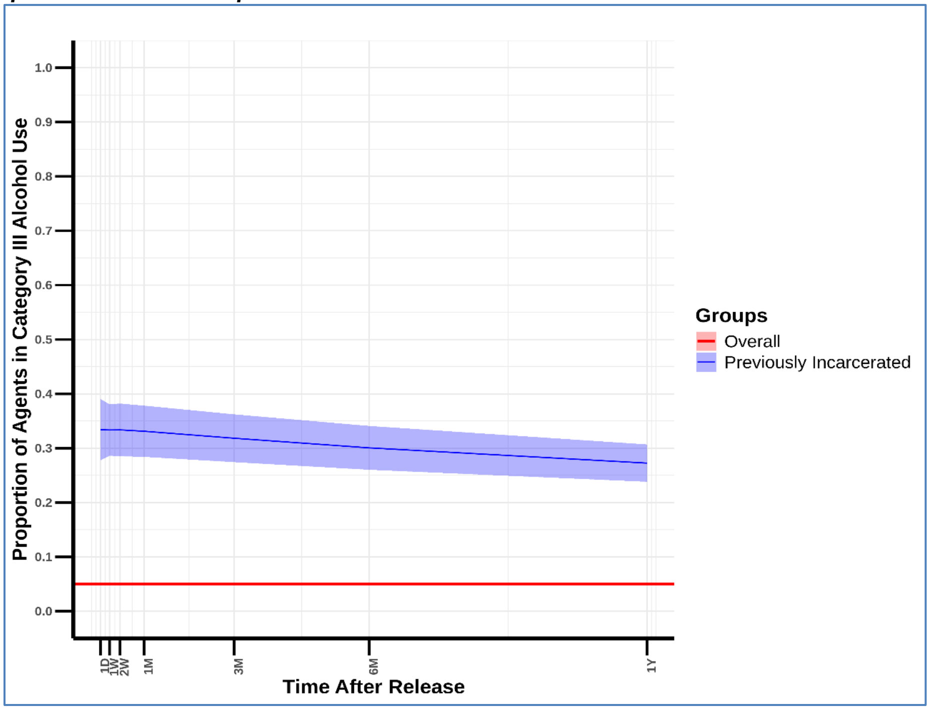


Figure 4b

Simulated Rate of AUD as a Function of Time Since Release



Social Network Effects of Tobacco Smoking and Heavy Alcohol Use

The rate of current smoking and heavy alcohol use in the direct network contacts of persons released over the past year, at the end of the simulation, are provided in Table 2, including the mean and standard deviation across the 30 simulated networks. A visualization of the social network structure in one simulated instance is provided in Figure 5.

Figure 5

Diagram of Agents Released in the Past Year (squares) and their Social Network Members (circles) highlighting Current Smoking and Heavy Alcohol Use

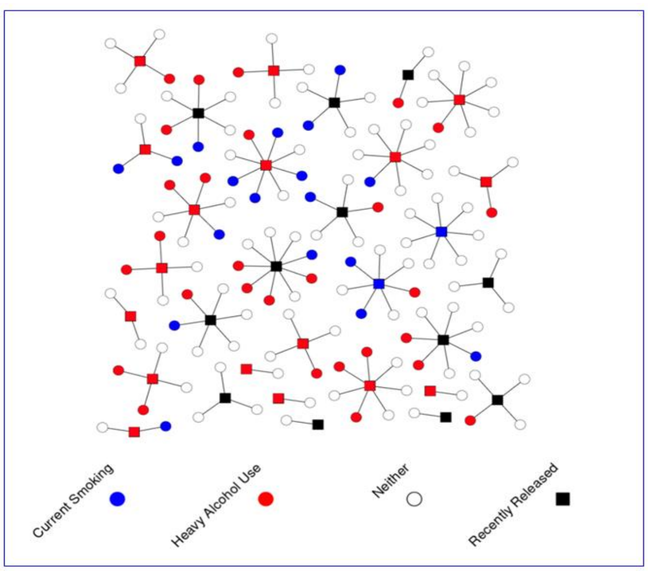


Table 2

Current Smoking and Heavy Alcohol Use Rates among Agents Released in the Past Year and their Social Networks at the End of the Simulation

	Current Smoking [mean (SD)]	Heavy Alcohol Use [mean (SD)]
Agents released (<1 year)	57.1% (6.3%)	27.9% (6.1%)
Social Networks of Agents (released <1y)	25.5% (27.4%)	9.1% (1.4%)
Overall Population	14.2% (0.3%)	5.0% (0.2%)

Discussion

In this study, we developed and implemented one of the first simulation models to incorporate the joint dynamics of tobacco smoking, alcohol use and incarceration. Our main conclusions note the elevated rate of smoking and heavy drinking in recently released persons, persisting up to a year after release, even when such agents are not incarcerated again. A second conclusion highlights the elevated rates of current smoking and heavy alcohol use in the social networks of persons released within the past year.

As mentioned above, our model simulates a "best case" scenario for decline in current smoking and heavy alcohol use over the course of a year after release. This is because agents in the model were exposed to the same transition rates as the general population after release. In reality, given continued life stressors after incarceration, smoking or heavy alcohol use in persons with a history of incarceration might decline more slowly. Thus, there is a greater chance for continued disease risk after release.

The focus on the syndemic of these behaviors in persons involved with the criminal legal systems (PCLS) and their social networks is an innovative factor of this modeling platform. The results of our model validation and calibration demonstrate that the model successfully replicated demographic and substance use parameters. The mean incarceration rate and duration are close to the empirical data. Additionally, the model effectively captures the elevated rates of tobacco smoking and heavy alcohol use among individuals released from the correctional setting. Moreover, the model produced estimates of smoking and alcohol use over the year post-release in released persons and their social networks, measures that are hard to empirically assess, despite their importance to overall population health.

Our study emphasizes the syndemic nature of tobacco smoking, alcohol use, and incarceration, rather than treating incarceration as an isolated causal event. This approach acknowledges the complex interrelationships among these factors and their synergistic effects on individuals involved with the criminal legal system and their social networks. By focusing on the syndemic, we aim to better understand the interconnectedness of these behaviors and conditions and how they jointly impact the health of PCLS and their social networks.

We note several limitations in the work. Smoking and alcohol use were modeled independently, when in real life use of the two is correlated (Gulliver et al., 2006; Weinberger et al., 2013). We also did not have precise data on the transition rates in the states of smoking and alcohol use, but we simulated transitions at rates so the overall distributions matched population level data. This allowed us to get a "best case" estimate of the decline in smoking and drinking upon release, but this estimate has limitations. Additionally, in modeling disparities related to race and sex within the criminal legal system, we relied on national-level data due to the absence of detailed, state-specific statistics for Rhode Island. While this approach is justified given the data constraints, our use of national data may not fully reflect the unique demographic and judicial dynamics of Rhode Island. Moreover, the decision-making process in our model is based on probabilistic rules rather than a cognitive or rational choice framework, which may not fully capture the complexities of real-life decision-making. Future model versions will consider integrating frameworks such as Belief-Desire-Intention (BDI) to better represent the control and impulsivity mechanisms underlying smoking and alcohol use (Rao & Georgeff, 1995). The model does not explicitly incorporate substance use as a mechanism to cope with the stress of incarceration or other life challenges in the social networks of PCLS. We focussed instead on the synergistic effect of increased tobacco smoking or alcohol use among PCLS and the social network reinforcement of the use of both substances. Also, social networks were modeled as relatively fixed over the course of the simulation, i.e., agents dissolved or formed new ties only at the time of entry or exit from the model. The modeled ties were also reflective of the general US population, not accounting for the complexities of relational turnover or tie strength that may be particular to PCLS. Our model primarily incorporates the behavioral diffusion mechanism of the impact of social networks on smoking and alcohol use. Future work will consider modeling frameworks that allow for explicit consideration of homophily or social selection. Finally, we tested the face validity of specified parameters and the emergent incarceration rate in the model, but external validation, i.e., comparing the model's outputs to independent real-world data, was not conducted due to the absence of suitable external data.

Despite these limitations, the model shows the likely persistence of elevated smoking and alcohol use in persons involved with the carceral system and their social networks. This has implications for the health and wellness of both communities. Importantly, the model provides a platform to build extensions connected to such health impacts. In ongoing work, this team is developing models to correlate incarceration-tobacco-alcohol syndemic with chronic disease, particularly cardiovascular disease and cancer risk factors (Howell et al., 2022; Puglisi et al., 2020). Another area of research for the team includes the impact of the syndemic on the children of PCLS, where early onset of tobacco smoking and alcohol use has continued health effects later in life (Davis & Shlafer, 2017). The model will thus continue to be used to aid in planning behavioral and policy interventions around criminal justice reform and supportive services for behavioral health for PCLS and persons in their social networks.

Conclusion

This study presents a novel agent-based network model (ABNM) that captures the complex interplay between tobacco smoking, alcohol use, and incarceration among persons involved with the criminal legal system (PCLS) and their social networks. Our findings reveal persistently elevated rates of smoking and heavy alcohol use among recently released individuals, and the broader network effects observed through elevated rates of tobacco smoking and heavy alcohol use in the direct social contacts of recently released individuals. By highlighting the interconnectedness of these behaviors within the context of criminal legal involvement, our model provides a robust platform for simulating the potential impacts of tailored interventions on both PCLS and their communities. While this is a simulation study, it underscores the importance of subsequent empirical work to validate these findings and refine intervention strategies. The insights gained from this model emphasize the need for interventions that address not only individual behaviors but also the broader social dynamics that perpetuate these syndemic conditions. Future research will build on this foundation by expanding the model to incorporate additional factors such as chronic disease risk and the long-term health impacts on the children of PCLS. This ongoing work aims to inform criminal justice reform and the development of supportive services that comprehensively address the complex needs of PCLS and their communities, ultimately contributing to improved health outcomes and reduced health disparities.

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