LETTERS IN BIOMATHEMATICS
An International Journal

EDITORIAL

Battling Epidemics and Disparity with Modeling: The Coupled Dynamics of the COVID-19 Pandemic with Social Epidemics

Anuj Mubayi[a,b], Jeff Sullivan[a], Jason Shafrin[a], Oliver Diaz[a], Aditi Ghosh[c], Anamika Mubayi[d], Olcay Akman[b], Phani Veeranki[a],

[a]PRECISIONheor, Los Angeles, USA; [b]Illinois State University, Normal, USA; [c]University of Wisconsin-Whitewater, Whitewater, USA; [d]Indian Institute of Technology, Kanpur, India

ABSTRACT

Policymakers are under intense pressure to respond effectively to the ongoing COVID-19 situation. Epidemiological models, which have been helpful in many previous infectious diseases' epidemics, have been inconsistent and often incorrect in predicting burden of COVID-19 outbreak. Modelers are struggling to identify and capture appropriate drivers of the current outbreak giving conflicting conclusions. COVID-19 is not only exerting unprecedented social pressure on the vulnerable population but also its patterns are getting impacted by existing and aggravating social problems. The present article stresses the role of this dual nature of the impact of COVID-19 and suggests modelers to incorporate challenges at the interface of COVID-19 preparedness and social epidemics such as homelessness and opioid use. There is an urgent need to encourage social distancing policies to protect people and prevent the spread of the virus, while ensuring that other social crises and vulnerable populations are not ignored.

KEYWORDS
COVID-19, social epidemics, homelessness, housing assistance

1 Introduction

The COVID-19 pandemic poses significant health risks, in particular to vulnerable groups such as older adults, population with pre-existing conditions, those addicted to drugs, and those with poor access to food, shelter and basic hygiene, which in turn provides dynamic nature to disease spread and to social issues as well. The current dynamical models around COVID-19 pandemic typically only incorporate the mortality rates and transmission rates, and possible healthcare and economic burden (Wynants et al., 2020). In this commentary, we argue that the dynamics of COVID-19 outbreak should be studied and tackled not in isolation but along with other ongoing social epidemics. To begin with, we pose the following research questions that we believe deserve urgent attention and are important to address:

- How are COVID-19 dynamics interacting with (and perhaps reshaping) pre-existing social epidemics – when various social and economic factors can either trigger or maintain higher levels of infection and severity of the disease?

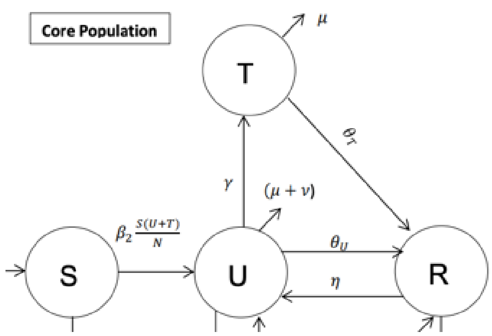
- Once links between social epidemics and COVID-19 are established and critical driving factors behind them are identified, how to evaluate the role of those pressure points on the coupled systems to help policy makers design cost-effective "humanitarian" and "public health" intervention strategies to address the co-dynamics of COVID-19 and pre-existing social epidemics?

In this commentary, we used two current social epidemics in the US as examples to provide a viewpoint on the coupled dynamics with COVID-19 pandemic: homelessness and the opioid crisis. Individuals who are homeless or addicted to opioids may be at higher risk of contracting COVID-19 and experiencing serious health affects (e.g., mortality) conditional on contracting the disease. Further, the intersection of these social epidemics and COVID-19 brings up important modelling questions. For instance, how are the dynamics of the current COVID-19 pandemic modified by social epidemics of homelessness when local governments

CONTACT Anuj Mubayi anujmubayi@yahoo.com

Table 1: A mathematical model capturing Dynamics of Drug with initiation due to social influences and available treatment.

S ("susceptible")	A group of individuals who are susceptible to social issue or a behavior (such as susceptible to opioid use or to homelessness). Some studies have stressed the fact that in general there is a susceptible at-risk population and a general population who will never initiate these behaviors due to strong family history or their socio-economic support.
U ("problem behaviors")	This class is composed of individuals who have been experiencing problem behaviors either due to pre-health conditions or socio-environmental stress.
T ("treatment/rehabilitation")	This sub population includes individuals who have realized their issue and are undergoing intervention to leave the problem behavior state. This group may also consist of individuals who can return to problem behaviors as a result of relapse or reinforcement.
R ("recovered/removed")	This set of individuals have successfully completed their intervention to come out of a problem behavior state and are declared recovered. These individuals may transition to susceptible class later in their life due to different episode of problem of behaviors.



(a) A mathematical model capturing Dynamics of Drug with initiation due to social influences and available treatment (Hameed et al., 2013).

(b) Opioid epidemic is on rise and constitute mostly vulnerable population.

Figure 1: Modeling framework of drug use and treatment.

are faced with large homeless encampments amid COVID-19-related job loss? There seems to be a positive feedback effect of COVID-19 outbreaks increasing job losses, which aggravates the existing homelessness problem, which may lead to larger or longer outbreaks. Additionally, COVID-19 may be accelerating the use of addictive medications such as opioids, derailing the progress made to curtail the opioid crisis during last decade (Alter and Yeager, 2020; Ghosh et al., 2020). An abundance of literature on mathematical models exists (Mubayi et al., 2010; Tragler et al., 2001; White and Comiskey, 2007) to address parts, if not all, of these questions. Use of these techniques will depend on a timeline and awareness of when COVID-19 started during the course of an ongoing social epidemic, and how the problem has changed as consequence of current COVID outbreak.

2 Modeling the dynamics of a social problem

Typically, dynamical studies stratify modeled populations into categories with different social behavioral mechanisms feeding into one another. A caricature of an example is shown in the Table 1.

The analysis suggests an existence of threshold or tipping point expression:

$$R_0 = \frac{\beta_2(\gamma + \theta_T + \mu)}{(\theta_T + \mu)(\theta_U + \mu + \gamma + \nu)} \tag{1}$$

Here R_0 is the basic reproductive number and the opioid epidemic dies down when $R_0 < 1$ and it spreads in community when $R_0 > 1$.

Table 2: Parameters of the Reproductive number.

β_2	Social interaction parameter showing influence of meth users (U) on at-risk susceptibles (S)
μ	Natural mortality rate
ν	Opioid overdose death rate
γ	Rate at which opioid users join rehab for treatment
θ_T	Rate at which opioid users quit as a result of rehab
θ_U	Rate at which opioid users quit without rehab
η	Rate of relapse back to opioid use

Figure 2: The current homeless situations are getting more intense due to COVID-19.

Apart from the transitions between categories, other critical aspects of the modeling system are how peer and contextual influences are captured to impact patterns of a problem (Mubayi, 2017). These classes are then tracked over time as the rates between the categories vary and shape the overall dynamics of the social issue in a population. The analysis of such models suggests the existence of threshold quantities or tipping points, a concept made popular for social problems by Malcolm Gladwell's book with that title. Gladwell used real life examples of social problems to highlight how individual behavior depends on the behavior of the herd and vice versa. In mathematical terms, the tipping point defines a critical value of model parameters at which a social problem shifts from being a localized and minor problem to a major crisis. For example, the Equation (1) provides an expression of the tipping point or the reproduction number for the model framework described in the Figure 1, Table 1 and Table 2. The expression can be interpreted as the tipping point of spread of drugs use, where the drug use will become an epidemic if the estimate of the basic reproduction number, R_0 is greater than one, otherwise drug use in the modeled population can be controlled. Note, the expression is a function of drug-related epidemiological (i.e., β_2, θ_U and ν) and therapeutical (i.e., γ and θ_T) parameters as well as demographical (i.e., μ etc.) factors.

2.1 Homelessness continues to grow in certain major cities of US

In recent days, researchers have scrambled to collect data and to model the transmission dynamics of COVID-19 under different groups' living situations in hopes of devising strategies to curb outbreaks in vulnerable cohorts (Baggett et al., 2020). A growing population of homeless individuals (Fig. 2) is a matter of concern as unemployment soars, local unrest spreads, and prisoners are released (with varying levels of support) to ease crowding and minimize SARS-CoV-2 spread (Alexander, 2020). Interventions such as providing rooms for individuals at high risk of severe disease because of underlying health conditions, additional and aggressive testing, etc. have been tried upon many times with little to no efficacy.

According to the National Alliance to End Homelessness, there are around 500,000 homeless individuals in the US with more than 30% consisting of family units with children. This group is more at risk of contracting infectious diseases as they may have less public health awareness, inability to do social distancing, limited access to healthcare, are often affected by severe malnutrition, and are unable to practice appropriate hygiene to curb transmission. In our previous study, we evaluated the impact of existing interventions in Los Angeles (LA) while capturing basic dynamics of homelessness (Azizi et al., 2020). The highlights of this study include incorporating local disparities in socio-economic conditions and linking parameters of the model to social surveys and intervention data. The modeling exercise has resulted in identifying conditions when each of the two different programs (temporary housing assistance programs and professional skills training programs), in isolation and jointly, might be effective in reducing homelessness in LA. Using current parameters for LA, our study estimated probability of elimination (see Table 3). Moreover, the magnitude of these differences varies based on the socio-economic conditions of the neighborhood with relatively higher difference in richer neighborhoods (see Fig. 3).

Table 3: Estimates of Probability of elimination of homelessness and average fraction of homeless at steady state from the model (Azizi et al., 2020).

Intervention Scenarios	Probability of homelessness elimination	Average fraction of homeless (disaffiliated) at quasi stationary sate
No intervention	0	0.966 (0.017)
Job training	0	0.837 (0.019)
Housing assistance	0.012	0.015 (0.893)
Both interventions	0.596	0.00 (0.165)

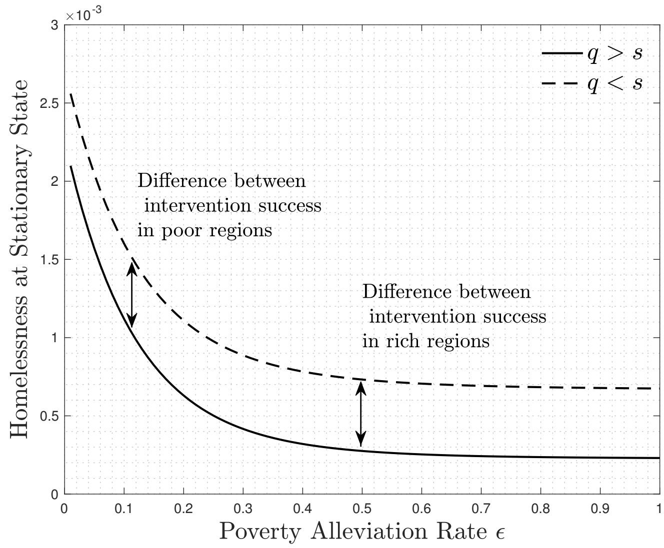


Figure 3: Difference in model-based homelessness proportion between rich and poor neighborhoods (Azizi et al., 2020).

2.2 Current level "Opioid crisis" in US

Despite a number of deaths of prominent cultural figures, the opioid crisis has gained steam in the latest decade. In 2016, a well-known American pop singer Prince died due to accidental overdose of (believed to be) opioid. The fentanyl that led to his overdose was contained in counterfeit pills made to look like a generic version of the painkiller. In spite of various investigations, there were no criminal charges filed (Strobl and Bracey, 2016). The publicity around the investigation led to increased awareness of many factors driving the opioid crisis including the excessive prescription of opioids, easy accessibility of opioids, counterfeit drugs, precursor laws, variations in drug-possession laws between states, stage-dependent interventions, data scarcity, and last but not the least magnitude of the current epidemic of the opioid crisis fueling into itself.

More broadly, US deaths due to opioid-related overdoses have drastically increased in last decade, increasing to approximately 50,000 in 2019 resulting in a substantial cost burden to society and individuals such as health care costs, criminal justice expenses, and productivity losses (Florence et al., 2013). Interventions to tackle the opioid crisis include restricting the opioid prescriptions via days-dose-limit laws and law enforcement-based control programs. These interventions have demonstrated only a modest decrease in the opioid outbreak burden, possibly due to uncertainty around data on overdoses, both fatal and non-fatal. The outbreak of opioid abuse can be modeled using a standard compartmentalized model similar to the one used for outbreaks of methamphetamine and heroin use (Hameed et al., 2013; White and Comiskey, 2007).

2.3 Epidemic Models of Co-dynamics

There has been immense modeling with other infectious disease (such as influenza, Ebola, MERS, SARS, etc.) and hence, there exists an extensive set of frameworks which can be drawn upon to study COVID-19 infection dynamics. However, recent COVID-19 models have primarily focused on gaining an understanding of how to flatten the curve and thus have been conducted with limited scopes (Jewell et al., 2020). Some individuals credit this limitation to restricted or inaccurate available data whereas others have identified reasons as fear-driven continuous behavior change of the population. Despite these limitations, such models may have resulted in some changes in the behavior of health officials, policymakers, and the general population.

Also, relevant has been a unidirectional focus of modelers ignoring components that are attributed to socio-economic structure and/or other simultaneously existing current epidemics or crises such as homelessness and drug abuse. Accuracy of models is typically based on assumptions derived from reality, available data, and how different components of the model interact. Models traditionally have helped to explain complex phenomena, providing projections of mortality and morbidity and evaluations of adaptive interventions such as mask use (for example, COVID-19-related modeling studies have identified that risk of infection to the mask wearer decreased by around 65% (Kushman, 2020)).

Multi-system models have flourished in the literature; however, most of them are either related to specific diseases (with limited to no modeling of a disease and a social epidemic) or have focused only on limited representation of socio-economic specifics of two systems (Roeger et al., 2009; Mukandavire et al., 2009). The study of the joint dynamics of COVID-19 and a social problem such as homelessness or opioid use may present some mathematical challenges, but with limited COVID-19-related data and a great deal of prior understanding of social systems, a coupled system may provide robust and more accurate trends of COVID-19. Individuals who are both infected as well as having these social problems may contribute not only to the spread of infection at higher level but also may have high mortality. Vice versa the severity of this disease may also impact the social and mental status of many individuals thus aggravating the problem on homelessness and opioid use.

Co-dynamics of a socio-economic problem and the COVID-19 outbreak is more important than studying the correlation between reproduction number and socio-demographic variables. Exploring socio-demographic variables using Spearman rank correlation, as was done by Grantz et al. (2016), is only sufficient to capture the dynamics of COVID-19 transmission related to socio-demographic factors in extremely restrictive scenario.

2.4 COVID-19 and Disparity Gap

The current COVID-19 pandemic is only exacerbating existing social problems. As COVID-19 kills thousands across the US, the homelessness and opioid crises have intensified its impact away from the spotlight, engulfing one public health problem inside another. Moreover, the homeless population and opioid users often have comorbidities that make them more vulnerable to contracting the COVID-19. Like any other major outbreak, the three epidemics have been disproportionately affecting minorities and the most vulnerable in society. Although incorporation of disparity into the model will add an additional layer of complexity to the disease modeling. The disproportionately large burden that COVID-19 has on disadvantaged populations needs to be modeled before it can be addressed.

Just like COVID-19-specific dashboards are being created for disseminating statistics about the pandemic, our aim as modelers should be to create a robust response to the dangerous blends of a social epidemic and the COVID-19 outbreak so that policymakers can study the interplay between them by varying critical parameters. In spite of many challenges related to data collection and availability, we should not underestimate the power of modeling studies to identify things that work and things that do not.

3 Conclusion

What needs to be understood is how the great social epidemics of the 21st century and the COVID-19 pandemic are intersecting in deadly ways. There is urgency in the call for modelers and policy makers to come together and think of the COVID-19 problem not in isolation but along with these outbreaks as a coupled system. Due to their ability to draw on a wide breath of established models in the field, applied mathematicians are in a unique position to bring their expertise to rapidly create and update these models. The important aspect, that the co-dynamics boil down to, is related to social determinants of health, which require systematic understanding of social and environmental co-mechanisms.

References

Alexander, A. (2020). Ramping up fight against COVID-19, NC begins releasing some inmates early. online report. https://www.charlotteobserver.com/news/coronavirus/article241977711.html. 107

Alter, A. and C. Yeager (2020). The consequences of COVID-19 on the overdose epidemic: Overdoses are increasing. Overdose Detection Mapping Application Program report, accessed on July 11, 2020. http://www.odmap.org/Content/docs/news/2020/ODMAP-Report-May-2020.pdf. 106

Azizi, A., J. Carpenter, M. Alharbi, J. Sánchez, V. Jones, C. Montalvo, V. Arunachalam, and A. Mubayi (2020). Evaluating the impact of job training and housing assistance programs on the dynamics of homelessness Los Angeles County of California: A mathematical modeling study. *OSF Preprints*. https://osf.io/4jyb2. 107, 108

Baggett, T. P., H. Keyes, N. Sporn, and J. M. Gaeta (2020). Prevalence of SARS-CoV-2 infection in residents of a large homeless shelter in Boston. *Jama 323*(21), 2191–2192. 107

Florence, C., C. Zhao, L. F., and X. Likang (2013). The economic burden of prescription opoid overdose, abuse, and dependence in the United States. online report. https://pubmed.ncbi.nlm.nih.gov/27623005/. 108

Ghosh, A., I. Berger, C. Remien, and A. Mubayi (2020). The role of alcohol consumption on acetaminophen induced liver injury: Implications from a mathematical model. *BioRxiv*. 106

Grantz, K. H., M. S. Rane, H. Salje, G. E. Glass, S. E. Schachterle, and D. A. Cummings (2016). Disparities in influenza mortality and transmission related to sociodemographic factors within Chicago in the pandemic of 1918. *Proceedings of the National Academy of Sciences 113*(48), 13839–13844. 109

Hameed, R., R. Bani, A. Mubayi, C. Castillo-Chavez, and P. J. Gruenewald (2013). Methamphetamine abuse dynamics in the state of California. 106, 108

Jewell, N. P., J. A. Lewnard, and B. L. Jewell (2020). Predictive mathematical models of the COVID-19 pandemic: Underlying principles and value of projections. *Jama 323*(19), 1893–1894. 108

Kushman, R. (2020). Your mask cuts own risk by 65 percent. UC Davis online article accessed on July 26, 2020. https://www.ucdavis.edu/coronavirus/news/your-mask-cuts-own-risk-65-percent. 109

Mubayi, A. (2017). Computational modeling approaches linking health and social sciences: Sensitivity of social determinants on the patterns of health risk behaviors and diseases. In *Handbook of statistics*, Volume 36, pp. 249–304. Elsevier. 107

Mubayi, A., P. E. Greenwood, C. Castillo-Chavez, P. J. Gruenewald, and D. M. Gorman (2010). The impact of relative residence times on the distribution of heavy drinkers in highly distinct environments. *Socio-Economic planning sciences 44*(1), 45–56. 106

Mukandavire, Z., A. B. Gumel, W. Garira, and J. M. Tchuenche (2009). Mathematical analysis of a model for HIV-malaria co-infection. *Mathematical Biosciences & Engineering 6*(2), 333. 109

Roeger, L.-I. W., Z. Feng, and C. Castillo-Chavez (2009). Modeling TB and HIV co-infections. *Mathematical Biosciences & Engineering 6*(4), 815. 109

Strobl, Q. A. and A. Bracey (2016). Midwest medical examiner's office. Online report. Accessed on July 12, 2020. https://www.anokacounty.us/DocumentCenter/View/10066/Press-Release-June-2-2016. 108

Tragler, G., J. P. Caulkins, and G. Feichtinger (2001). Optimal dynamic allocation of treatment and enforcement in illicit drug control. *Operations Research 49*(3), 352–362. 106

White, E. and C. Comiskey (2007). Heroin epidemics, treatment and ODE modelling. *Mathematical biosciences 208*(1), 312–324. 106, 108

Wynants, L., B. Van Calster, M. M. Bonten, G. S. Collins, T. P. Debray, M. De Vos, M. C. Haller, G. Heinze, K. G. Moons, R. D. Riley, et al. (2020). Prediction models for diagnosis and prognosis of COVID-19 infection: systematic review and critical appraisal. *bmj 369*. 105