



# Agent-Based Modeling: an Underutilized Tool in Community Violence Research

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## Abstract

**Purpose of Review** Community violence is a serious public health problem, and generational investments are being made to address it. Agent-based models (ABMs) are computational tools that can help to optimize allocation of those investments, analogous to how computer simulation models, broadly, have informed decision making in other fields, such as infectious disease control. In this review, we describe ABMs, explain their potential role in community violence research, discuss recent studies that have applied ABMs to community violence, and point to opportunities for further progress.

**Recent Findings** We identified three recent studies that applied ABMs to community violence research, which points to the paucity of this line of work. Each of these works leverages a major advantage of ABMs—their ability to study the natural evolution of a process governed by the actions of autonomous agents, and how that evolution changes under counterfactual conditions, such as different intervention strategies (e.g., violence interruption), and policy changes (e.g., alcohol outlet licensing policies).

**Summary** ABMs continue to be an underutilized tool for the study of community violence. Their increased use could add important information to help stakeholders decide between competing intervention strategies in terms of their costs and the overall resulting changes in violence rates. In addition, ABMs have value in identifying unintended changes/diffusions resulting from interventions. Regardless of the application, ABMs can only be impactful if stakeholders believe and use the information, pointing to the importance of engaging policy makers and other stakeholders in the model formulation process when possible.

## Introduction

Violence is a leading cause of injury-related death in the US, particularly among younger Americans. For example, recent data shows that homicide is among the top five causes of death in every age group from 1 to 44 [1]. Firearm

homicides comprise a majority of all homicides in the US [1] and have increased in recent years relative to the previous two decades [2–4], and reached their highest level of all-time in 2020 [5]. In fact, in the most recent year of data available, firearm mortality became the leading cause of death among those age 1–19, in the US [6]. This worsening public health problem has prompted federal action in the form of new research funding opportunities, and funding for community violence prevention included in federal infrastructure legislation proposals. Optimizing such opportunities requires using all available tools to decide strategically how to prioritize and combine prevention strategies to maximize their benefits.

Many community-based violence interventions rely on the idea that violence begets violence within individuals, social networks, and physical settings, producing a “contagion” effect. Violence contagion may operate through retaliatory violence [7, 8], through the fact that violence exposure increases their future risk of violence victimization [9], and/or through spread across social networks [10, 11],

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which may be due in part to peer influences and their effect on violence norms, which are known to be associated with violence propensity [12]. Social contagion of violence in particular has been leveraged for prevention by using social referents in schools to diffuse norms non-supportive of school bullying [13, 14], and in “violence interrupter” models, where credible messengers aim to disrupt cycles of retaliation that can fuel victimization within peer networks [15]. This contagion effect produces a feedback process similar to that present in infectious disease dynamics, suggesting that tools common in infectious disease research may be leveraged to enhanced community violence work.

Researchers typically use computer simulations, instead of traditional statistical models, to analyze contagion effects because the heterogeneity of the individuals, and individual-to-individual interaction, is not easily formulated within a statistically identifiable model. For this reason, computer simulations are dominant approach modeling infectious disease dynamics (e.g., [16]) and other “contagious” phenomena where one may want to, for example, compare how multiple counterfactuals differentially affect the evolution of a system. This review examines one specific type of computer simulation model—agent-based models (ABMs). These types of models have been applied across many areas of public health, including infectious disease, obesity, substance use, and violence (for a review and discussion, see [17]). ABMs are well suited to phenomena that arise from the actions and interactions between autonomous individuals and their environment, such as is the case with community violence.

The purpose of this review is to describe how ABMs can be applied to enhance community violence prevention in ways that are not feasible through “real-life” experimentation. We begin by broadly describing ABMs as applied to violence, including a simplified example. Next, we describe the few recent applications of ABMs to community violence research, and end with a discussion of novel opportunities for the application of ABMs to community violence research.

## Overview of ABMs

Agent-based models are computational models where autonomous individuals act according to a fixed set of rules, which are potentially a function of: (a) their individual characteristics; (b) the features of the space they inhabit; and (c) the characteristics of other “connected” agents (either through spatial proximity or, for example, a social network). A key feature of ABMs is that the autonomous agents affect the decisions of other agents and/or the characteristics of their spatial location, generating a feedback loop that evolves the entire system.

Figure 1 is a schematic diagram of a hypothetical ABM of community violence. At each time step, each agent has a probability of victimizing another agent and that probability is a function of each agent’s individual characteristics, the distance (social and physical) between the agents, and characteristics of the area. As the simulation progresses, agent characteristics can evolve as well (e.g., their violence exposure history would change if they were victimized) and, in turn, the spatial features can change. For example, a reasonable model could specify that when violence happens in a certain location, it decreases neighborhood collective efficacy and guardianship over public spaces, which increases future risk at that location, generating feedback. That model would be consistent with work showing that violence at specific places can become self-reinforcing once residents determine a location is unsafe and subsequently avoid it, thereby reducing informal social control [18].

Static spatial features may also affect community violence, such as alcohol outlet locations [19–21], and should be incorporated into the model, though their effects may interact with, and be related to other spatial characteristics, such as the income level of nearby residents [22, 23]. Though static spatial features are not subject to the aforementioned feedback, changes to them may be the target of counterfactual scenarios explored in an ABM. For example, one study explored the effects of hypothetical changes to alcohol outlet density on violence crime using ABMs [24]. Similarly, place-based changes such as “greening” vacant lots can reduce fear and restore safety, producing downstream effects on violence [25].

Both available data are for validation, and identifying a favorable balance between model parsimony and realism are distinct challenges in ABMs. Typically, the artificial spatial layout for an ABM is based on a real-world city where many data elements like those in Fig. 1 are available, in addition to population-level violence rates that the model seeks to reproduce. However, it is rare for all data elements to be available at the required spatial scale (e.g., city-specific rates of various risk factors, such as substance use, and other mental/physical health indicators), and less proximal data (e.g., state- and national-level rates) must be substituted. The model formulation exercise generally relies on specifying a plausible model—guided by behavioral theory when possible—for agent actions, with several tunable parameters corresponding to the effect of different data elements. The parameters of an ABM are not, in general, uniquely identifiable (i.e., different parameter settings can produce equivalent violence rates), which raises subjective choices about plausible parameter ranges that may disconcert those more comfortable with fully identified statistical models. This dynamic is a limitation, but also an opportunity to engage content experts and policy makers into model formulation

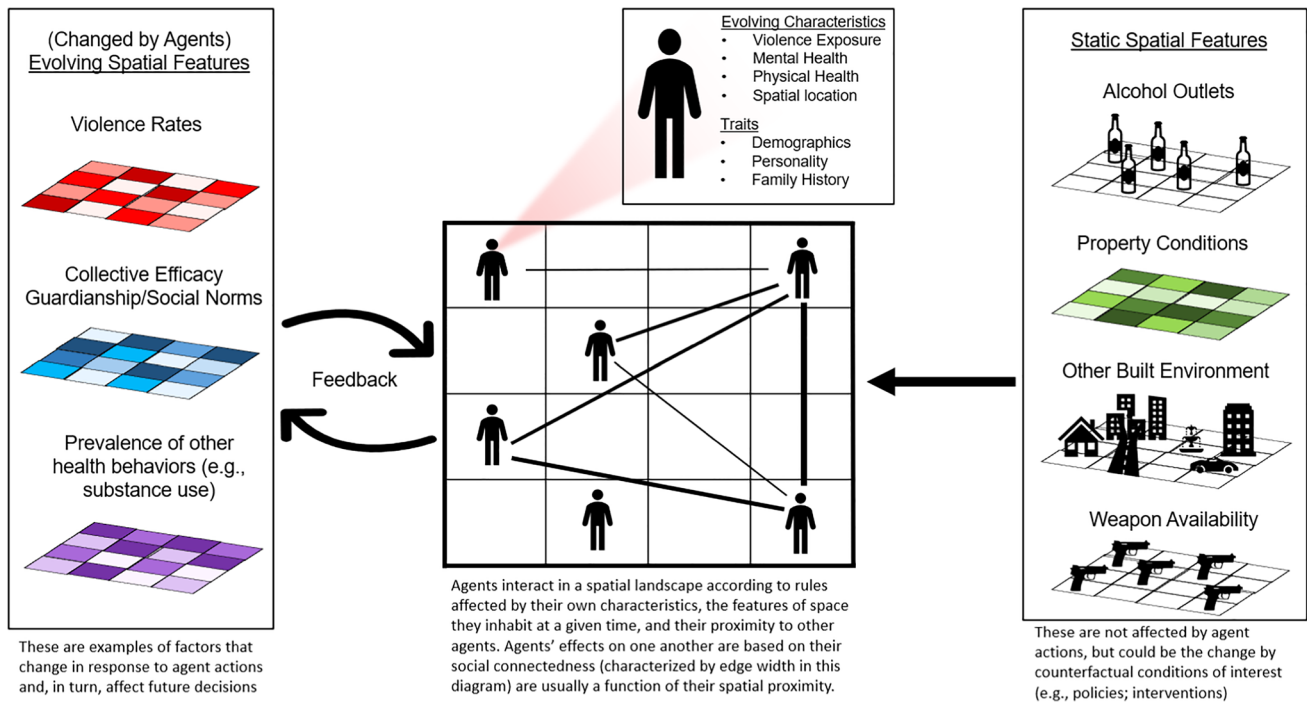


Fig. 1 Schematic diagram of a community violence ABM

choices, to increase the likelihood of buy-in to the eventual outputs.

### Simplified Example of a Community Violence

To illustrate the concepts above, we describe a simple example of a violence simulation guided by Routine Activity Theory, which posits that crime is more likely when there are three components present: a willing perpetrator, an available victim, and the perceived opportunity on the part of the perpetrator (e.g., a perception of insufficient guardianship). Under this theory, a reasonable model for the probability that agent  $i$  victimizes agent  $j$  at a given time point is

$$p_i \cdot v_j \cdot O(s_j) \cdot I(|s_i - s_j| < \delta)$$

where  $p_i$  is agent  $i$ 's covariate-dependent perpetration risk, and  $v_j$  is agent  $j$ 's covariate-dependent victimization risk,  $O(s)$  is the "opportunity level" of the location  $s$ , and  $I(|s_i - s_j| < \delta)$  is the indicator that the two agents sufficiently close to one another. In this illustrative example, we will broadly describe how one may specify  $p_i$ ,  $v_j$ , and  $O(s)$  in this model, though the precise parameterization, and other dynamics, such as the social network structure among agents and how they move around from one time point to the next, are left unspecified.

A sensible specification may be that  $p_i$  and  $v_j$  are calculated from logistic regression models fit to real data with predictors that are analogous to the agent characteristics incorporated into the model; an analogous approach has been taken in other recent ABM work [26]. Relevant agent characteristics in this model may include: demographics, substance use, firearm carriage, mental health, history of violence exposure, and coefficients could be generated by, for example, fitting logistic regression models to data from the Behavioral Risk Factor Surveillance System [27]. Updating these probabilities as the agent characteristics evolve would be one source of feedback in this model.

There are many reasonable specifications of the function  $O(s)$ , which points to the inherent subjectivity of ABM exercises. One logical component to include is property conditions, as prior work has suggested that urban greening can enhance social cohesion in a community, and signal guardianship that lowers perceived opportunity level [28, 29]. Similarly, other factors like alcohol outlet density, and the number of other agents nearby (providing "eyes on the street" [30]) could modulate the perceived opportunity level. Naturally, the perceived opportunity level should increase whenever an incident occurs and decrease when the location goes without any incidents occurring, creating another source of feedback. The relative impact of these factors would be varied to identify a setting that is consistent with observed violence rates in a locale with data available on the factors incorporated into the simulation.

The purpose of ABMs is often to introduce counterfactual conditions and examine how they affect the evolution of the system; in this case, logical counterfactuals to consider are environmental changes. For example, an ABM analogous to this one could be used to analyze—for a fixed level of resources available (e.g., money available for environmental remediation)—which greening strategies would result in the largest reductions in violence rates across the city. For instance, greening at low doses enables greater geographical coverage; however, high-dose greening may be required to overcome high perceived opportunity and low guardianship at the highest-risk locations. This type of choice is based on educated guesses from experts; a well-calibrated model like this could add an empirically-based piece of information to aid their decision making. For the same reasons, COVID-19 researchers use computer simulation models to anticipate the effects of vaccination and masking—population-level effects emerge in non-linear fashion, as group immunity interrupts feedback cycles (i.e., community transmission)—community violence researchers cannot simply assume that the average treatment effects estimated in prior work will translate across settings or intervention strategies.

## Recent Community Violence Research Using ABMS

To illustrate how ABMs have been used in violence research, we present three recent examples of violence-related ABMs in Table 1. These examples were identified from a Pubmed search, restricted to 2018 to the present, of publications including mention of ABMs and violence-related terms such as “violence”, “crime”, and “homicide”. While there have been other ABMs of violence in recent work, such as partner violence (e.g., [31–34]), the focus here is specific to community violence. Each example employs the same underlying ABM architecture: a model of violence in New York City, NY (NYC), which was originally introduced in earlier work [35] and subsequently refined. This model was parameterized using data specific to NYC when possible (e.g., alcohol use based on the World Trade Center Study [36]) and other data where necessary (e.g., association between violent victimization and moving residences, based on the Detroit Neighborhood Health Study [37]).

In one study, researchers compared place-based interventions by introducing violence prevention agents (i.e., violence interrupters and police officers) whose presence reduced the risk of violence in their immediate vicinity [38]. The researchers found that the public health approach (i.e., violence interrupters) produced moderate reductions in violence at much lower cost than the investment in policing required to achieve similar reductions; combining both interventions produced the largest violence reductions.

**Table 1** Examples of community-violence-related ABMs published since 2018

Title	Authors	Year	Type of violence studied	Study setting	Hypothetical intervention(s) studied	Summary of findings
Reducing urban violence: a contrast of public health and criminal justice approaches	Cerdá, Tracy and Keyes	2018	Non-fatal, fatal victimization	New York City, NY (NYC)	(a) Community-based violence intervention (b) Focused policing	CBVI produced similar reductions at much lower cost; combining both interventions produced the largest reductions
Limiting alcohol outlet density to prevent alcohol use and violence: estimating policy interventions through agent-based modeling	Castillo-Carmiglia, Pear, Tracy, Keyes and Cerdá	2018	Non-fatal, fatal victimization	New York City, NY (NYC)	Limiting alcohol outlet density (universal and targeted to highest-risk areas)	Limiting outlet density did not reduce victimization under either the universal or targeted intervention scenario
Assessing the impact of alcohol taxation on rates of violent victimization in a large urban area: an agent-based modeling approach	Keyes, Shev, Tracy and Cerdá	2019	Non-fatal, fatal victimization	New York City, NY (NYC)	Alcohol taxation (general and beer-specific)	Alcohol taxes reduced alcohol consumption and alcohol-related victimization. Reductions in violence disproportionately affected lowest-income individuals

In another experiment, researchers tested whether closing alcohol outlets would reduce alcohol-related violence. They found that reducing alcohol outlet density reduced light drinking, but, counterintuitively, increased heavy drinking, and did not reduce alcohol-related violence or homicides [24]. This study demonstrates an ABMs' ability to forecast unexpected results that may emerge from changes to complex systems. By contrast, in another study using the NYC violence ABM, alcohol taxation policies reduced the proportion of heavy drinkers and modestly reduced alcohol-related violence and homicides, particularly among people at the lowest income levels [39]. To achieve realistic outputs, the model accounted for known variation in the elasticity of alcohol demand by income, drink type, and overall consumption. Taken together, the two alcohol-related studies demonstrate how ABMs can illustrate the causal processes that produce violence outcomes, at least when mechanisms are reasonably well-understood (as they are for drinking and its connection to violence).

## Opportunities for ABMS in Violence Prevention Work

The feedback process generated by ABMs provides a basis for understanding the evolution of a complex system governed by the actions by autonomous individuals in a way that is not tractable within traditional statistical models. This evolution can be leveraged to further community violence research in several ways.

### Comparing Competing Counterfactuals

When designing a community-based intervention, or choosing the parameters of a policy, the optimal choice is not always obvious. Well-calibrated ABMs offer a possibility of comparing outcomes (e.g., population-level violence rates) under different design choices. In addition to the greening hypothetical mentioned in the simplified example, other choices, such as whether there are diminishing returns at increasing levels of policy strictness (e.g., firearm prohibition laws), or how multiple different approaches interact (e.g., policy changes; greening interventions; violence interruption) to inform an optimal combination. When possible, these analyses can be enhanced by comparing costs associated with different counterfactuals, generating a hypothetical cost–benefit analysis comparing multiple strategies.

### Studying Diffusion of Changes

Social contagion is observed in human systems and can be exploited to facilitate diffusion of individual-level

intervention effects. For example, school-based bullying interventions have leveraged this kind of contagion by choosing social referents in the school to publicly campaign against school bullying, which was effective in lowering bullying rates beyond the referents themselves [14]. In the context of community violence, an analogous dynamic could be at play, with social contacts impacting one's views towards violent retaliation. One possible use of ABMs in this setting would be to determine how different “seed selection” approaches (i.e., choosing which individuals in the community to intervene on) affected diffusion, and subsequent violence rates.

## Understanding Unintended Consequences of System Changes

System-level changes, such as policy changes or city-wide interventions (greening; violence interruption) can lead to unintended negative effects that are counter to the purpose of the change [40]. For example, an ABM experiment found that improving collective efficacy did not reduce racial disparities in violence, because it disproportionately reduced violent victimization among White agents, compared to Black agents, under conditions of high racial and economic segregation [35]. In that experiment, only the elimination of segregation reduced the resulting health disparities. ABMs have been leveraged in other fields—such as stock trading regulations [41]—to identify unintended consequences of changes before they appear in real-life markets, raising the question of whether similar logic could be applied to study more complex human behaviors, such as violence.

## Limitations of ABMs to Guide Public Policy

Agent-based modeling of complex social phenomena, such as community violence, poses two main challenges, which are interrelated. First, researchers must decide which components of the system to include in the model—for example, is it necessary to include substance use as an individual-level behavior, and if so, should alcohol use and drug use be separated? These decisions are inherently subjective, though tradeoffs between realism and parsimony are not unique to ABMs, and must be considered in all types of modeling.

A second challenge, alluded to earlier, is that researchers must identify suitable data sources with which to parameterize and validate the model. While this may be straightforward for some aspects of a community violence ABM (e.g., demographics by neighborhood, locations of alcohol outlets), it may be less clear, for example, how to parameterize the relationship between substance use and violence perpetration. Often, researchers must settle for data from different populations and/or time periods because it happens to be

the most spatiotemporally proximate information available. Similarly, some decisions about model parameterization must be made based on what is most tractable. Though gaps in existing data may be considered a limitation, researchers can (a) consult subject matter experts to ensure that modeling decisions represent the best available evidence and (b) conduct sensitivity analyses to determine which choices influence model outputs most strongly. The latter can point to directions for future research, e.g., by increasing available data on the highest leverage parameters of the model.

## Conclusions

Selecting between different community-based violence prevention strategies and effective policies requires a basis for prospectively understanding the effect of hypothetical changes to a complex system. For example, firearm violence is the end result of multiple factors, including firearm availability, social disadvantage, and structural racism; additionally, the occurrence of firearm violence can set off retaliation, increased firearm carriage, and other unhealthy dynamics that further reinforce cycles of community firearm violence. Ecological studies have shed light on effects of certain violence-related policies, such as background check laws [42, 43], firearm purchase waiting period laws [44], and laws limiting firearm access to those convicted of domestic violence [45–47], but a majority of policies have limited or inconclusive effects on homicides [48]. In addition, both observational [49, 50] and experimental [25, 28] studies have examined how interventions such as demolitions, blight remediation, and urban greening reduce community violence. Yet, the optimal choice for many design elements of violence prevention programs is not obvious. For example, evidence suggests blight remediation reduces firearm violence [51], but questions remain about how a city with fixed resources should proceed:

- Which lots should be remediated and with what intensity?
- Is partial remediation of many lots superior to complete remediation of a smaller number of lots?
- Can the diffusion of effects into neighboring areas be leveraged to achieve equivalent effects with fewer resources (e.g., by spreading out remediation efforts)?

Monetary limitations and feasibility inhibit the ability to test various possibilities, as there is often only “one chance” to get it right. Well-calibrated computational simulation models, such as ABMs, offer a valuable tool for helping to optimize that one chance. Yet, ABMs have found relatively limited impact in violence research to date, which points to the importance of engaging stakeholders during model

formulation, which would increase the probability of their results being used as a decision aid.

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## Declarations

**Conflict of Interest** Drs Goldstick and Jay have no conflicts of interest to report.

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