Agent-Based Modeling of Drinking Behavior: A Preliminary Model and Potential Applications to Theory and Practice

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Objectives. We developed a preliminary agent-based simulation model designed to examine agent–environment interactions that support the development and maintenance of drinking behavior at the population level.

Methods. The model was defined on a 1-dimensional lattice along which agents might move left or right in single steps at each iteration. Agents could exchange information about their drinking with each other. In the second generation of the model, a "bar" was added to the lattice to attract drinkers.

Results. The model showed that changes in drinking status propagated through the agent population as a function of probabilities of conversion, rates of contact, and contact time. There was a critical speed of population mixing beyond which the conversion rate of susceptible nondrinkers was saturated, and the bar both enhanced and buffered the rate of propagation, changing the model dynamics.

Conclusions. The models demonstrate that the basic dynamics underlying social influences on drinking behavior are shaped by contacts between drinkers and focused by characteristics of drinking environments. (*Am J Public Health.* 2006;96:2055–2060. doi:10.2105/AJPH.2005.063289)

Agent-based modeling and other computer-based simulations have been used increasingly in the social sciences since the 1990s as a means of understanding social processes and dynamics.[1] Agent-based modeling involves "growing" computerized social systems and structures based on the interactions of individual entities ("agents").[2] These agents use simple behavioral rules local to the agent's environment to move about their simulated environment and to interact with one another.[2] These modeling efforts enable researchers to test and develop theories in a way that might not be possible using analytic and experimental methods. For example, emotions or beliefs of the inhabitants of a simulated world such as "fear," "grievances," and "ethnocentrism" can be manipulated in a simulation in a way that would not be permissible for ethical reasons in an experiment. Thus, in agent-based modeling, the researcher builds an artificial environment that represents a simplified version of the real-world processes of interest and then observes the consequences of manipulating key input variables on attitudinal and behavioral outputs.[1]

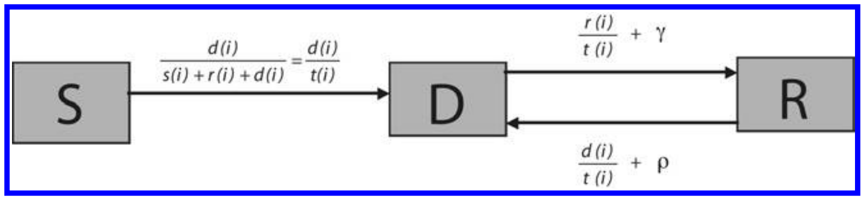
Agent-based modeling has proved especially useful in understanding complex social dynamics, notably those involving interactions between micro- and macrolevel processes and the development of emergent behaviors, such as racial segregation, innovations in human organizations, civil unrest, ethnic conflict, population movement, and the diffusion of innovations and fads.[3–7] In many of these applications, the central issue being explored is the way in which agents respond to their social context, specifically to how others around them are acting, and to the efforts of organized entities to influence them through either punitive or persuasive mechanisms of social control.[4]

Although the theories addressed by agent-based models generally involve complex macrolevel social processes, the models themselves are grounded in the actions and interactions of individual agents.[2,3,8] Indeed, it is a guiding principle of agent-based modeling that many social behaviors emerge from these local dynamic interactions rather than by being shaped from above by sociostructural forces.[2,3,6] In addition, given the underlying assumption of these models—that agents employ very simple, local behavioral rules—the goal of agent-based models is to "explore the simplest set of behavioral assumptions required to generate a macropattern of explanatory interest."[6(p146)]

Investigators in the field of alcohol research are also concerned with the effects of interpersonal and person–environment interactions, which are difficult to study using analytic and experimental techniques because of practical and ethical constraints. For example, peer group affiliation and neighborhood alcohol outlet density cannot be experimentally manipulated by researchers interested in these risk factors, nor can some individuals within a community be randomly subjected to a new policy or ordinance while others are not. In addition, 2 aspects of alcohol studies make the application of agent-based models potentially fruitful.[9] First, alcohol researchers are concerned with "what if" questions: for example, "What if another bar is situated in this neighborhood?" or "What if more alcohol is sold?"[10] Second, many alcohol researchers are interested in the underlying spatial dynamics of drinking behaviors. The questions of interest here pertain primarily to person–environment interactions: for example, "What happens when people drink in 1 location and then move about their environment, coming into contact with both other drinkers and nondrinkers?"[11] Although quasi-experimental community trials and ecologic studies have proved useful in answering these questions, a widening of research approaches could substantially benefit both theory development and prevention practices.[12]

We describe a preliminary agent-based model designed to explore both the social dynamics and the environmental influences that affect drinking behavior. Specifically, our model examines the interactions of 3 types of agents defined according to their current drinking status as well as by what happens to these interactions when an alcohol outlet is introduced into the environment. In line with the current literature on the dynamics of drinking behavior, our 3 types of agents are susceptible nondrinkers (those who have not started drinking alcohol and display some probability of initiating this behavior), current drinkers, and former drinkers; these are considered to be groups that do not have fixed, long-term memberships.[13] Indeed, research shows that "maturing out" and "natural recovery" are probably the rule, not the exception, among heavy and problem drinkers,[14–16] and that even among those classified as "alcohol dependent" as many as 75% will migrate from this class over a 1-year period.[17] And, similar to the initiation of drinking behavior, this movement into and out of heavy drinking is strongly affected by interpersonal influences and social context.[16,18,19]

It is this dynamic quality and fluidity, along with the effects of social and environmental influences, that we attempted to capture in our models. In terms of the former, we hypothesized that the dynamics of interactions between classes of drinkers and the movement into and out of drinking states can be modeled mathematically. As noted above, a simple set of behavioral rules is sufficient to develop an agent-based model, and so no attempt was made to specify the exact nature of the social influence. However, the literature pertaining to social influence suggests that the processes at work range from modeling and instrumental learning to more complex group-level mechanisms that operate through social norms and context.[19–21] In terms of environmental influences, we hypothesized that the introduction of an alcohol outlet into the model would increase contact rates among drinkers and maintain greater numbers of drinkers in the population.



Note. Susceptibles (S): each agent examines the site it is residing on, counts current drinkers *d(i)*, and converts to being a drinker with probability $\frac{d(i)}{s(i)+r(i)+d(i)} + \frac{d(i)}{t(i)}$, where *t(i)* = *s(i)*+*r(i)*+*d(i)* is the total number of individuals at site *i*. Current drinkers (D):each agent examines its site, counts former drinkers *r(i)*, and converts to nondrinker status with probability $\frac{r(i)}{t(i)} + \gamma$, where γ is a bias defined as a probability that a drinker would stop drinking even if there were no former drinkers at this site (e.g., as a result of broader socioenvironmental influences such as the price of alcohol). Former drinkers (R): each agent examines its site, counts current drinkers, and converts to a current drinker with probability $\frac{d(i)}{t(i)} + \rho$, where ρ is a bias defined as the probability that former drinkers would resume drinking even if there were no drinkers around (e.g., with relapse caused by genetic predisposition).

FIGURE 1—Rules governing interaction and movement of susceptible nondrinkers (S), current drinkers (D), and former drinkers (R).

METHODS

The Basic Model

In the situation to be modeled, current drinkers and nondrinkers (either susceptibles or former drinkers) interact with each other over time. The model is defined on a 1-dimensional lattice indexed by an integer, *i*. The lattice represents a set of locations that the individuals in a subpopulation frequent in a neighborhood. For simplicity, each site on the lattice is assumed to have the same "capacity"—i.e., it can accommodate the same number of agents. The total number of sites on the lattice is variable and denoted by *N*.

At each site *i* of the lattice there are 3 variables denoted by *s(i)*, *d(i)*, and *r(i)*. The variable *s(i)* denotes the number of individuals at site *i* susceptible to becoming drinkers, *d(i)* denotes the number of current drinkers at site *i*, and *r(i)* denotes the number of former drinkers at site *i*. There is no limit to the number of individuals at any given site. However, the total number of individuals in this model is conserved, and thus, the largest number of individuals at any given site is equal to the number of individuals initially present in the population.

The model applied in this study is 1 of a class of agent-based and dynamic system models currently under development to explore the social and environmental processes underlying the movement into and out of drinking states of varied severity.[12] In each of these models a pool of susceptible individuals initiate drinking, and then move back and forth between drinking and nondrinking states at certain rates.[22] These rates determine the dynamics and the stable states of drinking behavior within the population. Agent-based models are used in this context to explicitly identify ecological components of these processes. A simple set of rules, shown in Figure 1, governs the interactions of each type of agent with the other agents in the environment. It is through these rules that social influence is modeled. Each agent (whether susceptible, current drinker, or former drinker) performs a random walk with probability p of moving left or right, and probability $1-2p$ of staying at the same place on the lattice, where p ranges from .0 to .5. This parameter determines the velocity of agents' movement through sites. At any given site and iteration, the probability of conversion between states for each agent is determined by the number of agents of each type at that site. For example, a former drinker might convert back to current drinker status when on a site dominated by current drinkers.

Two other important parameters of the model are ρ, the probability that former drinkers would resume drinking even if they had no contact with current drinkers, and γ, the probability that drinkers would stop drinking even if they had no contact with current nondrinkers, or abstainers (who constitute a separate class from susceptibles and former drinkers). Note that the dampening effect of lifetime abstainers on the drinking of others is implicit in the model. Abstainers are treated as a fixed class with no dynamic evolution, and they act on the rest of the population in a uniform way in the model. In particular, we do not move the population of abstainers around because we assume each affects the rest of the population in a uniform way. In the current model, they influence population sizes of susceptibles, current drinkers, and former drinkers by directly offsetting probabilities of migrating between current and former drinker status through parameter γ, and indirectly moderating numbers of these different groups of agents at each site. The effects of larger numbers of abstainers in the population would be exhibited in larger values of γ.

The simulator for the study was written in MATLAB (The MathWorks, Inc, Natick, Mass). Individual simulations took no longer than several minutes of computation on a 64-bit AMD processor. (Memory requirements for 100 sites and 1000 iterations were extensive, however, requiring greater than 2 GB of memory. This problem could be resolved with additional programming changes, to a degree.) Each step in the iteration represents a fixed interval of time. Thus, the parameters of interaction represent average values valid for interaction within a neighborhood, over that time interval. A specific example would be of a college population in which 1 time step in the simulation corresponded to 1 day. If the probability of motion away from the site, left or right, is $2p=.2$, this means that, on average, a student would visit another neighboring site once in 5 days. These neighboring sites might be labeled as friends' apartments, neighborhood parties, or alcohol outlets.

Initial Conditions of the Model

In all of the simulations presented herein, the initial conditions were as follows: at every site on the lattice there was 1 susceptible agent, and at the middle site on the lattice there was just 1 current drinker. In the second generation of the model the environment was altered through the introduction of a bar onto the lattice. The purpose of the bar was to provide a fixed location on the lattice where drinking would take place, thereby altering the motion of current drinkers. If a site was designated as a bar, it "attracted" current drinkers. In the simulations we present, when there was no site designated as a bar, each agent had the same probability of moving to the left or to the right from its present site. In proximity to a bar, the probability of a current drinker moving away from its present site and toward the bar was greater than the probability of moving away from its present site and away from the bar. The movement of susceptibles and former drinkers was not affected by the presence of the bar. The number of bars in the simulation and their location is arbitrary, but this analysis presents results with just 1 bar.

It should be noted that although the term "bar" was used to describe the lattice site that attracted current drinkers, the names of other locations frequented more often by those who drink heavily than those who do not could have been used. These might include, for example, "liquor store," "after hours club," or "fraternity party." We chose to use the generally recognizable term "bar" in the present set of simulations because research shows that these are among the preferred venues of heavy drinkers, and that heavy drinkers tend to drink more per occasion in such settings than elsewhere.[23–25]

RESULTS

Observations on Dynamics

We investigated the dependence of the sizes of the different drinking classes on settings of the 3 parameters: p (agent motion), ρ (natural tendency of former drinkers to resume drinking), and γ (natural tendency of current drinkers to stop drinking). Figure 2a shows the evolution of the fraction of the population that is susceptible, with parameter values set at $p=.1$, $\rho=.3$, and $\gamma=.3$ (the latter 2 values crudely reflect rates of movement into and out of heavy and problem drinking).[14,15,17] This fraction dropped linearly to 0 at approximately 600 iterations.

The fraction of the population composed of current drinkers grew linearly until time reached approximately 500 iterations. At this point the fraction oscillated around .5, as shown in Figure 2b. A similar pattern was observed for the fraction of the population that was composed of former drinkers, and from this we conclude that the population of current and former drinkers equilibrates around .5 (Figure 2c). These features were universal in the model: if $P>0$ (so that each susceptible agent gets to meet a current drinker as it moves around the lattice), then all susceptibles converted to current drinkers at some point, and the population of susceptibles went to 0. In fact, for any value of p, ρ, or γ other than 0 the population of susceptibles went to 0, and current drinkers and former drinkers oscillated around the equilibrium.

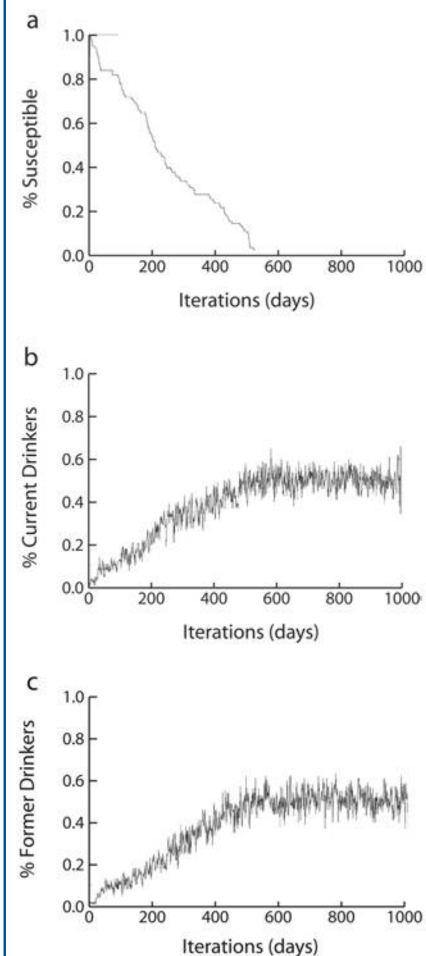


FIGURE 2—Evolution of the fraction of the population composed of those susceptible to becoming drinkers (a), those that are current drinkers (b), and those that are former drinkers (model parameters: $p=.1$, $\rho=.3$, $\gamma=.3$) (c).

The equilibrium value depended on γ/ρ. For example, if $\gamma/\rho=1$, equilibrium was one half current drinkers and one half former drinkers. Increasing γ did not bring the population of drinkers to 0, only down to an equilibrium value that reflected ρ (natural tendency to resume drinking, which is assumed fixed). Even if every agent was not drinking at some point in time, in the next step of the model the fraction ρ would return to current drinker status.

Effects of Motion on Model Evolution

It should be noted that even a single current drinker introduced into a population of susceptibles may cause every agent to become a current drinker at some point in time. Motion is essential for this process, for without it only a single site is affected. With partial motion (i.e., current drinkers sampling only a linked number of sites on the lattice), a limited population is affected. Thus, even in a relatively simple model it can be seen that topology starts to play a crucial role in drinking behavior.

To examine this issue in more detail, we next kept γ and ρ fixed, while changing p. We tested values of p from .01 to .5 (the largest value that p can assume). Figure 3a shows the results with parameters set at p=.5, γ=.3, and ρ=.3. The fraction of the agent population that was susceptible linearly dropped to 0 at approximately 500 iterations of the model (compared with 600 iterations in Figure 2a, with p=.1). At the same number of iterations, the number of current drinkers and former drinkers each equilibrated around .5. This was the case for any value of p, as explained previously.

As shown in Figure 3b, if p was set at the much smaller value of .01, it took a very large number of steps (approximately 5000) for the susceptibles to vanish. However, the time over which the population of susceptible agents went to 0 was not always a monotone function of p. When, as shown in Figure 3c, p was set at .2, the susceptible population vanished between 300 and 400 iterations, faster than for the case of p=.5. This can be explained by the fact that fast-moving populations of current drinkers move rapidly across sites, are more dispersed, and spend fewer iterations (less time) at any 1 site. Because conversion probabilities are a function of contacts with numbers of current drinkers, rates of conversion are lower in more dispersed populations of agents. An intermediate value of p is optimal for the initiation of drinking in a susceptible population; beyond that value, conversion rate saturates. (Note that, although the discussion here is in terms of average times to equilibrium, the specific examples presented in the figures are the outcome of a random variable and prone to fluctuation.)

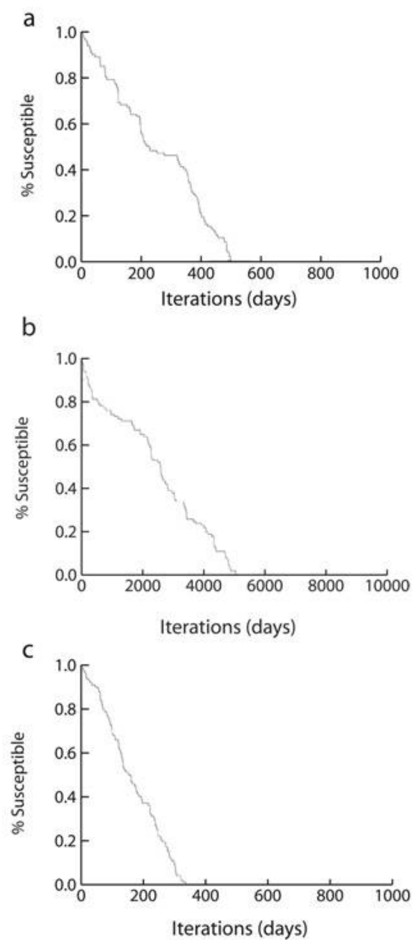


FIGURE 3—Effects of agent motion on susceptibility: evolution of the fraction of the population that is susceptible with model parameters set at p = .5, γ = .3, ρ = .3 (a); model parameters set at p = .01, γ = .3, ρ = .3 (b); and model parameters set at p = .2, γ = .3, ρ = .3 (c).

Effects of Introducing a Bar into the Environment

The introduction of a bar onto the lattice has the effect of attracting current drinkers to this site. As noted, current drinkers will acquire motions that are biased toward the bar location. For example, the probability of moving toward the bar may be .5, the probability of moving away from the bar may be .1, and the probability of staying at the same place may be .4. With this parameterization, current drinkers will spend a greater portion of their time at the bar site than at other

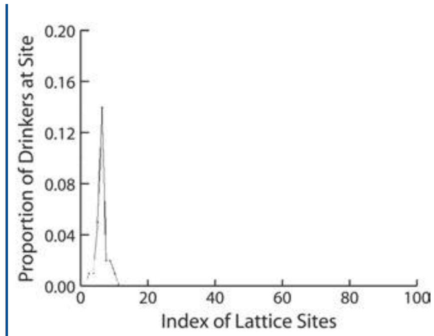


FIGURE 4—Effects of introducing a bar into the agent environment: population of drinking agents clustering around bar.

sites, thereby limiting their motion. The change in dynamics when such effects are included can be quite dramatic, as presented in Figure 4. The distribution across sites of the fraction of the population that drank after 1000 iterations is presented in Figure 4. Without bars in their environment, the population of current drinkers was evenly spread over all sites. With a bar present, the distribution was clustered around the bar location at the left edge of the domain. In addition, as current drinkers clustered around the bar, they did not mix effectively with the rest of the population (particularly susceptibles). Thus, the conversion process from susceptible to current drinker was linear and very rapid at first, but then considerably slowed. The number of susceptible agents did not go to 0 after 1000 iterations but appeared to level off at a constant nonzero value (Figure 5).

DISCUSSION

In this agent-based model of alcohol consumption dynamics, a population of susceptibles, current drinkers, and former drinkers interacted with each other on a 1-dimensional lattice. Susceptible agents were converted to current drinkers on the basis of "social influence," operationalized in terms of the number of current drinkers in their immediate environment (i.e., occupying the same cell on the lattice). Current drinkers may stop drinking and former drinkers may return to drinking because of the effects of social influence and "internal" tendencies to naturally desist or

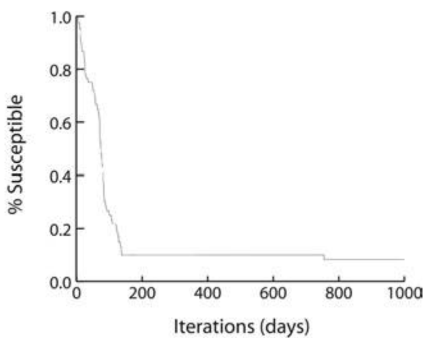


FIGURE 5—Effects of introducing a bar into the agent environment: evolution of the fraction of the population that is susceptible (model parameters: *p* = .3, □= .3, □= .3

resume (assumed to be based on previous social factors and genetic vulnerability).

Within this framework, the basic model showed that even a single current drinker introduced into a population of susceptibles could convert the entire population into current or former drinkers over time. This reflects the dynamic movement into and out of drinking states found in epidemiological surveys and studies of natural history.[14,15] Individual agents were allowed to move to neighboring sites on the lattice, and it was shown that the speed of conversion to drinking was not a monotone function of the vigor of motion in the population. Specifically, it was found that there was an optimal speed of population mixing at which susceptibles converted to current drinkers most efficiently.

The introduction of a bar into the environment had the effect of attracting current drinkers and limiting their movement, because they chose to spend a greater portion of their time at this site. This feature changed the model dynamics, leading to both a clustering of current drinkers at the bar and a reduction in their capacity to convert susceptibles in the population. Indeed, the conversion of all susceptibles to current or former drinker status would require a very long time. This reflects the impact of spatial heterogeneity on ecological dynamics, as noted by Durrett and Levin.[26,27] They showed that when space is treated explicitly in biological models of contagious processes, here exemplified by a simple social influence model, nonrandom mixing will cause the expected equilibrium dynamics to change. Sometimes these changes will be nontrivial and reflect the biological realities of such systems.

We believe that the results of this simulation reflect some of the realities of the roles that alcohol outlets play in shaping social processes related to alcohol use. For example, they may serve as a focus for behavioral contagion that supports use in certain venues and problematic use in society at large.[28] Thus, including a bar in the model resulted in limitations on the movement of current drinkers as well as the spread of their behavior. The susceptibles might therefore be safer in the sense that they have less exposure to direct social influences and pressures to drink (i.e., they experience a buffering effect). However, the bar also might serve to segregate and concentrate current drinkers into more insular subgroups. This concentration might further serve to narrow and solidify subgroup drinking norms and behaviors, thereby increasing its members' health risks and problem behaviors.[29] In addition, because drinkers travel to and from bars, the intensification of their drinking behavior has the potential to affect nondrinkers that share their environment through such contacts as road traffic accidents and violence (especially assault).[10,11]

Future Directions

In future models we will examine how this clustering and motion is affected by changes in variables such as the number and exact location of bars in the environment. We also intend to increase the sophistication of the simulations so that we can address more complicated theoretical questions pertaining to the interaction of drinkers and nondrinkers (with variable risk status) and the effects of environmental influences and controls on alcohol use and related problems. Indeed, there are a number of environmental theories of alcohol-related problems that readily lend themselves to the application of agent-based models, and specifically to modeling the interaction of agents with certain fixed and variable attributes within an environment that contains both punitive and persuasive forms of social control.

According to routine activities theory, for example, violent crime occurs when there is a motivated offender, a suitable target, and the absence of effective guardians.[30] Places that bring these elements together become criminal "hot spots." Whether or not bars and package goods stores become hot spots depends on features such as location, type of clientele, degree of crowding, and amount of heavy drinking tolerated.[31]

Although it is known that heavy drinkers have preferred drinking venues,[23–25] little is known about the risks associated with consuming alcohol in different contexts. For example, can we estimate multipliers that represent the increase in drinking levels associated with specific venues (e.g., a fraternity party vs an off-campus bar for college students) over average levels? Such data—which we are in the process of collecting—could be used to better calibrate our models, and the introduction of place-specific mechanisms for dealing with problems could be used as control variables in the models to be validated against their effects in the real world.[32]

Limitations

The findings of this study and their potential implications must be understood in terms of the limitations of agent-based modeling in general and the specific challenges encountered in applying this approach to the study of the initiation, maintenance, and cessation of alcohol use. As Bonabeau observed, the systems that social scientists typically want to model are intended to capture the interactions of individuals whose behavior is in many instances highly subjective and not entirely rational, and therefore very difficult to quantify and calibrate.[4] Thus, it is a challenging task to parameterize an agent-based model, because the data available from field studies are not necessarily directly correlated with the types of interactions that are being modeled. This is especially true of alcohol use and misuse, where movement into and out of drinking states is extremely fluid and where there appear to be different subtypes of heavy and problem drinkers, the underlying psychology and social influences of which vary considerably.[14,15,33,34] In addition, even if appropriate field studies exist, the parameters described in these studies frequently have a large range, indicating that they are not independent of the specific social context that the population inhabits or the methods used to collect data.[13]

Within these limitations, agent-based models make their contribution by helping to identify the basic social structures and processes that shape the development of social problems over time, enabling empirical investigators to focus their efforts on components of social systems most likely to bear fruit for our understandings of social problems. ■

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Contributors

D.M. Gorman reviewed and summarized the background material, contributed to the conceptualization and specification of the agent-based model, and led the writing. J. Mezic designed the agent-based model, executed the code, did parametric analysis, and prepared the relevant graphics output. I. Mezic designed the agent-based model and wrote the simulation code. P.J. Gruenewald contributed to the conceptualization and preliminary specifications of components of the agent-based model and to the writing of the article.

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Human Participant Protection

This study reports analysis of a computer simulation that included no data from human subjects.

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