RESEARCH ARTICLE

An Agent-based Model to Evaluate Positive Externality of Smoking Cessations
采用个体为本模型评估戒烟服务的正外部性

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Abstract

Introduction: Cigarette smoking can be viewed as a contagious disease whereby an active smoker will turn nonsmokers into passive smokers. Agent-based models (ABM) have been shown to have the advantage of exploring heterogeneity and inter-agent interaction, as compared with more aggregate models. In this study, we use an ABM framework and simulate a hypothetical tobacco control program in a multiunit dwelling, to examine the program's "return on investment" in terms of passive smoking reduction. **Method:** We assume that in a multiunit building of 121 people there are 30 active smokers, with their neighbors as passive smokers. We simulate different spatial distributions of these 30 active smokers. **Results:** Helping the last active smoker quit smoking gave us a net reduction of four passive smoking cases, revealing a pattern of marginal increase in return to smoking cessation efforts. For population segments where active smokers are more likely to be clustered together (in households, work sites, residential units, etc.) this pattern of "increasing returns to health investments" will be even stronger. **Discussion:** This hypothetical intervention experiment provides an insight for the potential impact of reducing active smoking prevalence on reducing passive smoking prevalence. A model-based discussion can help public health stakeholders strategize their approaches to design tobacco control programs.

Introduction

As the world's largest tobacco market, China had a smoking prevalence around 52.9% among men and 2.4% among women in 2010 [1]. As estimated in 2005, an annual total of 673,000 deaths in China were attributable to tobacco smoking [2]. This number may still be a serious underestimate since the high prevalence of passive smoking was not accounted for. Airborne nicotine was detected among 91% of the sampled public indoor environments [3], making the vast majority of the Chinese people potential victims of passive smoking.

Studies showed that participation and success rates of many smoking-cessation programs were considerably low [4, 5]. In the United States where one in five persons is a smoker [6], only 2-3% of smokers succeed to quit smoking each year [7]. This low cessation rate could be one reason why policy-makers have little incentive and are sometimes hesitate to promote expensive anti-tobacco interventions. However, evaluations of tobacco control programs typically did not accounted for the potential external benefits gained by passive smokers [8-10]. In other words, the positive externality of passive smoking reduction, whereby passive smokers are freed from secondhand smoke exposure because someone else quits smoking, has been often overlooked when researchers evaluate the effect of smoking cessation programs.

Accounting for passive smoking reduction associated with smoking cessation might not be an easy task, though, partly because there is a spatial aspect when counting the number of passive smokers around an active smoker. For instance, active smokers can turn their neighboring nonsmokers into passive smokers: if one active smoker quits smoking, the number of passive smoking cases averted will depend on the spatial distribution of smokers. Another complicating situation is that one active smoker surrounded by other active smokers will find himself a passive smoker once he quits smoking, adding a case of passive smoking to the pool of passive smokers

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rather than subtracting a case from it. Such spatial component cannot easily be addressed using conventional statistical methods.

Agent-based models (ABM) have been shown to have the advantage of exploring heterogeneity and inter-agent interaction, as compared with more aggregate models like differential equations. ABM has been applied in infectious diseases control [11], drinking behavior [12], adolescent sexual initiation [13] and health care management [14]. As cigarette smoking can be viewed as a contagious disease whereby an active smoker can change the cigarette smoke exposure status of nonsmokers around him or her, it is plausible to use ABM to simulate the scenarios of passive smoking. In this study, we use an ABM framework simulating passive smoking and conduct a hypothetical tobacco control program in a multiunit dwelling of 121 people. We show that a marginal increase in the return of passive smoking reduction for every additional case of smoking cessation.

Method

We assume that in a multiunit building of 121 people there are 30 active smokers randomly distributed throughout (where the smoking prevalence equals 24.8%), with their 4 closest neighbors ("Von Neumann neighborhood [15]," or sometimes referred to as "rook's neighborhood") as passive smokers, which is, each active-smoker can only affect his or her 4 adjacent neighbors. We will discuss the implication of assuming a "queen's neighborhood" (each smoker turning all 8 surrounding neighbors into passive smokers) in our future studies.

Initially, the model sets all 30 active smokers to be randomly distributed in an 11*11 grid. At each time step, the model allows one random active-smoker to quit smoking and reassigns passive smoker status to the quitter's neighbors. The model stops when all 30 active smokers, along with all passive smokers, become tobacco-free non-smokers. To understand the sensitivity of model results to the active smokers' spatial distribution patterns, we further explore alternative scenarios: an even distribution of active smokers throughout and a spatial distribution whereby active smokers are clustered together.

Results

We simulate the model for 100 times with randomized spatial distribution of active smokers in the population, and then calculated the average net reduction of passive smokers for every additional case of smoking cessation (Figure 1 & 2). We find that initially the first few cases of smoking cessations do not lead to a substantial reduction of passive smokers in an environment where active smokers are more clustered. But the "tipping point" [16] comes in when a threshold percentage of active smokers have quit. As shown in Figure 2, the first 15 smoking cessations only result in a net reduction of around 20 passive smokers, meaning that on average only 1.33 passive smokers return to the non-smoker status for each smoking cessation happening in his or her neighborhood. The next 15 smoking cessations give us a net reduction of 40 passive smokers, meaning that the number of passive smoking cases averted per smoking cessation now increases to 2.67. Not surprisingly, helping the last active smoker quit smoking results in a net reduction of 4 passive smoking cases, in sharp contrast to the small reduction of passive smokers as the first 15 active smoker quits. These results reveal a pattern of marginal increase in return ("return" here refers to the number of passive smoking cases averted) to smoking cessation efforts.

Based on our simple agent-based model, we further explore alternative scenarios. Two scenarios are evaluated. Under the first scenario, 30 active-smokers are evenly dispersed in the multi-unit dwelling of 121 people in total (Figure 3). Under Scenario 2, the active smokers are clustered together, which we mimic a space where smoking and non-smoking areas tend to be separated (Figure 4). We use the average Euclidean distance (AED) to define the spatial distances among active smokers. The AED in Cluster 1 is 6.297 (95% CI: 6.028 – 6.566), compared to 3.293 (95% CI: 3.156-3.430) in Cluster 2, meaning that active smokers in Cluster 1 is much less clustered than in Cluster 2. The model outputs two graphs for the two scenarios, respectively. The first graph (Figure 5)

shows that the number of passive-smokers decreases with reduction of active smokers in a linear pattern first, and then this number decreases at an accelerated rate when the intervention has successfully made a threshold proportion (nearly 50%) of active smokers quit smoking.

Figure 1: Number of Passive Smokers Reduction due to Every Successful Smoking Cessation (100 Simulations)
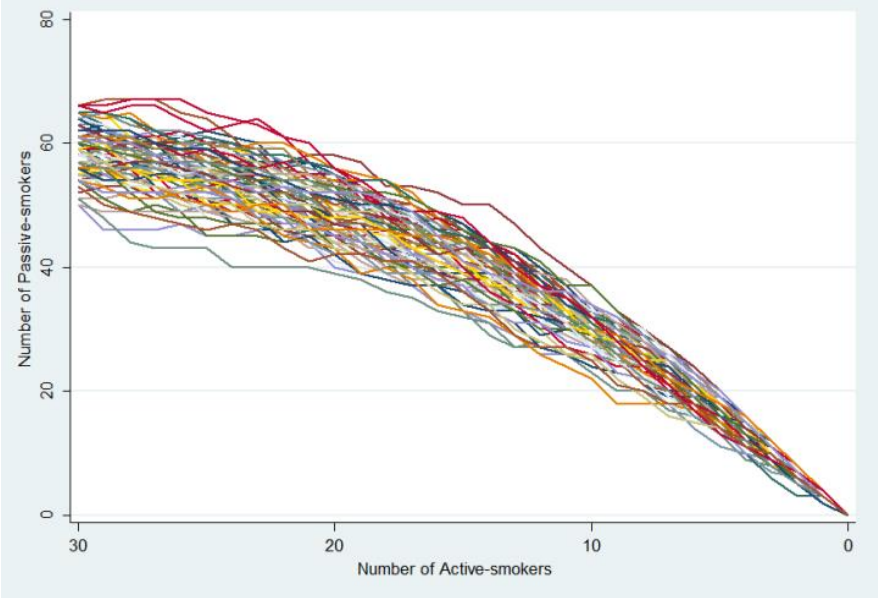

Figure 2: Marginal Increase in Return to Every Successful Smoking Cessation (100 Simulations)
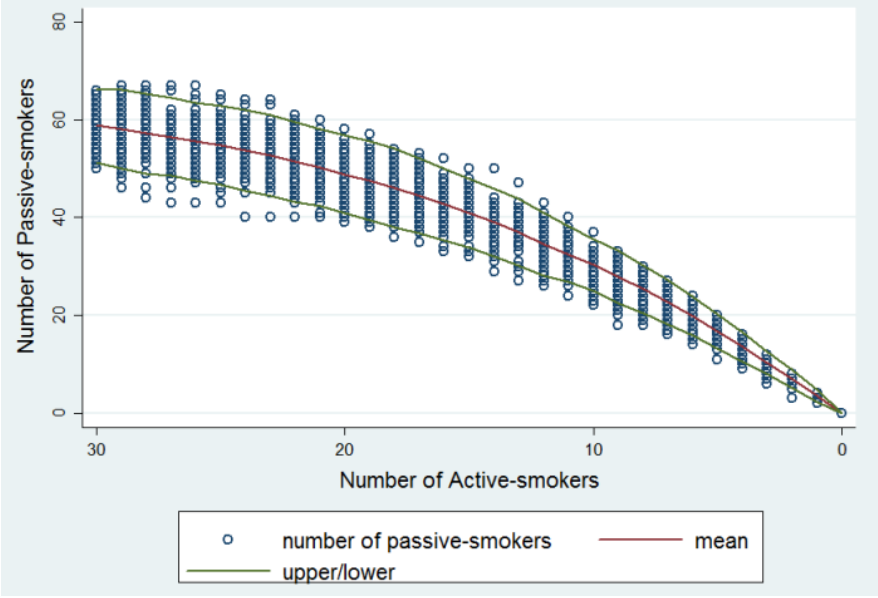
Table1. Average Euclidean Distance among Active-smokers in Different Cluster Patterns

	Mean	Standard Error	95% Confidence Interval	
Cluster Pattern 1	6.297	0.137	(6.028	6.566)
Cluster Pattern 2	3.293	0.070	(3.156	3.430)

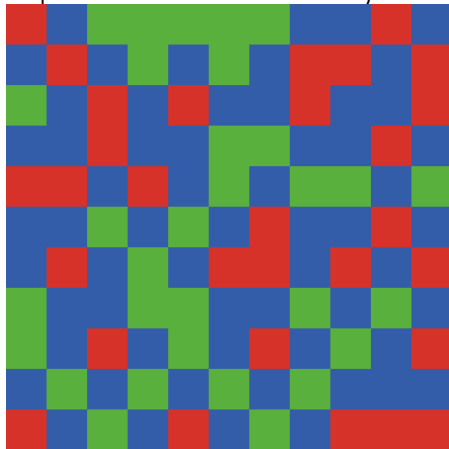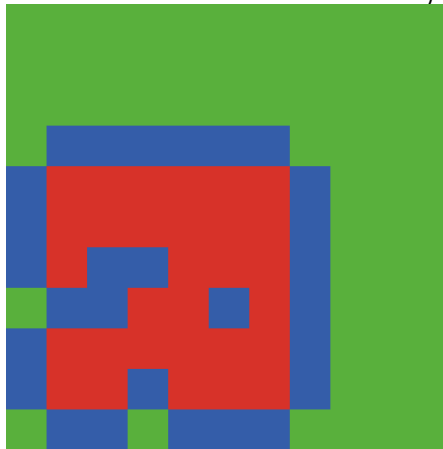Figure 3: Cluster Pattern 1 (Even dispersion of active smokers)

Figure 4: Cluster Pattern 2 (Spatial concentration of active smokers)

In the second graph (Figure 6) where smokers are more clustered together, we see no passive-smoker reduction at first when the intervention achieves only a few smoking cessations. The reason is that active smokers are clustered together with many "shared" neighboring passive smokers, and active smokers may actually become passive smokers when they quit smoking but have a neighbor who remains an active smoker. In other words, when active smokers are highly clustered together, having one active smoker quit might actually increase rather than decrease the total number of passive smokers. However, at a certain "tipping point" when a critical proportion of active smokers quit smoking, we see that the number of passive smokers decreases rapidly for every additional success of smoking cessation. Figure 7 shows that the two clustering patterns generate two very different curves of passive-smoking reduction. Under the scenario where active smokers are highly clustered, we find that the intervention is effective in reducing passive smokers only when it reaches a tipping point – a threshold number of active smokers (around 20) successfully quit smoking.

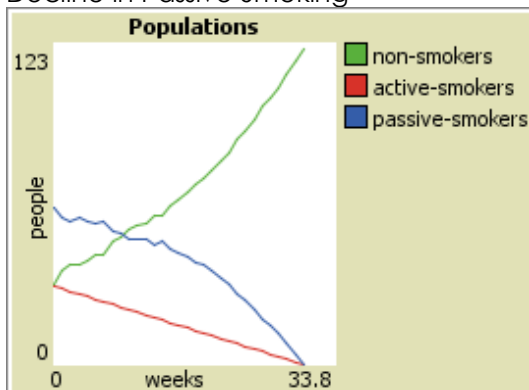Figure 5: Model output 1 for Pattern of Decline in Passive Smoking

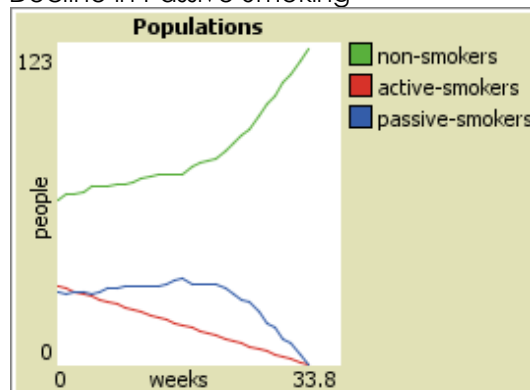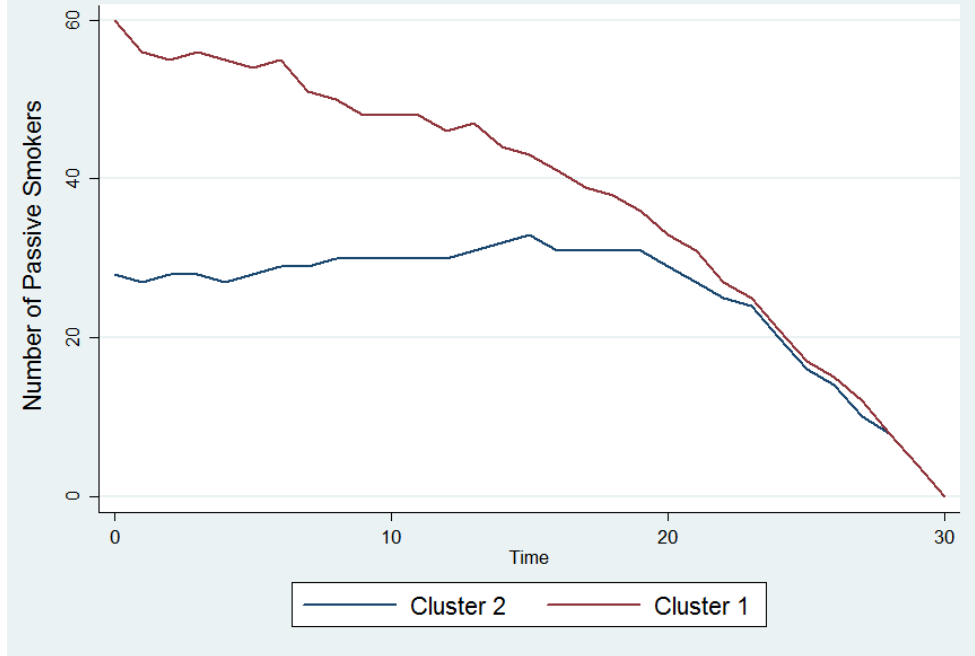Figure 6: Model output 2 for Pattern of Decline in Passive Smoking

Figure 7: Reducing Passive Smoking in Two Different Cluster Patterns of Active Smokers

Discussion

This hypothetical intervention experiment provides an insight for researchers to forecast the potential impact of smoking cessations on reducing passive smoking prevalence. In the short-term, tobacco control interventions may not be very effective in changing the environment and reducing number of passive smokers, especially when the active smokers are spatially clustered together. However, with a steady rate of achieving more and more smoking cessations, a rapid reduction in passive smokers will be observed after the "tipping point." Such phenomenon was actually witnessed in the US history of tobacco control. From year 1980 to 1990, the total percent of adults who smoked in the US was decreased from 33.2% to 25.5% [17], while the prevalence of secondhand smoking remained approximately 87.9% in the late 1980s [18]. But from 1990 to 2000, the prevalence of tobacco smoking was reduced only from 25.5% to 23.3% [17], secondhand smoke rate was steadily decreased to approximately 52.5% during the 1999-2000 period [18]. Even though this reduction in passive smoking coincided with the introduction of smoking ban in public places, it is plausible to hypothesize that there has been increasing returns of smoking cessation when a tipping point was reached in the 1990s, given that household exposure remains a dominant source of passive smoking [19].

Our model has the following limitations. We does not consider the peer effect of smoking cessation among active-smokers, i.e., we assume that seeing other smokers quit smoking has zero effect in increasing one's likelihood of smoking cessation. This assumption is likely to be an overly pessimistic one compared with the real world. If we have accounted for this peer effect, the rate of return on passive-smoking reduction would be even larger. , we make an arbitrary assumption that one active smoker only affects his or her 4 neighbors, but we can enhance the model by parameterizing the distance of passive-smoking exposure, as well as defining the exact spatial location of a population to make the model a better approximation of a real setting.

The finding of this study holds certain policy significance. First, it means that regular smoking cessation programs may be more cost-effective than researchers and policy-makers may have previously supposed, as the effectiveness extends beyond the quitter himself. Helping an active smoker quit smoking also benefits secondhand and even third-hand smokers who are affected by

the active smoker. Second, the spatial distribution of smokers may have implications for intervention design. For example, in regions when active smokers are highly clustered, it is very important to maintain the smoking cessation intervention to see the "tipping point" appear in passive smoking prevalence trend. Or if there is limited budget, it may be possible to first focus the intervention on those active smokers who are located among nonsmokers (e.g., husbands of nonsmoking wives, smoking parents of nonsmoking children, etc.). In general, we hope that a model-based discussion of this vital issue can help policy-makers and public health stakeholders strategize their approaches to design tobacco control programs.

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