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Article

Comparing methods of targeting obesity interventions in populations: An agent-based simulation

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ABSTRACT

Social networks as well as neighborhood environments have been shown to effect obesity-related behaviors including energy intake and physical activity. Accordingly, harnessing social networks to improve targeting of obesity interventions may be promising to the extent this leads to social multiplier effects and wider diffusion of intervention impact on populations. However, the literature evaluating network-based interventions has been inconsistent. Computational methods like agent-based models (ABM) provide researchers with tools to experiment in a simulated environment. We develop an ABM to compare conventional targeting methods (random selection, based on individual obesity risk, and vulnerable areas) with network-based targeting methods. We adapt a previously published and validated model of network diffusion of obesity-related behavior. We then build social networks among agents using a more realistic approach. We calibrate our model first against national-level data. Our results show that network-based targeting may lead to greater population impact. We also present a new targeting method that outperforms other methods in terms of intervention effectiveness at the population level.

1. Introduction

The obesity epidemic has been linked to a web of interdependent causes operating at multiple cascading levels (Galea, Riddle, & Kaplan, 2010; Glass & McAtee, 2006; Huang, Drewnoskski, Kumanyika, & Glass, 2009) including environmental influences, genetics, cultural preferences, environmental cues, food pricing and availability, and peer influence (Myers & Rosen, 1999). These complex relationships have been widely studied using conventional study designs and regression-based models. However, it is increasingly understood that obesity is an outgrowth of complex dynamic processes at multiple levels that demonstrate non-linear features such as feedback loops and endogenous peer influences that are not well-captured using conventional approaches (Finegood, 2012; Finegood & Cawley, 2011; Galea et al., 2010; Hammond & Dubé, 2012; Huang & Glass, 2008; Ip, Rahmandad, Shoham, Hammond, & Huang, 2013). The complexity of the obesity epidemic has drawn attention from researchers from a wide range of disciplines seeking new strategies to study the drivers of and solutions to the epidemic. Therefore, increasingly, agent-based computational models (ABMs) have been explored as an alternative approach for addressing scientific and policy questions and as a focal point for collaborations of multidisciplinary teams.

Agent-based models are computational simulations of real-world dynamic patterns of adaptive behavior (Auchincloss & Diez Roux, 2008; Bonabeau, 2002; Gilbert & Troitzsch, 2005). Their principal strength is the ability to model and capture emergent collective behavior arising from dynamic adaptation of knowledgeable actors who seek strategic solutions in the face of environmental constraints and whose complex interactions create emergent patterns that cannot be predicted or understood using conventional methods that do not permit non-linear dynamics (Epstein, 2006; Epstein & Axtell, 1996; Macy & Willer, 2002; Maglio & Mabry, 2011). In obesity research, ABMs have been used previously to understand the role of the food and physical activity (PA) environments (Auchincloss & Diez Roux, 2008; Widener, Metcalf, & Bar-Yam, 2013; Yang, Diez Roux, Auchincloss, Rodriguez, & Brown, 2011; Yang & Diez-Roux, 2013), social norms (Auchincloss, Riolo, Brown, Cook, & Diez Roux, 2011; Hammond & Ornstein, 2014; Mooney & El-Sayed, 2014; Shoham, Tong, Lamberson, Auchincloss, & Zhang, 2012; Wang, Xue, Chen, & Igusa, 2014), network and peer effects (El-Sayed, Scarborough, Seemann, & Galea, 2012; Hammond & Ornstein, 2014; Shoham et al., 2012; Trogdon & Allaire, 2014), and diffusion of interventions

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(El-Sayed, Seemann, Scarborough, & Galea, 2013; Rahmandad & Sterman, 2008; Widener et al., 2013; Zhang, Giabbanelli, Arah, & Zimmerman, 2014). It is this last application that is our principal focus, to which we now turn.

A central challenge in public health response to the obesity epidemic is the lack of consensus about the optimal strategy for targeting intervention resources. While behavioral interventions to prevent and reduce pathogenic weight gain in various populations have proven difficult, there are strategies that have been tested and found to be, to varying degrees, efficacious. These include interventions to reduce caloric intake and increase physical activity over a sustained period for purposes of weight reduction or obesity prevention. For instance, given a fixed pool of available resources, policy makers, program managers, and other decision makers must decide how to target resources to achieve the maximum desired benefit across a target population. Given a behavioral intervention of fixed efficacy and fixed cost per person (on average), should we target those who are obese, those who live in high-risk areas, or choose at random? This is an ideal problem for agent-based simulation models that can be used to conduct counterfactual experiments to test alternative targeting strategies (El-Sayed et al., 2013). This approach has been effective in tobacco. For example, Levy used a simulation model to show that targeting youth smokers results in limited impact compared to targeting all age groups (Levy, Cummings, & Hyland, 2000).

The main goal of this paper is to develop and use an ABM to evaluate different methods of targeting obesity interventions. Therefore, a model is needed that can, at minimum, incorporate three key factors determining the diffusion of intervention effects throughout a population: personal characteristics of actors, social network ties and social influence, and the role of environmental factors (Andajani-Sutjahjo, Ball, Warren, Inglis, & Crawford, 2004). We assume a fixed funding pool from which a fixed number of persons can be enrolled in a well-validated behavioral intervention.

To evaluate population intervention effectiveness, we begin by selecting the state-of-the-art behavioral intervention shown to be efficacious in randomized experiments of two key behavioral pathways: dietary intake and physical activity. For this analysis, we assume an average intervention effect size based on Cochrane Reviews of obesity prevention interventions (Brown, Avenell, Edmunds, Moore, & Whittaker, 2009; Doak, 2002; Mastellos, Gunn, Felix, Car, & Majeed, 2014; McTigue, Harris, Hemphill, Lux, & Sutton, 2003; Prevention & Glickman, 2012). We identified and reviewed randomized trials of adults who represented all weight classes or overweight and obese. We included only studies that reported behavioral outcomes (change in diet or physical activity) with at least 6 months of follow-up. We prioritized studies that involved intensive non-pharmacological interventions that would be moderate in cost and could be scaled up with sufficient resources. Studies of disease groups (e.g., diabetes) or among only obese adults were excluded. We selected the best studies that also reported pre-post intervention change in diet or PA, where the latter was measured with a pedometer or accelerometer. For each category (diet or PA) we summarized the top and bottom of estimated proportional change. For our final estimate, we chose the midpoint of the range. For dietary change, we used the America on the Move trial for the upper bound estimate (Rodearmel, Wyatt, Stroebele, Smith, & Ogden, 2007; Stroebele, de Castro, Stuht, Catenacci, & Wyatt, 2009) and the Diabetes Prevention Program (DPP) (Group, 2002; Mayer-Davis, Sparks, Hirst, Costacou, & Lovejoy, 2004) for the lower bound. The mid-point estimate is 15% reduction in total kcals of consumption at 6–12 months. For physical activity, we base the upper-bound estimate on the trial by Dinger, Heesch, Cipriani and Qualls (2007) that used pedometers to investigate increased walking after intensive intervention based on the transtheoretical model of behavior change. For a lower bound estimate, we used the Reasonable Eating and Activity to Change Health study (REACH) a randomized trial of 665 overweight men and women ages 40–69 followed for 2 years after an intensive behavioral intervention tailored to the subjects stage of change (Logue, Sutton, Jarjoura, Smucker, & Baughman, 2005). The mid-point estimate for proportional change in physical activity based on these trials is 17%.

Existing research show that obesity patterns can be contagious; friends and family can affect an individual's behavior (Ali, Amialchuk, Gao, & Heiland, 2012a; Ali, Amialchuk, & Rizzo, 2012b; Baker, Little, & Brownell, 2003; Blanchflower, Landeghem, & Oswald, 2009; Centola, 2011; Christakis & Fowler, 2012, 2007; Crandall, 1988; de la Haye, Robins, Mohr, & Wilson, 2011a, b; Eisenberg, Neumark-Sztainer, Story, & Perry, 2005; El-Sayed et al., 2012; Sentočnik, Atanasijević-Kunc, Drinovec, & Pfeifer, 2014). For instance, an individuals' chance of becoming obese increases as their friends or family became obese. As Trogdon and Allaire (2014) point out , the burgeoning literature on peer effects on obesity has important policy implications: social multiplier effects imply that interventions to reduce obesogenic behaviors may spill over and translate to increase overall population impact. A key goal of this analysis was to evaluate which targeting strategy leads to larger overall impact via social multiplier effects.

We address this problem from a computational modeling point of view, and build an ABM that simulates the outcomes of different targeting methods including selected realistic factors that may interact. There exists a limited but rapidly developing literature for modeling social influence on obesity patterns, and studying network-based obesity interventions. However, the literature seems to provide contradictory conclusions. On one side, Zhang, Tong, Lamberson, Durazo-Arvizu, and Luke (2015) finds no differences between selecting random vs. overweight opinion leaders. El-Sayed et al. (2013) claims that interventions that target the most well-connected individuals in a population will have little or no added value compared with at-random implementation. On the other hand, Bahr, Browning, Wyatt, and Hill (2009) find that random targeting approaches require more individuals to effect the same change as targeting well-connected individuals on cluster edges. Similarly, Trogdon and Allaire (2014) show that the effect of population-level interventions depend on the underlying social network, and selecting the most popular obese agents for weight loss interventions resulted in greater population impact. These models have been estimated using different datasets in both adult and adolescent populations. Moreover, different network structures have been used to build simulated networks. This includes random, lattice, scale-free, small-world and online social networks (Barabasi, 2009).

In all of existing work, the concept of behavioral induction has been used to implement peer influence, which leads to diffusion of behavior change throughout the network. The structure of the network, for instance small-world vs. scale-free, does not affect intervention outcomes significantly (El-Sayed et al., 2013; Trogdon & Allaire, 2014). However, the social diffusion dynamics have differed dramatically, which may explain differences in results. Since the population effectiveness of any simulated intervention is directly determined by the model's assumptions about the diffusion process, it is critical to validate this part of the model before exploring intervention strategies with the model. In this paper, we limit ourselves by holding the diffusion dynamics under consideration constant, focusing exclusively on how different targeting strategies alter population impacts. The question of whether alternate diffusion dynamics may magnify or weaken the impact of interventions across targeting strategies will be the subject of a subsequent analysis.

2. Materials and methods

In this section we introduce the details of our ABM, and describe the diffusion model that was used for simulating the spread of the intervention's effect through social networks. By diffusion model, we refer to the social diffusion dynamics that are assumed for the propagations of behavior change and obesity in a social network. We