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ARTICLES
INTERVENTION AND PREVENTION

Exploiting Social Networks to Mitigate the Obesity Epidemic

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Despite significant efforts, obesity continues to be a major public health problem, and there are surprisingly few effective strategies for its prevention and treatment. We now realize that healthy diet and activity patterns are difficult to maintain in the current physical environment. Recently, it was suggested that the social environment also contributes to obesity. Therefore, using network-based interaction models, we simulate how obesity spreads along social networks and predict the effectiveness of large-scale weight management interventions. For a wide variety of conditions and networks, we show that individuals with similar BMIs will cluster together into groups, and if left unchecked, current social forces will drive these groups toward increasing obesity. Our simulations show that many traditional weight management interventions fail because they target overweight and obese individuals without consideration of their surrounding cluster and wider social network. The popular strategy for dieting with friends is shown to be an ineffective long-term weight loss strategy, whereas dieting with friends of friends can be somewhat more effective by forcing a shift in cluster boundaries. Fortunately, our simulations also show that interventions targeting well-connected and/or normal weight individuals at the edges of a cluster may quickly halt the spread of obesity. Furthermore, by changing social forces and altering the behavior of a small but random assortment of both obese and normal weight individuals, highly effective network-driven strategies can reverse current trends and return large segments of the population to a healthier weight.

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INTRODUCTION

Most Americans today are overweight or obese, and the gradual weight gain of the population that created the obesity epidemic continues (1,2). The obesity field now recognizes the importance of addressing the physical environment when sustaining healthy lifestyles (3). Recently, Christakis and Fowler analyzed data from the Framingham Heart Study and reported that weight gain spreads from person to person along social networks (4). In particular, increases in an individual's weight will correlate with weight gain in friends and family. Whether deliberate or unintended, conscious or unconscious, the interactions between an individual and others in their social network will bias their weight; this indicates that in addition to the physical environment, the social environment must also be considered when addressing obesity.

Predictive models can be used to better understand the influence of the social environment on the spread of obesity. Using these models, each person can be placed in a social network that indicates his/her connections to friends, family, and other individuals (collectively referred to as "network neighbors," though no spatial relationship is assumed and geographical distance is irrelevant; see **Supplementary Methods and Procedures** online). If appropriate rules of interaction can be specified, then a numerical model can simultaneously evaluate the interactions of millions of people. In other words, each individual's weight and BMI can be concurrently and repeatedly updated to reflect the influence of their network neighbors (**Figure 1**). Tracking such changes across an entire population can establish and predict long- and short-term trends in BMI.

Epidemiologists, biologists, sociologists, economists, and political scientists have used similar numerical network models to evaluate the spread of infectious disease, voter behavior, rioting, group opinion formation, flocking, and other collective actions (e.g., 5–14). In the classic model, an individual assesses the "state" of his/her network neighbors and then follows a specified rule to change his/her personal state. In general, a simple "majority rule" explains many observed social phenomena—the individual changes to a state that matches the majority of their neighbors. To reflect uncertainties, models include random noise (to model unpredictability), "social volatility" (roughly a measure of rationality vs. irrationality), and "social force" (a measure of external influences like television advertising and law enforcement). Both numerical models and mathematical

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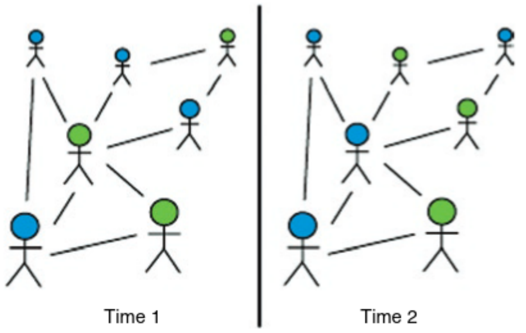

Figure 1 A hypothetical social network with each individual's initial state colored as normal weight (green) or overweight (blue). The neighbors of any individual are the friends, family, or other acquaintances indicated by the connecting lines. At each time step, the individuals update their current state to reflect the majority of their network neighbors (including themselves). At time 2, for example, the central figure changes from normal weight to overweight because the majority of its neighbors were overweight. With the same number of normal weight and overweight neighbors (including itself), the lower-left individual had an equal probability of staying overweight (as shown) or becoming normal weight. Our simulations explored this and many other possible interaction rules to extract behaviors and trends that are common to all interactions. The **Supplementary Methods and Procedures** online outlines how to map a real social network.

arguments (15,16) show that many group behaviors will remain the same even when the details of specific person-to-person interaction rules are allowed to vary. This ability to model group dynamics without a precise knowledge of details is key; it is a well-understood property of large collections of interacting objects (in this case, people) and is the mathematical basis for statistical mechanics which chemists and physicists use to accurately predict large-scale material behaviors without knowing the precise details of every individual atom (16). So although there is significant sociological evidence supporting the "majority rule" and its variants at the microscale, we can make reasonable predictions about macroscale trends in obesity without needing a completely precise description of human interactions. In other words, in a network model, a wide variety of "majority rule" interactions that differ in precise details will still make the same general predictions about obesity.

Long-term studies can test the effectiveness of a proposed weight loss intervention, but predictive models are urgently needed to guide the choice of intervention strategies. With the advent of modern computing tools, such network-based models have recently gained a wider acceptance in the medical sciences (14), and in particular, for evaluating trends in obesity (17,18). We hypothesize and demonstrate that network-based models can simulate the spread of obesity along social networks and predict the correlation of weight observed in the Framingham study. Furthermore, the models can be used to predict population-scale trends and to propose novel large-scale weight management interventions. Before committing resources to a long-term longitudinal study, network-based models can predict the effectiveness of a proposed intervention.

METHODS AND PROCEDURES

Our simulations used large social networks with 10,000 to 1,000,000 individuals. All network models use an underlying topology that specifies the manner in which each person is connected to others (Figure 1). All of the results presented below were tested on a variety of network configurations ranging from square lattices, to random networks, to small-world, scale-invariant topologies commonly observed and used in social network analyses (12,19) (for additional details on the tested networks, see **Supplementary Methods and Procedures** online). Real social networks can be mapped using well-known social science techniques (see **Supplementary Methods and Procedures** online), but testing with this wide variety of networks ensures that the results are not sensitive to particular network configurations. Furthermore, testing with a range of population sizes shows that the following results are not sensitive to the number of interacting individuals except for exceedingly small groups where tiny fluctuations can have disproportionately large effects.

Each individual on the network was assigned a random initial BMI (or weight) from one of four classes: underweight, normal weight, overweight, and obese. Several simulations used up to 50 class delineations intended to represent increments of weight rather than BMI, but the following results remained unchanged. At regular but arbitrary time steps, the model updated every individual's BMI simultaneously.

To ensure that the results are not sensitive to details of the rule, we tested a wide range of interactions, although all were carefully designed to be consistent with the Framingham observation that an individual's weight gain is positively correlated with the weight gain of family and friends (see **Supplementary Methods and Procedures** online for additional mathematical details on selecting appropriate rules). In any given simulation, every individual used the same rule. However, this is not a fundamental restriction, and the probabilistic nature of many rules means that each individual can react to the same stimuli in different ways. Specific tested interactions included (i) the majority rule, (ii) a probabilistic majority rule, (iii) weighted probabilities and weighted threshold rules (with various critical values) (iv) the same as previous rules, but with the addition of social volatility or irrational decision making (see below), (v) the same as previous rules, but with the addition of social forces that bias toward particular BMI classes (see below), (vi) the same as previous rules, but with neighbors having variable levels of influence on each individual (a generalization of the directional and bidirectional ties in the Framingham study), (vii) the same as previous rules but with an additional bias so that BMI preferentially increases (the idea that we are living in an obesigenic environment that leads to weight gain (3,20)), (viii) the same as previous rules but with individuals restricted to moving up or down one BMI class per time interval, (ix) the above rules with additional noise that randomly changes an individual's BMI with some probability, and (x) the above rules with additional noise that is restricted to randomly moving individuals up or down one BMI class per time interval.

The social volatility used in some rules can be thought of as the amount of resources necessary to change the BMI of an average individual in the population. High volatility means that social interactions are irrational, and the individual is more likely to ignore the influence of neighbors. Very few resources would be needed to push an individual toward a particular weight. As a result, weights are more transitory and prone to relatively rapid change. Low volatility means that interactions are more rational, and weights are more stable and resistant to change. Very high volatility would correspond, for example, to the irrational group mentality before a riot. Low volatility would correspond to the carefully balanced and rational decision making during courtroom deliberations. The quantity has a precise mathematical definition outlined in the **Supplementary Methods and Procedures** online, and it relates closely to the physical concept of temperature (indeed, it is called "social temperature" in some publications (e.g., 15)). The ability to include irrational decision making is an advantage of this model vs. many previous models that used only rational decision making (e.g., 8–10).

Similarly, the social forces used in some rules have a precise mathematical definition (see **Supplementary Methods and Procedures** online), but more intuitively, a social force acts as a "carrot or stick" that pushes individuals toward a particular BMI class. Food and gas pricing, advertising, and law enforcement, are classic examples. For example, an individual's BMI depends on the BMI of network neighbors, but if a dictator passed a decree jailing anyone who is obese, then there will be a strong incentive to push away from the obese BMIs no matter what the neighbors are doing. That push is the social force. An example of a strong social force is China's one-child policy that punishes families with multiple children.

Additional details of the model and modeling methodology are provided in the **Supplementary Methods and Procedures** online.

RESULTS

We only present results that are common to all tested rules and networks (see Methods and Procedures and **Supplementary Methods and Procedures** online for a list). In all simulations, regardless of the interaction rule, individuals with a similar BMI will cluster together into groups (**Figure 2**). The models do not build this behavior into the interactions. Instead, the interactions exist (in whatever form), and the clusters emerge as a directly predicted consequence. This supports and provides a theoretical foundation for the Framingham observations which found clusters of obesity. In fact, the BMI clusters are so pervasive that the models show almost all public health and population-scale behaviors are dominated by their existence and must consider their influence. If the population's initial distribution is biased toward any particular BMI class, then a cluster with that BMI will eventually dominate. Simulations show an obvious "tipping point" beyond which the dominant BMI rapidly forms a cluster that expands to fill the entire population (see **Supplementary Methods and Procedures** online).

The 2003–2004 distribution of BMIs in the United States was ~32.2% obese, 34.1% overweight, 32.2% normal weight, and 1.5% underweight (1). In 2005–2006, 34% of adults were classified as obese, a small but insignificant increase in the prevalence of obesity (2). Starting with the 2003–2004 distribution, simulations show that obese, overweight, and normal weight are closely balanced, but that the slightly greater prevalence of overweight individuals will slowly tip the cluster distribution. Unfortunately, earlier surveys from 1976 to 1980 and from 1988 to 1994 also show that the percentage of overweight has remained relatively constant while obesity has been steadily rising and normal weight have been falling (21). This would suggest that strong social forces (i.e., obesigenic environment) are pushing individuals toward greater BMIs and in particular is pushing toward obesity. In fact, a recent Centers for Disease Control and Prevention report notes that "the entire population is heavier, and the heaviest have become much heavier since 1980" (2). Simulations show that normal weight individuals are not "passing through" the overweight population and straight into obesity. Instead, under the influence of social forces, the obese clusters are recruiting from the overweight population at roughly the same rate as overweight clusters recruit from the normal weight population. However, at some point the normal weight population is depleted, and any simulation that includes such social forces shows that our current BMI distribution will inevitably transition into a dominantly obese BMI cluster. In other words, in all but the most optimistic scenarios, and barring any mitigating interventions, the model shows that we can expect a continuing shift toward obesity. Not only has the US population already exceeded the critical threshold for overweight individuals, but the social forces are also pushing the overweight toward obesity.

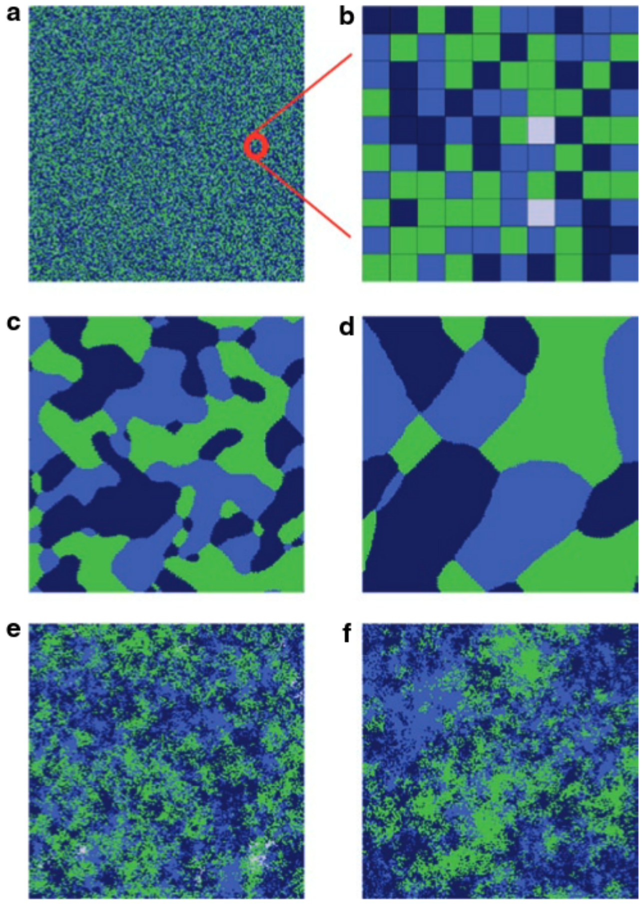

Figure 2 Clustering of BMI shown for simulations with 40,000 individuals. (**a**) The initial random configuration with 1% underweight (white), 33% healthy weight (green), 33% overweight (blue), and 33% obese (dark blue). (**b**) A close-up of 100 individuals in the initial population. (**c**) The evolution of **a** after 100 time steps. The population shows obvious clustering. In this simulation, social volatility is 0.002 and individuals are making entirely rational choices. (**d**) The continued evolution of **a** after 1,000 time steps. Over time, the clusters have evolved in shape and size. (**e** and **f**) Same as **Figure 1c,d** but with a social volatility of 1.0. Evolution of clustering is still evident but with significant noise. (For visual clarity, this and all following figures show a square nearest-neighbor network, but statistics show that clusters are present on all tested networks including scale-invariant and random networks; see text and **Supplementary Methods and Procedures** online. Except as noted, each figure uses majority probably rules with a social volatility of 0.002. In all figures, other interaction rules produce similar results.)

Our simulations can be used to understand why it has been difficult for individuals to sustain weight loss and to evaluate the likely success of different strategies for addressing obesity. As with populations, clusters dominate individual behaviors. For example, once a large cluster has formed it is self-sustaining, because an individual in the middle of the cluster (e.g., social network of obese friends) will have a very difficult time sustaining weight loss. Effectively, the surrounding sea of obesity ensures that even a temporary loss of weight is reversed, a result that is frequently observed in weight loss intervention studies (22–24).

Weight loss with friends

Unfortunately, without uprooting their social network, an individual has no choice about their location on the interior or edge of a cluster. As recently suggested by the popular press, an ostensible solution is to lose weight with friends. If an individual is surrounded by neighbors (friends) that have moved into the same lower BMI class (via diet and/or physical activity), then together they create a miniature lower-weight cluster. Regrettably, simulations show that such tiny clusters are not stable because everyone is either on or near the edge of his/her small cluster. In other words, the friends are still surrounded by a much larger cluster of higher BMI, and the friends will regain their weight. In a domino-like effect, the original individual will then regain their weight. Therefore, losing weight with friends may work as a short-term solution, but simulations show that it will not be effective as a long-term strategy (unless one or more of the friends happen to be very well connected in the social network, as detailed below).

Simulations show that a better approach is to lose weight with friends of friends. For example, an individual (host) can invite a group of friends for dinner. At dinner, each guest can be asked to write down a short list of his/her friends (not every friend needs to be included). The host can select an unrecognized name from each list. This new list of unrecognized names is a set of "friends of friends" and can form a weight loss cohort. Effectively, the dinner host has mapped out a very small subset of the total social network.

With this weight loss cohort, all of an individual's immediate network neighbors (the friends) are completely or partially surrounded by individuals with lower BMIs (the friends of friends who are losing weight). Therefore, the neighbors are also more likely to convert to a lower BMI. The original individual is now surrounded by a substantially larger group of lower BMIs (both the friends and the friends of friends), and the time it takes to regain lost weight is correspondingly longer, albeit still ineffective as a long-term solution.

The real benefit of this strategy is for individuals that are in an overweight (or obese) cluster, but on or near the edge of a lower BMI cluster. Simulations show that the nearby lower BMI cluster will expand and shift its boundary to encompass the "friends of friends" weight loss cohort (see **Supplementary Figure S1** online). Compared to losing weight with friends, the larger size of the "friends of friends" cohort ensures that the expanded lower BMI cluster is stable. When the individual stops trying to maintain their BMI, they will be safely ensconced in the lower BMI cluster. Although only those on the edge of a cluster receive this long-term benefit, dieting with friends of friends will have a higher overall success rate than dieting with friends.

Of course, a dinner host considering weight loss is unlikely to map the larger social network to find out whether they are on the edge of a cluster. The host only hopes that the dieting cohort is near the edge of the cluster where maintaining weight loss will be most effective. In effect, any individual trying this technique is inefficiently "rolling the dice," though public interventions and weight management agencies could maximize success by mapping the larger network and identifying cluster edges on a client's behalf.

Designing effective weight loss interventions

Our simulations can be used to develop novel strategies for reducing the global burden of obesity. Many observed social networks are characterized by a few individuals with extremely high connectivity and a majority of individuals with very low connectivity. Representations of these network lattices are typically generated with power-law (small world), exponential or random connectivity distributions (12,19). Using these types of networks, our simulations show that the most highly connected individuals play a disproportionately important role by influencing a tremendous number of neighbors. By definition, the best-connected individuals may be labeled as "celebrities" (not just in film and television, but also in business, politics, etc.). If the population's social network has a strongly biased distribution (e.g., power law or scale free), then the predominant BMIs of celebrities will have a disproportionate effect on the population. For example, if celebrities are predominantly normal weight, then simulations show that their influence will significantly slow the spread of obesity. Similarly, if most celebrities gain weight, then their influence will significantly speed the spread of obesity.

From a public health perspective, one of the most effective weight loss strategies would be to identify well-connected individuals on the edge of a cluster (i.e., those whose social network contains individuals of more than one BMI cluster) and target them for long-term intervention designed to achieve and/or maintain a normal weight. In fact, targeting anyone on the edge of a cluster will be productive; simulations show that pinning (i.e., maintaining) their BMI at the current value will prevent their surrounding cluster from retreating and shrinking (**Figure 3**). Similarly, pinning their BMI at a lower value will cause any neighboring lower-BMI cluster to expand and surround them. With this strategy, only a small fraction of the individuals on the edge of a cluster need to be pinned to prevent retreat or to encourage expansion. In a small-world network, simulations show that pinning the BMI of one well-connected individual can stabilize or convert an entire cluster.

A partial solution

Even if identifying edges of clusters proves difficult, pinning the weight of random individuals within a cluster may have some benefit. Assuming that everyone has roughly the same number of neighbors, then mathematical derivations with "majority probably rules" show that the critical mass is defined as the location of the steep transition in an "error function" (the integral of a Gaussian; see **Supplementary Methods and Procedures** online). Using this function, numerical solutions show that n people can convert $n + 1$ additional people to a new weight class at any given time step when social volatility is

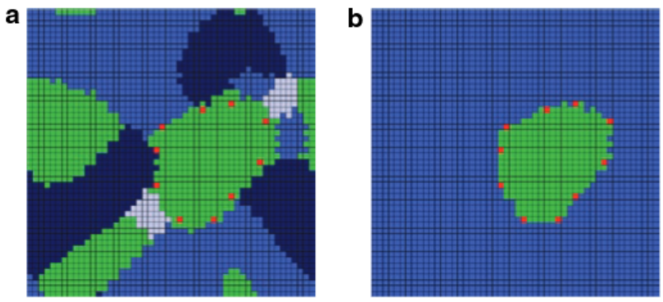

Figure 3 Clusters can be stabilized by pinning the weight of a small number of individuals on the edge of a cluster. (**a**) The 10 individuals shown in red have been pinned to a normal weight (green). (**b**) After 1,000 time steps, the overweight (blue) individuals have dominated and eliminated all other clusters except the one that was stabilized.

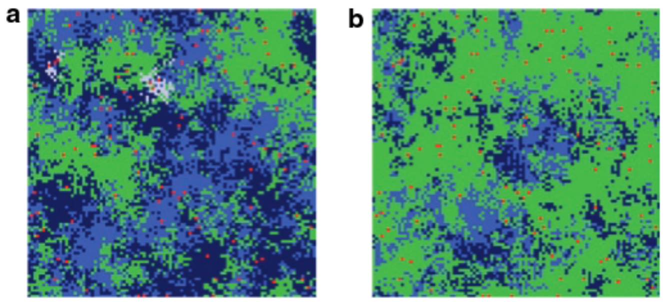

Figure 4 Pinning the weight of a small fraction of the population can dramatically improve the distribution of BMIs. (**a**) A population of 10,000 with an initial distribution of 0.7% underweight (white), 32.8% healthy weight (green), 33.7% overweight (blue), and 32.8% obese (dark blue). As shown in red, 1% of the population is pinned to a normal weight. (**b**) After 100 time steps, the normal-weight cluster has rapidly recovered and now dominates the population with 0% underweight, 69% normal weight, 17% overweight, and 14% obese. This simulation used a social volatility of 1.0.

not too low (15). In fact, simulations show that this doubling is pessimistic except at the lowest volatility levels (an unlikely scenario where everyone makes exceedingly rational decisions). With realistic volatility, each conversion has the potential to convert additional individuals at the next time step; so over time, the actual number of conversions is substantially larger (a "social multiplier" effect (17)).

As an example, consider a large cluster of overweight individuals. If an intervention on 99 people in the overweight cluster converts and maintains them at a new normal weight BMI, then we can expect to convert at least an additional 100 individuals to a normal weight. Of course, as soon as the BMI of those 99 individuals is no longer maintained (a likely scenario given existing social forces), then they will still be surrounded by an overweight cluster, and everyone will convert back. Thus, for this strategy to be effective, individuals must maintain weight loss. This finding highlights the importance of developing effective weight maintenance interventions.

Solution: target small number in all BMI groups

Another potentially effective public health intervention would focus intensive resources on reducing and/or maintaining the BMIs of some fraction of the entire population. Simulations show that pinning the weight of some random but very small percentage of the population (≤1%) while increasing social volatility will effectively stabilize or improve the BMI distribution. This would require a novel intervention that brings intensive efforts and resources to target a relatively small number of normal weight, overweight, and obese individuals. At low social volatility, the necessary percentage increases as the number of normal weight individuals decreases. However, at higher social volatility the effects are particularly dramatic; as little as 1% of the population creates a critical mass that converts most or all of a population to the specified BMI regardless of the initial BMI distribution (**Figure 4**). High social volatility encourage people to make irrational choices, and generating irrational decisions about weight loss could be as simple as making it a controversial topic. In essence, "stirring up the pot" will encourage some people to choose weight loss when they might not otherwise ("rationally") make that decision. These volatile individuals only need to lower their BMI temporarily, and then this decision will be reinforced and maintained by the individuals with a pinned BMI. With this process, clusters are very quickly converted to the value of the pinned BMIs.

Solution: change social forces

Changing social forces can have a similarly positive effect on BMI distribution and may be particularly effective when combined with targeted interventions (either on well-connected individuals or a random percentage of the population). An advertising campaign targeted at weight loss will bias decisions that are then reinforced by the individuals who are maintaining a lower BMI. Our simulations show that the combination of social forces and a targeted intervention results in the lower BMI cluster quickly dominating the BMI distribution. Unfortunately, social forces work in both directions. If current social forces are encouraging weight gain (25), then to affect a change, a targeted intervention must include many more individuals who maintain a lower BMI. When derived mathematically from a "majority probably rules" interaction (see **Supplementary Methods and Procedures** online), the relative influences of social forces and pinned neighbors are exponential vs. linear. In other words, relative to other interventions, changing social forces may be particularly effective.

DISCUSSION

Interactions on a social network lead inevitably to clusters of BMI classes, similar to those found in the Framingham study. The clusters dominate long- and short-term trends in BMI distribution and are very sensitive to social forces. Both data and simulations imply that the United States has already reached or passed a "tipping point" and without effective interventions will continue its rapid slide toward obesity. New longitudinal studies may suggest appropriate mitigations but could be irrelevant by the time they are complete. Fortunately, simulations predict the same cluster-driven behaviors for a wide variety of social interactions and network structures—the results are not sensitive to the details. Therefore, public officials can act confidently on the model predictions, while continuing corroborative longitudinal studies and refining the precise rules and network structures to suggest increasingly targeted and novel approaches to weight loss.

Traditional weight loss interventions and dieting strategies will not work. Simulations show that changing the BMI of an individual in the center of a cluster is very difficult because surrounding neighbors will pull the individual back to their original weight; and because of this cluster-based inertia, our simulations demonstrate the ineffectiveness of interventions targeted toward obese individuals without regard to their social network.

Public health interventions will be most successful when applying social forces (tax incentives, advertising, and other "carrots and sticks") while targeting specific well-connected individuals at the edge of a cluster for weight management. Stabilizing and reversing trends in weight gain are also possible by selecting random obese, overweight, and normal weight individuals at any location (not just on cluster edges) and pinning their BMI at a desired value while increasing social volatility (irrational behavior). This scattershot approach requires more individuals to effect the same change as targeting well-connected individuals on cluster edges, but random selections eliminate the need to identify clusters and their edges and may be more politically palatable than the potentially sensitive targeting of specific individuals. With any intervention, social forces have an exponentially greater influence than pinning the weight of individuals.

SUPPLEMENTARY MATERIAL

Supplementary Methods and Procedures is linked to the online version of the paper at http://www.nature.com/oby

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DISCLOSURE

The authors declared no conflict of interest.

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