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Activating a community: an agent-based model of Romp & Chomp, a whole-of-community childhood obesity intervention

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Abstract

Objective: Successful whole-of-community childhood obesity prevention interventions tend to involve community stakeholders in spreading knowledge about and engagement with obesity prevention efforts through the community. We refer to this process as "stakeholder-driven community diffusion" (SDCD). This study uses an agent-based model (ABM) in conjunction with intervention data to increase our understanding of how SDCD operates.

Methods: Our ABM retrospectively simulates SDCD during Romp & Chomp, a four-year whole-of-community childhood obesity prevention intervention in Victoria, Australia. Stakeholder survey data, intervention records, and expert estimates were used to parameterize the model. We evaluate model output against criteria derived from empirical data and experts' estimates of the magnitude and timing of community knowledge and engagement change.

Results: Our model was able to produce outputs that met our evaluation criteria: increases in simulated community knowledge and engagement driven by SDCD closely matched expert estimates of magnitude and timing.

Conclusions: We find strong suggestive evidence in support of a hypothesis that SDCD was a key driver of the success of the Romp & Chomp intervention. Model exploration also provides additional insights about these processes (including where additional data collection might prove most beneficial) as well as implications for the design and implementation of future interventions.

Keywords

intervention; childhood obesity; community health; behavioral science

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Introduction

Overweight and obesity is a major health issue internationally, affecting all age groups in most high-income countries. In Australia, national data show that 27% of school-aged children have overweight or obesity, while estimates suggest a prevalence of 20% among children ages two through four [1]. The early onset of excess weight gain implies that interventions that seek to promote healthy behaviors and weight must begin in the first years of life, and that parents and caregivers should be supported in helping their children develop lifelong, healthy habits [2].

Among the most promising approaches to supporting healthy weight among young children are community-based or whole-of-community interventions that target multiple settings and a wide array of behaviors and environmental influences within communities [3,4]. Common features of successful whole-of-community obesity prevention interventions include the involvement and support of community leaders; activation of resources and existing networks; broad community engagement and partnerships; implementation of a range of complementary intervention actions in multiple community settings; adaptation to local conditions; recognition and embrace of the complexity of causes; and a focus on children and adolescents [3,5,6]. Typically, these interventions define a community in geographic terms (a town, suburb, or city) and are catalyzed through the formation of a group of community stakeholders from multiple sectors (which we refer to as a “steering committee”) that meets regularly to discuss and plan obesity prevention efforts.

Numerous whole-of-community interventions have helped reduce child overweight and obesity [7–12]. A recent review found that steering committees can be important components in the success of these interventions [5]. For example, *Healthy Living Cambridge Kids* convened a task force of stakeholders that included parents, educators, health care professionals, and researchers, who together pushed for policies and programs that promoted child health. Over the course of the three-year intervention, obesity rates fell substantially among K-5 students [12]. Similarly, *Shape Up Somerville* engaged a community leadership group that helped design, implement, and champion obesity prevention initiatives in schools and elsewhere, leading to significant decreases in child BMI z-score compared to control communities [8,9].

A central, hypothesized mechanism through which steering committees drive intervention success is that understanding of obesity prevention in the community (broadly termed “knowledge”), combined with enthusiasm for and commitment to obesity prevention (including communication, access, resourcing, and advocacy, termed “engagement”), will diffuse from the steering committee to the rest of the community. This is expected to result in midstream impacts on policy and practice in settings such as child care, health care, and local government. These midstream changes are in turn expected to have downstream impacts on behaviors and, through those, anthropometry of children. This hypothesized mechanism, which we term “stakeholder-driven community diffusion” (SDCD), is cost-effective. Interventions leveraging SDCD approach provide initial stimulus and expert guidance to initiate obesity prevention-related activity, but the responsibility for driving and

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resourcing the intervention rests with community stakeholders, utilizing their existing networks, skills, and social capital.

In order to explore SDCD processes, we employ an agent-based model (ABM) to retrospectively simulate a successful, whole-of-community childhood obesity prevention intervention. ABM is a computational simulation approach well-suited to the research question because it can capture time-variant social interaction between heterogeneous members of a community (i.e., agents) and how community-level change emerges from interaction between socially connected individuals. By comparing trends in knowledge and engagement over time to those observed in the real world, we hope to provide insight into the operation of SDCD that can guide future research and intervention design.

Background

One of the first examples of a whole-of-community obesity prevention intervention that substantially impacted weight status in children under five years old was the Romp & Chomp project in the state of Victoria, Australia [7]. Romp & Chomp was conducted between 2004 and 2008 in the city of Geelong (total population ~170,000, with 12,000 children in the target age group). The intervention took a broad, inclusive approach to creating healthier environments for young children in the region, promoting healthy eating and active play in education and child care settings.

Romp & Chomp sought to connect, motivate, and engage relevant stakeholders in the region around the project. A central steering committee was formed to manage and administer the intervention with representation from local government, early childhood care and education settings, health care practitioners and experts, a local sports and recreation network, and a local university with expertise in obesity prevention that provided project support, capacity building, and evaluation. This committee held periodic meetings over the course of the intervention, during which they planned intervention activities across the community, including professional development for early childhood care and education staff members, social marketing, and policy development and implementation in early childhood settings [7,13,14].

Romp & Chomp was evaluated using individual biometric and behavioral measures taken from children in the intervention community pre- and post-intervention as well as in control communities across the remainder of the state [7]. The evaluation results demonstrated that there was a significant decrease in overweight and obesity prevalence (based on measured height and weight records) among children in the intervention community relative to controls. There were also significant improvements in behavioral indicators, including lower consumption of packaged snacks and sugar-sweetened beverages [7].

Understanding the success of Romp & Chomp may provide insights into how future interventions can have positive impacts. Because Romp & Chomp was designed to leverage existing community leadership and social connections, we hypothesize that SDCD played a central role. And because these processes are inherently situated in social networks and involve interactions between individuals, we employ an agent-based modeling (ABM) analytic approach.

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Methods

This paper describes an ABM of diffusion of knowledge and engagement that occurred during a successful, whole-of-community childhood obesity prevention intervention. The model uses survey measures and expert estimates of community members' relevant knowledge, engagement, and social network ties at the start of the intervention to generate agents, who represent individuals that together form a socially connected community. Agents interact with one another over time, affecting each other's knowledge and engagement. We also simulate the salient aspect of the intervention: a subset of agents who represent members of a steering committee who attend periodic meetings that increase their knowledge, engagement, and connections to one another.

Model initialization

Agents are generated using input parameters summarized in Table 1; they have (fixed and mutually exclusive) community group affiliations as well as initial knowledge and engagement values and social network connections. Community groups are organizations or organization types that define each community member's primary role in childhood obesity prevention. Group affiliations include child day care centers, maternal and child health services, and local government. Knowledge is a vector of five independent, continuous variables ranging from −1 to 1. Each of these variables describes the direction and accuracy of information an individual agent possesses about a pertinent aspect of children's health in the community,[1] with −1 representing complete misinformation and 1 representing complete accurate information. For example, an individual who fully understands the importance of intervening in multiple community settings would have a high positive value for knowledge, while an individual who strongly disagrees that childhood obesity is a problem in the community would have a high negative value. Due to uncertainty about initial knowledge levels in the community relative to levels after the Romp & Chomp intervention, we explore high and low variations of initial mean community knowledge that imply, respectively, low and high estimates of knowledge change in the community during the intervention (Figure 1). Engagement is a continuous variable, ranging from 0 to 1, that describes an individual's level of personal interest and investment in childhood obesity prevention in the community. The model allows us to specify whether and to what extent initial, individual-level community knowledge and engagement are correlated.

Agents are endowed with two social network properties—connectivity (degree) and within-group assortativity (clustering)—that are based on the group-specific means shown in Table 1. Connectivity defines the number of undirected (bi-directional) ties an individual agent has with others in the community. Within-group assortativity characterizes the propensity of individual agents to be socially connected with other members of their community group.

[1]We do not have sufficient data to satisfactorily differentiate between domain variables during initialization or analysis. The five domains are: obesity as a problem; intervention factors and modifiable determinants; the roles of stakeholders and others; available resources; and sustainability of efforts.

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Model dynamics

During each simulated day, there is a probability that agents influence the knowledge and engagement of those with whom they are socially connected. We allow this probability to change as a function of change in mean community engagement; this reflects the theory that highly engaged communities will more frequently discuss childhood obesity prevention issues.

Agents' knowledge values are more likely to be affected by interactions with more engaged peers. When interacting with another agent whose knowledge value on a particular domain is of the same sign (+/−)—an indication that the agents agree—knowledge can only increase in that direction (e.g., if an agent with positive knowledge interacts with another agent with a positive, but lower, knowledge value, the agent does not "lose" knowledge). When interacting with another agent whose knowledge on a particular domain is in disagreement, there is a probability that their knowledge value moves toward zero; this probability is based on an agent's own engagement (i.e., it is harder to change the beliefs of highly engaged agents). When agents update their engagement values, they do so based on the collective values of all other agents with whom they are socially connected. Model dynamics are described in more detail in our Supplemental Appendix.

Modeling the intervention

The steering committee is a collection of 21 specific agents, all of whom attend up to 22 simulated meetings. We initialize the steering committee based on available data in one of two ways: stochastically (steering committee agents' attributes are drawn from a specified distribution) or hard-coded (read in directly from data); this allows us to explore whether and to what extent intervention effects stem from specific combinations of attributes observed in data. Either way, on average, simulated steering committee agents have higher initial knowledge and engagement and more social network connections than non-committee agents by a factor greater than two. Attendance at committee meetings increases committee member agents' knowledge and engagement values. This reflects new information about, and interest in, childhood obesity prevention efforts that attendees gain from meeting participation. Meetings can also create new social network ties and lead to knowledge and engagement diffusion between attendees. Diffusion during meetings occurs according to the update rules described earlier in Model Dynamics, with agents treating other meeting attendees as their full set of social network connections.

Modeling exogenous effects

The model also accounts for exogenous effects both related to and separate from Romp & Chomp—specific projects, events, and other activities that affected knowledge and engagement in the community at the time of the intervention beyond the SDCD process (e.g. the concurrent "Smiles for Miles" oral health promotion program). These exogenous effects are discussed in greater detail in the Supplementary Appendix.

Data sources

A combination of three approaches was used to obtain data for model inputs (i.e., to parameterize the ABM) and outputs (i.e., to assess model behavior): 1) document analysis of

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intervention records; 2) analysis of retrospective knowledge, engagement and network survey response data; and 3) development of expert estimates and consensus. The list of parameters and the approach(es) used for each are outlined in Table 2.[2] A detailed description of each of these data sources can be found in our Supplementary Appendix.

Model use

Since the impacts of SDCD on the community are expected to be lagged, we run the model beyond the last simulated steering committee meeting (day 1246) to allow it to stabilize and observe the full impact of the intervention. Specifically, each model run consists of 2,000 simulated days (5.5 years). By design, our model allows for substantial flexibility in inputs. Specifically, input parameters that determine initialization and operation fall into three categories: those used to characterize diffusion mechanics, those that control the simulated intervention, and those that are used to generate our simulated community. Using these parameters (as opposed to hard-coded model functionality) allows us to explore uncertainty in each of these categories. In addition, our model contains probabilistic elements to abstract away from details such as when specific agents interact with one another. We run 50 simulations for every combination of parameter values listed in Table 3.

Model output evaluations

The model outputs knowledge and engagement values on every simulated day of each run. In order to test hypotheses about SDCD, we compared model output to criteria derived from empirical data and experts' observations. Our strategy for this was twofold. First, we made three broad assertions about what occurred in the actual community during the intervention, listed in decreasing order of our confidence in their accuracy:

1) Knowledge and engagement both moderately increased, and generally did so monotonically (i.e., never decreasing substantially), during the intervention.

2) The SDCD process had a causal effect on this increase in knowledge and engagement.

3) Knowledge and engagement increased along specified trajectories (as estimated by intervention experts).

We then translated these assertions into specific criteria that we could use to evaluate the output of a simulation run. To do this, we utilized available data in combination with threshold values that we believed sensibly reflect our assertions (i.e., are tied to data by intuitive multipliers such as "double" or "half") and, *a priori*, we expected would allow us to differentiate between model runs (i.e., are not so strict or loose that they were likely to never or always be met). These criteria are:

1) Mean community knowledge and engagement during a simulation run both: a) increase from run start to end by a magnitude between 50 and 200% of the increase estimated by intervention experts and b) never decrease from one simulated day to another by more than 10% of the overall estimated increase.

[2]This study was approved by the Deakin University Human Research Ethics Committee.

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2) Both mean final community knowledge and engagement with the intervention active are greater than those under analogous conditions with the intervention inactive by a magnitude equal to or greater than 10% of the estimated increase.

3) The mean, per-simulated-day difference between expert estimates of both mean community knowledge and engagement and those produced by the model is less than 10% of the estimated increase.

In order to analyze the large number of runs (described above in “model use”), we calculate the proportion of runs using each parameter value that we vary that meet each of our evaluation criteria. Results from this are presented in Table 3 and discussed below.

Results

Our model is able to produce output that fits our evaluation criteria quite well. Figure 2 shows knowledge and engagement trends from a set of runs using the combination of parameter values that best matches expert estimates (criteria 1 and 3). Figure 2 also compares the “best fit” intervention scenario to one with matching parameterization but no simulated intervention (i.e., no active steering committee), showing the positive effect of SDCD on knowledge and engagement (criterion 2).

Interpretation of the results described in Table 3 is driven by two goals. The first is to determine whether our primary finding (that the model can produce expected patterns in knowledge and engagement) is a “knife edge” result, occurring only under an extremely narrow set of conditions. The second is to see how changes in specific parameter values affect whether model output meets our evaluation criteria and identify those values that best meet the criteria; as discussed below, these results can help guide future research (e.g. where to focus data collection efforts in conjunction with interventions). The “overall” row of Table 3 indicates that our criteria are met under a substantial proportion of the parameter space that we explore, suggesting that our primary finding is robust. Both overall and across all parameter values, criterion 2 (a positive causal impact of SDCD) was nearly always met; we discuss this further below. We group more detailed findings for criteria 1 and 3 into three distinct parameter categories.

Diffusion mechanics

Runs with the lowest magnitude of “knowledge diffusion rate” and “engagement diffusion rate”—the parameters that determine how much agents adjust their values in a given interaction—most frequently led to moderate and monotonic increases in knowledge and engagement (criterion 1: 43.8% and 22.1% of runs, respectively) and matched estimated trends in these variables (criterion 3: 25.1% and 14.1% of runs, respectively). Similarly, the two parameters that determine the probability of an interaction between agents (“initial diffusion probability” and “diffusion probability change”) both satisfied criteria 1 and 3 more frequently at lower magnitudes.

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Steering committee meeting effects

Model output was somewhat sensitive to changes in intervention magnitude. Runs with low magnitude effects satisfied the “moderate, monotonic increase” criterion in 23.7% of runs, compared to just 6.3% of runs when intervention magnitude was high. Similarly, under low magnitude conditions, 20% of runs met the “match of estimated trends” criterion, compared to just 2.8% of runs with high magnitude.

Model initialization

We found that whether the steering committee was initialized stochastically or was hard-coded, results were similar. In contrast, model output was sensitive to changes in assumptions about initial community conditions. When initial community knowledge was high and the overall estimated change in knowledge low, the “moderate, monotonic increase” and “match with estimated trends” criteria were each met in fewer than 5% of runs —much less frequently than when initial community knowledge was low and estimated change in knowledge was high. Changes in individual-level correlation between initial knowledge and engagement did not lead to large differences in model behavior.

Discussion

Main findings

Our ABM is a first attempt to understand the mechanisms through which the Romp & Chomp intervention’s steering committee of stakeholder representatives were able to effect change that ultimately translated into substantive reductions in childhood obesity and gains in children’s health outcomes. Specifically, we built an agent-based model that could retrodict estimated trends in community knowledge about and engagement with childhood obesity prevention given plausible model inputs and effect pathways, and could be used to compare the intervention to a “virtual counterfactual” where it had not taken place. We find that the presence of the simulated steering committee intervention substantially amplified the diffusion of knowledge and engagement in the community, and did so along trajectories that closely matched expert estimates of the real-world Romp & Chomp intervention. This provides strong suggestive evidence in support of the hypothesis that stakeholder-driven community diffusion (SDCD) was a key mechanism that drove the success of the Romp & Chomp intervention.

By exploring the sensitivity of simulated trends in knowledge and engagement to model input parameters, we were able to provide insight into how our characterization of this diffusion process and the community context affects model behavior. Specifically, we found that expected trends in knowledge and engagement were most frequently observed when diffusion operation parameter values were on the lower end of the range that we explored, suggesting that diffusion in the Romp & Chomp intervention may have occurred relatively slowly; this finding can be corroborated and refined with future research. Simulations suggest that initial community knowledge in Romp & Chomp was closer to our lower estimates; although this is a context-specific finding it might nonetheless prove useful for future analyses of model output data. We also found that whether we characterized the steering committee based on hard-coded data or stochastically did not appreciably affect

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model behavior; thus, it does not appear that idiosyncrasies of individual steering committee members' knowledge, engagement, and network connections drove our results.

Comparison to the literature

This work represents a novel combination of two robust bodies of literature: whole-of-community interventions and diffusion of social phenomena through networks [5,15–20]. This combination allows us to build upon the powerful insights of each. We were able to use the former as a starting point for our central hypothesis about SDCD and the latter to determine how to mechanistically operationalize the ways in which socially connected individuals affect one another's knowledge and engagement. Thus, although we believe that this is pioneering work, it is also well-grounded in validated theory and empirical evidence.

Strengths and weaknesses

Our model approach is able to provide explanatory evidence for the ways in which a completed childhood obesity prevention intervention operated. It is also highly extensible: having used it to gain intuition about our central hypothesis as well as diffusion mechanics and community contexts, we can now begin applying it prospectively to provide useful input into the design and deployment of future interventions, such as whom to recruit into a steering committee and how much meetings need to increase their knowledge, engagement, and connections to one another. Whole of community interventions continue to form an important plank in global efforts to prevent obesity [21], and tools such as the ABM described here, which may prospectively provide insight to create more effective coalitions and diffusion of knowledge, represents a critical next step in whole-of-community childhood obesity prevention.

We relied on relatively sparse data, supplemented and strengthened with expert estimates, to parameterize our agent-based model. In large part, this was because data collection was done several years after the conclusion of Romp & Chomp. Future efforts to use simulations to explore whole-of-community childhood obesity interventions should incorporate more extensive, contemporaneous data collection in order to increase confidence in and granularity of model findings. Our model results provide some guidance on data collection: simulated changes in knowledge and engagement are sensitive to diffusion details and community attributes that can be explored using interviews with and surveys of community members. Future work here should place an emphasis on high-volume, low-burden data collection (e.g., through mobile phone applications) in order to take full advantage of an agent-based model approach to intervention exploration.

Implications for practice

The results presented in this paper support an interpretation that intervention effects represent a "match" between intervention design and deployment and community context; what works in one place may be insufficient elsewhere, so it is important to consider this match *a priori*. For example, we observed that within almost all of the parameter space that we explored (including the parameter combinations that generate the best matches to estimated trends), simulated intervention activities had a positive causal effect on community knowledge and engagement. This suggests that the community may have started

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out at a high level of readiness to change, a “tipping point” where even relatively infrequent, low-impact steering committee meetings would have been able to “nudge” the community forward. Understanding this ahead of time would allow intervention planners to make informed decisions about implementation (e.g., meeting focus and activities). Therefore, we believe that the model could be a potent tool for designers of future childhood obesity prevention interventions.

Questions for future research

This article represents intervention effects on knowledge and engagement in a single community setting. Future research can expand this by studying additional settings, aided by richer, contemporaneous data collection, and evaluating the predictive accuracy of the model. Not only would this allow us to further test our central hypothesis about SDCD, but it would also provide a way to answer additional questions. These might include how diffusion processes differ across contexts; how steering committee meeting activities affect specific domains of knowledge and engagement; how committee selection and composition affect intervention effectiveness; and how social network connections might be “weighted” (e.g., by trust between individuals).

Future research can extend model boundaries in two ways. More can be done to explore how community leaders can work in conjunction with intervention experts to recruit and support a steering committee to maximize knowledge and engagement change in communities. In addition, there is a need to study the “downstream” effects of interventions: how knowledge and engagement translate into changes in policy and practice, and how these in turn affect health outcomes.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Study Importance Questions:

What is already known about this subject? What does your study add?

- Research shows that whole-of-community interventions that leverage the influence and social networks of key stakeholders can be effective in increasing knowledge about childhood obesity prevention and lead to a reduction in obesity rates.
- However, little is known about the dynamics of these changes in the community. Our study uses a computational simulation model—based on data from a successful intervention—to test a theory of stakeholder-driven community diffusion, with the goal of better understanding the underlying diffusion mechanisms that drive the “downstream” effects of interventions.

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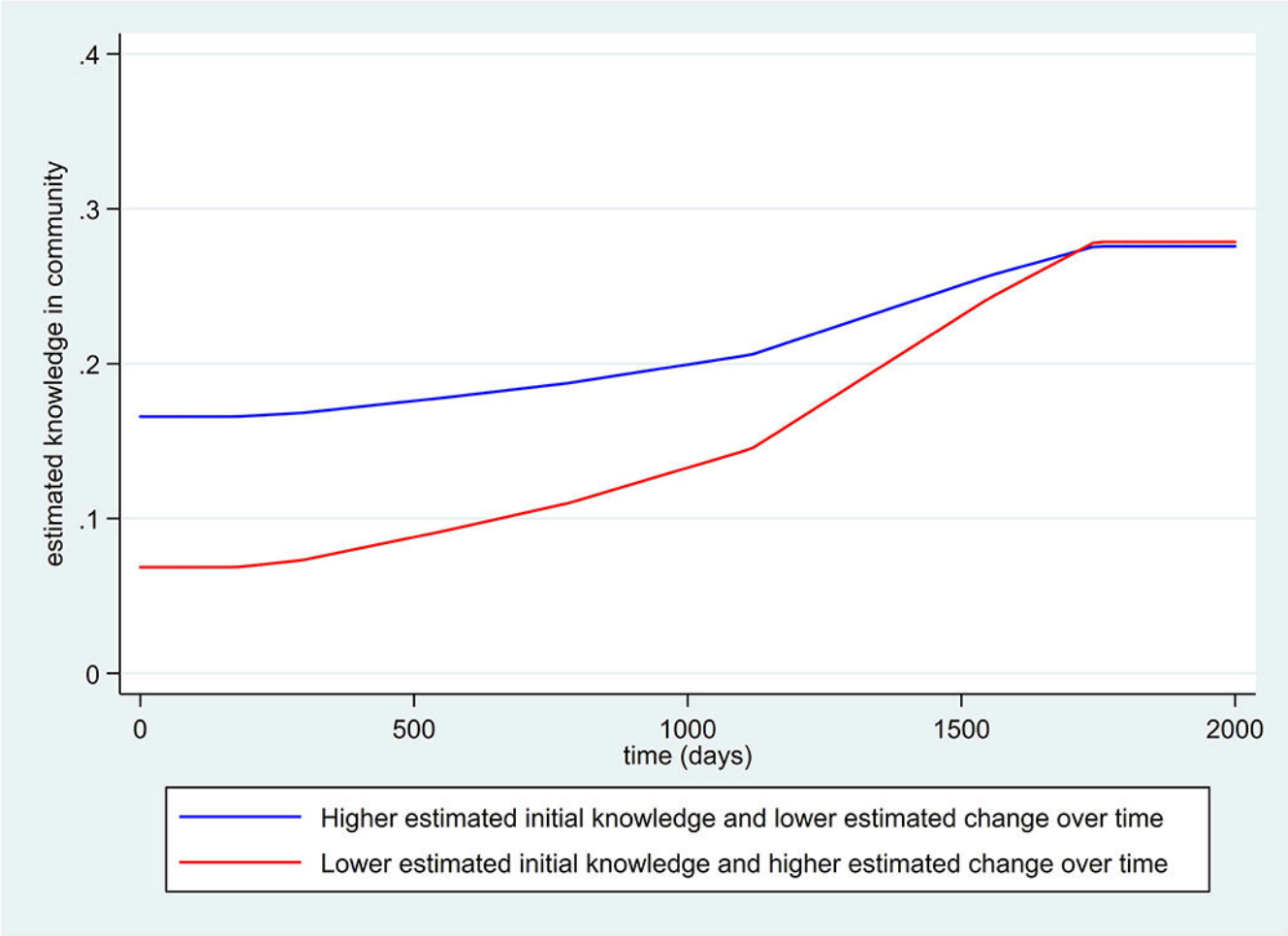


Figure 1: Two expert estimates of possible trends in community knowledge.

Low initial community knowledge is paired with the high estimate of community knowledge change, while high initial community knowledge is paired with the low estimate of community knowledge change.

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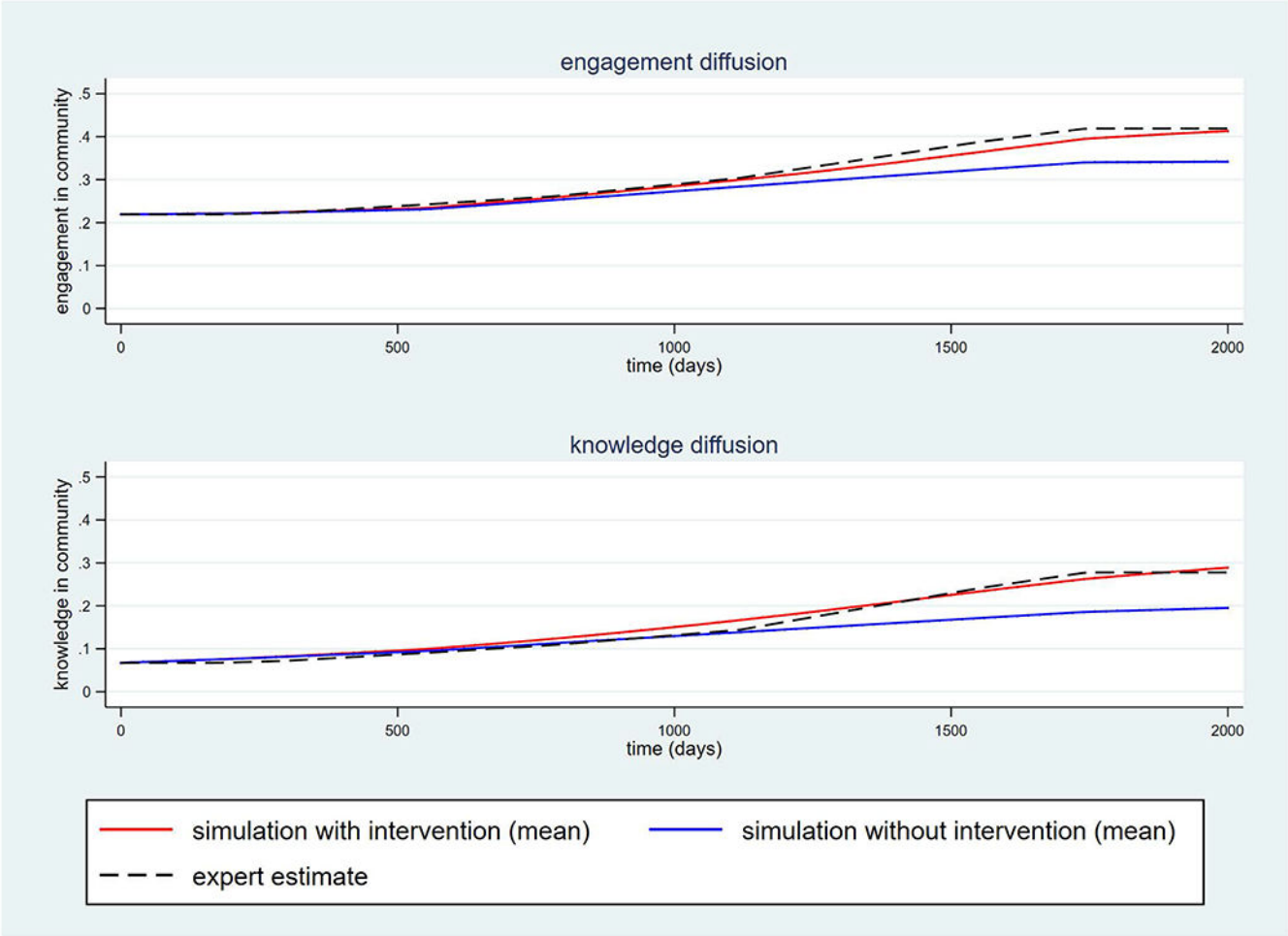


Figure 2:

Mean knowledge and engagement over 50 simulations in each of two scenarios: the model scenario with intervention active that produces the best fit to expert estimated trends, and the identical scenario with the intervention inactive. Parameters values for these scenarios are: knowledge diffusion rate = 0.01; engagement diffusion rate = 0.01; diffusion probability (initial) = 0.05; diffusion probability change = 1; intervention magnitude = low; SC scenario ID = hard-coded; initial community conditions = lower initial knowledge; correlation between knowledge and engagement = −0.1.

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Table 1:

Community knowledge, engagement, and network input parameter values by group.

Knowledge is scaled [−1,1], representing complete inaccurate information about childhood obesity prevention efforts to complete accurate information. Engagement is scaled [0,1], representing level of personal interest and investment in childhood obesity prevention efforts. Connectivity and within-group assortativity refer, respectively, to the mean number of ties an agent has in total and the mean number of ties an agent has specifically with other agents in the same community group.

Group	Label	Size (n)	Knowledge [−1, 1] high estimate (mean)	Knowledge [−1, 1] low estimate (mean)	Knowledge [−1,1] (sd)	Engagement [0,1] (mean)	Engagement [0,1] (sd)	Connectivity	Within-group Assortativity
Group 1	University	4	0.59	0.49	0.20	0.70	0.10	21.83	0.87
Group 2	Partner organization: Health Service	4	0.60	0.50	0.30	0.54	0.30	23	0.90
Group 3	Partner organization: Local Government	5	0.52	0.42	0.20	0.68	0.10	21.83	0.90
Group 4	Maternal and Child Health service	31	0.35	0.25	0.25	0.45	0.30	15	0.95
Group 5	Long Day Care centers	416	0.15	0.05	0.20	0.20	0.10	6	0.95
Group 6	Family Day Care service	69	0.10	0.00	0.20	0.15	0.10	3	0.95
Group 7	Partner organization: Department of Human Services	5	0.40	0.30	0.50	0.40	0.30	16	0.87
Group 8	Partner organization: Kindergarten Association	2	0.25	0.15	0.10	0.50	0.10	15	0.90
Group 9	Partner organization: Sport and Recreation Network	3	0.25	0.15	0.10	0.30	0.10	25	0.87
Group 10	Kindergartens	194	0.15	0.05	0.20	0.20	0.10	4	0.95

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Table 2:

Data sources

Category	Model input parameter or expected model behavior	Sources of data
Model Inputs		
Knowledge and engagement (initial)	Group knowledge (mean)	Combination of survey data and expert estimates
	Group knowledge (standard deviation)	Expert estimates only (n too small from survey)
	Group engagement (mean)	Combination of survey data and expert estimates
	Group engagement (standard deviation)	Expert estimates only (n too small from survey)
	SC[3] member knowledge	Survey data combined with expert estimates
	SC member engagement	Survey data combined with expert estimates
Social network structure	Group membership	Survey data and intervention records
	Group connectivity (avg. # links per agent)	Combination of survey data and expert estimates
	Group assortativity (probability of within-group links)	Expert estimates only (could not be calculated due to incomplete network data)
	SC member connectivity	Survey data combined with expert estimates
SC Meetings	SC composition	Survey data and intervention records
	Meeting schedule and attendance	Intervention records
	Effects on knowledge, engagement, and links between SC members	Expert estimates
Exogenous effects	Magnitude and timing of effects on community member knowledge and engagement	Intervention records and expert estimates
Model Outputs		
Knowledge and engagement (end of intervention)	Community knowledge (mean)	Average of group data
	Community engagement (mean)	Average of group data
Knowledge and engagement change timing	Estimated change in community knowledge that reflects observed changes in policy, practice, and implementation of intervention components.	Expert estimates

[3]Steering committee is abbreviated “SC” in this table

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Table 3:

Summary of 50 model runs for each of 324 parameter value combinations (i.e., every combination of the values listed in the first column). The results shown are the percentage of all runs using the parameter values in the first column that satisfy each of three criteria (see the Methods section for more detailed descriptions):

Criterion 1: Knowledge and engagement both moderately increase, and do so monotonically, over the course of the run.

Criterion 2: The SDCD process has a causal effect on the increase in knowledge and engagement.

Criterion 3: Knowledge and engagement increase along trajectories that are similar to those estimated by intervention experts.

Parameter (values)	Definition	Criterion 1			Criterion 2			Criterion 3		
		Value 1	Value 2	Value 3	Value 1	Value 2	Value 3	Value 1	Value 2	Value 3
Knowledge Diffusion Rate value 1 = .01, value 2 = .03, value 3 = 0.05	The fraction of the difference between an agent's knowledge and the knowledge value they are moving toward by which the agent adjusts its knowledge when diffusion occurs.	43.81%	4.69%	0.00%	99.45%	99.46%	99.47%	25.07%	1.70%	0.00%
Engagement Diffusion Rate value 1 = .01, value 2 = .03, value 3 = .05	The fraction of the difference between the agent's and neighbor's engagement by which the agent adjusts its engagement when diffusion occurs.	22.05%	12.91%	13.55%	100.00%	99.88%	98.50%	14.06%	6.21%	6.51%
Diffusion Probability (initial) value 1 = .05, value 2 = .1	The probability that an agent has an interaction with a neighbor during which diffusion can occur.	19.90%	12.44%		99.77%	99.16%		12.59%	5.26%	
Diffusion Probability Change value 1 = 1, value 2 = 2	The factor by which initial diffusion probability changes over time relative to change in community engagement.	19.93%	12.41%		99.58%	99.35%		12.55%	5.30%	
Steering Committee Effect Magnitude value 1 = low, value 2 = moderate, value 3 = high	The extent to which steering committee agents form new links with one another and increase knowledge and engagement as a result of committee meetings.	23.71%	18.51%	6.28%	98.39%	100.00%	100.00%	20.04%	3.94%	2.79%
Steering committee Scenario ID value 1 = stochastic, value 2 = hard-coded	Whether steering committee agents' knowledge, engagement, networks, and meeting attendance are taken directly from data or probabilistic.	15.74%	16.60%		99.49%	99.43%		8.19%	9.66%	
Initial Community Conditions value 1 = higher initial knowledge value 2 = lower initial knowledge	Whether the high or low estimate was used to initialize community knowledge.	3.84%	28.50%		99.44%	99.48%		4.31%	13.54%	
Correlation between knowledge and engagement value 1 = −.1, value 2 = 0, value 3 = .1	The Spearman's rho correlation coefficient of agents' initial knowledge and engagement.	16.63%	15.89%	15.99%	99.45%	99.46%	99.46%	9.56%	8.45%	8.76%
Overall		16.17%			99.46%			8.93%		