Using Simulations for Exploring Interventions in Social Networks
Modeling Physical Activity Behaviour in Dutch School Classes

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Abstract: The reduction of childhood obesity through the promotion of a healthy lifestyle is one of the most important public health challenges at the moment. It is known that the unhealthy habits of children can cause unavoidable side effects in their early stage of life, including both physical and mental consequences. This work considers that the physical activity level of children is a behaviour that can be spread throughout the social relations of children in their daily life at school. Therefore, the aim of this work is to define what the best strategy is to find 'targets' (i.e., influential children that can initiate behavioural change) for physical activity (PA) interventions that would affect the average PA of a population of Dutch school classes. We tuned a model based on the influence of the children's peers in their social network, based on the data set from the *MyMovez* project – Phase I. Five intervention strategies were implemented, and their efficacy was compared. Once the targets were chosen, an increase of 17% was applied to their initial PA. Then, the diffusion model was run to verify the improvement on the PA of the whole network after one year. We discuss implications of the simulation results on which strategies may be used to make informed choices about the setup of social network interventions and future model improvements. Our results show that targeting more vulnerable children (i.e. in a worse environment) and applying a network optimization algorithm are the best solutions for this data set indicating that future interventions should aim for these two strategies.

1 INTRODUCTION

One of the most important public health challenges is the prevention and reduction of childhood obesity. It has worldwide priority because the prevalence of childhood overweight and obesity is still rising. Childhood obesity has persisting effects on adult adiposity and can lead to diseases such as diabetes and cardiovascular diseases (WHO et al., 2017). Evidence is accumulating which shows that the social environment is an important factor underlying the development of inappropriate weight gain due to its powerful impact on energy-balance related behaviours (Christakis and Fowler, 2007). Youth are especially susceptible to environmental influences and are surrounded by influential individuals (i.e., role models such as family and peers) who support and/or undermine their health behaviours. For example, studies have shown that individual peers as well as peer groups shape a youth's consumption behaviour and physical activity (Salvy et al., 2012; De La Haye et al., 2011; De la Haye et al., 2010). Numerous studies have shown that the health of individuals is connected to each other and that social networks influence peoples well-being (Smith and Christakis, 2008; Hammond, 2010).

Social network interventions aim to use influential individuals to correct unhealthy behaviours within social networks by letting them promote specific health behaviours (Valente and Pumpuang, 2007). It is suggested that when influential individuals stimulate and spread the targeted behaviour successfully, the behaviour will turn into a group norm supporting long-term behaviour change. The term network interventions "describes the process of using social network data to accelerate behaviour change or improve organizational performance" (Valente, 2012). Social network interventions have been successful in reducing behaviours such as smoking and unsafe sex

(Campbell et al., 2008; Valente et al., 2003; Kelly et al., 1991). To date, there is great necessity to target the physical activity of youth because they are even less active than previous generations and the majority of adolescents do not meet daily guidelines of being active for at least 60 minutes (Hallal et al., 2012). Hence, social network interventions are now not only dedicated to reducing childhood obesity by targeting water and sugar-sweetened drinks but also increasing physical activity (Hunter et al., 2017; Smit et al., 2016; Hallal et al., 2012; Van Woudenberg et al., 2018).

An important step in the design of such interventions is the selection of influential individuals. This is usually called "influence maximization" (Kempe et al., 2003; Chen et al., 2009), which is the task of selecting a small subset of nodes (seed nodes) in a social network that could maximize the spread of influence. Many algorithms have been suggested and developed, e.g. (Chen et al., 2010; Nguyen and Zheng, 2013; Liu et al., 2014). However, most of these papers focus on the efficiency of the algorithm for selecting the influential nodes. The aim of this paper is to explore how a diffusion model can be used to compare the effect on the spread of behaviour of: (1) different ways to build the network from questionnaires, (2) different strategies for selecting influential nodes, and (3) different percentages of the people that are targeted. In order to do this, we created an agent-based model that is supported by real data collected from Dutch primary and secondary school children (Bevelander et al., 2018). The diffusion model is based on the one used by (Beheshti et al., 2017) and (Giabbanelli et al., 2012). We tuned the model parameters on actual data on physical activity collected among Dutch school children.

In this paper, we first discuss the literature on using agent-based models for predicting the effect of contagion in social networks. Then, in Section 3, we describe the data and model that we used and the ways in which we can generate network graphs from the questionnaires. In Section 4, we report on the simulations that we have performed to tune the model and to compare the different strategies and networks. Finally, we discuss the consequences of our findings in Section 5.

2 BACKGROUND

This section starts by presenting an overview of previous research studies that implemented agent-based models to predict intervention effects in social networks. Most of them consider the social or peer influence on the agent's particular health-related behaviour. The basis of our model is an agent-based model (ABM) of network diffusion of obesity behaviour, that looks at both environmental and social influences on physical activity and energy intake in a network. We continue by looking in detail at the work of (Beheshti et al., 2017) and (Giabbanelli et al., 2012), as our model builds on the model introduced in these papers.

There are numerous factors to be considered when selecting an appropriate network intervention, such as the type of network data, environmental context (e.g. geographic distance), network structure (highly centralized network versus decentralized network), prevalence of behaviour or agent's personal characteristics. In the following paragraphs, we review previous research on network-based interventions for reducing obesity and/or increasing physical activity in networks. Most of them compare different targeting methods for testing their effectiveness in diffusion of health behaviour.

The effects of targeting the most connected individuals as opposed to random individuals was investigated by El-Sayed and colleagues (El-Sayed et al., 2013), with the goal of reducing population obesity in a social network. They looked at two different interventions, the first one preventing obesity, and the latter treating obesity, both by targeting 10% of the population. They concluded that targeting the most connected individuals may not be effective in reducing obesity in the network.

The selection of intervention strategy should depend on the purpose (the goal) of the particular intervention, as suggested by (Zhang et al., 2015a). They have studied network interventions for increasing children's physical activity on a real-life social network, composed of 81 children living in low socioeconomic status neighborhoods, out of which 41% was labeled as overweighted or obese. They used three different network intervention strategies and concluded that targeting opinion leaders is better for increasing the physical activity levels in the network as a whole, while targeting intervention in the most sedentary children is best to increase their own physical activity levels.

(Zhang et al., 2015b) have studied the effect of both the social networks dynamics, and peer influence on overweight in adolescents in a real-life social network. They proposed an ABM for simulating the environment, and conducted several experiments on modifying the network's dynamics or changing strength of peer influence, to get a more refined model. They showed that peer influence can significantly affect those who are overweight. Bigger peer influence lowers the prevalence of being overweight, especially in low-obesity networks. On the other hand, in high-obesity networks, inducing stronger peer influence can have an unwanted reversed effect of further increasing the population's weight.

A "bottom-up" agent-based approach was introduced by (Trogdon and Allaire, 2014), modeling the food consumption and friend selection at individual levels, for weight loss interventions. They have shown that the underlying social network can influence the effect of population-level interventions. Looking at the network structure, they have concluded that aggregate effects of population-level interventions are bigger in clustered networks, compared to scale-free networks. In addition, targeting particular agents of the network can be important for social network interventions. Selecting the most popular obese agents for the weight loss intervention, resulted in greater weight loss in the population than selecting a random assortment of obese targets.

Looking at the related work, we can conclude that literature gives contradictory outputs, possibly as a result of the complexity of social networks and the numerous factors that can influence network interventions as explained above. Choosing leaders as targets for intervention is shown as effective in (Zhang et al., 2015b), (Trogdon and Allaire, 2014), as opposed to (El-Sayed et al., 2013). Evaluating new methods of targeting obesity interventions is needed in order to create both cost-effective and time-effective social networks interventions. Following this idea, (Beheshti et al., 2017) have developed an ABM, an adaptation of the model proposed by (Giabbanelli et al., 2012), that simulates the results of five targeting approaches, and integrates three key factors that influence the diffusion of intervention effects in a social network. These factors are: personal characteristics of agents, social network ties (social influence) and environmental influence. The authors propose two network interventions, the first one with the aim of reducing energy intake and the latter for increasing physical activity, both targeting 10% of the population. The individual traits of the agents, like BMI, sex, energy intake, environment, etc. were attributed based on the NLSY79 data set. The same data set was used to validate the model, and compare the simulated weight changes trends of the model, with the historical weight trends of the NLSY79 dataset. Comparing the effectiveness of the proposed targeting strategies, they concluded that targeting based on network information, outperforms more traditional targeting approaches like selecting high-risk agents or vulnerable categories (e.g., obese or low-income agents, respectively). Their most efficient targeting method is based on influence maximization and is explained in details in Section 3. (Beheshti et al., 2017) simulations are based on an artificial network built following a power law degree distribution and homophily properties. In this work, a real social network is used, which is derived from data collected through surveys, as explained in Section 3.

3 METHODS

This section presents the methods used for this research. First we describe the data collected and how the characteristics of the population of children were used for the design of the ABM. Next we explain the model in detail, as well as the process of tuning the parameters to better fit the model to the empirical data. Then, we explain the strategies tested for selecting the targets for the interventions.

3.1 The Data

The data have been collected in the *MyMovez* project – Phase I (Bevelander et al., 2018). This is a large-scale cross-sequential cohort study among school children (N=953; 8-12 and 12-15 years-old) from 21 primary and secondary schools in the Netherlands. The *MyMovez* project – Phase I consists of five data collection waves over 3 years, starting in 2016: February/March 2016 (Wave 1), April/May 2016 (Wave 2), June/July 2016 (Wave 3), February/March 2017 (Wave 4) and February/March 2018 (Wave 5). In this paper, we used data from the 4 first waves, as the data collected for wave 5 is still being processed. The collected data contains information about the children's social network, media consumption, psychological determinants of behaviour, physical environment, eating behaviour, socialization characteristics and physical activities. The children were surveyed in many aspects through the *MyMovez* application on a research smartphone provided by the project in order to collect their impressions about their classmates and their own routine and habits. Participants' weight and height are measured individually by a trained researcher following standard procedures (without shoes but fully clothed) in Wave 2 and 4. The BMI is calculated as $\frac{weight(kg)}{height(m)^2}$. Data on physical activity is collected using a wearable device (bracelet) that tracks the steps of the participants for 5 days in a row (week and weekend days). For more detailed information, see the *MyMovez* project (Bevelander et al., 2018). For the current study, we selected school classes with more than 80% of participation in the experiment, resulting in 26 classes out of 196. 455 participants were removed from the data set for not taking part in the selected classes. The total number of children after the cleaning of the data (removal of participants with missing data) is 451. The data was processed using Python 3 and the NetworkX library combined with Pandas data frames.

3.2 Model Implementation

The network-oriented model used for this work is based on diffusion dynamics of behaviour throughout a social network. That means we assume that behaviour change regarding obesity aspects (physical activities and energy intake) are spread throughout one's relationships. The model is based on the work of (Giabbanelli et al., 2012) and some of the adaptations of (Beheshti et al., 2017) were also taken into account, as explained below. Two main factors are considered as determinants for the agents' behaviour change: the influence via the social network and the environmental influence.

Social network influence is the influence from peers, i.e. those people who are connected to the agents. The *environmental influence* is based on the social-economical conditions of each child. Many factors are important to assess the lifestyle of children and quantify it. In this paper, we focus on the spread of physical activity (PA) as a measure of healthy behaviour. Therefore the interventions applied will increase the PA of the selected participants.

The PA changes for the simulations are calculated in 3 steps, according to the method presented by (Giabbanelli et al., 2012):

1. the influence on the individual by their friends;
2. the combination of the friends influence with the influence from the environment; and
3. a threshold used to decide if an individual's PA will be changed or not.

(Beheshti et al., 2017) and (Giabbanelli et al., 2012) treated the connections as binary variables, where a connection has a weight of 1 in case a relationship exists and 0 otherwise. For this work we measured the strength of the connections as float numbers between 0 and 1, as is going to be explained in Section 3.3. For this reason, we adjusted the formulas for step (1) regarding the weights of the edges as being part of the calculation of the peers' influences. For step (1), equation 1 show the friends influences based on the weight of the connections and the difference between the states of PA.

$$inf_{PA_i}(t) = \frac{\sum_j (PA_j(t-1) - PA_i(t-1)) \times w_{(j,i)}}{\sum_j w_{(j,i)}} \quad (1)$$

A positive inf_{PA_i} for node i means that the overall influence from i's friends is positive towards the PA of agent i. In these circumstances, a good environment will further increase PA, while a bad environment would do the opposite. For the simulation, the environment is beneficial when $0 < env < 1$ and harmful when $1 < env < 2$. The environment calculation is explained in detail in Section 3.4.1. Equations 2 and 3 show how step (2) is calculated, combining the influence of the peers with the influence of the environment.

$$inf_{PA_i(t),env} = env \times inf_{PA_i(t)},\ if\ inf_{PA_i} < 0 \quad (2)$$

$$inf_{PA_i(t),env} = \frac{inf_{PA_i(t)}}{env},\ if\ inf_{PA_i} \geq 0 \quad (3)$$

The last part of the influence spread is to compare the amount of influence with the given threshold. (Beheshti et al., 2017) defined the values for low and high thresholds for EI and PA as 0.002 and 0.2. When testing these values, many problems with convergence and steepness were raised in our simulations. For that reason, we went back to the original model, by (Giabbanelli et al., 2012) and kept only one threshold, applying a simulated annealing algorithm to fine tune it, as explained in Section 3.5. The threshold is used to define the minimum amount of impact that is going to cause the behaviour change to take effect. Equations 4 and 5 show the final value for PA in the next time step t, where $factor = 1 + I_{PA}$, in case $inf_{PA_i(t),env} > 0$, and $factor = 1 - I_{PA}$ otherwise.

$$PA_i(t) = PA_i(t-1),\ if\ |inf_{PA_i(t),env}| < T_{PA} \quad (4)$$

$$PA_i(t) = PA_i(t-1) \times factor,\ if\ |inf_{PA_i(t),env}| \geq T_{PA} \quad (5)$$

3.3 Building the Network

The simulations in (Beheshti et al., 2017) are based on an artificial network, which is built following a power law degree distribution and homophily properties. In this work, a real social network is used, which is derived from data collected through surveys. Twelve questions about the relationships and impressions of other classmates were asked. In our experiment, we compared three different subsets of questions to build the network:

1. **(Friendship).** One question regarding friendship: "who are your friends?";
2. **(General).** 6 general questions, including the question about friendship regarding respect, advice, leadership and who they would like to resemble; and
3. **(All).** The questions from 1 and 2 (above) plus questions regarding physical activities and food intake behaviours, 12 in total. The extra questions are related to peers that influence you to eat healthier, exercise and practice sports.

Table 1: Density of the networks generated by the different subsets of questions.

Class	Friendship	General	All
1	0.45	0.67	0.75
2	0.29	0.65	0.71
3	0.34	0.66	0.80
4	0.69	0.85	0.86
5	0.48	0.65	0.72
6	0.58	0.80	0.84
7	0.30	0.46	0.51
8	0.64	0.88	0.95
9	0.60	0.78	0.87
10	0.70	0.79	0.80
11	0.53	0.83	0.87
12	0.53	0.67	0.76
13	0.63	0.81	0.89
14	0.42	0.68	0.73
15	0.50	0.76	0.84
16	0.57	0.78	0.81
17	0.72	0.89	0.89
18	0.46	0.69	0.76
19	0.64	0.91	0.96
20	0.32	0.62	0.73
21	0.40	0.64	0.77
22	0.39	0.59	0.68
23	0.62	0.89	0.91
24	0.50	0.77	0.85
25	0.43	0.67	0.70
26	0.25	0.58	0.72

The edges of our network are bidirectional, and they account for the amount of influence that the origin of the edge has on the destination. Every question generates a nomination from node i to j. This nomination is interpreted as the influence that node j has on i. The more nominations a node i gives to j, the stronger the influence of node j is over i, and therefore the value for the edge $w_{j,i}$ is higher. Each question receives a different weight of 0 or 1. For each subset of questions, a different configuration of the weights for the questions q_n is given. The total weight for the edge from node j to node i is given by equation 6.

$$w_{j,i} = \frac{\sum_{n=1}^{k}(q_n \; nomination_{i,j})}{\sum_{n=1}^{k} q_n} \tag{6}$$

The use of different subsets of questions is a way of mapping different networks based on levels of influence that can affect a social network. We assume that the question about friendship explains well who the people that children prefer to spend their time together with are, but it can be biased towards other children in the class who they want to be like, but are not as close as they want to be. For instance, popular children in the classroom might influence others, even if they don't spend much time together, or are considered friends. Table 1 shows the density of the networks for each of the classes selected. As can be seen, the networks generated by the single friendship question alone are the least dense, while the networks generated by using all questions present more connections that raise other levels of influence between the children.

Table 2: Hamming Distance between the three graphs generated by the subsets of questions.

Classes	All x General	General x Frienship	All x Friendship
1	0.08	0.22	0.30
2	0.06	0.36	0.41
3	0.14	0.32	0.46
4	0.02	0.15	0.17
5	0.06	0.17	0.24
6	0.04	0.22	0.26
7	0.05	0.15	0.20
8	0.07	0.24	0.31
9	0.09	0.18	0.27
10	0.00	0.10	0.10
11	0.03	0.30	0.33
12	0.09	0.14	0.23
13	0.08	0.18	0.26
14	0.05	0.26	0.30
15	0.07	0.26	0.34
16	0.04	0.21	0.25
17	0.00	0.17	0.17
18	0.07	0.23	0.30
19	0.05	0.27	0.32
20	0.11	0.29	0.40
21	0.14	0.24	0.37
22	0.09	0.20	0.29
23	0.02	0.27	0.29
24	0.08	0.27	0.35
25	0.03	0.24	0.27
26	0.14	0.33	0.47

To verify if there are significant differences between the three generated networks, a Hamming distance was applied to the edges in the graphs. Table 2 shows the Hamming distance for each of the classes and the three possible comparisons between the generated graphs. As is shown, the distance is close to zero to almost all the classes when comparing the graph for all questions (3) and the graph of general questions (2), while the friendship graph (1) presents a bigger distance compared to the other two. That means that the network generated by all questions and the network generated by the general questions present almost the same edges in their graphs, while the graph generated with the friendship question alone has many different edges from the other networks.

3.4 Agents Characteristics

The agent-based model for the behaviour spread explained in Section 3.2 requires some information about the agents. More specifically, it is necessary to know the PA-level of each agent, as well as the influence of the environment on each of them, calculated using socio-economic status (SES). The BMI is also important to know for the interventions that target high risk children. Here we explain how these characteristics of the children were extracted from the empirical data set.

3.4.1 Environment

One of the most influential factors for a healthy lifestyle is a person's living environment. Family wealth can be a good predictor for a child's healthy living environment, with better opportunities for healthy eating and physical activity facilities. The Family Affluence Scale (FAS) is a simple metric created to avoid the difficulties that youth have in reporting family income or other measures for wealth (Boyce et al., 2006). (Boyce et al., 2006) argue that the FAS measures are related to food intake habits and to physical activity, meaning that this questionnaire can also be a good predictor for factors related to health aspects of a youth's lives.

In *MyMovez* project the participants were asked the following questions:

1. Does your family own a car, van or truck? (No [0]; Yes, one[1]; Yes, two or more[2]);
2. Do you have your own bedroom for yourself? (No [0]; Yes [1]);
3. During the past 12 months, how many times did you travel away on holiday with your family? (Not at all [0]; Once [1]; Twice [2]; More than two [3]); and
4. How many computers does your family own? (None [0]; One [1]; Two [2]; More than two [3]).

The model used for the simulation consider that more obesogenic environments have a scale factor between 1 and 2, while healthier environments present a scale from 0 to 1 (Beheshti et al., 2017). An environment factor of 1 means neutral. We normalized the values so all four questions have the same weight in the overall calculation.

3.4.2 BMI

The Body Mass Index (BMI) is the metric used to define children with higher risk. That means that the higher the BMI the higher the risk of a child to become an obese adult. We compared the BMI of the children from the same class and sorted them to define the best targets for high risk interventions.

In (Giabbanelli et al., 2012) the overall change in BMI is used as the outcome measure of the effect of interventions. Their assumption is that the population is made of adults, and their height is fixed. But for children the same assumptions do not stand, as children have a much more dynamic and complex process of growing (Schönbeck et al., 2011), which is followed by their BMI. For that reason, in our experiments we do not use the BMI as the outcome measure, but the PA level instead. The BMI is only used for the selection of the targets to apply the interventions.

3.4.3 PA

The participants in the experiment were asked to wear a Fitibit Flex bracelet for 5 days. The device measured their steps in continuous time with minute to minute precision. The PA used for the simulations was based on the number of steps. In (Giabbanelli et al., 2012) the PA of the simulated agents were drawn as a normal distribution with a mean value of 1.53, the level of sedentary individual according to (Food and of the United Nations, 2004). To normalize the values for PA in our data set we took the mean PA (in steps) and converted it to 1.53, in order to keep the same scale presented in the previous work.

The initial PA for the simulations is calculated as the average of the 3 first waves, and the final PA is given by wave 4. Waves 1, 2 and 3 are closer in time to each other, and also closer to the initial date of the experiment, while wave 4 is 1 year further.

3.5 Parameter Tuning

Two parameter tuning algorithms are used to fine tune the thresholds and the speed factors of the model.

First we applied a grid search in the bi-dimensional space with the threshold (T_{PA}) and the factor (I_{PA}) of change. These variables are explained in Section 3.2 in detail. The grid search guided us to a subspace where the best results were obtained. Then we applied simulated annealing to fine tune our optimization search. The simulated annealing algorithm is an optimization combinatorial method for problem solving. It is inspired by condensed matter physics, where annealing denotes a process in which a solid in a heat bath is heated up to a maximum temperature so all particles are liquid, and then cooled down slowly so the solid particles are reorganized (Van Laarhoven and Aarts, 1987).

We started our simulations with a temperature of 1.0, and the cooling factor was 0.9, until the temperature was less than 0.01. For each temperature we explored 20 neighbors. The parameters found by the simulated annealing are used for the spread of behaviour model.

3.6 Strategies for Selecting Targets for Intervention

The aim of this work is to explore the effect of different strategies to find targets for PA interventions. Several selection strategies were implemented, and the effect of applying an (imaginary) intervention to the selected agents on the overall PA is simulated.

The effect of the imaginary intervention to an individual is modeled as an increase of 17% of their initial PA. This value is taken from (Beheshti et al., 2017) and is chosen based on other research that apply different sorts of strategies to increase the amount of PA of people. The initial states of the remaining nodes is based on the empirical data. Then, the diffusion model is run to verify the improvement on the PA of the whole network after one year.

The strategies to select the targets are:

1. Higher risk children (BMI);
2. More vulnerable children (Environment);
3. Most central children in the network (degree centrality);
4. Optimized selection based on the impact of the children in the whole network;
5. Random selection of the targets.

Strategies (1) and (2) are based on the children's characteristics. Strategy (1) uses the BMI as indicator for the risk (the higher the BMI, the higher the risk). For the BMI we used the data about the children's height and weight in the first wave, as shown in Section 3.4.2. Strategy (2) targets vulnerable children. Vulnerability is measured based on the child's environment. The worse the environment (i.e. lower socio-economic status), the higher the vulnerability. For environment we used the FAS measures, as explained in Section 3.4.1. Strategies (3) and (4) are based on network characteristics. Strategy (3) is based on degree centrality of the nodes given by the Python toolbox NetworkX 2.1. The degree centrality for a node v is the fraction of nodes it is connected to. These values are normalized by dividing them by the maximum degree possible in the graph.

Strategy (4) selects the k nodes that propagate (or influence) the other nodes in the network the most. This is a simple algorithm in which the diffusion model algorithm is run for each of the nodes in the network after applying the intervention to each of these nodes separately. After running for all the nodes, the selected agent is the one that causes the biggest increase of PA in the whole network. Then after the first node is selected, the same is done to the other nodes that were not selected, together with the first node in the subset of targets. This strategy is based on the "influence maximization" algorithms used for viral marketing and advertising (Chen et al., 2010; Morone and Makse, 2015). The difference here is that instead of searching for nodes being "activated" as an objective function, we quantify the impact spread throughout the network as our optimization goal. (Beheshti et al., 2017) used the same strategy, but the goals were related to the decrease of the number of obese people in the network as the goal. For our optimization algorithm we are interested in the overall increase in PA for all the participants.

Lastly, strategy (5) selects the targets by random. This strategy is useful to verify if the other strategies provide better results than just selecting targets without any criteria.

Table 3: Ratio between boys and girls per class and amount of targets for each fraction selection.

Class	Total of kids	Boys	Girls	10%	15%	20%
1	18	9	9	2	3	4
2	20	13	7	2	3	4
3	20	14	6	2	3	4
4	12	6	6	1	2	2
5	19	6	13	2	3	4
6	20	10	10	2	3	4
7	25	12	13	2	4	5
8	28	15	13	3	4	6
9	14	7	7	1	2	3
10	16	8	8	2	2	3
11	20	10	10	2	3	4
12	18	7	11	2	3	4
13	17	12	5	2	3	3
14	14	10	4	1	2	3
15	11	9	2	1	2	2
16	17	7	10	2	3	3
17	11	7	4	1	2	2
18	14	9	5	1	2	3
19	9	6	3	1	1	2
20	21	10	11	2	3	4
21	11	8	3	1	2	2
22	20	8	12	2	3	4
23	18	8	10	2	3	4
24	19	9	10	2	3	4
25	20	7	13	2	3	4
26	19	6	13	2	3	4
Total	451	233	218	45	70	91

As a third variable (in addition to the different methods to build the network and the different selection strategies), we compared the effect of the amount of different percentages of people to which the (imaginary) intervention was applied. We compared three different fractions: 10%, 15% and 20% of the nodes in a class. Table 3 shows the ratios between boys and girls per class, as well as the amount of targets to select in each fraction selection.

4 RESULTS

The experiments aim to explore the effect of different networks, different target selection strategies and different fractions of targets on the overall PA of the social network. We first present the results of the model tuning on the empirical data, and then we present the results of the different simulation scenarios.

4.1 Tuning of Threshold and Change Factor

Section 3.2 explained the model and the two parameters that should be tuned in order to fit the empirical data to the simulations: threshold T_{PA} and the factor of change I_{PA}. T_{PA} is the amount of influence a child needs to receive from their peers combined with the environment to be affected and change their behaviour. The factor of change I_{PA} is the amount of influence that is going to be propagated to the receiving

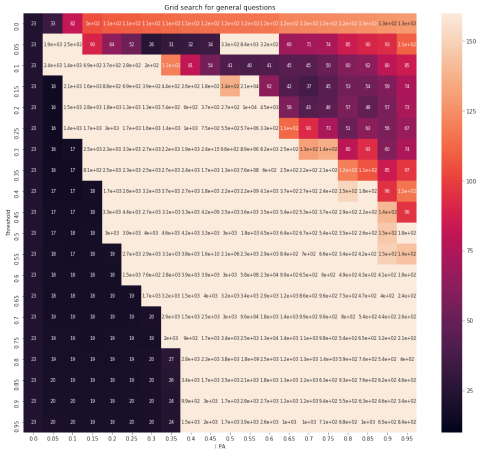

Figure 1: Grid search for the general questions.

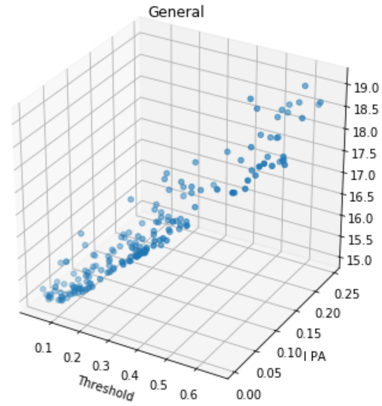

Figure 2: Simulated annealing space of search explored for the general questions.

node within the network. We used a grid search followed by a simulated annealing algorithm to minimize the difference between the empirical data and the simulated data and find the best values for T_{PA} and I_{PA}. The tuning was performed in two steps: first, a grid search algorithm was applied to identify the search space, and then a simulated annealing algorithm was used to find the optimal values.

4.1.1 Grid Search

The grid search was performed with interval steps of 0.05. The values for T_{PA} and I_{PA} were tuned for each of the networks generated with: (1) all questions, (2) general questions and (3) friendship questions. As can be seen in Figure 1, the space where $I_{PA} < 0.35$ showed the smaller errors. The grid search for the other graphs follow almost the same pattern as the one presented in Figure 1.

4.1.2 Simulated Annealing

After the space was defined, the simulated annealing was run. As a result of the grid search, the value of I_{PA} was restricted to a maximum of 0.4. To calculate the error (i.e. the difference between the empirical data and the simulation) we compared the simulation outcomes with the data in waves 1 and 4. Waves 2 and 3 were ignored because they are too close to Wave 1. For the simulated annealing, the initial temperature was 1.0, with an alpha (cooling factor) of 0.9, and a number of neighbors explored was 20. Increasing the number of neighbors or slowing down the speed of the cooling process didn't significantly improve the results obtained. The initial parameters for the simulated annealing were $threshold = 0.2$ and $I_{PA} = 0.05$. Figure 2 shows the space of search on the simulated annealing algorithm for the graph created from the general questions.

Table 4: Best threshold and factor of change for the three networks generated with (1) all questions, (2) general questions and (3) friendship question.

	All (1)	**General (2)**	**Friendship (3)**
Threshold	0.0942	0.0588	0.0426
I_{PA}	0.0055	0.0057	0.0041

The best results for threshold and I_{PA} for each of the three networks are presented in table 4.

4.2 Exploring Different Strategies

After fine tuning the model parameters, the diffusion model was run combined with the strategies to select targets for intervention in the network. For each class, three different percentages of the children were chosen as targets. To select the targets, we compared the use of 5 different strategies: (1) Random selection; (2) High-risk selection; (3) Vulnerability selection; (4) Degree centrality selection; and (5) Optimization selection.

Figure 3 shows the comparisons between the random selection of 10, 15 and 20% of the agents for the three networks generated with all questions, general questions and friendship question.

We used the random selection (1) of the children to receive interventions on their PA as a baseline. We run the random selection for 100 samples and used the mean to evaluate the average impact of this method. Increasing the number of tests didn't cause any difference to the results.

The selection of the high-risk agents (2) is based on the BMI of the children in the classes. The children with a higher BMI have a higher risk of obesity later on. As shown in Figure 3, the "high risk" is the worse intervention causing the smallest influence on increasing PA. Table 5 shows the differences between the initial (and final) mean PA of the whole network with no interventions and the initial (and final) mean

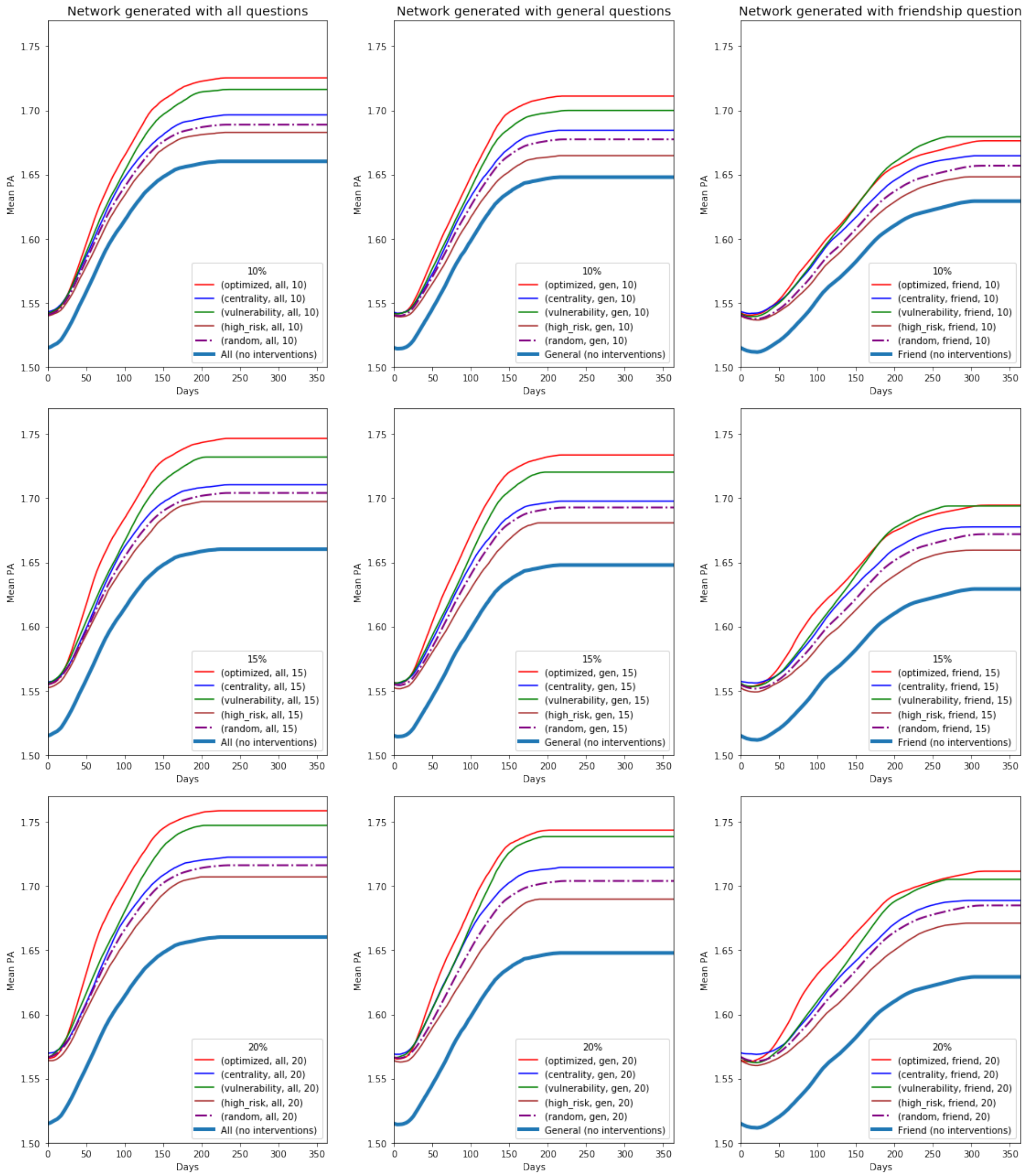

Figure 3: Simulation of average PA for all the strategies for the different percentages of targets in the three rows. The left column shows the results for the network generated with all questions. The center column is for the network generated with the general questions set. The right column shows the results for the network generated using the friendship question alone.

PA for the networks with the interventions applied. The overall difference is how much the difference of the mean PAs increased (or decreased) from the beginning to the end of the simulation (start-to-end difference). The overall difference for the high risk is the only negative one, meaning that after one year of simulation the mean PA of this intervention is closer to the simulations without interventions.

The vulnerability (3) was used to select the children with the least socio-economic situation as targets for the interventions. For most of the scenarios, this strategy was one of the two best interventions, perfor-

Table 5: Differences between initial and end mean PA for the network generated with all questions and 20% of the nodes selected for intervention.

	Diff (day 0)	**Diff (day 364)**	**Overall diff**
High Risk	0.0491	0.0469	-0.0022
Vulnerability	0.0515	0.0871	0.0356
Random	0.0516	0.05599	0.0044
Centrality	0.0548	0.0623	0.0075
Optimized	0.0508	0.0985	0.0476

ming almost as well as the optimized solution especially for the network created with the single friendship question. Strategy (3) shows an overall difference of 0.0356, the second highest (see Table 5).

Strategies based on network degree centrality (4) were also tested and compared with the others. This intervention presents better results than the random selection (1), but are not as good as the strategies (3) and (5). Some positive improvement in the distance to the expected changes in the network without interventions is also perceived (Table 5).

The highest overall PA increase are in the interventions based on the optimization algorithm. This strategy is beaten by strategy (3) in one of the nine scenarios, though it shows the best results for all the other remaining scenarios. Table 6 presents the values for the differences between the strategies applied and the simulation with no interventions. The column Beginning (day 0) is the initial point and the difference between the mean PA for each strategy and no intervention. The same is valid for the column End (day 364), that represents the distance (or difference) on the last day of simulation. The column Difference is calculated as the value for the day 364 minus the day 0 for each of the percentages. The Difference (%) column represents how much increase (or decrease) of PA is caused by increasing the amount of intervention targets from 10 to 15% of the agents, and from 15 to 20% of the agents. The results from table 6 are important in order to make the right decision of selecting the appropriate nodes for real-life intervention. Therefore, increasing the fraction for the "high risk" strategy is not beneficial, as there is a degradation of the difference between mean PA for this strategy and for the simulation without any interventions.

Choosing targets based on centrality shows that selecting 15% of agents is better than selecting 20%. For random and vulnerability selections the improvements caused when increasing the percentage of targets shows that 20% is a good choice, while for the optimized strategy there is a very small percentage increase from 15 to 20% (3.03%), which would require further investigation to decide if selecting 20% of the nodes instead of 15% is a good decision.

5 DISCUSSION

The simulation results allow us to discuss potential strategies that may be used to make informed choices about ways to improve simulation models as well as the setup of social network interventions.

The strategy of targeting children with high risk (i.e., higher BMI) turned out to be the least successful compared to the other strategies in this specific data set and model. It should be noted that our sample had a small variance in BMI. The majority of the BMIs are healthy. Therefore, future studies should test whether a more heterogeneous sample would generate different findings. In addition, the model can be further improved. For example, if BMI would be used as the dependent variable, it would show how the overall prevalence of obesity in social networks is reduced by the intervention. For this, a more complex model is required which accounts for the dynamic change in the BMI categorization in adolescents. The inclusion of the information regarding the energy intake of the children would also enrich the model by providing another independent variable which directly affects the obesity of the group. The difficulties of including this variable are related to the data collection, as it would be required to have a method for assessing the children's food intake habits. Targeting children who reported to live in a less wealthy home environment appeared to be one of the best solutions and very close to—or even better than—the optimized strategy in some scenarios. This insight can also be helpful for the selection of targets in the absence of the network structure, as a personal characteristic provides good improvement of the overall PA of the whole group.

The change in the networks based on different subsets of question did not reflect drastically different results for the scenarios. That is a good indicator that the weights of the connections present some stability when you compare the different graphs, and it does not affect the spread of behavior process. This suggests that previous peer-driven intervention studies which used subsets of 5 nomination questions to identify the peer leaders have chosen a sufficient number of questions (Smit et al., 2016; Campbell et al., 2008). For future research and data collection, these results indicate that a small subset of nomination questions can be asked to the participants, without losing quality on the description of the influential ties and overburdening the participants with questions.

With respect to the fraction of people that are targeted, our results show that it differs per strategy whether it is beneficial to increase the target group. This is a finding with important consequences, as the

Table 6: Differences from the mean PA for each intervention to the simulations without any intervention. The results are referred to the network generated from all the questions combined.

	Beginning (day 0)			End (day 364)			Difference			Difference (%)		
	10%	15%	20%	10%	15%	20%	10%	15%	20%	10%	15%	20%
High risk	0.0250	0.0374	0.0491	0.0225	0.0371	0.0469	-0.0024	-0.0003	-0.0022	0.00	-88.16	664.07
Vulnerability	0.0267	0.0408	0.0515	0.0560	0.0718	0.0871	0.0294	0.0310	0.0356	0.00	5.69	14.71
Random	0.0256	0.0398	0.0516	0.0286	0.0439	0.0560	0.0030	0.0041	0.0044	0.00	37.31	8.45
Centrality	0.0280	0.0418	0.0548	0.0362	0.0503	0.0623	0.0082	0.0085	0.0075	0.00	3.81	-12.28
Optimized	0.0268	0.0401	0.0508	0.0650	0.0863	0.0985	0.0382	0.0462	0.0476	0.00	20.92	3.03

costs of an intervention usually increases linearly with the increase of the size of the target group.

6 CONCLUSION

This paper shows how an agent-based model can be used to explore the effect of different scenarios on the diffusion of physical activity in children. It is the first study in which simulations are based on real social networks and the model has been tuned on actual measurements of physical activity in the network. Study findings indicate that social network interventions aimed at increasing physical activity should take the socio-economic status of children into account. In addition, a small subset of peer nomination question is sufficient to map the children's social network.

In this study, we have simulated the effect of targeting specific children and applying an intervention that increases in 17% their PA. We have compared 5 strategies for the selection, in 3 differently generated networks and with 3 different percentages of targets selected. We compared these 45 different scenarios with the expected results when no intervention is applied. Although this is a comprehensive strategy, the model used in the simulations is a straightforward diffusion model. As a future work, we would like to test other, more realistic, contagion models on the same data set. For example, an option is to use a differential equation model that includes personality traits to account for other factors that play a role in the process of social contagion. Other potential ways to improve the results would be to combine an optimized strategy with the vulnerability trait of the agents to verify if it can show better results than of two strategies alone.

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