MODELING THE JOINT IMPACTS OF SOCIAL NETWORK AND BUILT ENVIRONMENT ON ADOLESCENTS' PHYSICAL ACTIVITY

By

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ABSTRACT

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This research stems from the worldwide public health problem of childhood obesity and insufficient physical activity (PA) among adolescents. Studies have shown that both social networks and the built environment could affect PA, but how do they jointly exert influence? Understanding the scale and mechanism of this joint impact could shed light on developing an effective intervention to promote PA. The goal of this dissertation is to try to disentangle the joint influence of social networks and the built environment on changes in PA through social network analysis and test a novel intervention based on the findings from the social network models.

This study uses two waves of Add Health data from two sample schools. Chapter Two investigates how school-based friendship networks could influence Physical Education (PE) class enrollment. Chapter Three examines the influence of home location, neighborhood characteristics, as well as the demographic characteristics and change in PA of peers who were nominated as friends in the Add Health social survey on high school student's friend selection and PA dynamics between two academic years. Chapter Four presents a spatial agent-based model that was derived from the social network model and integrates a location-based mobile game similar to Pokémon Go as a PA-promoting intervention to test different intervention scenarios.

Through this research, I demonstrate that friends' PE enrollment status has a weak influence on the change of individual's PE enrollment in two consecutive years. Another

observation is that student's total PA change can affect their PA behaviors. Contrarily, the built environment of the neighborhood did not prove to exert significant influence. Due to social influence, students participating in an intervention program may cause a change in PA of non-participants, i.e., we can observe a spillover effect of the intervention program.

This dissertation enriches the field of health geography by integrating social network analysis and spatial thinking to jointly investigate the influence of environmental and social spaces and to facilitate a more comprehensive understanding of the complex system of childhood obesity. It also extends existing models and provides a spatial agent-based model as an intervention exploration tool that can be calibrated for research and education by other scholars.

This dissertation is dedicated to my parents, Mr. Yinquan Liu and Mrs. Huanting Sun.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

INTRODUCTION

Statement of the Problem

This study stems from the prevalence of obesity among adolescents in the US, which is a severe public health issue. The prevalence of obesity in the US has been rising since 1999 with only a temporary pause between 2009 and 2012, and it is predicted that about half of the adolescents aged 12 – 19 will be obese or overweight by 2030 (Wang et al. 2020). Usually, obesity and overweight are due to imbalance of caloric intake and expenditure, thus dieting and promoting physical activity are considered the most important and effective methods for obesity treatment and prevention methods. However, obesity is a very complex problem that involves various driving forces.

In this study, I narrowed down my focus to only investigating adolescents' PA for two reasons. Firstly, simply "eat less" can be counterproductive. A five-year (2004 – 2009) longitudinal study (Neumark-Sztainer 2006) of adolescents shows that most dieters were back to their original weight and about 40% of them even gained more weight than before the study. Dieting and unhealthy weight control behavior may lead to eating disorders or disordered eating. Similar conclusion was also drawn by Field et al. (2003), whose longitudinal study of children and adolescents showed that dieting is not effective in weight control and may lead to weight gain. Secondly, in addition to preventing obesity, PA offers many other health benefits, such as reducing the risk of cardiovascular disease (Andersen 2006) and improving overall wellbeing (Ussher et al. 2007).

Many adolescents in the US do not do enough PA. While adolescents (age 6-17) are suggested to do at least an hour of PA per day, in 2017, only 26.1% of high school students met this requirement (Kann et al. 2018a). Although schools provide elective Physical Education (PE) classes, only 51.7% of high school students take these classes in an average week and less than a third students took PE classes daily (Kann et al. 2018a).

Recognizing inadequacy of adolescent PA, many scholars have investigated the variation among adolescents based on gender, different ethnic background, and socioeconomic status (SES). For example, in 1996, the National Longitudinal Study of Adolescent Health (NLSAH) data showed that female and minority adolescents in grades 7 to 12 (except for Asian females) were most inactive (Gordon-Larsen 1999). In a different study of high school students in San Diego, Sallis et al. (1996) demonstrate that high socioeconomic status can be associated with higher frequency of participating in PE classes and extracurricular PA. While ethnic differences could be observed on some specific activities, there was no significant ethnic or socioeconomic status difference on vigorous exercise outside of school.

Participation in PA is not only related to demographic characteristics and personal preferences but is also affected by adolescents' observation of and interaction with peers, i.e. the social network impacts. For example, in a study using data from NLSAH, Mueller et al. (2010) build a number of different multi-level models to investigate the influence of social comparison in a school context. Their findings show that girls who have similar Body Mass Index (BMI) values are more influential on individual girl's weight control behavior than others who have different BMIs. They also illustrate that the school context matters – with more overweight girls, chances of an individual trying to lose weight decrease and vice versa. In another study, Zhang et al. (2015b) use the Add Health data (Harris et al. 2009) to build an Agent-Based Model (ABM) to study the role of adolescent social network. Their simulation demonstrates that peer influence can impact the prevalence of overweight, but the effect is dependent on the distribution of BMI.

Given the significant impacts of social network on PA of youth, scholars propose interventions that explicitly employ social networks to address obesity prevalence. For instance, a study by Bahr et al. (2009) illustrates that it is important to consider larger network impacts. Targeting individuals at the edges of a network cluster can better control the prevalence of obesity. They also suggest dieting with friends' friends as an effective strategy.

In addition to the school environment, another important space where adolescents spend most of their time is the neighborhood around their homes. Studies have shown that built environment also affects individual PA. Yang et al. (2012) demonstrate that, for a group with low SES and the associated low level of PA, when the positive attitude towards walking is increased, this positive attitude will gradually fade over time if the environment is not walkable. However, if walkability of the neighborhood is improved, there is a potential of increase in walking of youth, which can effectively increase their total PA (Carlson et al. 2015). Apart from walkability, accessibility to amenities and natural space (parks, beaches etc.) is also positively associated with physical activities of young people (Edwards 2014, Floyd 2011). Safety has also been identified as influential on adolescent outdoor activity (Molnar et al. 2004a).

Despite the proliferation of studies on adolescent PA, the distinctive role of the built environment and social networks is unclear as contradictory findings have been reported (Voorhees et al. 2005, Christakis and Fowler 2007a, Cohen-Cole and Fletcher 2008). Also, although scholars provide suggestions on interventions involving environment and/or social network, it remains to be seen whether these interventions are effective when the entangled impacts of space and social networks are considered. More studies are needed to investigate the joint impacts of social network and environment to facilitate designs of effective policies and interventions to promote PA and prevent the prevalence of obesity among adolescents.

Purpose of the Research

The overarching goal of this study to investigate the joint impact of social network and built-environment on high-school students' PA and, with this joint impact, how PA-promoting interventions would affect participants and non-participants. We examine PA from Physical Education (PE) separately as it is different from leisure-time PA. PE is also little influenced by the neighborhood environment.

In this research, we are trying to answer three research questions:

1) Does the social influence in a school context play an important role in affecting adolescents to conform in taking PE classes?

2) How does the neighborhood environment and friendship network jointly influence high school students' weekly PA?

3) How can PA-promoting interventions would affect participants and non-participants given the joint impact of social network and space?

Organization of the Research

The dissertation is organized as follows. In Chapter One, I build a social influence model to investigate how friend networks in a school context could influence students' PE enrollment. In Chapter Two, I use a stochastic actor-based model called Siena to analyze Add Health data to investigate the influence of the home location and neighborhood characteristics on high school student's friend selection and PA. In Chapter Three, I extend an ABM derived from a Siena model by testing the Pokémon Go mobile game as an PA- promotion intervention to investigate the spillover effects on non-players due to social network dynamics and social influence. In terms of format, Chapter One, Two, and Three are presented as standalone manuscripts, independently addressing each of the three research questions mentioned above. In Conclusion, I summarize key findings of this research, point out limitations, and discuss directions for future research.

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CHAPTER 1: MODELING THE SOCIAL INFLUENCE ON HIGH SCHOOL STUDENTS' PHYSICAL EDUCATION ENROLLMENT

Abstract

Physical Education (PE) contributes to adolescents' total physical activity, which is vital for weight control and providing other health benefits. However, the enrollment rate of PE classes is not high in US high schools, especially in higher grades. We hypothesized that observing friends and similar others' PE taking behavior in school could be one of the reasons that influenced one's PE enrollment. This study used two waves of data from the National Longitudinal Study of Adolescent Health and a regression-based social influence model to examine the role of peers' behavior in adolescents' PE enrollment. Specifically, we investigated whether PE enrollment of nominated friends had a significant impact on individual's PE enrollment in the following year in two selected sample high schools. Analyses results showed that students' previous year PE enrollment was significantly ($p<0.001$) associated with their enrollment in the following year. Higher grade was associated with lower enrollment rate. PE enrollment of close friends showed a weak influence on individual's choice, but enrollment status of similar others (i.e. peers of the same gender and the same grade) may exert impacts. This study sheds light on understanding the driving forces of high school students' PE taking, which has implications for educators and decision-makers to seek effective interventions for promoting PE taking and preventing obesity among high school students.

Keywords: Physical Education; friendship; social influence; adolescence

Introduction

Obesity among adolescents is a serious public health problem. In 2015-2016, the prevalence of obesity among adolescents (12-19 years) in the US was 20.6%, and there was a significant increase in obesity rate from 1999-2000 through 2015-2016 (Hales et al. 2017). Obesity is associated with many health risks, such as diabetes, cardiovascular disease, cancer, disability as well as mortality (Prospective Studies Collaboration et al. 2009, Ahima and Lazar 2013). Moreover, adolescent obesity is also a risk factor for adult obesity and its associated diseases (Baker, Olsen and Sørensen 2007, Magarey et al. 2003, Llewellyn et al. 2016, Park et al. 2012, Rundle et al. 2020), thus weight control at an earlier age is of vital importance.

Regular physical activity can not only help with weight control (Tappy, Binnert and Schneiter 2003) but provide other physical health (Janssen and LeBlanc 2010b) and mental health (Eime et al. 2013a) benefits. Physical Education (PE) is recognized as the primary source of physical activity for adolescents (Kann et al. 2018b, USDHHS 2001). Besides, PE and other school sports benefit children in many other aspects such as engendering positive social behaviors, improving psychological health, enhancing academic performance etc. (Bailey et al. 2009). However, high school students' PE enrollment rate was not high in the US, and many adolescents did not do enough physical activity on regular basis (USDHHS 2001, Troiano et al. 2008). According to a national survey in 2017, less than a third of students were physically active for at least an hour per day on all seven days before the survey, and less than half of students were active for at least an hour on five or more days in the week (Kann et al. 2018b). Also, only 51.7% of students went to a PE class on one or more days in an average week (Kann et al. 2018b). In the US, many high school students no longer choose to take elective PE classes after they fulfill the PE credit requirements for graduation thus PE participation rate decreases with age in high schools (Shen 2010, Kann et al. 2018b, Ahima and Lazar 2013).

Given the prevalence of adolescent obesity and the benefit of physical activity (including PE), it is important to better understand factors that shape adolescents' behavior to inform behavioral interventions. Many studies have identified the influences from peers and/or friends on adolescents' physical activity via factors such as social support, peer norms, friendship etc. (Fitzgerald, Fitzgerald and Aherne 2012). As a major form of adolescents' physical activity, in this study we hypothesize that taking PE can also be influenced by the enrollment status of peers in the school.

Background

Friendship may affect PE enrollment because taking a PE class with friends could be a way of maintaining and strengthening friendship for adolescents. School is a bounded environment where adolescents peer culture forms, thus it is important in shaping adolescents' behavior. In a school context, conforming to the norms and behavior of others could help a student gain acceptance of other students and obtain his/her social status (Coleman 1961), which in turn, could affect an individual's social opportunities and personal development (Crosnoe, Frank and Mueller 2008). Friendship, as part of the social opportunities, is of great value to adolescents as it provides socioemotional resources such as comfort and support as well as instrumental resources such as help for coursework (Frank et al. 2008). A recent study showed that the amount of physical activity from PE was significantly associated with perceived acceptance among adolescents (Lee, Shin and Smith 2019).

Once friendship is established, students' PE taking behavior can be directly affected by their friends as they behave like their friends over time, i.e. a result of social influence. For example, close friends may encourage an individual to take the same class together as companions over time. The social influence from peers could also affect one's behavior indirectly through observation. When an individual observes others taking PE classes, who were existing friends or considered as potential friends, the individual may enroll in the class as well.

The homophily theory, a phenomenon of individual inclining to associate with similar others (John, Rodgers and Udry 1984, Joyner and Kao 2000), may also imply the potential relationship between friendship and taking/maintaining participation in PE. For example, it was found that body size had an influence on friend selection among adolescents (Crosnoe et al. 2008). Non-overweight students were more likely to be friends with non-overweight others (Schaefer and Simpkins 2014). Given the role of homophily, students who share similar characteristics such as gender and age have higher chance of establish friendship and the behavior of these "potential" friends may also influence students' behavior. Moreover, it could be possible that physically active students tend to be friends with other active students, while physically inactive students would like to associate with inactive students. This may lead to reinforcing feedback of the social influence on behaviors, in which case, physically active students became more active. In contrast, inactive students got more inactive after they were influenced by friends and conformed to similar behaviors.

Apparently, besides influence from peers and the school context, there are also other factors affecting student's decision. For example, individual-level driving forces, such as interests in sports or pursuing a more appealing physical appearance through physical activities (Crosnoe et al. 2008), could lead to the enrollment of PE. Influence could also come from family and acquaintances outside school via communication or observation.

Research question

Understanding the driving factors of adolescents' participation in PE could lead to designing effective strategies of promoting future enrollment. Among many driving forces, our research question is that whether the social influence in school context plays an important role in affecting adolescents to conform in taking PE classes. Specifically, in this study, we built a social influence model to test the following hypothesis: observing PE enrollment of friends and cohorts of the same gender in the same grade in school could influence individual's PE taking in the following year.

Methods

Data

In this study we used the Add Health data - The National Longitudinal Study of Adolescent to Adult Health data (Harris 2009) - to test our hypothesis. Add Health is a nationwide school-based longitudinal data with the first wave data collected in the 1994-95 school year (Wave 1) and the second wave in the 95-96 school year (Wave 2). More details about Add Health study design and additional information could be found elsewhere (Harris et al. 2009). Given the difficulty of collecting data of a complete longitudinal social network of adolescents in a school context, Add Health was the most suitable dataset that we could access and use to test our hypothesis.

Among all Add Health sample schools, students from 16 selected schools were interviewed at home and they were asked to provide the names of up to five male and five female friends.

These nominated friends were identified and linked with their corresponding participant ID if they enrolled in the Add Health project. These schools are called saturated schools as they have completed social network data. In the study, we chose the two largest saturated schools (called School A and School B throughout this paper) to test our hypotheses.

Data Preparation

To prepare data for our analysis, a few data filtering steps were undertaken. In the raw data, there were 832 students from School A and 1721 students from School B of Wave 1. Since we focus on high school students with both Wave 1 and Wave 2 data, students who were in 12th grade or under 9th grade and those who had missing data in either wave were removed from the dataset. We also excluded students with incomplete PE enrollment information in Wave 1 and Wave 2. To investigate peer influence, a social network was built based on nominations in the survey at Wave 2 because friendship nomination at Wave 2 was considered to reflect experience between Wave 1 and Wave 2. We then excluded nominations that were not in the two selected schools of this study. In our final dataset, there were 447 observations from School A and 626 observation from School B.

PE enrollment information during a school year was extracted from the "WAVE III Education Data Academic Courses Component Physical Education" data file. This dataset contains information about whether, when and what type of PE classes participants took between grades 9 and 12. There were four PE course categories: "General PE", "Competitive Sports", "Marching Band", and "Dance/Pep/Squad/Cheerleading/Drill Team", with value 1 indicating enrollment and 0 otherwise. After plotting the data, then maximum enrollment was two PE categories based on data of School A and B. Consequently, we assigned "PE enrollment" a value of 1 if a student enrolled in one or more types of PE classes within a school year, and a value of

0 if he/she was not enrolled any PE class. For each participant, we calculated the average "PE enrollment" of students of the same gender and the same grade in Wave 1 and 2, in order to describe the exposure to PE enrollment of students not nominated as friends, which we called the "similar others" within schools.

Data preparation and data analyses were done in R (R Core Team 2018).

Social Influence Model

To test our hypothesis mentioned in the research question section, we proposed a logit social influence model defined in Equation (1). Based on the social influence theory, we hypothesized that students' PE enrollment behavior was influenced by their exposure to the behavior of their close friends as well as similar others. Specifically, we hypothesized that a student's PE enrollment at Wave 2 was influenced by the Wave 1 PE enrollment of this student's nominated friends (nominated at Wave 2) in the school, as well as the PE enrollment of similar others who were of the same gender in the same grade between Waves 1 and 2, while controlling for one's PE enrollment and grade at Wave 1.

$$Y_{it} = \gamma y_{i\,t-1} + \rho_0 \frac{\sum_{j=1}^{n} x_{ij,t-1\to t} y_{j\,t-1}}{n} + \rho_1 Grade_{i\,t-1} + \rho_2 Avg_{i\,t-1} + \varepsilon_i \qquad (1)$$

Y_{it}: a binary variable of student i's PE enrollment at time t (Wave 2)

$y_{i\,t-1}$: PE enrollment of i at time t-1 (Wave 1)

j: nominated friend j of student i at Wave 2

$\rho_0 \frac{\sum_{j=1}^{n} x_{ij,t-1\to t} y_{j\,t-1}}{n}$: A mean exposure term that describes observation of PE enrollment from all nominated friends of i at Wave 1.

$\rho_1 Grade_{i\,t-1}$: Student i's grade at Wave 1

$\rho_2 Avg_{i\,t-1}$: The average PE enrollment of similar others, i.e., students of the same gender AND in the same grade as i but NOT nominated as close friends at Wave 1

$\gamma, \rho_0, \rho_1, \rho_2$: Coefficients

ε_i: Error term

To account for the multicollinearity due to the correlation between the two major variables of interest, i.e., the mean exposure to friends' PE enrollment status and the exposure to the average PE enrollment of similar others, we compared three versions of the influence model to investigate the potential effects of multicollinearity. Version one is the social influence model with only the mean exposure to friends' PE enrollment as shown in Equation (2) below. Version two is the social influence model with only the exposure to average PE enrollment of similar others shown in Equation (3). Lastly, version three is the proposed full social influence model shown in Equation (1).

$$Y_{it} = \gamma y_{i\,t-1} + \rho_0 \frac{\sum_{j=1}^{n} x_{ij,t-1\to t} y_{j\,t-1}}{n} + \rho_1 Grade_{i\,t-1} + \varepsilon_i \qquad (2)$$

$$Y_{it} = \gamma y_{i\,t-1} + \rho_1 Grade_{i\,t-1} + \rho_2 Avg_{i\,t-1} + \varepsilon_i \qquad (3)$$

Results

Table 1 shows the descriptive statistics of sample students in School A and B. There was approximately the same amount of male and female students in both schools. School A was dominated by White students while school B had a more diverse student composition. After data filtering, more samples from school A were in grade 9 (39%) and fewer in grade 11 (27%), but in School B the majority of samples were from grade 10 and 11.

Table 1: Descriptive analysis of samples

		School A		School B	
Sample size		447	%	626	%
Gender	Male	231	51.7	315	50.3
	Female	216	48.3	311	49.7
Race (more than 1 categories allowed)	White	442	98.8	147	23.5
	Black or African American	0	-	140	22.4
	Asian or Pacific Islander	6	1.3	222	35.5
	American Indian or Native American	19	4.3	25	4.0
	Other	2	0.4	142	22.7
Birth year	1976	5	1.1	8	1.3
	1977	61	13.6	94	15.0
	1978	139	31.1	315	50.3
	1979	153	34.2	208	33.2
	1980	89	19.9	1	0.2

According to the PE records shown in Table 2, in general both schools showed that PE enrollment decreased as students entered higher grades, especially among male students as they transitioned from grade 10 to 11. Compared to school A, grade 11 students from school B had a relatively higher average PE.

After applying the proposed influence model on the network datasets of the two schools separately, we received slightly different results for the two tests.

Table 2: Average total PE at Wave 1 and Wave 2

School	Grade at Wave 1	Average PE enrollment Wave 1		Average PE enrollment Wave 2	
		Male	Female	Male	Female
A	9	0.951	0.977	0.939	0.943
	10	0.976	0.945	0.083	0.164
	11	0.138	0.218	0.046	0.145
B	9	1.000	1.000	1.000	1.000
	10	0.973	0.974	0.453	0.409
	11	0.598	0.487	0.451	0.327

Table 3 shows the results for both schools. Based on the results of full models, we can infer that in School A students' PE enrollment at Wave 2 was significantly ($p<0.001$) associated with their PE enrollment at Wave 1 (prior), their grade, and the behavior of similar others. The association with the prior year enrollment was positive, which indicated that students who take PE activities in Wave 1 are more likely to enroll in PE in Wave 2. PE enrollment at Wave 2 showed a negative association with an individual's grade at Wave 1, indicating that higher grades have a lower total enrollment. PE taking status was also negatively associated with that of peers of the same gender and grade, which suggested that an increase in PE taking among similar others was associated with less likelihood that one took PE in the following year, or vice versa.

At School B, total PE at Wave 2 was strongly associated with prior year enrollment, which is similar to School A. However, the results of School B did not show significant association with the social influence from close friends or similar others, nor was it associated with the grade.

For both schools, the coefficients and standard errors of both exposure terms did not vary a lot in sub-models compared to the full model, indicating that there is no multicollinearity issue caused by these two independent variables.

Table 3: Social influence model results

School A

	Full model - Equation (1)			Sub-model - Equation (2)			Sub-model - Equation (3)		
Independent variable	Coefficient	Standard error	P value	Coefficient	Standard error	P value	Coefficient	Standard error	P value
intercept	-127.359	15.369	<0.001***	-113.965	13.488	<0.001***	-128.997	15.213	<0.001***
prior	2.584	0.588	<0.001***	1.894	0.488	<0.001***	2.661	0.579	<0.001***
mean exposure to friends	0.231	0.352	0.511	0.229	0.347	0.508	NA	NA	NA
exposure to similar others	-1.457	0.676	0.031*	NA	NA	NA	-1.460	0.677	0.031*
birth year	1.599	0.198	<0.001***	1.421	0.172	<0.001***	1.622	0.195	<0.001***

School B

	Full model - Equation (1)			Sub-model - Equation (2)			Sub-model - Equation (3)		
Independent variable	Coefficient	Standard error	P value	Coefficient	Standard error	P value	Coefficient	Standard error	P value
intercept	6.532	11.844	0.581	16.488	9.715	0.09	6.436	11.823	0.586
prior	1.835	0.261	<0.001***	1.701	0.248	<0.001***	1.836	0.261	<0.001***
mean exposure to friends	0.024	0.184	0.894	0.014	0.183	0.939	NA	NA	NA
exposure to similar others	-0.892	0.534	0.095	NA	NA	NA	-0.890	0.534	0.095
birth year	-0.098	0.155	0.525	-0.233	0.125	0.063	-0.097	0.154	0.53

Significance codes: P< 0.001 '***', P<0.05 ‘*’

Two observations with null exposure to similar others in School B were removed from analysis

Discussion

The results from the social influence model, as applied to the two schools in our study, indicated the PE enrollment among the high school students in the second year was positively associated with the previous year's PE enrollment. Thus, a student who had enrolled in PE classes at a given school was more likely to keep taking PE classes at higher grades. Both schools' data showed a dramatic decrease in PE enrollment at higher grades, which is consistent with the observation that after students fulfilled the minimum PE credits requirement, they would prefer to use that time for other classes and prepare for college (Shen 2010, Kann et al. 2018b, Ahima and Lazar 2013).

Unexpectedly, we found a negative association between one's PE enrollment at Wave 2 and the average PE of students of the same gender and grade at Wave 1 in School A. The relationship was positive but not significant in School B. The average PE taking of students of similar others was introduced to the model as a variable representing the exposure to potential friends who were not nominated as friends in the survey. A possible reason for this negative relationship in School A might be that while there was an overall trend that fewer high school students took PE classes when they entered higher grades, many students who were actively engaged in the PE classes had a developed habit and were more likely to enroll in a PE course in the following years. Another explanation might be that there were limited PE resources in school A thus the more PE one's peers were taking the fewer PE courses a student could enroll in that year.

In both schools, one's PE enrollment status at Wave 2 has a positive relationship with this students' nominated friends' PE enrollment status at Wave 1 but the influence from nominated friends was not significant. This may indicate that direct observation of PE enrollment behavior of nominated students did not serve as a major driving force that motivated students to keep enrolling in PE courses in these two selected sample schools. However, the influence from friends on PE taking behavior may be effective in other forms, such as social supports via verbal encouragement. A study showed that social support from friends could predict intention for vigorous physical activity as well as partly buffer lack of self-efficacy (Hamilton, Warner and Schwarzer 2017). One's nominated friends may not enroll in PE classes themselves. However, they could still exert influence through encouragement to promote one's physical activity (such as taking PE classes in the following year).

PE enrollment from combined data

Given the inconsistency of results in the two sample schools and their difference in student compositions in terms of grade and race, we combined data for the two schools. We then tested the interaction between schools and exposures (to nominated friends and to other students of the same gender and grade).

Table 4 shows the results of the influence model with interaction terms using data from both schools. The exposure effect from nominated friends was not significant, and their coefficients showed small effects. The moderator "school" was significantly associated with PE enrollment at Wave 2, indicating the PE enrollment status varied in different school contexts. The exposure to similar others was significantly and negatively associated with PE enrollment status in Wave 2. Such association was affected by school contexts which was indicated by a significant interaction with "school". This is consistent with the results shown in Table 3, where the exposure to similar others was significant for School A but not for School B. Based on this extended model with interaction terms, we can conclude that the influence from nominated friends did not act as a strong driving force in terms of individual's PE enrollment, and PE enrollment status varied in different school contests.

Table 4: Social influence model with interactions results

Combining School A and School B			
Independent variable	Coefficient	Standard error	P value
intercept	-55.947	8.791	<0.001***
prior	1.906	0.239	<0.001***
mean exposure to friends	-0.038	0.187	0.838
exposure to similar others	-2.559	0.500	<0.001***
birth year	0.692	0.112	<0.001***
school	-2.543	0.263	0.003**
mean exposure to friends * school	0.559	0.362	0.122
exposure to similar others * school	2.781	0.614	<0.001***

Significance codes: P< 0.001 '***', P<0.005 ‘**’

Exposure terms were centered on their means before being entered in the above model. Two observations with null exposure to similar others in School B were removed from analysis.

Conclusions from results

Given the findings of this study, to boost high school students’ physical activity through PE classes, it is important to seek effective strategies to engage more students in exercise in higher grades. The social influence effect from nominated friends was not strong based on our data but there might be other aspects where social influence might work. For example, friends could exert influence through encouragement instead of the actual behavior of taking PE courses. Furthermore, friends outside school were not included in the analysis but their behaviors and attitudes could also have impacts. We also did not include family influences, such as education and the physical activity level of parents and siblings. Students who were not enrolled in PE might still be physically active via other paths. However, to keep simplicity and to focus on our hypothesis, and also due to the limited information provided in the dataset, we did not investigate other social influences. Our study was also limited by the age of the data, as the way high school students interact has greatly changed compared to the 1990s.

For instance, studies have shown that online social networks, such as Facebook™ groups, could provide social support and serve as promising intervention tools to promote physical activity (Cavallo et al. 2012, Todorovic et al. 2019). As shown in this study, exposure to other students within the school context might also influence students' behavior. Similarly, observation of posts from social networking systems could also lead to attitude and behavior change. For example, there was an association between wanting to look like model figures in the media and an increased level of physical activity among adolescents (Taveras et al. 2004). Given the potential impact of online social networks on adolescents nowadays, collecting comprehensive longitudinal social network data of adolescents in the near future would be of great value to further investigate the influence of peers and understand how this influence has changed over the years.

Conclusion

This study used Add Health longitudinal data to test the effects of social influence on students' PE enrollment in two sample high schools. Analyses results showed that a student's previous year PE enrollment had a significant influence on his/her enrollment in the following year. Higher grade was associated with a low enrollment rate, and such a relationship was significant in both sample schools. PE enrollment of nominated friends had a weak influence on individual's choice. However, the overall enrollment status of students of the same gender and grade might exert some effects on students' decision.

Our findings contribute to a better understanding of the driving forces of PE enrollment in high schools with a focus on social influence in school contexts. Unlike some other behaviors, one's PE enrollment did not seem to be greatly influenced by friends. On the other hand, the requirement of PE credits and previous experience might be the key driving forces in future enrollment. Requiring PE credits at high grades and engaging students in PE classes at lower grades may increase the overall enrollment and promote students' health during high school.

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CHAPTER 2: HIGH SCHOOL STUDENTS' FRIENDSHIP NETWORK, PHYSICAL ACTIVITY AND RESIDENTIAL LOCATIONS

Abstract

Evidence shows that adolescents do not do enough physical activity (PA). We used a stochastic actor-based model to analyze Add Health data to investigate the influence of the home location and neighborhood characteristics on high school student's friend selection and PA. Result indicates that students' PA level emulated peers' PA levels and students who lived closer together, increased the likelihood of forming friendships. This study informs policy makers of the joint impacts of social networks and home location on adolescents' friend selection and level of PA.

Keywords: Adolescents, Stochastic actor-based model, physical activity, social network, built environment

Introduction

Obesity, physical activity, environment, and social network

Obesity has been one of the leading public health problems in the U.S. in the past few decades (Flegal et al. 2016). Obesity among adolescents is also a serious health issue. Between 2015 and 2016, nearly one-fifth of all U.S. adolescents were obese (prevalence rate = 18.5%) (Hales et al. 2017). As obesity and overweight are due to an imbalance of caloric intake and expenditure, the lack of exercise is a major direct cause of unhealthy weight.

While exercising provides many physical and mental health benefits (Janssen and LeBlanc 2010a, Eime et al. 2013b), U.S. adolescents do not do enough physical activity (PA) regularly (Kann et al. 2018b, Troiano et al. 2008). A national sample of 24800 U.S. high school students between 2013 and 2015 showed that about 66% of boys and 75% of girls did not get daily PA. On the contrary, approximately one-fifth of students spent over 5 hours on screen devices (e.g. computers, smartphones etc.) per day (Kenney and Gortmaker 2017), an activity counter-productive to exercise.

Among many factors that are associated with obesity and PA, built environment is an important one. Since the late 2000's, scholars started to investigate the association between public health outcomes, in particular obesity, and the low-density, automobile-dependent urban form in the U.S., and an increasing number of studies started to investigate the influence of built environment on PA (Ledoux et al. 2016). Studies revealed that a pedestrian and bicycle-friendly built environment, which is characterized by high population and housing density, mixed land uses, and highly connected road network, promotes people's PA (Handy et al. 2002). Availability and accessibility to PA facilities (Powell et al. 2006, Mason, Pearce and Cummins 2018), as well as neighborhood safety (Harrison, Gemmell and Heller 2007, Molnar et al. 2004b), also exert a positive influence on PA. Meanwhile, travel behavior, accessibility, safety, and PA are also shaped by socio-demographic variables including class, ethnic, and racial composition (Vojnovic et al. 2019).

In the last decades or so, an increasing number of studies started to investigate the relationship between obesity and social networks. In the longitudinal Framingham Heart Study, Christakis and Fowler (2007b) conducted a social network analysis, and their findings suggested that obesity is "contagious" via social influence. Such a spreading mechanism among social networks was also found to be associated with other health-related factors, such as smoking (Christakis and Fowler 2008), happiness (Fowler and Christakis 2008), and loneliness (Cacioppo, Fowler and Christakis 2009). Christakis and Fowler's study on obesity attracted wide attention and aroused public debates (Zhang et al. 2018). Controversial arguments suggested that the clustering of obesity observed in a social network could result from the shared environment (Cohen-Cole and Fletcher 2008, Lyons 2011), or the friendship selection process, i.e., the homophily effect where people tend to associate with those who share similar characteristics (Lyons 2011). These debates inspired researchers to further investigate the complex relationship between social networks and health. In terms of social networks and obesity, studies were conducted to disentangle social influence from social selection as well as other confounding processes (Zhang et al. 2018).

SAB models of obesity and PA: a brief review

Among studies exploring the underlying causal relationship between obesity (and obesity-related behaviors) and social networks, a commonly used method is called a Stochastic Actor Based (SAB) model or a 'stochastic actor-oriented' model. SAB models use longitudinal data to simulate the evolution of a network as a stochastic process driven by actors who decide on their outgoing ties (e.g., friendship). Network dynamics are affected by its structure and exogenous factors, i.e., the characteristics of actors or dyads (ties). SAB models have the advantage to simultaneously analyze the coevolution of the network and the behavior(s) of its actors. This dynamic system is the outcome of a Markov process, where a number of unobserved small changes are assumed to occur between each of the successive observed states of a network and behavior. A SAB model has two discrete parts: a friendships' dynamic model and a behavior dynamic model. More details about the SAB model can be found in Snijders (2001) and Snijders et al. (2010).

Most studies on social networks and obesity using SAB models are about children and adolescents. To demonstrate how the SAB model was applied in studies about the relationship between social network and obesity, we reviewed research articles included in two recently published systematic review papers (Zhang et al. 2018, Prochnow et al. 2020). De La Haye et al. (2011a) used longitudinal data of four waves from a high school in Australia. They found that similarities in the weights of friends were mainly driven by friend selection (both homophily and weight-based stigma) instead of influence. Meng's (2016) study investigated the relationship between social network and body weigh in a virtual space through analyzing social network data collected from a social networking site for weight management. The results indicated that homophily predicted preferential selection in an online social network and individual's weight tended to be similar to 'health buddies' over time as an outcome of social influence (Meng 2016).

Two studies (Shoham et al. 2012, Simpkins et al. 2013) both using the National Longitudinal Study of Adolescent Health (Add Health) data and the SAB models, found evidence of the homophily effect based on PA and social influence from peers. The effect was in the form of assimilation, i.e., over time, individual's PA level was becoming closer to that of their friends. Consistent results about PA's influence on friend selection and assimilation of PA among friends were also found in an Australian study (De La Haye et al. 2011b). Different from the above studies, Gesell, Tesdahl, and Ruchman (2012) found that PA had no impact on forming or dissolving friendships in an after-school friendship network. They found that students would adjust their PA level to emulate the activity levels of their peers. Although the same sample of schools from Add Health data were used, the study by Long, Barrett, and Lockhart (2017) only found significant assimilation to friends' PA but no significant homophily effect of PA on friend selection.

Purpose of study

The review of existing studies points to a gap in the literature. Previous longitudinal studies using SAB models on PA among adolescents yielded mixed results, even those that used the same datasets. More importantly, existing studies using social network analysis did not emphasize the role of geographic space when investigating adolescent's friendship and PA. The environmental influence was not considered and tested. Since little research has been conducted to investigate the combined influence of the environment and social network on adolescent PA using longitudinal data, this study aims to integrate the environmental drivers within the social network models to investigate their joint impact. Specifically, we aimed to test the following hypotheses: **(1) home location has a significant influence on high school student's friendships, and (2) neighborhood environment has a significant influence on high school student's PA while controlling for friendship networks.**

We used the SAB model to extend the existing studies by including the environmental variables and the home distance to schools. The SAB model was implemented using the

Simulation Investigation for Empirical Network Analysis package in R (R-SIENA version 4) (Ripley and Snijders 2009).

Method

Study population

This study used the Add Health Data a nationwide school-based longitudinal dataset with the first wave data collected in the 1994-95 school year (Wave 1) and the second wave in the 95-96 school year (Wave 2). More details about Add Health sampling methodology and study design can be found elsewhere (Harris et al. 2009). Among all Add Health sample schools, students from 16 selected schools were interviewed and they were asked to nominate up to five male and five female friends they considered to be close, i.e., a maximum of 10 friends in total. In this research, Wave 1 and Wave 2 data of students from two largest schools were used for analysis. These two selected schools are good for comparative analysis because one is in a mid-sized town dominated by non-Hispanic white students while the other one is in an urban setting with more diverse population (Shoham et al. 2012). The Institutional Review Board of Michigan State University approved the use of Add Health data for this study (IRB# x16-380e).

There were 2553 samples in total from Wave 1 in-home survey (school A: N = 832; school B: N = 1721). We excluded students in grade 12 because they would not be at school in Wave 2 due to graduation; thus, 756 students were removed (192 from school A and 564 from school B). After merging with Wave 2 data, 222 students were removed (78 from school A and 144 from school B) due to no observations at the second wave. Lastly, we examined the friendship data and excluded students who did not nominated any other student as their friends or were nominated by others in both waves. This is because this study simultaneously focused both on the dynamics of the social network and the influence of peers. In the final sample set used in this study, there were 557 students from school A and 948 students from school B.

Measurements

a) Friendship network

During the in-home interviews in both waves, students were asked to nominate up to five male and five female closest friends. Among all the nominees, we excluded those who were not students in the two selected sample schools. As mentioned earlier, students who did not nominate any friends in their school and were not nominated by any other participants were dropped from this study.

b) PA

Three ordinal variables measuring students' PA were selected to create an index reflecting their PA on a weekly basis. There are a number of times that students:1) went "roller-blading, roller skating, skate-boarding or bicycling"; 2) played "an active sport, such as baseball, softball, basketball, soccer, swimming, or football"; and 3) exercised, "such as jogging, walking, karate, jumping rope, gymnastics or dancing". Each variable ranged from 0 to 3, where 0 indicates no such PA at all, 1 indicates 1 or 2 times, 2 indicates 3 or 4 times, and 3 indicates 5 or more times in a week. We calculated the sum of all three variables as the Total PA, of which value ranged from 0 – 9. "Refused" and "don't know" were treated as missing values during the calculation.

c) Spatial data

The coordinates of home addresses were collected during Add Health survey and GPS reads were converted to relative coordinates based on the central point of a community to ensure anonymity among the students. Samples of the same school are in the same community in this research. We calculated the Euclidian distance between home locations of each pair of students from School A and School B respectively to control for propinquity among students affected by where they lived.

The Obesity and Neighborhood Environment (ONE) database linked Add Health respondents' residential locations with their community-level data spatially and temporally, which enabled us to investigate the influence of neighborhood environment on students' behavior. Among all the available measures, we extracted five variables that we hypothesized to influence students' PA:

(1) distance from home to school;

(2) counts of all types of PA resources within 3, 5 and 8 km road network radius;

(3) road connectivity index within 3, 5, and 8km of Wave I respondent locations, i.e. the Gamma index, which is the ratio of actual links over the maximum number of all possible links between nodes in the road network;

(4) the Simpson's diversity index (ranging between 0 and 1) of land cover within 3, 5 and 8km radiuses, with a higher value indicating greater land cover diversity;

(5) the population of year 1990 within 3, 5, and 8km buffers around each residential location.

Distance to school could affect available time for extracurricular sports. Amount of PA facilities might influence the availability and accessibility to PA resources. Road connectivity, land-use diversity, and population density were related to neighborhood walkability (Handy et al. 2002). Distribution of sample students' home location and neighborhood environment variables included in this study were mapped and can be found in Appendix A.

d) Other related measurements

(1) *Sex*. Information on student's sex was recorded as male = 1 and female = 2.

(2) *Race and ethnicity*. Race information was stored in five different binary variables (White, Black or African American, American Indian or Native American, Asian or Pacific Islander, and Other). We integrated all five variables and recoded values (1 = White, 2 = Black or African American, 3 = American Indian or Native American, 4 = Asian or Pacific Islander, 5 = Other, 6 = missing value). Ethnicity was a binary variable with value 1 indicating Hispanic or Latino origin and 0 as not.

(3) *Body Mass Index (BMI)*. Students reported their height and weight in both waves. The BMI value was calculated using the weight (kg) and height (m) reported in the survey (BMI = weight/height^2). BMI at Wave 1 was used as a constant covariate in our models.

(4) Motivation. During the in-home survey, participants were asked whether, in the past seven days, they exercised to 1) lose weight/keep from gaining weight, or 2) gain weight/build muscle. To control one's motivation, we created two variables called "exercise to lose weight" and "exercise to gain muscle". The value of motivation variables was set to 1 if the answer to the corresponding motive was true and to 0 otherwise.

(5) Course overlapping. Add Health data provide information about the extent of courses common to each pair of students. A weighted course-overlap measure was used in this study to control for the influence of taking the same course on friend selection. Weights were determined based on the number of Carnegie units taken by students and the number of classes per course.

Analytic plan

In this study, we adopted the SAB models to understand the relationship among high school student's friendship in the school, PA, and their residential location. In a SAB model, the evolution of a network is treated as a stochastic process driven by actors (i.e. students) who decide on their outgoing ties (i.e. friend nominations). SAB model assumes many unobserved micro-steps between two consecutive observations (in our case, a certain number of micro-steps between Wave 1 and Wave 2). A rate parameter determines the number of micro-steps. In each micro-step, one change occurred in the network (forming a new tie, dropping an existing tie, or no change to current network). Which tie and how it will change is captured by a linear additive objective function, consisting of many effects, whose value can be translated into an expected probability. To test our first hypothesis about the influence of home location on friend selection, we included Euclidean distance between home locations of each pair of students from the same school as a covariate in the SAB selection. A significant coefficient would reject our null hypothesis that residence distance between two adolescents has no impact on forming or maintaining friendship between them. Other effects in the selection model include (1) structured effects that represent the endogenous network processes; (2) homophily effects that captures the assimilation process during friend selection; and (3) behavior effects, which helped to investigate the influence of PA on the dynamics of a social network. Descriptions of effects included in the model is shown in Table 5.

Coevolution of behavior is also integrated into the SAB model, which enabled us to analyze peers' influence on participants' PA. Similar to the selection model, the SAB behavior model also has a rate parameter and a linear additive objective function describing how different effects would influence change in actor's PA (increasing one unit, decreasing one unit, or no change per micro-step). To test our second hypothesis about the influence of the built environment on PA, we included five environmental effects (see Table 5) at three different geographic scales (3km, 5km, and 8km) with each scale as a separate SAB behavior model.

To test our hypotheses, we built SAB models using the RSiena package in R. We used a forward selection process (Snijders et al. 2010) and only kept the significant effects in the selection model before we modeled the coevolution of selection and behavioral change. Since there were two schools and three geographic scales of environmental effects, a total of six models were tested. Detailed model specifications for both SAB selection and behavior model can be found in Appendix B.

Table 5: Description of effects in SAB friend selection and SAB behavior submodels

Effects on friendship dynamics	Description
structural effects	
out-degree effect	the tendency to send out a tie a random alter
reciprocity effect	The inclination of a nominee to form a friendship tie back to the nominator
transitive triplets effect	the tendency of network closure ("becoming a friend with friend's friend")
in-degree relate popularity effect	the tendency of an individual to attract more incoming ties
homophily effects	
same sex	preference to nominate friends of the same sex
same grade	preference to nominate friends of the same grade
same race	preference to nominate friends of same the race
same ethnicity	preference to nominate friends of the same ethnicity
BMI similarity	preference to nominate friends based on similar BMI
Course overlapping	preference to nominate friends taking the same courses
behavior effects	
PA ego	effect of actor's PA on friendship nominations
PA alter	effect of alter's PA on friendship nominations
PA similarity	preference to nominate friends based on similar PA level
spatial effect	
distance to friends	effect of home distance on friend nominations
Effects on PA dynamics	**Description**
Shape effects	
linear shape, quadratic shape	two effects of PA upon itself
Friend effect	
PA similarity	effect of friends' PA on actor's PA based on similarity
Motivation effects	
lose weight	effect of actor's intention to lose weight via exercising
gain muscle	effect of actor's intention to gain muscle via exercising
Environment effects	
distance to school	effect of actor's home distance to school
PA resources (3km, 5km, 8km)	effect of counts of PA resources within 3km/5km/8km neighborhood
road connectivity (3km, 5km, 8km)	effect of road connectivity within 3km/5km/8km neighborhood
land use mix (3km, 5km, 8km)	effect of land use mix within 3km/5km/8km neighborhood
population density (3km, 5km, 8km)	effect of population density within 3km/5km/8km neighborhood

SAB – stochastic actor-based; BMI – body mass index; PA – physical activity

Results

Descriptive statistics

Table 6 shows the descriptive statistics of the characteristics of students from two schools. There was about an equal number of male and female students in both schools. School A was dominated by white students, while School B was more diverse in terms of race and ethnicity. In both sample schools, we observed a slight increase in average BMI and a small decrease in average total PA from Wave 1 to Wave 2. Specifically, among 557 students in School A, 254 students (45.6%) had a decrease in PA, 186 students (33.4%) had an increase in PA, and 117 students (21.0%) had no change in their reported total PA from Wave 1 to Wave 2. Among 948 students in School B, 458 students (48.3%) had a decrease in PA, 294 students (31.0%) had an increase in PA and 196 students (20.7%) reported no change in total PA.

In both schools, more than half of the students indicated motivation to increase PA at Wave 1. Also, on average, students from School A had lower BMI and more PA than School B. In terms of environmental variables, there were no dramatic differences among index type variables (road connectivity and land cover diversity) at different scales while count-type variables (total PA resources and population) increased along with the scale.

Table 6: Descriptive statistics of two sample schools (percent in parentheses)

		School A (N = 557)		School B (N = 948)	
gender (%)	male	297 (53.3)		478 (50.4)	
ethnicity (%)	Hispanic	5 (0.9)		385 (40.6)	
race (%)	White	525 (94.3)		178 (18.8)	
	Black	0 (0)		200 (21.1)	
	American Indian	23 (4.1)		34 (3.6)	
	Asian	6 (1)		312 (32.9)	
	other	3 (0.5)		224 (23.6)	
motivation (%)	lose/maintain weight	473 (56.2)		259 (27.3)	
	gain muscle	54 (9.7)		93 (9.8)	
distance to school in meter (sd)		4614.42 (3634.31)		2648.19 (3814.25)	
PA resources count (sd)	3km	2.09 (1.66)		10.99 (3.85)	
	5km	3.26 (1.85)		18.40 (4.62)	
	8km	4.33 (1.86)		33.40 (5.36)	
road connectivity index (sd)	3km	0.49 (0.04)		0.46 (0.02)	
	5km	0.47 (0.02)		0.47 (0.01)	
	8km	0.46 (0.01)		0.49 (0.01)	
land cover diversity index (sd)	3km	0.65 (0.08)		0.65 (0.02)	
	5km	0.64 (0.07)		0.65 (0.01)	
	8km	0.64 (0.05)		0.65 (0.01)	
population (sd)	3km	5819.73 (3131.82)		67489.37 (18620.52)	
	5km	11423 (5665.17)		180667.80 (26695.65)	
	8km	21637.69 (10429.76)		481745.00 (72757.53)	
		Wave 1	Wave 2	Wave 1	Wave 2
BMI* (sd)		22.86 (4.34)	23.23 (4.52)	23.51 (4.67)	23.86 (4.88)
PA (sd)		3.87 (2.09)	3.49 (2.04)	3.69 (2.02)	3.26 (1.93)

BMI – body mass index; PA – physical activity

*Due to missing BMI values, N differed between Wave 1 and 2; N = 556 in Wave 1 and N = 552 in Wave 2 for School A; N = 931 in Wave 1 and N = 935 in Wave 2 for School B.

Both schools had very sparse social networks. In School A (Table 7), the network density was, on average, 0.0065 (including both Waves). In School B, the network density was 0.002 in both Waves. The overall average degree was 3.513 for School A, and 1.76 for School B. Both schools had a slightly higher average degree in Wave 1 (School A: 3.711; School B: 1.92) than Wave 2 (School A: 3.316; School B: 1.608). Because Wave 1 had more nominations (School A: 2067; School B:1820) than Wave 2 (School A: 1847; School B: 1524), there were more dropping ties (School A: 1275; School B: 1209) than forming ties (School A: 1055; School B: 913). The Jaccard similarity indices of both schools were not high (School A: 0.254; School B: 0.224), which is associated with network sparsity.

Table 7: Descriptive statistics of friend networks

	School A		School B	
Wave	1	2	1	2
Density	0.007	0.006	0.002	0.002
Average degree	3.711	3.316	1.92	1.608
Number of ties	2067	1847	1820	1524
Tie change from Wave 1 to Wave 2				
Create a new tie (0 ->1)	1055		913	
Drop an existing tie (1 -> 0)	1275		1209	
No change	0 -> 0	306570	0 -> 0	895023
	1 -> 1	792	1 -> 1	611
Jaccard similarity	0.254		0.224	

SAB friend selection model

Table 8 shows the results of the SAB friend selection model. The overall convergence ratios of both schools were under 0.25. All the convergence t-ratios were under 0.1. Together they indicate an adequate convergence of the model for two sample schools.

First, the spatial effect we examined in the friend selection model - the distance between individual's home and friends' home - had a significantly negative coefficient in both schools. This important finding suggests that an alter living far apart from the ego was slightly less likely to be selected as a friend (estimate = -0.0712, esp(-0.0712) = 0.93). Consequently, we reject our first null hypothesis and conclude that home location had a significant impact on the dynamics of the friendship network.

In terms of other effects, all included structural effects exerted significant influence ($p < 0.05$) on the network dynamics and the results of two schools were consistent with each other. According to the estimates, outdegree had a significant negative coefficient, suggesting that the actors in the network were not inclined to make friends with random alters. The significant positive coefficients of reciprocity indicated that students liked to maintain existing friendship ties or nominated those who nominated them as friends. Estimates for transitive triplets and popularity were also significant and positive. The former suggests that the individual was inclined to become a friend with their friend's friends. The later indicates that students who received a lot of nominations would attract more incoming ties.

In terms of the homophily effects, for School B, all variables included in the selection model exerted significant ($p<0.05$) influence on forming or maintaining ties. However, race, ethnicity, and BMI homophily effects were not significant for School A. Students who had more course overlapping were more likely to be friends. If two students were of the same gender, they would be 19% (School A) and 61% (School B) more likely to be friends than students of different gender (School A: estimate = 0.1747, exp (0.1747) = 1.19; School B: estimate = 0.48, exp (0.48) = 1.61). For School A, students from the same grade were 1.74 times more likely to form or maintain a friendship tie (estimate = 0.5547, exp (0.5547) = 1.74). For School B, the chance of being friends was 1.63 times,1.51 times, and 2.14 times higher, if students were in the same grade (estimate = 0.4887, exp (0.4887) = 1.63), of the same race (estimate = 0.4093, exp (0.4093) = 1.51), and of the same ethnicity (estimate = 0.7610, exp (0.7610) = 2.14), respectively. Students from School B who had similar BMI value were more likely to become friends or keep their existing friendship. However, such associations were not significant in School A's friend selection model.

The behavior effects included in the selection model were used for testing if different levels of general PA would influence an individual's social network in school. The PA alter effect was not significant, indicating that a physically active student and a physically inactive student had no difference in terms of being nominated as a friend by others, with all other characteristics unchanged. Also, the insignificant coefficient of PA similarity suggested that similar PA level had no impact on attracting more incoming ties. The estimate of PA ego was significantly negative in School B's selection model, which indicated that the more physically active students in that school were less likely to form or maintain friendship ties with others.

Following our analysis plan, only significant covariates in the selection model were kept in developing the network-behavior coevolution model. Given the inconsistency in the results of two sample schools, the coevolution model of School A had fewer covariates than School B.

Table 8: SAB selection model

	School A		School B	
Parameter	Estimates	SE	Estimates	SE
Rate	13.0037	0.6008*	7.011	0.0006*
Structural effects				
Outdegree	-3.4596	0.1589*	-6.0472	0.1151*
Reciprocity	2.2063	0.0693*	2.3885	0.0895*
Transitive triplets	0.4565	0.0258*	0.5047	0.0377*
Popularity (alter sqrt)	0.1262	0.0377*	0.4794	0.0355*
Homophily Effects				
Course overlap	0.0415	0.0096*	0.2398	0.0568*
Same sex	0.1747	0.0378*	0.48	0.0544*
Same grade	0.5547	0.0377*	0.4887	0.0539*
Same race	-0.1062	0.0608	0.4093	0.0528*
Same ethnicity	-0.202	0.1349	0.761	0.0704*
BMI similarity	0.1484	0.1427	0.5445	0.2000*
Behavior effects				
PA ego	0.0041	0.0099	-0.0452	0.0165*
PA alter	0.0123	0.0093	-0.0042	0.0165
PA similarity	0.0615	0.1035	0.069	0.1237
Spatial effect				
Distance to friends	-0.0113	0.0039*	-0.0712	0.0111*

*Absolute value of the estimated coefficient was greater than 1.96 standard error (SE), suggesting $p < 0.05$.

School A convergence t ratios all < 0.05; Overall maximum convergence ratio 0.1044.

School B convergence t ratios all < 0.09; Overall maximum convergence ratio 0.1668.

SAB coevolution model

In the SAB network-behavior coevolution model, PA was treated as another dependent variable to test the influence of student's social network on their PA behavior. Since the estimates and significance test results were consistent with the selection model that the coevolution model is built from, we only focused on the results of the behavior model in this section.

For School A (Table 9), the PA total similarity effects were positive and significant ($p<0.05$) in all models of different spatial scales (3km, 5km, 8km), indicating an assimilation process where adolescents tended to adopt a similar level of PA of their friends. In our model we used and reported the total similarity effect which means the total influence of nominated friends was proportional to the number of nominations. We also tested the average similarity effect at different spatial scales while holding all other effects the same, and results showed that the average similarity effect of PA remined significant. For school B (Table 10), the PA total similarity effect showed a consistent result as in School A, i.e. the effect was significant at all three geographic scales ($p < 0.05$). All estimates were positive thus we concluded that like in School A, students in school B also tended to adopt their friends' PA level.

In terms of other direct effects (motivation and environmental effects), we did not observe any significant influence for both schools among different spatial scales. Thus, in this study, we were not able to reject our second null hypothesis (i.e., built environment exert no significant influence on adolescents' PA dynamics in selected sample schools between Wave 1 and Wave 2).

Table 9: SAB coevolution model - School A

Parameter	School A					
	3km neighborhood		5km neighborhood		8km neighborhood	
	Estimates	SE	Estimates	SE	Estimates	SE
Network Dynamics						
Rate	13.0146	0.5564*	13.0086	0.4500*	13.0169	0.5832*
Structural effects						
Outdegree	-3.7746	0.0838*	-3.7740	0.0865*	-3.7745	0.0873*
Reciprocity	2.2025	0.0658*	2.2000	0.0683*	2.2022	0.0768*
Transitive triplets	0.4573	0.0256*	0.4567	0.0287*	0.4574	0.0267*
Popularity (alter sqrt)	0.1385	0.0331*	0.1389	0.0360*	0.1378	0.0339*
Homophily Effects						
Course overlap	0.0405	0.0112*	0.0408	0.0094*	0.0409	0.0095*
Same sex	0.1764	0.0380*	0.1753	0.0375*	0.1772	0.0408*
Same grade	0.5564	0.0390*	0.5574	0.0423*	0.5576	0.0415*
Same race	-	-	-	-	-	-
Same ethnicity	-	-	-	-	-	-
BMI similarity	-	-	-	-	-	-
Behavior effects	-	-	-	-	-	-
PA ego	-	-	-	-	-	-
Spatial effect	-	-	-	-	-	-
Distance to friends	-0.0117	0.0043*	-0.0118	0.0044*	-0.0120	0.0042*
Behavior Dynamics						
Rate	9.6362	1.0774*	9.6221	0.8355*	9.6869	1.5003*
Shape effects						
Linear shape	-0.0943	0.0209*	-0.0944	0.0194*	-0.0936	0.0269*
Quadratic shape	-0.0129	0.0098	-0.0138	0.0112	0.0141	0.0112
Friend effect						
PA total similarity	0.6436	0.1764*	0.6342	0.2022*	0.6325	0.2355*
Motivation effects						
Exercise to lose weight	0.0268	0.0496	0.0266	0.0485	0.0272	0.0526
Exercise to gain muscle	-1.1171	0.0889	-0.1123	0.0811	-0.1079	0.1099

Table 9 (cont'd)

Environmental effects						
Distance to school	0.0008	0.0079	-0.0069	0.0094	-0.0122	0.0108
Amount of PA resources	-0.0058	0.0133	-0.0177	0.0150	-0.0028	0.0165
Road connectivity	-0.4755	0.5386	-0.9994	1.1947	-2.9467	3.8037
Land use diversity	-0.5108	0.3808	-0.4676	0.4033	-0.4108	0.5583
Population density	0.0078	0.0124	0.0116	0.0084	0.0064	0.0041

*Absolute value of the estimated coefficient was greater than 1.96 standard error (SE), suggesting $p < 0.05$.

Convergence t ratios all < 0.1; Overall maximum convergence ratio all <0.25.

Table 10: SAB coevolution model - School B

	School B					
	3km neighborhood		5km neighborhood		8km neighborhood	
Parameter	Estimates	SE	Estimates	SE	Estimates	SE
Network Dynamics						
Rate	7.0505	0.3360*	7.0215	0.3294*	7.0301	0.4004*
Structural effects						
Outdegree	-6.0327	0.1126*	-6.0340	0.1185*	-6.0366	0.1383*
Reciprocity	2.3922	0.1015*	2.3864	0.0883*	2.3861	0.0891*
Transitive triplets	0.5056	0.0365*	0.5052	0.0405*	0.5045	0.0438*
Popularity (alter sqrt)	0.4781	0.0368*	0.4779	0.0348*	0.4795	0.0363*
Homophily Effects						
Course overlap	0.2410	0.0516*	0.2388	0.0519*	0.2434	0.0553*
Same sex	0.4783	0.0516*	0.4795	0.0495*	0.4817	0.0560*
Same grade	0.4830	0.0544*	0.4849	0.0536*	0.4829	0.0513*
Same race	0.4093	0.0474*	0.4106	0.0554*	0.4100	0.0505*
Same ethnicity	0.7564	0.0651*	0.7564	0.0897*	0.7579	0.0896*
BMI similarity	0.5324	0.2190*	0.5394	0.2047*	0.5354	0.2131*
Behavior effects						
PA ego	-0.0465	0.0145*	-0.0462	0.0155*	-0.0463	0.0141*
Spatial effect						
Distance to friends	-0.0708	0.0120*	-0.0707	0.0128*	-0.0701	0.0135*
Behavior Dynamics						
Rate	10.7074	0.9316*	10.6890	0.7664*	10.6794	0.8970*
Shape effects						
Linear shape	-0.0983	0.0175*	-0.0985	0.0151*	-0.0983	0.0168*
Quadratic shape	-0.0424	0.0066*	-0.0424	0.0070*	-0.0421	0.0070*
Friend effect						
PA total similarity	0.4653	0.2170*	0.4632	0.2269*	0.4695	0.1998*
Motivation effects						
Exercise to lose weight	0.0084	0.0090	0.0092	0.0097	0.0084	0.0105
Exercise to increase muscle	0.0008	0.0091	0.0016	0.0100	0.0011	0.0111

Table 10 (cont'd)

Environmental effects						
Distance to school	-0.0052	0.0049	-0.0076	0.0044	-0.0065	0.0043
Amount of PA resources	0.0077	0.0053	0.0044	0.0044	0.0010	0.0032
Road connectivity	-0.8073	0.7468	-1.0438	1.4494	-1.1876	2.0609
Land use diversity	-0.5558	1.3342	-2.7064	2.2493	-1.1432	1.6769
Population density	-0.0011	0.0016	-0.0011	0.0013	-0.0001	0.0005

*Absolute value of the estimated coefficient was greater than 1.96 standard error (SE), suggesting $p < 0.05$.

Convergence t ratios all < 0.1; Overall maximum convergence ratio all <0.25.

Discussion

This study extended prior research conducted by other scholars and contributed to the physical inactivity and childhood obesity literatures by using the combined social, spatial, and environmental variables to test their influences on the dynamics of friend selection and adolescent PA. Our results show that, in the friend selection model, home distance between high school students was significantly and negatively associated with tie creation and maintenance, which means that students who live closer together are more likely to be friends. This can indicate that students interact outside of school contexts, such as spending time together after school or during summer and winter breaks, and perhaps even walking to and from school together. We also found that student's PA could be influenced by friends via an assimilation process. Together, these two findings imply that intervention outside school, such as PA involved activities in the community centers or self-organized outdoor sports arranged by parents, might be able to facilitate promoting PA of adolescents by direct participation or indirect influence via a change in the behavior of friends.

The environment variables that described adolescents' residential neighborhood did not show a significant influence on students' PA dynamics. This is consistent with some existing studies which showed the built environment had trivial to small impacts on PA among youth (McGrath, Hopkins and Hinckson 2015). However, other reasons could contribute to an insignificant association between the built environment and PA dynamics in this study. One might be that the Wave 1 and Wave 2 were only one year apart, but the shaping effects of the environment on behavior may take a longer time. Another possible reason is that for students participating in Add Health survey, the neighborhood outdoor environment was not their primary location for PA. Without further detailed information, we were not able to figure out if the PA reported in the survey took place near home or mostly in school. Unlike adults who may largely rely on public amenities such as parks to do certain sports, adolescents spend a great amount of time in school and have easy access to facilities available for students provided by the school. It is also possible that the features of neighborhood environment we chose to investigate were not very important for adolescents' decision making about PA in their neighborhood. In future studies, it may be useful to examine other variables such as safety.

Some of our results are consistent with the findings of Simpkins et al. (2012) and Shoham et al. (2012) who used the same dataset. These include homophily effects of grade and gender, and the effects, of course, overlapping in friend selection. However, we also ended up with some inconsistencies. For instance, in our study, the PA ego effects and BMI similarity effects in SAB selection model were only significant in School B, whereas they were both significant in the work of Simpkins et al (2012). We hypothesize that these disparities can be attributed to differences in data filtering and the selection of explanatory variables due to different research questions. In the model of Simpkins et al (2012), BMI was classified whereas we used raw (numerical) BMI values, which may also cause differences in the level of significance.

This study has some limitations. First, in our analysis, we used secondary data collected in 1994/1995. We realize that, after 30 years, the way that high school students interact with peers may have changed, or not. Compared to millennials, the lifestyle of centennials (people born between the late 1990s and 2010) is greatly influenced by online interaction, which may have a varying effect on PA. Online social network is playing an important role in adolescents' daily life and physical distance is probably much less obstructive for the interaction and communication between children living farther apart. According to the United States Census Bureau (2010), in 1993, only 22.9% of households in the U.S. owned computers, whereas now, computers are ubiquitous. In 1997, 18% of households had access to the internet. After ten years, in 2007, that percentage increased to

61.7%. Based on a survey from 2015, around three-quarters of teenagers had cellphones (Lenhart 2015). The popularization of computers, cellphones and internet not only greatly influence the social network of adolescents, but also contribute to their screen time, which might otherwise be devoted to PA. Friendships and their influence on students may also be moderated by screens and how influential a friend is compared to one-on-one contact relationships. Given these changes in the society and culture, samples used in this study might not well represent the behavior pattern and attitudes of adolescents in current times. More recent large-scaled longitudinal data with complete social network will be of great value for future studies.

Another limitation is that the data was self-reported rather than measured. For example, the key variable that we used in our analyses, total PA, only reflected the reported frequency of PA in seven days preceding the survey. However, the duration and intensity of the activity were unknown. This could lead to inconsistency and uncertainty when trying to investigate the changes in PA and the difference of PA between a pair of students.

Third, this study did not reveal the actual processes behind adolescents' influence on their peer behavior. Although we found some association between change in one's PA and the average PA of this student's nominated friends, it is not clear what mechanisms cause these associations. There is a lack of information about whether or not the reported PA was done with an individual's friends. The influence from peers could be from direct interactions. It is possible that a student was frequently invited by friends to participate in PA together after school, which boosted her PA to be similar to her physically active friends. Or, on the contrary, she could be invited to watch TV or play video games together which borrowed her leisure time for PA and made her less physically active. A student could also be influenced by friends by simple observation or verbal communication. A student may not participate in PA with her friends together, but she might see her physically active friends as role models and mimic their behavior when she is in a more private setting. It is also possible that she devoted more time to certain activities, such as doing sports or watching TV, in order to have a conversation with friends as a way of maintaining the friendship or becoming more popular among peers.

Regardless of these limitations, we believe that this study lays a strong foundation to further our understanding of the joint impact of social network and neighborhood environment on adolescents' friend selection and PA.

Summary

In this study, we used two waves' Add Health data of two sample schools. We built SAB models to investigate the relationship among friend network, home location, neighborhood environment, and adolescents' PA. We found that students were inclined to be friends with those who lived closer, but we failed to detect a significant influence of the built environment on PA level. This study contributes to the field of children's studies by extending existing research via incorporating spatial and environmental variables in the analysis. Due to limitations of this study, the relationship between environment, PA and obesity is still not clear and further research with more recent data are required in the future.

APPENDICES

APPENDIX A:

Distribution of Environment Variables

APPENDIX A: Distribution of Environment Variables

In this document, we presented the distribution maps of home locations, physical activity (PA), and neighbourhood environment characteristics of sample students from two sample schools included in our study.

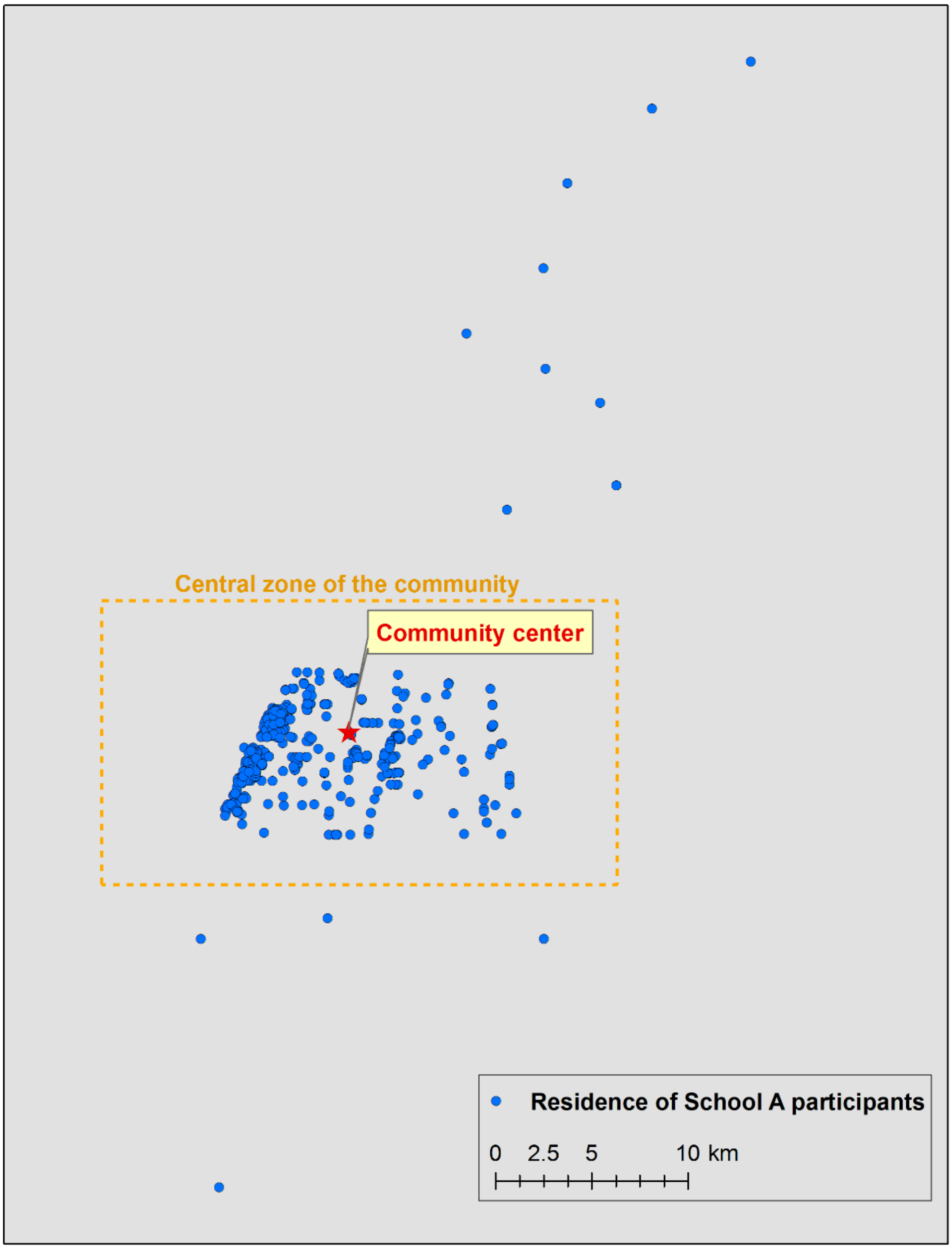

Figure 1: Home location of sample students from School A

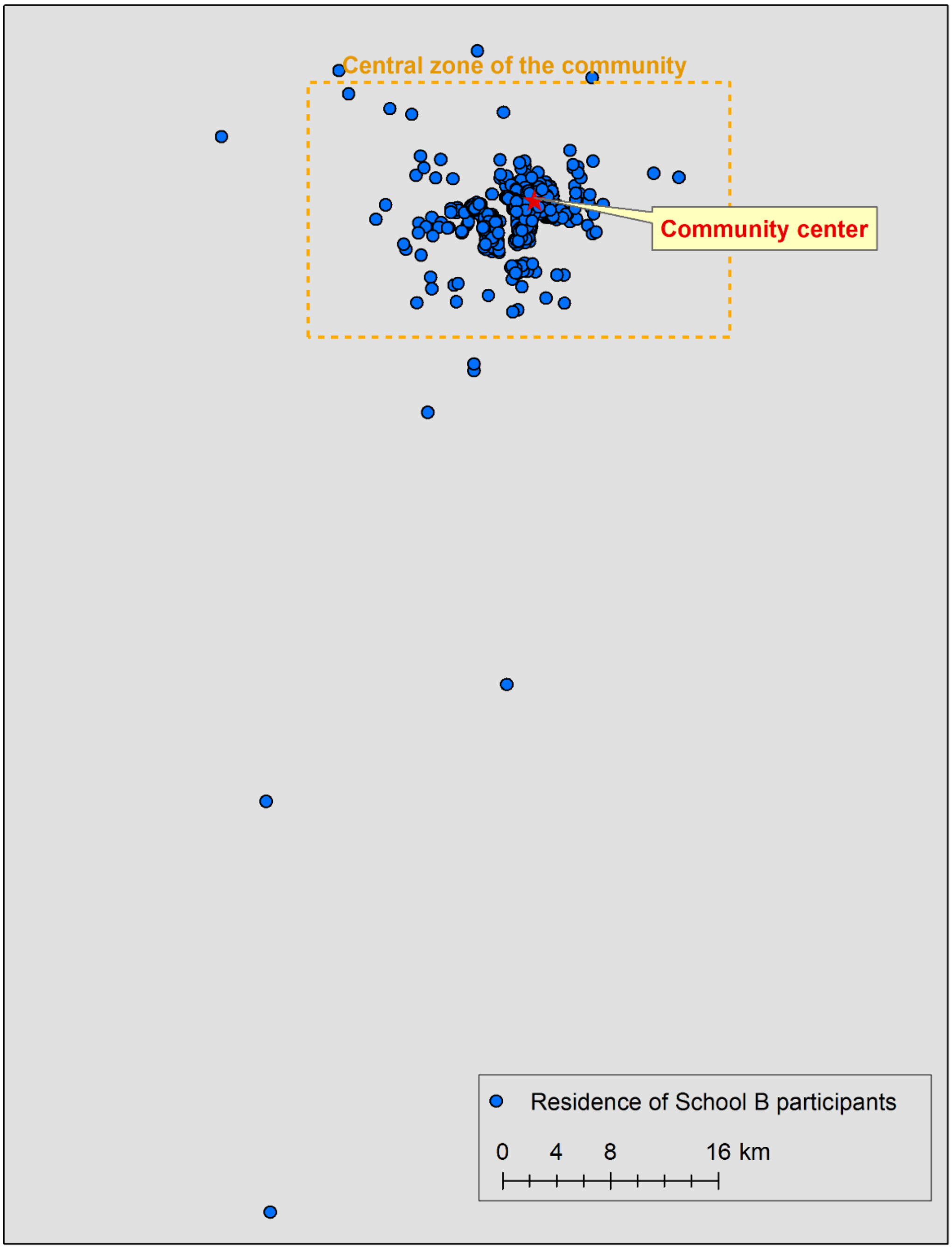

Figure 2: Home locations of sample students from School B

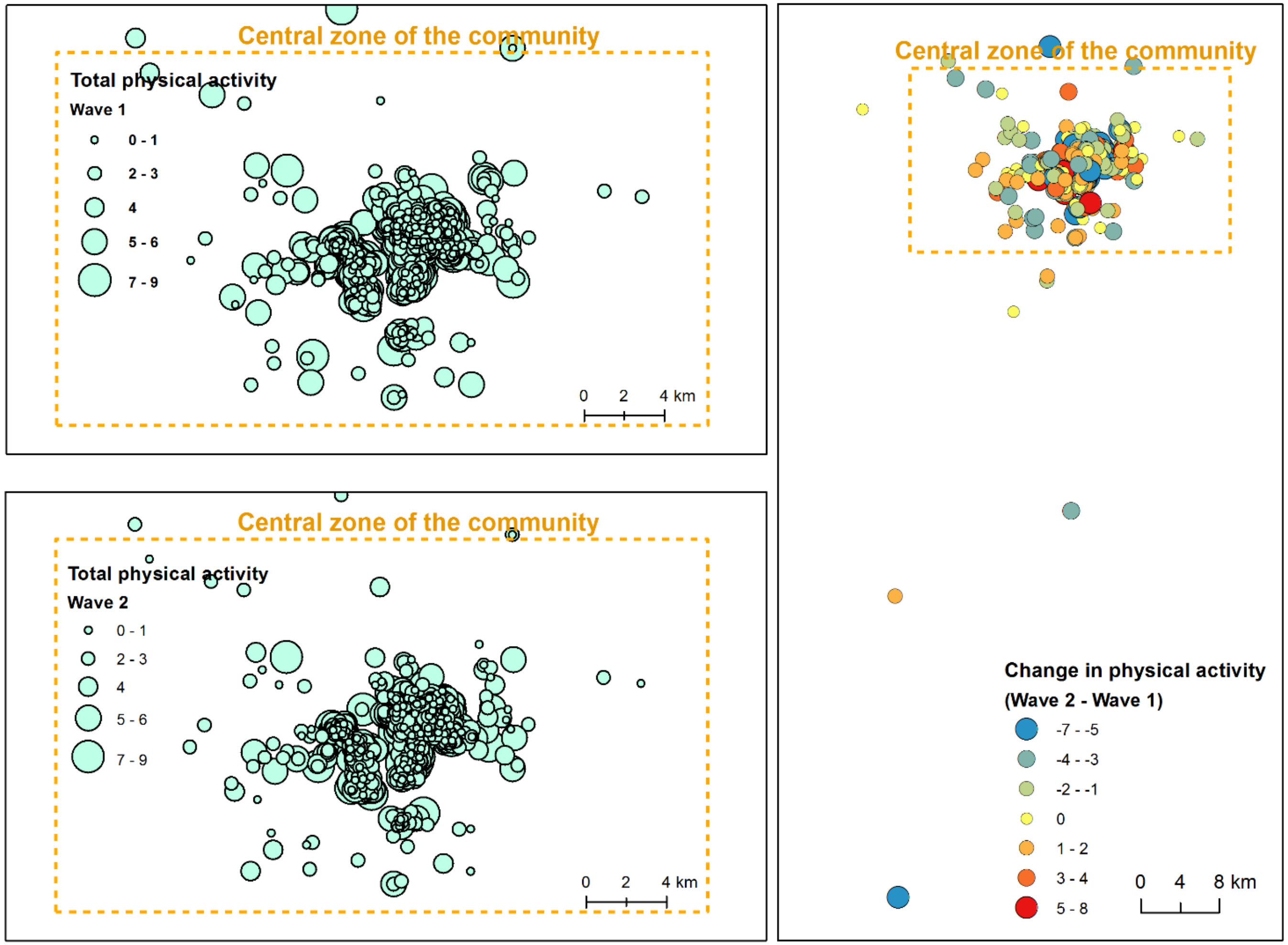

Figure 3: Distribution of total physical activity and change between Wave 1 and Wave 2 of sample students from School A

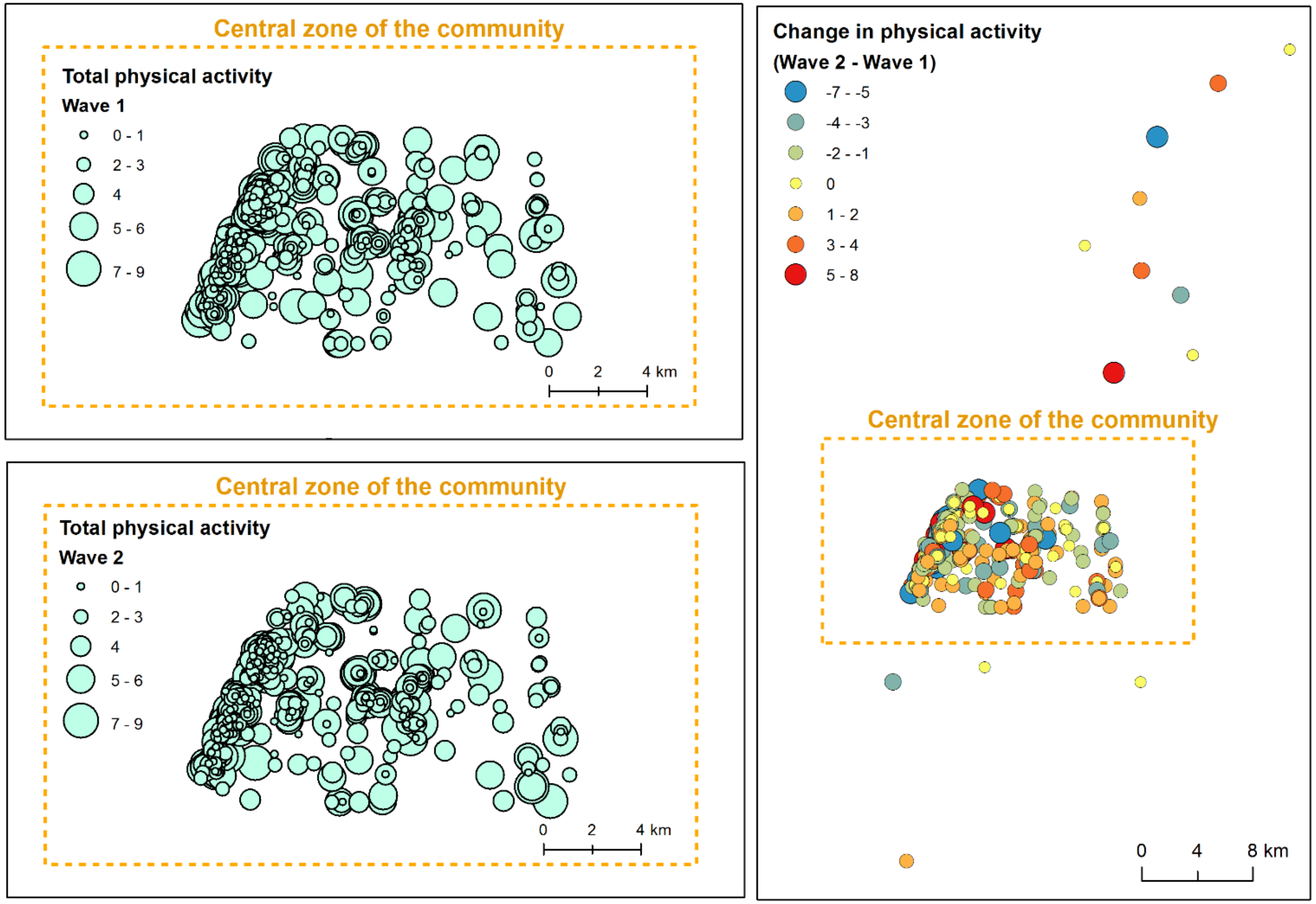

Figure 4: Distribution of total physical activity and change between Wave 1 and Wave 2 of sample students from School B

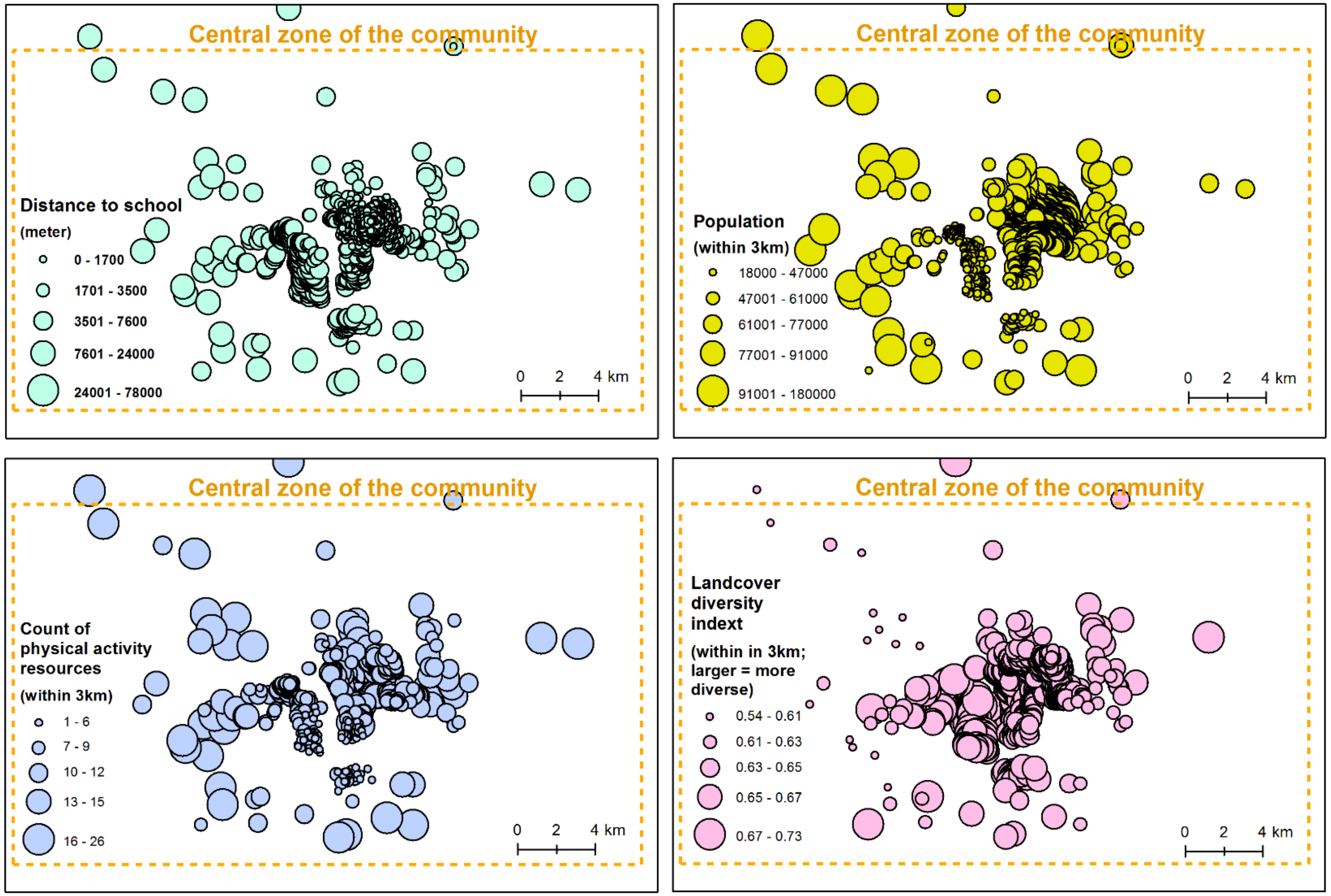

Figure 5: Distribution of neighborhood built environment of sample students from School A

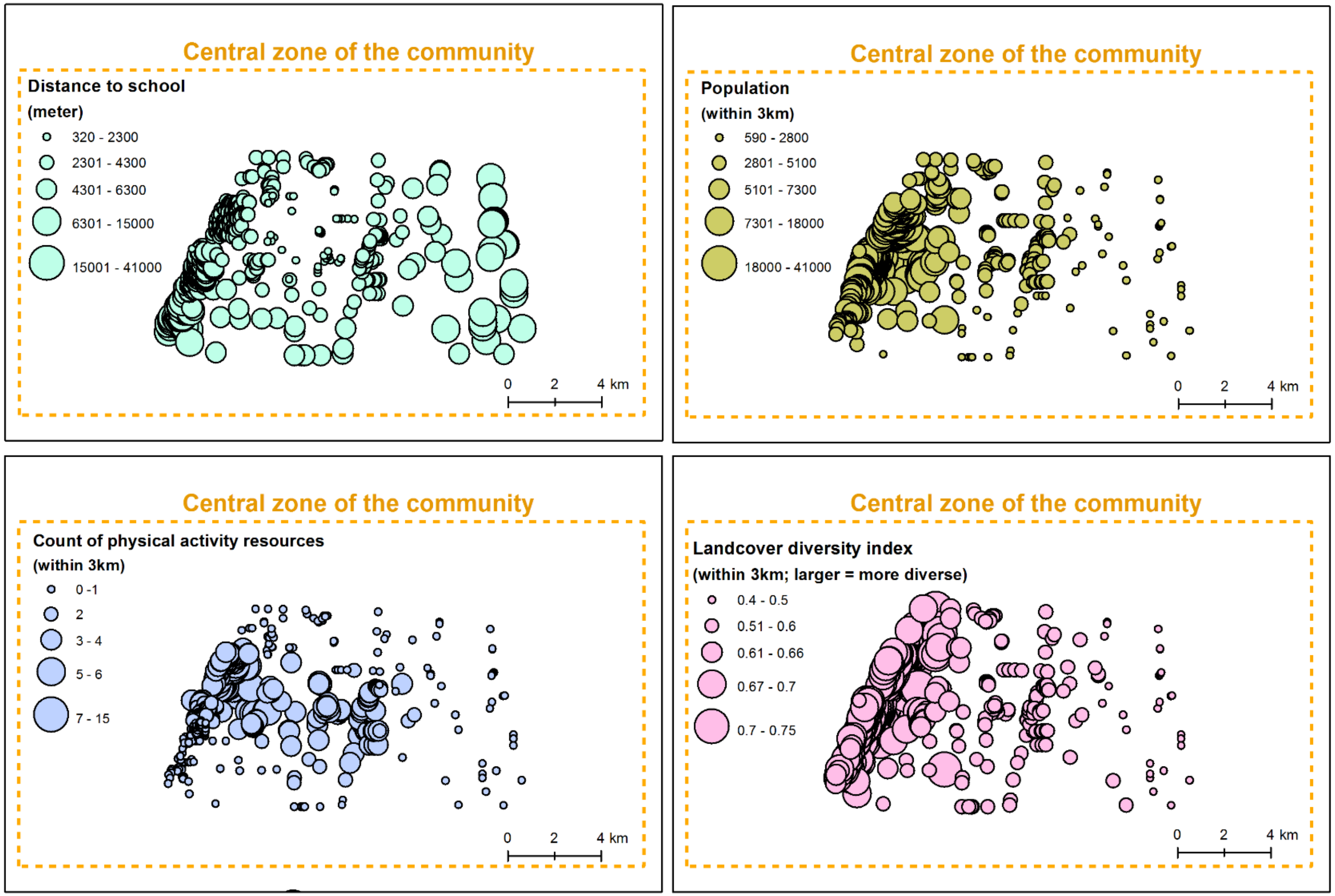

Figure 6: Distribution of neighborhood built environment of sample students from School B

APPENDIX B:

Specification of the SAB Model

APPENDIX B: Specification of the SAB Model

The Stochastic Actor-based (SAB) Model used in this study had two sub-models, a friend selection describing the dynamics of the friend network, and a behavioral evolution model predicting changes in adolescents' physical activity (PA).

SAB friend selection model

As shown below, the SAB selection model is a linear combination of many components, which consist of covariates and their weights (i.e. coefficients β). Each component exerts an effect on the network, thus the selection model helped us investigate how actor's or dyad's characteristics influence the network dynamics. We classified these components into five categories based on different types of covariates included in the model.

In the SAB selection model, the function f_i^{net} measures the status of dyad x in friendship adjacency matrix X of student i. y represents covariates in the model and z represent actor's behavior (i.e. PA in this study). For the friendship adjacency matrix, if student i nominated j as a friend, then $x_{ij} = 1$, else $x_{ij} = 0$.

$f_i^{net}(x, y, z) =$

$\beta_{deg} \sum_j x_{ij} + \beta_{rec} \sum_j x_{ij}\, x_{ji} + \beta_{ttip} \sum_{j,h} x_{ij} x_{ih}\, x_{hj} +$

$\beta_{popsqrt} \sum_j x_{ij} \sqrt{\sum_h x_{hj}}$ ……..………………………………….…..Structured Effects

$+ \beta_s \sum_j x_{ij}\, I\{s_i = s_j\} + \beta_g \sum_j x_{ij}\, I\{g_i = \mathrm{g}_j\} + \beta_r \sum_j x_{ij}\, I\{r_i = r_j\} + \beta_r \sum_j x_{ij}\, I\{e_i = e_j\}$

$+ \beta_{BMI,sim} \sum_j x_{ij} \left(sim_{BMI,ij} BMI, average\right) + \beta_{acad} \sum_j x_{ij}\, WCO_{ij}$…… Homophily Effects

$+ \beta_{PA,ego}\, x_{ij} PA_i + \beta_{PA,alt} \sum_j x_{ij} PA_j$
$+ \beta_{PA,sim} \sum_j x_{ij} \left(sim_{PA,ij} PA, average\right)$……………………………….………Behavior Effects

$+ \beta_d \sum x_{ij} Dist_{ij}$ ……………………………..……………….............. Spatial Effects

Structural effects

The structural effects represent the endogenous network processes, i.e. effects depending on the network only. The evolution of a social network is greatly influenced by the existing network ties thus these endogenous effects need to be controlled in the network evolution model. We included:

1) $\beta_{deg} \sum_j x_{ij}$ – the out-degree effect (density effect); x_{ij} means that there is a tie from i to j. A strong positive coefficient (β_{deg}) indicates a greater tendency to send out a tie to a random alter. In our case, that is a tendency to create or maintain a friendship tie.

2) $\beta_{rec} \sum_j x_{ij}\, x_{ji}$ – the reciprocity effect; this effect describes the inclination of a nominee j to form a friendship tie back to the nominator i.

3) $\beta_{ttip} \sum_{j,h} x_{ij} x_{ih}\, x_{hj}$ – the transitive triplets effect; this effect describe the tendency of network closure through the number of transitive triplets in the network. Significant positive coefficient suggests the tendency of "becoming a friend with your friend's friend".

4) $\beta_{popsqrt} \sum_j x_{ij} \sqrt{\sum_h x_{hj}}$ – in-degree related popularity (sqrt) effect; it expresses the tendency of a popular individual to attract more incoming ties (i.e. getting more nominations) than others.

Homophily effects

Studies have shown that people tend to make friends with those sharing similar characteristics, such as age and gender. To control for the homophily effects on friendship network dynamics, we included homophily effects for participant attributes and total PA. By default, covariates were centered in RSiena by subtracting the mean.

1) $\beta_s \sum_j x_{ij}\, I\{s_i = s_j\}$, $\beta_g \sum_j x_{ij}\, I\{g_i = \mathrm{g}_j\}$, $\beta_r \sum_j x_{ij}\, I\{r_i = r_j\}$, and $\beta_r \sum_j x_{ij}\, I\{e_i = e_j\}$ – these four homophily effects are covariate-related identity effects based on actor's sex (s), grade (g), race (r) and ethnicity (e), respectively. The effect is defined by the number of ties where actor i and j had the same value on a selected attribute.

2) $\beta_{BMI,sim} \sum_j x_{ij} \left(sim_{BMI,ij} BMI, average\right)$ – this component in the function controls for the homophily effect of body image, which is represented by BMI value. It is defined by the sum of centered BMI similarity scores between actor i and i's nominated friend j. The similarity score is a function of the absolute difference between two values and is normalized between 0 and 1, where 1 indicates equal values.

3) $\beta_{acad} \sum_j x_{ij}\, WCO_{ij}$ – this component was introduced to the model to control for the influence of course overlapping. We viewed it as an inbreeding homophily introduced by student's preference for selecting the same course and their similarity caused by sharing the environment and receiving education in the same classes.

Behavior effects

These effects were included in the model specifically to investigate the influence of PA on high school student's friend selection.

1) $\beta_{PA,ego}\ x_{ij}PA_i$ – the covariate-ego effect is defined by the outdegree of actor i weighted by its PA value. A significant positive coefficient would then indicate that physically active student tends to select more friends.

2) $\beta_{PA,alt}\sum_j x_{ij}PA_j$ – this is a covariate-alter effect, also called the covariate-related popularity effect. It is defined by the sum of PA over all students that i nominated as a friend. Based on its definition, a significant positive coefficient would suggest that the physically active students are more likely to be selected as a friend.

3) $\beta_{PA,sim}\sum_j x_{ij}\left(sim_{PA,ij}PA, average\right)$ – like the homophily effect of PA, this effect captures the likelihood of forming or maintaining friendship tie depending on similarity in total PA.

Spatial effect

To investigate the influence of physical distance between a pair of actors in the network, we included a spatial effect $\beta_d\sum x_{ij}Dist_{ij}$ in the SAB selection model. A significant coefficient would reject our null hypothesis that residence distance between two adolescents has no impact on forming or maintaining friendship between them.

SAB behavioral evolution model

Our SAB behavioral evolution model consists of nine components that we classified into three types of effects. Here, we hypothesized that actor's behavior, i.e. their total PA, is influenced by the prior, the nominated friends' PA, the motivation for boosting PA and the neighborhood environment. This model was utilized for us to identify the driving forces of adolescent's PA. The behavior evaluation function for actor i is defined as:

$f_i^{beh}(z,x)$ = $\beta_{lin}z_i$ + $\beta_{quad}{z_i}^2$ ……………………………………..……..shape effects

+ $\beta_{beh}x_{i+}^{-1}\sum_j x_{ij}$ PA$sim_{z,ij}$ ……………………………..…….…......friend effect

+ $\beta_{ml}L_i$ + $\beta_{mg}G_i$ ……………………………………………....…...motivation effects

+ $\beta_{dist}d_i$ + $\beta_{count}r_i$ + $\beta_{con}c_i$ + $\beta_{lc}l_i$ + $\beta_{pop}Pop_i$ ……………environment effects

Shape effects

In our Siena behavioral evolution model, we included a linear shape effect ($\beta_{lin}z_i$) and quadratic shape effects ($\beta_{quad}{z_i}^2$) to account for the influence of one's behavior in Wave 1 on the behavior in Wave 2, i.e. control for the prior. Variable z is centered, which means it is the original total PA minus the overall mean of all observations.

Friend effect

$\beta_{beh} x_{i+}^{-1} \sum_j x_{ij}$ PA$sim_{z,ij}$ - the average similarity effect is defined by the average centered similarity scores between actor i and alters j that i has ties with. A significant positive coefficient suggests that if friends are more physically active, the student's PA will be promoted. Together with the PA effects in the selection model, the friend effect in the behavior model allows us to assess whether PA is "contagious" or rather reflects the "birds of a feather flock together" effect.

Motivation effects

$\beta_{ml} L_i$ and $\beta_{mg} G_i$ were included to control for self-motivation of losing or gaining weight through PA.

Environment effects

β_m was included to control for self-motivation of losing or gaining weight through PA. To investigate whether home location influences participant's PA, we also added environment related components in the model, including distance to school ($\beta_{dist} d_i$), amount of PA resources in the neighborhood ($\beta_{count} r_i$), road connectivity ($\beta_{con} c_i$), land use mix ($\beta_{lc} l_i$) and population density ($\beta_{pop} Pop_i$). As mentioned in the "Measures" section previously, neighborhood environment measures were of different scales (3, 5, and 8 kms) thus we created three versions of the model to test each spatial scale separately.

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CHAPTER 3: EFFECTS OF POKÉMON GO AS AN INTERVENTION TO PROMOTE ADOLESCENTS' PHYSICAL ACTIVITY - A SPATIAL STOCHASTIC AGENT-BASED MODEL SIMULATION

Abstract

Studies have shown that the location-based augmented reality mobile game Pokémon Go could be a promising tool to promote physical activity. In this research, we built an agent-based model (ABM) based on a stochastic actor-based social network model (Siena) as a baseline model to simulate the dynamics of friendship and physical activity (PA) among students from a sample high school. We then introduced a game-based intervention that is similar to Pokémon Go to convert the baseline model to a spatial ABM. Three scenarios were tested: enrolling different number of players, enrolling students with large body mass index (BMI), and enrolling students based on home distance to community center. Results of the computational experimentation indicate that 1) the intervention could lead to an increase in non-players' total PA; 2) enrolling more students would lead to greater impacts on non-players, which we called a spillover effect; 3) targeting students with large BMI proved to be not effective in terms of promoting the average PA of the entire school, but it had the greatest impact on players' total PA during the intervention; and 4) the spillover effect on non-players was the greatest by enrolling far-from-community-center students, and the weakest by enrolling close-to-community-center students.

Keywords: spatial agent-based model, game-based intervention, Pokémon Go, spillover effect

Introduction

Prevalence of obesity and overweight among adolescents is a public health issue worldwide. In the U.S., research has shown that the prevalence of obesity among adolescents (between 12 and 19 years old) was 20.6% in 2015 – 2016 (Hales et al. 2017). Promoting physical activity (PA) is one of the most well-accepted and effective approaches to prevent and control obesity, and regular exercises also provide other health benefits such as lowering risks of depression, cardiovascular disease, type 2 diabetes, and some cancers (CDC 2020).

Various interventions have been designed and adopted to motivate and encourage adolescents to engage in PA, often combined with interventions on dietary intake and sedentary behaviors. Some common forms of PA interventions on children and adolescents include behavior change counseling, group session therapy, discussion with or without parents, lifestyle education, group physical activity, and games such as team sports and running games (Cliff et al. 2009). Recently, video games have turned into a very common and popular activity among children and adolescents. Active video games, which engage players to participate through movement, have been increasingly explored as an approach to induce light to moderate PA among children and adolescents (Biddiss and Irwin 2010, Graf et al. 2009, Norris, Hamer and Stamatakis 2016). More recent studies indicate that active video games are effective, as well as more acceptable and sustainable tools than many conventional approaches, to promote PA among adolescents (Williams and Ayres 2020, Gao et al. 2020, Merino-Campos and Del Castillo Fernández 2016).

When augmented reality came into being and was applied to games, more possibilities were offered to mobile game-based intervention for PA promotion. An interesting case is the launch of an augmented reality game called Pokémon Go (PG) released in the summer of 2016. The game was not meant to be a health and fitness app. However, due to its location-based features requiring players to explore outdoor spaces to play the game, it has proved to be useful in promoting both physical and mental health (Khamzina et al. 2020, Baranowski and Lyons 2019, Watanabe et al. 2017, Liu and Ligmann-Zielinska 2017). When evaluating PG's impact on PA, most of the studies among young adults or adolescents indicated that the game led to an increase in PA (Baranowski and Lyons 2019).

Mobile games, like PG, provide new possibilities for PA promotion interventions. It also possible to induce spillover effects of the beneficial influence on players' PA to non-PG players due to their social network dynamics. Studies have found evidence that individuals would adjust their weight-related behaviors to be similar to peers' or conform to social norms due to social influence (Eisenberg et al. 2005, Marks et al. 2015). Thus, an increase in PA of PG players may also exert effects on non-players. Investigating the scale of the spillover effect of PA promotion intervention could help with a more comprehensive assessment and evaluation of the intervention program. Moreover, the geographical scale and distribution of such a spillover effect are not always incorporated in PA promotion intervention studies.

One approach to investigating the potential impacts of an intervention in terms of both magnitude and distribution is to build a computational simulation model, such as a spatial Agent-based Model (ABM). ABMs are "digital representations of systems, composed of a community of heterogeneous and interacting individuals distributed within a shared environment, which they transform to achieve their objectives" (Ligmann-Zielinska 2010, 28). ABM is a bottom-up modeling approach to simulate individual behavior and interactions, while introduceding changes (such as modification to the environment, rules, policies, or interventions) at the system level. The decision-making rules and behaviors of these individuals, like game agents, and their environment (game space) can be defined by the model maker, which enable ABMs to be employed in both theoretical and empirical studies, and used as virtual experiment labs to answer many "what if …" questions (An 2012).

Some existing studies have used ABMs to simulate children and adolescents' physical activity, tested interventions, and/or incorporated social network in the model (Yang 2019). For example, several ABMs were developed with social network components to test network-based intervention on behavior change, e.g. intervening the most connected individuals within the social network. Interestingly, their simulations yielded controversial results, which showed that targeting the highly networked individuals in the intervention did not always outperform an at-random intervention (El-Sayed et al. 2013, Zhang et al. 2015b, Zhang et al. 2015a, Van Woudenberg et al. 2019, Shi, Zhang and Lu 2020). In addition, many ABMs of obesity focus on social influence yet lack health behavior components built into the model (Li et al. 2016). ABMs have also been used to investigate the influence of environment on physical activity, such as Yang's work on adults' walking behavior and children's active travel to school (Yang et al. 2011, Yang et al. 2012, Yang et al. 2014). Their limitations are the lack of empirically grounded social network representations.

Although an increasing number of ABMs have been developed in the field of non-communicable disease control (Tracy, Cerdá and Keyes 2018), few ABMs in public health have integrated both empirical data based social network, health behavior such as physical activity, and geographic components in one integrated complex system model to explore dynamics of agents' behavior and health outcomes. Consequently, our goal for this study is twofold: **(1) using a spatial ABM to simulate and investigate the impact and the spillover effects of PG on promoting PA of high school students; (2) demonstrating the advantages of using ABM public health by providing an example of a model that integrates empirical social network data, spatial components, and interventions that bring about behavior change.**

Methods

Baseline Model and Empirical Data Analysis

In this study, we used a national longitudinal survey data (Harris et al. 2009) called Add Health (National Longitudinal Study of Adolescent Health). Two waves of data for consecutive years (Wave 1: 1994-95 school year; Wave 2: 1995 – 96 school year) from a selected saturated school were analyzed in R. A saturated school is a sample school with a complete social network dataset where each participant was asked to nominate up to five male and five female friends. Descriptive analysis of students in the selected sample school is provided in Table 11. More details about Add Health data can be found elsewhere (Harris et al. 2009). We used Wave 1 data as the ABM input to allow the model to simulate one school year and then compare the simulation results with the Wave 2 data for baseline model validation.

Table 11: Descriptive statistics of students from the sample school

Sample School (i.e., School B in Chapter 1 & 2) (N = 948)			
gender (%)	male	478 (50.4)	
ethnicity (%)	Hispanic	385 (40.6)	
race (%)	White	178 (18.8)	
	Black	200 (21.1)	
	American Indian	34 (3.6)	
	Asian	312 (32.9)	
	other	224 (23.6)	
distance to school in meter (SD)		2648.19 (3814.25)	
		Wave 1	Wave 2
Average BMI (SD)		23.51 (4.67)	23.86 (4.88)
Average total PA (SD)		3.69 (2.02)	3.26 (1.93)

BMI – body mass index; SD – standard deviation.

Our baseline model was created based on the design of the ABM of an existing study (Zhang et al. 2015a), which was derived from a SIENA social network model. SIENA social network model is a stochastic actor (aka agent) based model that simulates the dynamics of actors' outgoing ties (in our case, the nomination of friends) and the dynamics of behavior change (in our case, change in total PA).

We built and calibrated our own SIENA social network model in R using the R-SIENA package and the first two waves of Add Health data of the selected sample school to identify key factors that influence networks and behaviors. Only effects with statistically significant ($p<0.05$) coefficients were included in the final model which include factors affecting network dynamics like network structure effects, homophily effects, behavior effects, and spatial effects. Structure effects account for endogenous impacts coming from the network itself. Homophily effects (the tendency for people to have social ties with people who are similar to themselves) consist of same sex, same grade, same race, same ethnicity, BMI similarity, and course overlapping. Behavior effect refers to the PA ego effect, which is the effect of the actor's PA on friendship nominations. The spatial effect captures the influence of home distance on friend selection. In terms of behavior dynamics, effects include shape effects (i.e. linear and quadratic shape effects that capture the endogenous trend of change) and a friend effect, which is associated with the similarity of an individual's PA level to friends' PA level. All these effects and their estimated coefficients are shown in Table 12.

Table 12: Significant coefficients from SIENA model

	Effects	Coefficients
Network dynamics	Basic rate	7.0422
	Structural effects	
	Outdegree	-6.0322
	Reciprocity	2.3882
	Transitive triplets	0.5051
	Popularity (alter sqrt)	0.4777
	Homophily Effects	
	Course overlap	0.2431
	Same sex	0.4834
	Same grade	0.4862
	Same race	0.4102
	Same ethnicity	0.7517
	BMI similarity	0.5403
	Behavior effects	
	PA ego	-0.0458
	Spatial effect	
	Distance to friends	-0.0700
Behavior dynamics	Basic rate	10.6079
	Shape effects	
	Linear shape	-0.0981
	Quadratic shape	-0.0408
	Friend effect	
	PA average similarity	0.4769

Since our baseline model was designed based on the ABM by Zhang et al. (2015b), we will not elaborate too much on how SIENA model parameter estimates were translated into probabilities for network and behavior dynamics in the ABM. However, we want to briefly describe three aspects where our baseline model different from the model by Zhang et al. (2015b). First, our outcome variable is different. Instead of modeling change in BMI as behavior dynamics, our model simulates changes in total PA (an ordinal variable that indicates the amount of different kinds of PA in a week). Second, our model consists of different effects that influence social network and behavior dynamics. Third, we used empirical data from a different sample school. The sample high school (number of respondents = 948) we chose to simulate was a school located in an urban area with racial heterogeneity, whereas the one simulated by was a rural school primarily dominated by white students. More details of the social network model used to construct our baseline mode can be found in Chapter 2 of this dissertation.

Baseline model validation

In the baseline model validation, we compared the simulated total weekly PA and the empirically-driven social network PA at the end of one simulated year. In terms of network structure measures, we compared the edge density, the distribution of in-degree (an in-degree means that the agent is nominated as a friend by another agent in the school), and the distribution of out-degree (an out-degree means that the agent nominated one student as a friend) with values calculated from Wave 2 observed data. We also checked the triad census, which are counts of different types of tie-configuration among three agents. There are 16 possible types of triads in a directed network (Holland and Leinhardt 1970). Specifically, we inspected if the model over-simulated 3-cycles (Holland and Leinhardt type 030C: A ← B ← C, A → C), which should be rare, or under-simulated the complete graph (Holland and Leinhardt type 300: A ↔ B ↔ C, A ↔ C), which should be common (Davis 1970, Snijders et al. 2010, Zhang et al. 2015b).

Extended baseline model with PG intervention – the PGABM

1. Game environment

After validating the baseline ABM, we introduced PG to the model as an intervention to promote agents' PA, and we called this extended ABM as PGABM. PG is a location-based augmented reality game where players need to move around and explore places to capture a randomly spawned Pokémon creature. Three types of features in PG could influence the game activity of players: spawnpoints, Pokéstop, and Gyms. Spawnpoints are locations where new Pokémons appear in the game, and either disappear in 30 minutes or are "caught" by the player. Pokéstops and Gyms were associated with the landmarks in geographic space, where players can collect items, such as Poké Balls used to capture more Pokémon, or where they can train their Pokémon (training happens in Gyms within the game).

To simulate PG interventions and implement the aforementioned game features, whenever possible, we used secondary data from other published studies. If data was not available, we resorted to best guess values. To set up the game environment, we parametrized it using secondary data from the study by Juhász and Hochmair (2017), whose PG-related point data was collected in two areas, South Florida and Boston. Based on the demographic statistics, the sample school was more likely in an urban setting with a diverse population, thus we assumed that the Boston point density data is more accurate to account for the actual game feature distribution in our sample school community. Due to unknown landcover of the sample school community, we used the average density (i.e., total observation counts divided by total area) of three major land use types (commercial, public, residential) to initialize game features in the PGABM environment as shown in Table 13.

Table 13: PG-related point density in Boston

Land-use	Area (km2)	Pokéstop counts	Spawnpoint counts	Gym counts
Commercial	6.8	589	1249	35
Public	6.0	544	1112	41
Residential	17.2	305	1806	25
Total	30.0	1438	4167	101
Average density (count/km2)		48	139	3

* Calculated based on field data reported in Juhász and Hochmair (2017).

At model setup, if the intervention is applied (i.e., number of player agents > 0), a number of PG-related features will be randomly populated based on the calculated average density within the system boundaries. System boundaries were created using the maximum and minimum XY bounding box coordinate values student agents' homes, plus a 2km buffer around the box. For each PGABM execution, Pokéstops and Gyms have set locations, while spawnpoints are refreshed only once per simulated day to reduce computational load.

2. Player agent's game behavior

To simplify the complex variation of player agents' PG behaviors, we designed rules and made assumptions for the agents to follow. These are:

1) *Gaming frequency*: a player agent plays the game 2 – 5 times per week (Barkley, Lepp and Glickman 2017) and, for simplicity, only once per day. According to the total number of ticks in a simulated year, a day was calculated proportionally (e.g., if 16732 ticks in a year, a day lasts for 46 ticks, and a week lasts for 322 ticks).
2) *Pokémon Collection:* Player agents always choose the next closest feature when playing the PG, but a visited location will not be visited again within the same play. The nearest neighbor was searched using a K-Dimensional Tree algorithm. An existing study on college student players indicated an average of 1.36 hours of play every day (Delello, McWhorter and Goette 2018). Assuming the walking speed is 5 km/h (about 3.1 mile/h), the total average walking distance amounts to 7 km (1.36 h * 5km/h). If, on average, there

are about 139 Pokémon randomly distributed per square kilometer (Table 13, Boston spawnpoints), then the expected point spacing would be 84.8 meters ($(1/\text{point density})^{-2}$). A player would encounter around 83 Pokémon in 7 kilometers. To account for agent heterogeneity, we also introduced variability by drawing different values for player agents from a truncated normal distribution with the mean set at 83 (sd = 20, min = 20, max = 140. We arbitrarily set the minimum value to 20, and the standard deviation is then calculated to be about 1/3 of the different between the mean and minimum/maximum so that 97% value will fall in the range if the variable has a normal distribution).

3) *Vising Pokéstops and Gyms*: Training Pokémon and competing with other players are important game activities, thus, in the PGABM, we included visits to Pokéstop and Gyms. This also adds variations to the routes the player agents take during game journeys. A player agent would visit a Pokéstop on each game day, and a Gym at least once per week. During a game day within a week, before the player agent finishes collecting a target number of Pokémon, a random step is picked at which the player agent visits the nearest Pokéstop. Similarly, among all game days within a week, a game day is randomly selected in which the player agent visits the nearest Gym at a randomly picked step.

4) *Converting gameplay to total PA*: in the baseline model, Wave 1 total PA was the sum of three ordinal PA variables from the Add Health survey data. These three variables are times of (1) “roller blading, roller skating, skate-boarding or bicycling”, (2) “active sport”, and (3) “exercise” in the past 7 days. Each of these three PA variables contains four values, 0 = none, 1 = 1 or 2 times, 2 = 3- 4 times, and 3 = 5 or more times. Thus, the total PA ranges between 0 and 9. We converted PA resulting from playing PG to total PA based on the total ‘game walking distance’ per week and then classified it into three levels: 2.5 – 7.5 km, 7.5 – 12.5 km, and over 12.5km, corresponding to 1, 2, and 3 total

PA units, respectively. Game PA is added on top of the total PA by assuming that it is independent from other PA. For a player agent, the total PA (game PA plus other PA) is used to estimate social network and behavior dynamics, and the game PA is adjusted based on each week's game walking distance.

5) *Game engagement*: All enrolled player agents are assumed to have the same level of game attachment. In a previous research, it was found that PG players' interests in the game faded over time (Liu and Ligmann-Zielinska 2017). To implement the game attachment fading process, based on the truncated normal distribution of the number of Pokémon to be collected, we assumed that the mean of the truncated normal distribution decreases by 15% every week. A target number of 5 Pokémon to collect is set as the threshold. Once the number of the Pokémon to collect drops to 5 or fewer, the player agent is no longer considered an active player agent and quits the game completely in the following weeks.

6) *Model output*: every player agent's weekly game PA, total PA, and total walking distance due to playing the game are recorded. None-player agents' total PA is also exported for analyzing the spillover effect.

A flowchart of the ABM with PG intervention is shown in Figure 7.

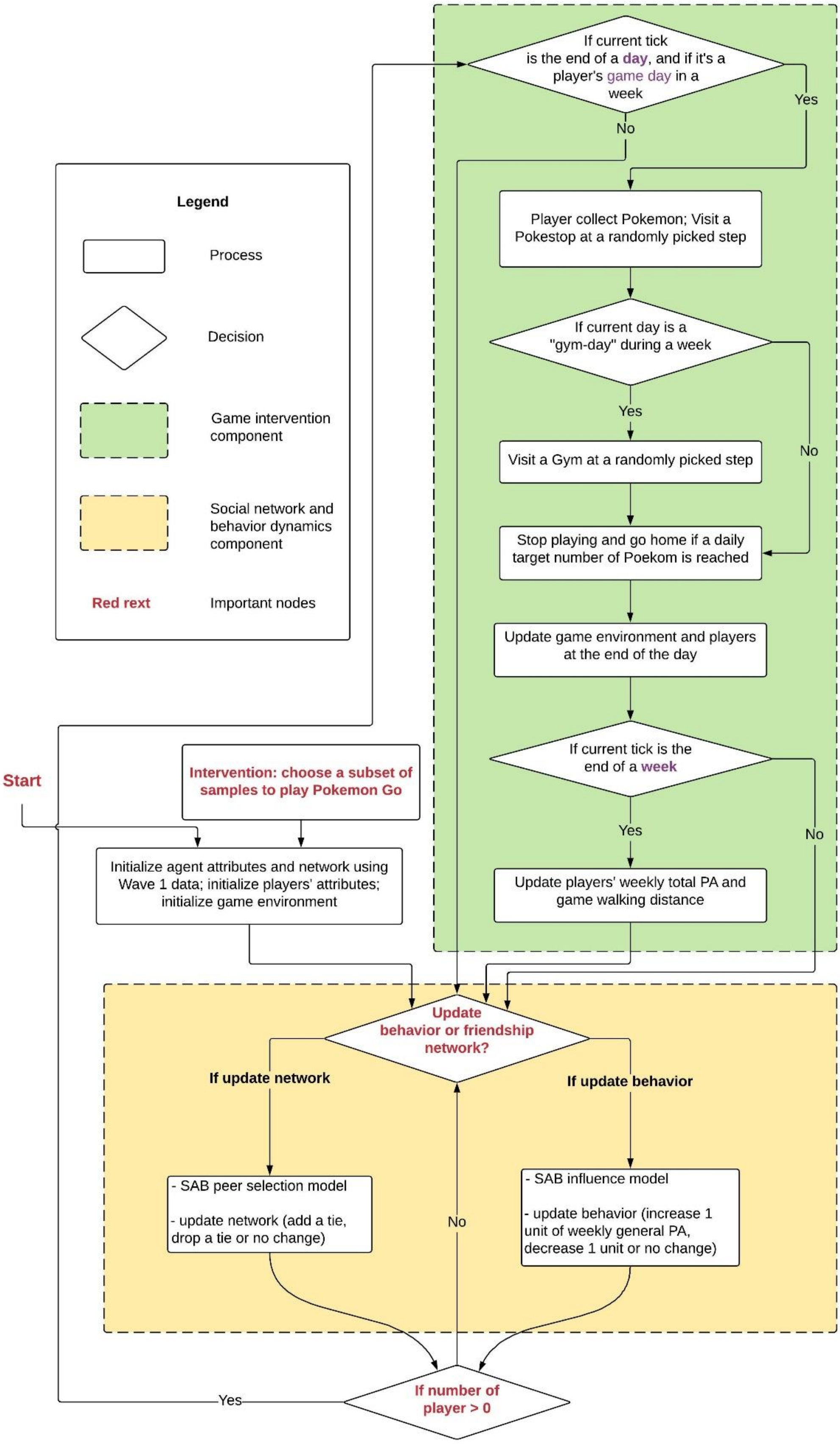

Figure 7: Flowchart of PGABM

Intervention scenarios

To explore the effects of the intervention, we tested three scenarios listed below. In each scenario, we ran the ABM 20 times with different random seeds. This number is a compromise between a sufficient level of randomness introduced in the model and its computational cost. We focused on the end-of-year average PA of all student agents, including both player and non-player agents, to evaluate intervention impacts and comparing them to the baseline model results. We also inspected changes in average total PA across time. All interventions start on the first day of the simulated year and among all intervention scenarios, randomly enrolling 200 students was set as the baseline-intervention scenario to be compared with other scenarios.

1) *Scenario 1 - Effects of different scales of the program*: to account for the scope of the intervention, we conducted two separate experiments in which we enrolled 100 and 300 student agents as player agents, respectively.
2) *Scenario 2 - Effect of targeting students with larger BMI as a measure of overweight and obesity*: 200 student agents with BMI over 25 were randomly selected as PG player agents as the intervention.
3) *Scenario 3 - Effect of distance to community center*: we performed two experiments by (1) randomly selecting 200 student agents who live close to the community center (within 1000m radius to the center point (0,0), and (2) student agents who live farther from the center (beyond 3000m radius to the center point (0,0)), as shown in Figure 8.

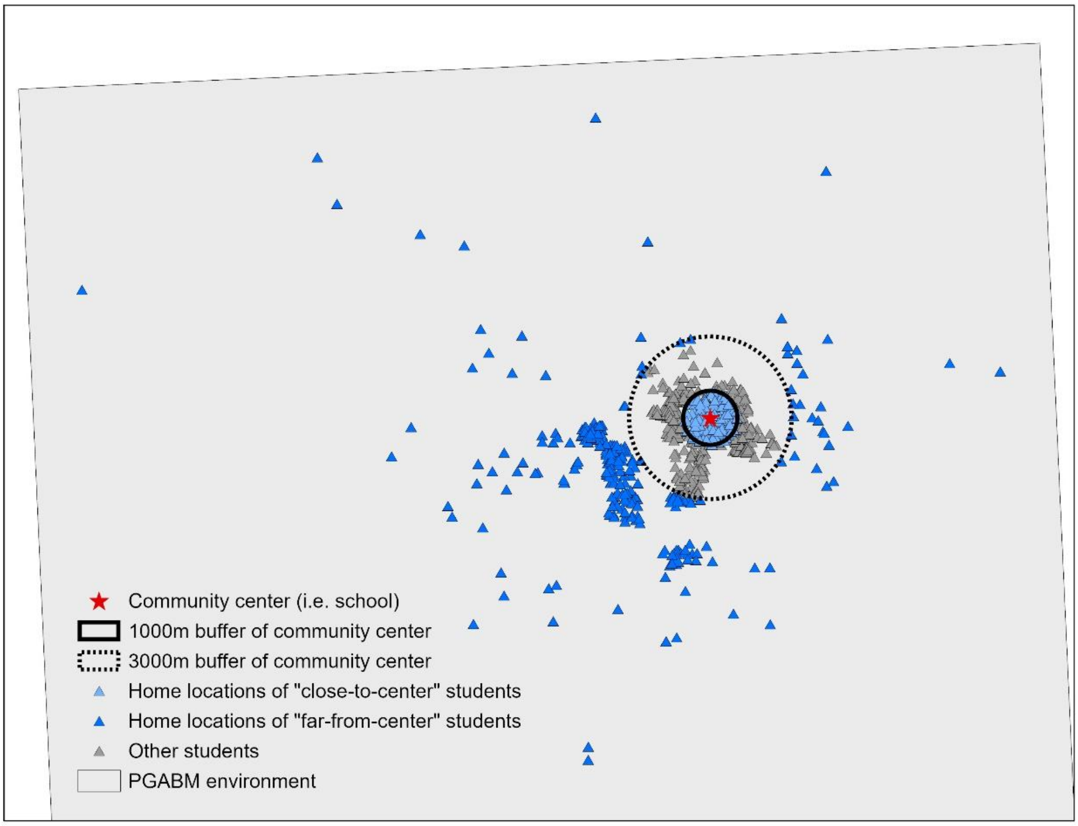

Figure 8: Illustration of scenario 3

(Note: for demonstration purpose, not all students' home locations of the sample school are shown in the figure)

Simulation and data analyses platforms

The ABM was coded in Python 3.8.3. The run time per experiment (N = 20) was about 688 minutes (34.4 minutes per run) on a desktop (Intel ® Core ™ i5-4460 CPU, 3.2GHz, 8GB RAM). Data analyses were performed in R 3.5.3.

Results

Baseline model

The mean of simulated total PA was slightly higher than the observed mean at Wave 2. After 20 runs, the baseline model yielded an average of 3.400 (SD = 1.759) total PA of all 948 students at the end of the simulated year, whereas the mean of observed total PA at Wave 2 was 3.262 (SD = 1.929). In terms of distribution, the majority of student agents had a total

PA of 4, but, in the observed data, the total PA at Wave 2 peaked at the value of 3. The modeled data fitted well at extreme values (total PA = 0 or total PA > 6).

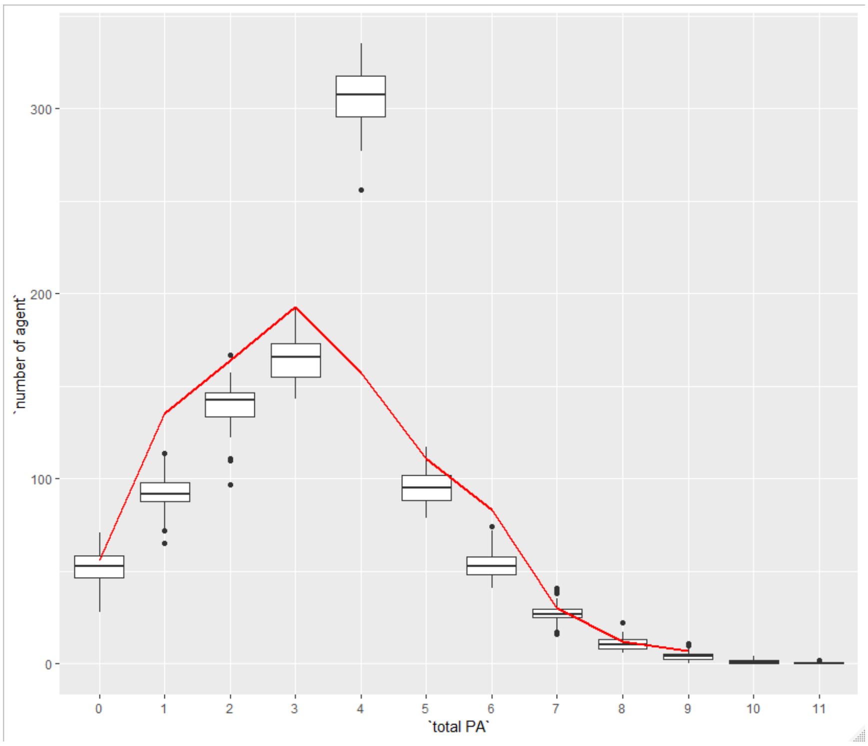

Figure 9: Distribution of simulated weekly total PA (boxes) and observed value at Wave 2 (solid line)

We then examined the structural characteristics of the simulated networks. In general, our simulated networks were sparser than the observed data at Wave 2. In terms of edge density, i.e. the number of friend-nominates over the total possible number of nominations, the simulated networks (mean = 0.0012, SD = 2.3×10-5) had lower values than the observed network at Wave 2 (edge density = 0.0017). Regarding triad census, in the empirical data, there were only one 3-cycles (type 030C in Holland and Leinhardt (1970)), which was also rare in simulated data (mean = 0.240, SD = 0.476), thus it was not over-simulated. On the other hand, there were 22 complete cliques of size 3 (type 300 in Holland and Leinhardt (1970)) and 78.880 (SD = 3.788) in simulated networks, indicating that it was not under-simulated.

Lastly, we inspected the distribution of in-degrees and out-degrees. As shown in Figure 10, the model over-simulated the number of isolates (in-degree = 0) and, in turn, the frequencies of other in-degree values were lower than the empirical data. The out-degree distribution is shown in Figure 11. The model over-simulated low values (0 and 1) and under-simulated higher values (2 to 6). It fitted high out-degrees (> 6) well compared to the empirical data.

In general, we think the baseline model is acceptable for exploring the impacts of the interventions due to serval reasons, which are elaborated in the discussion section.

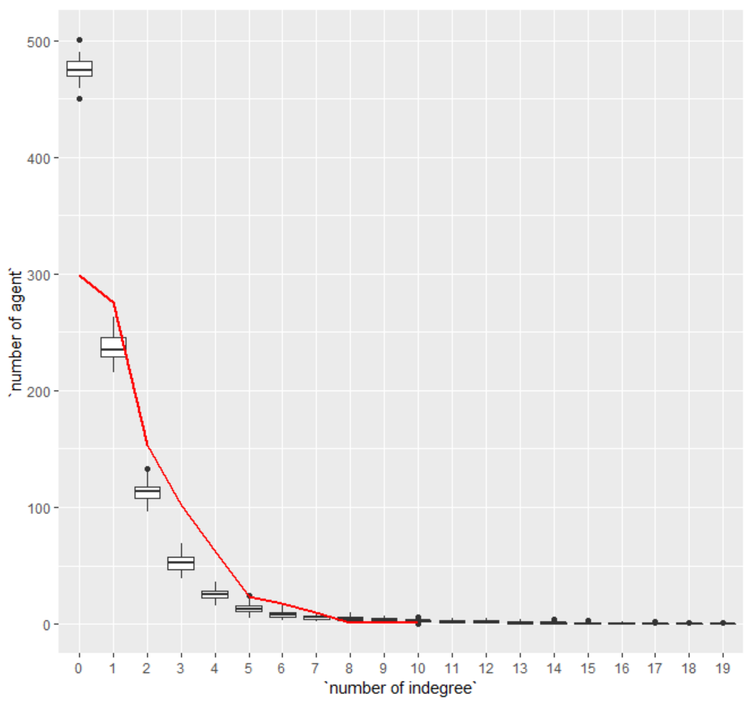

Figure 10: Distribution of simulated in-degree (boxes) and observed network at Wave 2 (solid line)

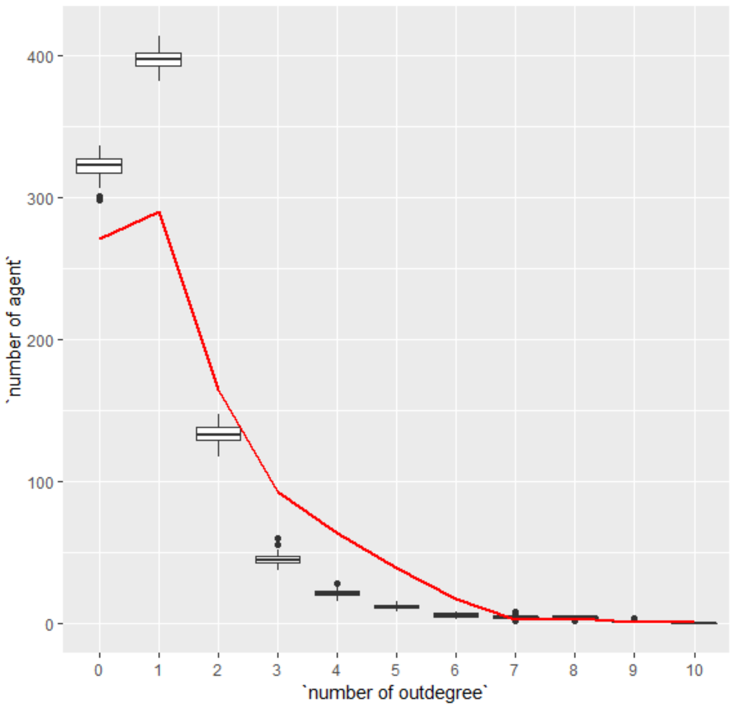

Figure 11: Distribution of simulated out-degree (boxes) and observed network at Wave 2 (solid line)

Scenario results

The average total PA of all student agents, player agents, and non-player agents for each scenario is shown in Table 14. Below, we briefly describe the results of all the scenarios we tested.

Table 14: Summary of scenario tests

Mean simulated school average total PA (SD of total PA) (Number of runs = 20)							
	Timepoint	100 Players	200 Players (**baseline scenario**)	300 Players	200 players with BMI > 25	200 players close to center	200 players far from center
All student agents	end of simulation	3.791 (1.763)	3.767 (1.784)	3.773 (1.761)	3.757 (1.785)	3.787 (1.788)	3.780 (1.786)
	end of 1st Week	4.413 (1.815)	4.659 (1.950)	4.901 (2.039)	4.658 (1.964)	4.660 (1.983)	4.640 (1.876)
	end of 51st Week	3.793 (1.766)	3.770 (1.784)	3.779 (1.762)	3.763 (1.780)	3.790 (1.788)	3.783 (1.781)
Player agents	end of 1st Week	6.478 (1.952)	6.474 (1.978)	6.445 (1.955)	6.502 (2.056)	6.632 (2.010)	6.163 (1.856)
	end of 51st Week	3.745 (1.752)	3.684 (1.762)	3.707 (1.762)	3.686 (1.808)	3.783 (1.770)	3.591 (1.786)
Non-player agents	end of 1st Week	4.169 (1.634)	4.174 (1.630)	4.186 (1.643)	4.165 (1.614)	4.140 (1.615)	4.237 (1.663)
	end of 51st Week	3.799 (1.767)	3.793 (1.789)	3.812 (1.761)	3.783 (1.771)	3.791 (1.792)	3.833 (1.776)

PA: physical activity; BMI: body mass index.

1. Scenario 1 - Effects of different scales of the program

With 100 randomly selected player agents, the average total PA of all student agents, henceforth referred to as the **school average total PA**, 20 model runs at the last tick of the simulation was 3.791 (SD of total PA= 1.763, SD of simulation mean = 0.058), which is 11.5% higher than the average value from the baseline model (3.400 at the end of the year). We also examined the school average total PA by the end of each week throughout the year. The highest average value (4.413) was recorded in the first week. This was expected given that the PG intervention took place on day one. The weekly average total PA had a decreasing trend (as shown in Figure 12) since player agents gradually collected fewer Pokémon creatures over time due to fading interests. According to the simulation data, all players quitted the game completely around the 20th week. We also separately analyzed player agents and non-player agents. Player agents had average total PA at 3.745 at the end of the 51st week, which is 10.1% higher than the end of simulation mean of the baseline model, indicating that, even though the players quitted the game before the middle of the year, the impact of the intervention prevailed. Interestingly, although non-player agents did not directly engage in the intervention, their total PA was boosted due to social influence, which is the spillover effect we hypothesized. In the 51st week, non-player agents' average total PA was 3.799, slightly higher than the mean of player agents (3.684) at the end of the year.

When increasing the number of player agents, we observed a similar decreasing pattern of the school average total PA. With more player agents, the school average total PA was higher at the beginning of the simulation. However, after 16 weeks, when the majority of player agents quit the game, the school average total PA curves started to merge as shown in Figure 12. Surprisingly, a higher number of player agents did not affect the school average total PA at the end of the year. Moreover, with more player agents in the system, the average total PA of player agents did not vary much at the end of week one, suggesting that, by enrolling more students in the intervention program, the magnitude of the intervention effect on the average total PA of player agents would not be greatly influenced. On the other hand, the average total PA of non-player agents at the end of week one increased along with the higher enrollment, which suggested that a larger scale of the intervention would cause greater spillover effects on students who did not participate in the intervention program. This is because with more player agents enrolled in the program, more non-player agents have more friends playing the PG, which led to greater impact on non-players through social interactions.

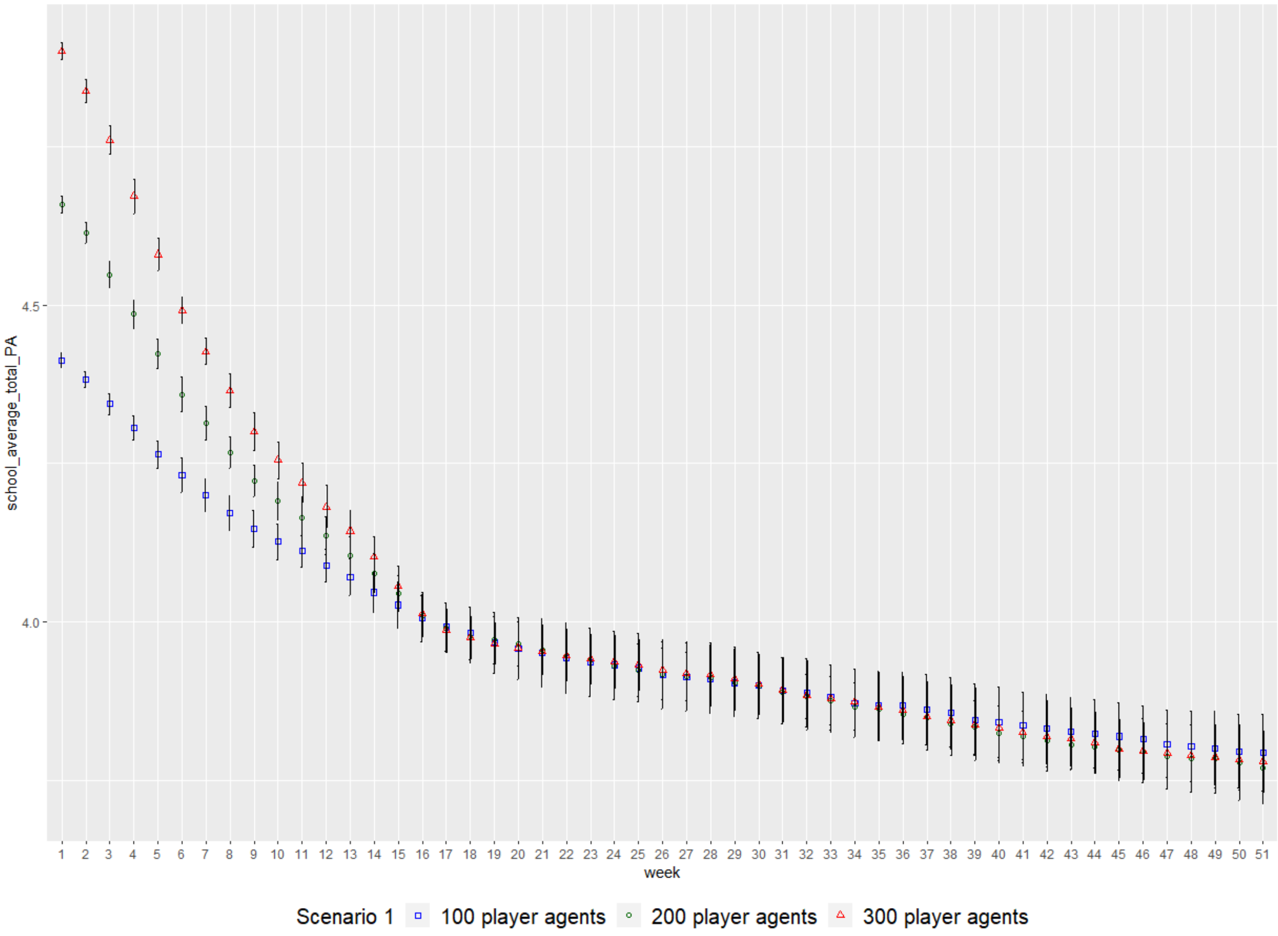

Figure 12: Scenario 1 - Effects of different scales of the program (dots: mean of 20 models runs; bars: ± 1 standard deviation of simulation means)

2. Scenario 2 - effects of targeting students with larger BMI

The second intervention focused on targeting student agents with BMI larger than 25, to see whether the game could exert an impact on the school average total PA. Results (Figure 13) show that, during the simulated year, enrolling 200 student agents will larger BMI leads to little change in school average total PA when compared to the baseline scenario (i.e., randomly selecting 200 of player agents). This suggests that, to promote overall PA, targeting large-BMI students does not necessarily lead to a change in the intervention impact. According to Table 4, at the end of the first week, the average total PA of player agents seemed to be slightly higher and the average total PA of non-players seemed to be slightly lower comparing to the baseline scenario, which might suggest that the intervention effect was slightly stronger among overweighted player agents but the spillover effect was weaker.

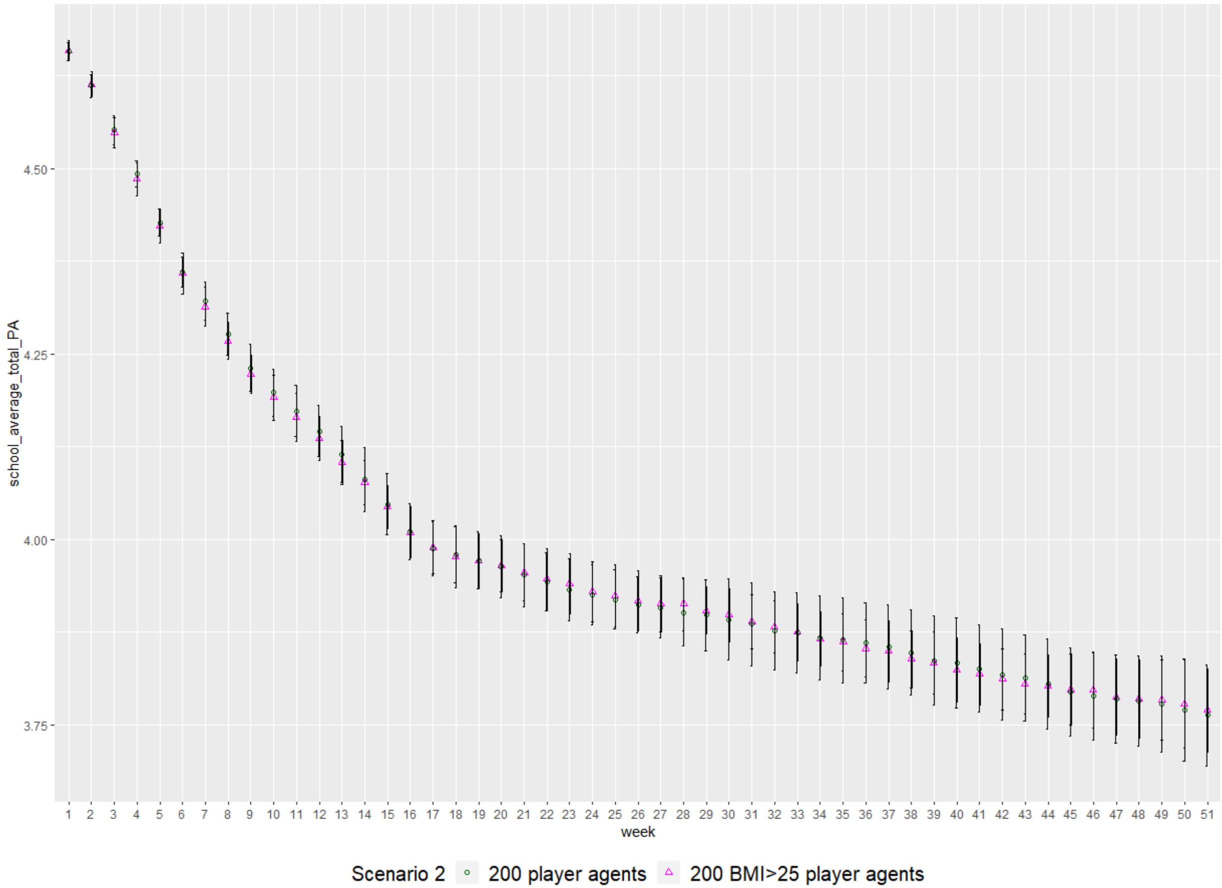

Figure 13: Scenario 2 - Effects of targeting students with larger BMI (dots: mean of 20 models runs; bars: ± 1 standard deviation of simulation means)

3. Scenario 3 - Effects of distance to the community center

In this scenario, we did two tests: randomly (1) enrolling 200 student agents who lived within 1km of the community center, and (2) enrolling 200 random students who lived over 3km from the community center. Based on our observation of the Add Health data, the higher residential density was closer to the community center, gradually decreasing with distance. In the baseline model, distance to friends can influence agent's social network dynamics i.e., agents were more likely to be friends with those who lived closer to them.

In the test of selecting player agents living close to the community center, we noticed that there was little difference in the initial impacts on all student agents between the test and control groups in terms of the school average total PA at the end of the first week (4.660 and 4.659, respectively). As shown in Figure 14, the close-to-community-center group overlapped well with the baseline scenario at the beginning, and towards the end of the year, the close-to-center group showed a slightly higher mean than the control group. This suggests that the lasting impact of the intervention might be a little stronger in terms of boosting the school average total PA. When we examined player agents and non-player agents separately (Table 14), the player agents' average PA was higher whereas non-player agents' average PA was lower than the baseline scenario group. This pattern was consistent in both week 1 and week 51. Within scenario 3, at the beginning of the year, player agents' average total PA was much larger than non-player agents', but smaller at the end of the year. This could indicate that, during the intervention, enrolling close-to-community-center student agents would exert greater impact on player agents, but such an impact would not last long after player agents quitted the game.

Interestingly, enrolling student agents living far from the community center led to an opposite pattern. While the school average total PA in "enrolling close-to-community-center student agents” scenario aligned well with the baseline scenario at the beginning of the intervention, the school average total PA in “enrolling far-from-community-center player agents” scenario started with a lower mean on week 1 and then overlapped with the baseline scenario towards the end of the simulated year. As shown in Table 14, when applying intervention on player agents who lived on the periphery, the direct impact of the intervention on player agents’ PA was weaker, but the spillover effect on non-player agents was stronger (compared to the baseline scenario group). The spillover effect was also larger than other tested groups.

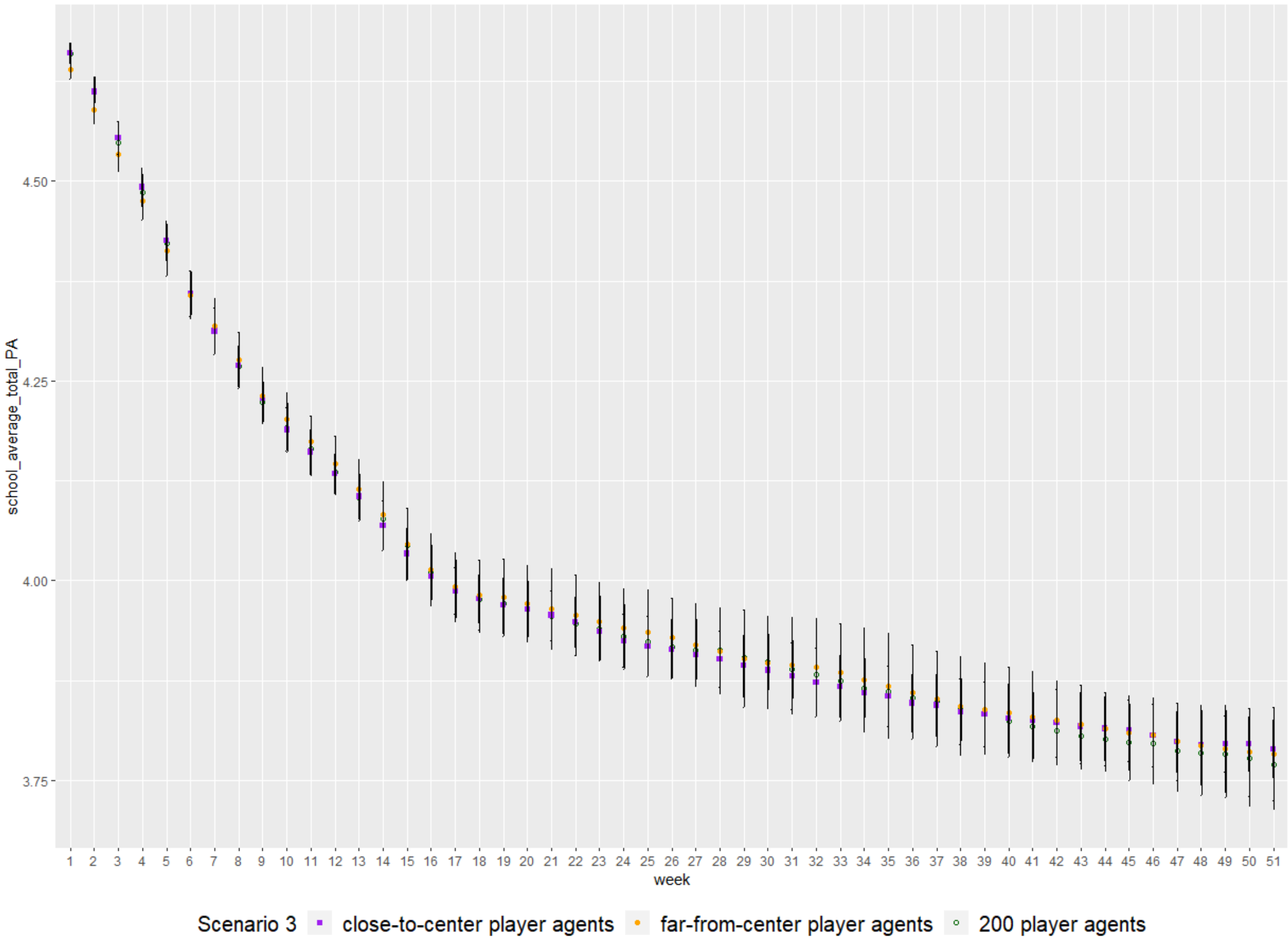

Figure 14: Scenario 3 - Effects of distance to community center (dots: mean of 20 models runs; bars: ± 1 standard deviation of simulation means)

Discussion

In this study, we presented a modified and extended ABM that integrates: (1) social network dynamics developed from empirical data, (2) spatial components, and (2) a novel PG-based intervention on behavioral change. To the best of our knowledge this is the first study that integrates these three components to address public health problems. In the context of our PGABM experimentation, we found that 1) an increase in PA of player agents due to the intervention can influence non-player agents' total PA by a considerable amount; 2) enrolling more student agents into the intervention would not lead to more increments in school average total PA, but the spillover effect on non-player agents was slightly greater with an intervention on a larger scale; 3) targeting student agents with large BMI values was not effective in terms of promoting the school average total PA, but had the greatest impact on player agents' total PA during the intervention; and 4) The spillover effect on non-player agents was the greatest by enrolling far-from-community-center student agents, and the weakest by enrolling close-to-community-center student agents.

The spillover effects were expected in the simulation results because our baseline ABM and PGABM were built based on a social network model. Our social network model indicated that individual's PA level would affect that student's friend selection, and in the meantime, an induvial would adjust his or her PA level to be close to the PA level of close friends via an assimilation process. These friend selection and social influence processes were built into the baseline ABM and the PGABM. Through our PGABM, as expected, we demonstrated that PA-promoting intervention can not only boost the PA of program participants but also influence non-participants through social interaction. The same mechanism is very likely to stay true for other forms of PA interventions. We also observed some variations among scenarios, mainly related to the difference between players and non-players.

However, due to the complexity of the system caused by multiple influential factors in both friend selection and behavior change dynamics, the magnitude and the scale of the impacts from the intervention could vary. We hypothesize that the slightly stronger PA-promoting benefits during the intervention among high BMI players and close-to-community-center players are associated with homophily/spatial effects (BMI similarity/home distance to friends) and social influence from associated peers. The PA-promoting influence of the intervention was exerted directly on players. For example, the school average total PA was 3.694 at the beginning of the simulation, and by the end of week one of the PG intervention simulation of enrolling 200 random player agents, player agents' average PA was 6.474 (Table 4), which was a 75.3% increment. Students who had similar BMI or live closer to each other were more likely to be friends, and their friends’ behavioral change influenced theirs. Now, these students sharing a common attribute (i.e., similar BMI or live close to each other) happened to be the intervention participants at the same time. The impact of the intervention on themselves, as well as the increased PA of their friends, formed a reinforcing feedback. Consequently, while in the intervention program, the PA promotion impact on players was larger. On the contrary, for students who live around the periphery of the model environment, the average home distance between players was much larger and it was very likely that many of the players’ friends were not in the player groups. As a result, the within-group reinforcing influence was week but the spillover effect on non-players became stronger, compared to other scenarios.

Strengths and limitations

This study has a number of strengths. The ABM we built for exploring PA intervention integrated empirical social network data, geographic locations, and a novel mobile-game-based intervention, which few studies have done to the extent of our knowledge. We also lay out a framework for creating such an intervention exploration platform from a social network analysis, which makes this model easy to replicate. It can also be migrated to other study areas with different types of interventions. The exploration of the different intervention scenarios demonstrated that the impacts of the intervention on participants and non-participants would vary due to social network and network dynamics. This could shed light on the importance of considering the social interactions among adolescents in policy making or launching school-based or community-based interventions. Also, when evaluating existing or on-going intervention programs, this study demonstrates that the spillover effect could be prominent, but its benefits and its underlying social interaction mechanism can be easily overlooked.

We recognize some limitations to this study. While ABMs are useful for exploring different intervention scenarios, they are not well-suited for prediction either at the population level or at the individual level. Moreover, the limitations of the underlying models were carried over to our ABM (social network and behavior dynamics are based on a Siena social network model and the ABM baseline model was derived from an existing study (Zhang et al. 2015b)). We also noticed that our baseline model did not fit the observed data as well as the ABM in Zhang et al. (2015b). There are several possible reasons for that. First of all, our model used a different sample school with a diverse population and included different social influences and homophily effects. There might be more uncertainty due to the different model inputs from another school context. Secondly, unlike the other model that used BMI (a continuous variable) as the outcome variable, our model simulated total PA, which is an ordinal variable. In the Zhang et al. (2015b) model the extreme BMI values were treated separately. On the contrary and due to our objective of studying the impact of PG intervention on PA, we did not set upper and lower bounds for total PA values. The total PA value in the observed data ranges from 0 to 9, but our simulated total PA can be as large as 15, thus the average total PA simulated from our baseline model is higher than the observed data.

With that being said, we still think the baseline model is acceptable to be used for addressing our research questions due to its empirical data-driven background and rooted from well-established computational models. Unlike most ABMs that generate a social network by randomly selecting agents or used simplified social network models like small worlds, the Siena stochastic actor-based model was calibrated using true and complete social network data. Consequently, using parameters and algorithms based on the Siena model to simulate social interaction in our ABM ensures a more reasonable linkage with reality (Auchincloss and Diez Roux 2008). Also, in our baseline model validation, the distribution patterns of network characteristics were persevered when compared to the observed data.

We also recognize other limitations of our ABM. Although we tried to cover the major game features and parameterize the model based on published studies, there are still a lot of simplifications and arbitrary assumptions in the intervention component of the model. This again, made the model not suitable for prediction. Also, this model may not be generalizable and applied to other schools, as Siena model parameters were estimated based on data from a specific selected school. There are also limitations in the Add Health data, especially the age of the datasets. The first two waves of data were collected between 1994 and 1996 and are now ~25 years old. Friend selection and social influence processes and as well as influential factors most likely changed since then.

We need to point out that our PGABM was not designed as a prediction model but created with a goal of exploring possible outcomes and answering “what if…” questions when it is hard and resource-consuming to test all those intervention scenarios in the real world. Among countless possibilities to design and simulate the proposed interventions via an ABM, our PGABM is only one candidate model under a series of assumptions introduced previously in our Method section. We argue that among the infinite number of ways to model this complex system, our PGABM is a good proxy as we made most of our assumptions based on empirical data. On the other hand, a wide range of possibilities are open to other scholars to modify our PGABM or employ a completely different model design.

Finally, given the number of uncertain inputs in our model, in the future we plan to perform comprehensive uncertainty and sensitivity analyses to further identify the most influential variables and improve the accuracy of our model.

Policy implications

This study demonstrates how mobile games may influence players’ PA and lead to behavioral change among non-players, which may shed light on policymaking or initiatives of PA-promotion interventions on adolescents. In our study, we used PG as an example, but there are innumerable possibilities of taking advantage of mobile games in general to provide health benefits. Studies suggest that self-motivation and determination play an important role in long-term weight loss and weight control (Teixeira et al. 2012). However, interventions targeting overweighed or physically inactive adolescents may not engage participants with less motivation to commit to behavioral change. Mobile game-based intervention may make it easier to engage more adolescents into the program.

Previous studies have shown that players' interests in the game fade gradually over time. The same issue of long-term efficacy is faced by other active video games that have been considered as means of PA promotion (Biddiss and Irwin 2010). It remains to be seen whether and how such an intervention could lead to a long-term increase in habitual PA. Retaining the loyalty of users is also a challenge to game developers. Consequently, there are plenty of opportunities for the industry and academia to work together on developing more effective PA promotion apps or mobile games with health benefits as an added bonus.

We were only able to explore a limited number of scenarios of intervention. In future work, we are interested in investigating more scenarios if more contexts and spatial data are available. Currently, most of the obesity prevention programs are behavior-oriented. Fewer are focused on environmental community or environment-based prevention (Weihrauch-Blüher et al. 2018). While the intervention proposed in this study directly targets humans, we have also demonstrated that PA behaviors can be shaped by the environment through interactions between agents, i.e. student players, and the community neighborhood. For instance, the density of PG creatures, Pokéstops, and Gyms can directly influence game enjoyment. Other environmental factors, such as walkability, climate, safety, or neighborhood aesthetics, can also affect player's experience and experiences of all other outdoor exercisers.

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CHAPTER 4: CONCLUSION

Revisiting research questions

In this dissertation, I investigate the influence of social network and built environment (including home locations) on dynamics of adolescents' physical activity (PA) aiming to answer three research questions.

Question One focuses on testing whether the social influence in a school context plays an important role in affecting adolescents to conform to taking Physical Education (PE) classes. I address this question in Chapter One, where I use two waves of Add Health data and a regression based social influence model. Results show that, among all factors we examined, previous year's enrollment status had a significant impact on the following year's enrollment, which is consistent in both sample schools tested. On the other hand, the model results show that observation of PE enrollment status from all nominated friends in the previous year was not significantly associated with individual's enrollment status in the following year, indicating that the influence from nominated friends was weak. Interestingly, I found that the exposure to the PE enrollment behavior of 'similar others', defined as students of the same gender AND the same grade, exerted impact on a student's PE enrollment, and this influence varied in different school contexts. These results suggest that school culture and norms may be more influential on adolescents' PE-taking behaviors compared to the direct impact from nominated friends.

Question Two focuses on studying the joint influence of the neighborhood environment and friendship network on high school students' weekly PA. In Chapter Two, I use two waves of Add Health data from two large sample schools to build two Siena coevolution models. I found that environment of neighborhoods had exerted weak influence on adolescents' network and PA dynamics, but their PA could be influenced by friends via an assimilation process. However, space still matters as we discovered that students who lived closer together were more likely to form a friendship tie. Thus, I am not able to draw a certain conclusion about whether social network and/or the environment exert influence on adolescents' PA, or which one is more influential.

Question Three studies the effects of PA-promoting interventions on both participants and non-participants, given the joint impact of social network and space. In Chapter Three, I replicate an existing ABM derived from a Siena social network model by introducing a Pokémon-Go-type mobile game as an intervention to promote adolescents' PA. I found that due to social influence and friend selection processes, the intervention impact on participating students might also influence students who did not enroll in the intervention program, called a spillover effect. By testing different scenarios, I also found that the impact on intervention participants and non-participants could vary, when the intervention targets students with larger body mass indexes or students living close to versus far from the community center.

By addressing these research questions, this research contributes to the current literature on childhood obesity and health geography in two ways. First, spatial and environmental variables are often overlooked in existing studies on the relationship between obesity and social networks. Empirical social network data and social network dynamics are usually missing components in studies on obesity in the field of health geography. This interdisciplinary research integrates social network analysis and spatial thinking to investigate the joint influence of environmental and social spaces, facilitating a more comprehensive understanding of the complex system related to childhood obesity. Second, this research extends an existing model and develops a spatial agent-based model as a tool to explore a novel intervention, the Pokémon

Go mobile game. In addition to detangling social influence, friend selection, neighborhood environment, and location of homes, this study also provides an experimental platform for seeking possible mitigation strategies for the childhood obesity problem. The ABM presented in this research can be used by other scholars and can be calibrated using more up-to-date social network data from different sample schools for the purpose of either exploration or education.

Additional thoughts about the practical implications

From the Add Health data, I observed a decreasing enrollment rate when students enter higher grades. Based on the results of the analyses, in terms of promoting high school students' PA through PE, it may be important to cultivate a habit of participating in PE since the freshman year. In reality, however, promoting PA and preventing obesity among adolescents through PE could be very challenging. PE taking is greatly influenced by policies, rules, cultures, and many other factors. Oftentimes, for students entering the ninth grade, their PE participation suddenly becomes challenging because they have to change clothes in a crowded locker room, which could be an embarrassing and overwhelming experience (Kunichoff 2018). In many schools, PE classes are required for freshman and sophomore students, but after fulfilling the credit requirements, many students stop taking PE and devote time to preparing for college. Some athletic students and students in the marching band may apply for waiver to skip PE classes (Fieldman and Chuck 2017). On the other hand, those senior students who stay in PE feel that they have no friends in the class and they do not want to make friends with students from lower grades (Hwang 2017), which makes it hard for senior students to stay in PE classes. Consequently, it is important to initiate policy changes by putting ourselves in adolescents' shoes to understand their needs and challenges instead of simply forcing PE enrollment.

PA-promoting interventions could be school-based, family-based, or community-based, but many times, the implementation and evaluation are actually multi-scaled. In this study, the intervention can be viewed as a school-based one since participants were all selected from the same school, and the social interaction that contributes to the spillover effect was due to the friendship network formed in the school context. However, the "playing" behavior itself actually happened in the neighborhood. As it was discussed in Chapter Three, PA behavior can also be shaped by the environment, which is a neighborhood level factor. Taking the Pokémon Go intervention as an example, if the neighborhood environment is equipped with amenities that encourage mobile gaming, such as more Pokéstops, increased safety, better pedestrian paths, more greenspace and trials in parks, participants will most likely increase the frequency and intensity of playing. At the family level, if parents play the game with their kids, it may encourage the student players to stay active longer due to family support, while the spillover effects also extend to their family members.

Limitations and future work

The limitations of this study have been discussed in Chapter One, Two, and Three, respectively. A common limitation of all these analyses is the age of the data. The Add Health Wave 1 and Wave 2 data used in this study were from 1990s, which is almost 30 years ago. The relationship among students, their friends, the school contexts, and the built environment may have dramatically changed. The sedentary and active behaviors that high school students did two to three decades ago were also different from nowadays. Due to limited resources, I was not able to access or collect more current data to answer my research questions. Future improvements are limited until new and complete social network data is collected. Such longitudinal data from other countries can also be used for comparative analyses, since obesity is a worldwide issues, even in some developing countries (Bhurosy and Jeewon 2014).

A second limitation of the entire research is its generalizability. Since models used in this study were calibrated using two selected sample schools, it is hard to apply model parameters and findings to other cases. Additional analyses are needed to test if the significant relationship detected in the selected sample schools stays true elsewhere.

Third, many of the environmental and sociodemographic factors have not been fully explored due to the lack of data. To protect participant identities, the actual geographic location of their schools and homes are unknown. This makes it impossible to fully understand the social contexts of the study subjects. For example, the finest resolution of the neighborhood environment variables is 1km. Without knowing the actual network, our estimation of accessibility is most likely biased. For example, if there was a park within 1km Euclidean Distance, but there was also an interstate highway between the participant's house and the park, it would make the park not accessible by walking even though it was not far. Another example is that, in our ABM, we spread the game features evenly across space. If local distribution data were available, and we could allocate more features alone the road network and the game environment would closer to reality. I also did not add visualization to our spatial ABM due to its computational cost. I would like to add to this functionality the current ABM in the near future. The users of the model would then be are able to visualize the spillover effects and the dynamics of PA during simulations.

Lastly, a comprehensive sensitivity analysis would be a very important and helpful supplement to this research, which is my next step. The sensitivity analysis could be useful to detect variables that contribute the most to the output variance and facilitate model simplification. It would also be helpful in guiding future data collection in terms of data resolution and accuracy control.

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