The Distribution of Physical Activity in an After-school Friendship Network

WHAT'S KNOWN ON THIS SUBJECT: New, effective approaches to obesity prevention are urgently needed. Social network interventions warrant our attention. Social networks play a significant role in adult and adolescent obesity. The role of social networks in pediatric obesity has not been examined.

WHAT THIS STUDY ADDS: Afterschool friendship ties play a critical role in setting physical activity patterns in children as young as 5 to 12 years. Children's activity levels can be changed by the activity level of their social network during a 12-week afterschool program.

abstract

OBJECTIVE: To examine whether a child's friendship network in an afterschool program influences his/her physical activity.

METHODS: Three waves of data were collected from school-aged children participating in aftercare (n = 81; mean [SD] age, 7.96 [1.74] years; 40% African American, 39% white, and 19% Latino) a name generator survey was used to map each child's social network, and accelerometers were used to measure physical activity. We applied stochastic actor-based modeling for social networks and behavior.

RESULTS: Children did not form or dissolve friendships based on physical activity levels, but existing friendships heavily influenced children's level of physical activity. The strongest influence on the amount of time children spent in moderate-to-vigorous activity in the afterschool hours was the activity level of their immediate friends. Children consistently made adjustments to their activity levels of 10% or more to emulate the activity levels of their peers (odds ratio [OR] = 6.89, $P < .01$). Age (OR = 0.92, $P < .10$) and obesity status (OR = 0.66, $P < .10$) had marginally significant and relatively small direct effects on the activity. Gender had no direct effect on activity.

CONCLUSIONS: These results suggest that friendship ties play a critical role in setting physical activity patterns in children as young as 5 to 12 years. Children's activity levels can be increased, decreased, or stabilized depending on the activity level of their immediate social network during a 12-week afterschool program. Network-based interventions hold the potential to produce clinically significant changes to children's physical activity. *Pediatrics* 2012;129:1064–1071

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KEY WORDS

obesity, physical activity, attitude, causality, child, humans, longitudinal studies, social behavior, social support, sociology, medical, friendships, social networks, stochastic actor-based modeling, social influence, peer effects, selection

ABBREVIATIONS

MVPA—moderate to vigorous physical activity

OR—odds ratio

This trial has been registered at clinicaltrials.gov (identifier NCT01063413).

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Although obesity has stabilized in some US populations, it is still at epidemic proportions with >23 million children classified as overweight or obese.[1,2] The cascade of adverse health effects associated with childhood overweight and obesity is well established and includes type 2 diabetes, hypertension, hyperlipidemia, abnormal glucose tolerance, cardiovascular disease, and psychosocial problems such as weight prejudice, depression, social isolation, poor self-esteem, and poor academic performance.[3–5] Given the resistant nature of obesity once established, prevention efforts must start early in life. Antiobesity interventions have generally failed.[6–8] New, effective approaches to obesity prevention are urgently needed.

An innovative approach to public health interventions has been proposed by scientists studying social networks. Social networks, the "thick webs of social relations and interactions"[9] that connect individuals to one another, exert measurable influence on our health.[10–20] Several independent research teams have linked social networks to obesity in adults and adolescents.[12,14,20–22] In contrast, there are limited data on social networks and obesity in children.

The extent to which healthy lifestyle behaviors can be influenced by children's social networks is unknown. If healthy lifestyle behaviors can be facilitated through children's social ties, such that when one child engages in physical activity, those children with whom he or she is connected will be more likely to engage in physical activity, then we could develop novel intervention strategies that leverage the social influences of social networks to make a real impact on childhood obesity. Specifically, to deem physical activity a candidate for network-based intervention strategies, we would need evidence of not just individuals clustering (ie, choosing to form or dissolve social ties) based on physical activity levels, but evidence of changes in their behaviors (ie, being more or less active) because of influence from their social ties.

One promising model for research on this topic is derived from studies on the coevolution of adolescent social networks and the use of alcohol and tobacco.[23–26] Through the use of newly developed stochastic actor-based models, these studies have been able to disentangle the complicated interplay between friendship selection (along lines of visible health behaviors) and behavioral influence (due to social ties). In this study, we extended such actor-based models to the study of the coevolution of friendship networks and physical activity. Thus, the purpose of this article is to test two research questions:

Research Question 1: Do children form or dissolve friendships based on physical activity levels? (Selection Effect)

Research Question 2: Is there child-to-child influence on physical activity behaviors over time? (Influence Effect)

METHODS

Study Population and Design

Public school students in 2 structured aftercare programs were invited to participate in a study to evaluate the routine physical activity levels of children in aftercare programs. Inclusion criteria included the following: (1) child age ≥5 years; (2) enrolled in school; (3) parental permission to copy official school records. The aftercare programs followed similar formats, operated from 3:00 to 6:00 PM Monday through Friday, and included time for snacks, homework, and play (eg, playground, gymnasium, art, board games). One aftercare program was based in a school. The other was based in a community center and drew children from the same school that the school-based program was located in, and from other schools in the same district, as well. Baseline data were obtained from 83 children, of whom 81 provided useable social network data.* The study was approved by the Vanderbilt University Institutional Review Board (IRB#090986).

Data Collection

All data were collected by trained study staff during the normal operating hours of the afterschool programs. All data were collected at 3 points over a school semester (February through May 2010), with 6 weeks separating each wave of measurement. The measurement period was guided by the Cochrane Review that pediatric obesity prevention interventions should be at least 12 weeks in duration for behavior change to occur.[27]

Measures

Physical Activity

Physical activity was assessed by using the ActiGraphGT1M accelerometer (ActiGraph LLC, Pensacola, FL). The ActiGraph is a small, lightweight monitor that is worn on a belt around the waist and measures the intensity of physical activity associated with locomotion. Monitors were programmed to record in continuous 10-second epochs to capture the short, spurtlike activity characteristic of children. Accelerometry has been used successfully in studies with children,[28–32] including Latino and African American children,[28–32] with high reliability, $r = 0.93$.[33] For each of the 3 waves of measurement, children wore monitors for 5 consecutive days from the time they signed into the afterschool program until

*Because of the nature of the statistical methods used in this study (stochastic actor-based modeling) pre hoc power analysis in the traditional sense of the term was not directly applicable. Given 3 measurement waves of behavioral data on 81 participants and $N \times (N - 1) \times 3$ social network data points, we were confident at the outset of the study that sufficient power would be achieved. See ref 26.

they were picked up. The monitors did not provide the wearer with any feedback. Every child wore an accelerometer for a minimum of 60 minutes each day of measurement. Validated threshold values were used to derive time spent in sedentary, light, moderate, and vigorous activity.[34] The analysis of raw accelerometer data was performed by using a procedure similar to that used to analyze the NHANES data.[35]

Social Network

To map each child's social network, an open-ended survey was administered in private 1:1 interviews. Students were asked, "Please tell me the names of the friends you hang around with and talk to and do things with the most here in this after-school program." Children were allowed to nominate as many friends as they liked. This sociometric question (known as a name generator) is comparable to that used in other youth social network studies.[20] At waves 2 and 3, children were not shown the names of friends they had previously generated, but rather were asked to report on their friendships entirely anew to capture the friendships that were most salient to children at each time of measurement. The size of each child's network was reflected in both the number of friend nominations made, as well as the number of nominations received. To maximize the statistical power available for these analyses, sociometric data from each afterschool setting ($n = 46$ and $n = 35$ respectively) were combined into 1 single network of 81 nodes, where ties between children not attending the same afterschool program were coded as structurally impossible. By combining these networks for analysis, we made the assumption that the dynamics of friendship selection and friendship influence on physical activity behavior were consistent across these 2 aftercare settings, an assumption we found reasonable.

Anthropometrics

Body weight was measured, while wearing light clothing without shoes after voiding, to the nearest 0.1 kg on a calibrated digital scale (Detecto, Webb City, MO, model 758C). Body height without shoes was measured to the nearest 0.1 cm with the attached stadiometer. BMI percentile was calculated by using the Centers for Disease Control and Prevention calculator, where children with BMI ≥95th percentile were classified as obese.[36]

Demographics

Parents completed a demographic survey on the child's date of birth, gender, race/ethnicity, and school.

Statistical Analysis

Physical Activity Data Analysis

Physical activity was obtained from ActigraphGT1M accelerometer data collected in 10-second epochs. Time spent in physical activity intensities was based on activity counts: thresholds <420 activity counts for sedentary, 420 to 1679 counts for light, 1680 to 3379 counts for moderate, and >3379 counts for vigorous intensity activity per minute.[37] Time spent in sedentary behavior or physical activity was determined by summing minutes in a day where the count met the criterion for that intensity. Daily averages for each level of intensity were computed across all days of measurement. Start and stop times for play were recorded at each site and used as precise cutoff points. This captured the timeframe during which the children had control over their activity level, as opposed to the scheduled snack and homework times, which imposed sedentary behavior. Children spent varying amounts of time in aftercare depending on their family needs. Thus, our outcome measure was the proportion of play time spent in moderate-to-vigorous physical activity (MVPA), rather than absolute minutes in MVPA. Although our outcome measure was continuous, the social network analysis package that was used (SIENA)[38] requires categorical outcome variables for the analysis of social influence on behavior. Therefore, for analysis, we collapsed the data into deciles of percentage of play time spent in MVPA: 0% to 9%, 10% to 19%, 20% to 29%, etc, to 100%.

Social Network Data Analysis

Longitudinal analysis of physical activity and social network data were performed by means of stochastic actor-based modeling as implemented in SIENA† version 4.0.[38] Actor-based modeling assumes that changes observed over time in social ties and individual behaviors are the result of actors' decisions to optimize their position in the network at a given point in time. Observed social networks and behavior, such as can be collected in panel data, are assumed to be outcomes of an underlying continuous-time Markov process. That is to say, between each of the successive observed states of network and behavior captured in panel data, a number of smaller changes occur that are unobserved.[39] The estimation algorithm of SIENA works to arrive at the series of microchanges between observed waves of data that are most likely to have occurred when actors change their social ties or behavior. The rules governing such microchanges take the form of model parameters. Complete descriptions of this method are given by Snijders, Steglich, and colleagues.[39–41]

This approach affords major advantages over those based in classic regression analysis. The first of these is that stochastic actor-based methods allow researchers to directly model the complex dependencies between actors (ie, individuals) in a network. As such, this approach allows for the simultaneous examination of network structural

†SIENA is an acronym that stands for Simulation Investigation for Empirical Network Analysis.

properties resulting from endogenous network effects such as transitive closure (the tendency for a friend of a friend to become a friend), dyadic effects (shared characteristics among members of a dyad), and exogenous effects (such as actor attributes).[40] Inclusion of such network structural properties in the modeling of socially mediated phenomena represents a notable advancement in methodological rigor in that such structural properties (ie, statistical nonindependence between cases), when neglected, have been shown to lead to biased results.[40,41] Of particular interest in this study is the ability of stochastic actor-based modeling procedures to disentangle the twin forces of selection and influence. Selection refers to factors observed in our data that may influence a child's friendship decision-making; these factors include structural properties such as those just named, but also may include actor attributes such as physical activity level, obesity status, gender, age similarity, etc. For each of these factors, the selection portion of our model will report on the likelihood of forming a tie with another child based on their particular attributes. Influence refers to factors observed in our data that may affect a child's behavior, in this case, physical activity level. In this study, we are primarily interested in understanding the effect of activity levels of friends upon the activity level of an individual child, but other direct effects on activity level are also included as controls. Changes in the activity level of a child's social network that precede changes to a child's activity level are the primary source of variability upon which this portion of the model is based. We describe our modeling in further detail in the Supplemental Information.

RESULTS

Sample Demographics

The sample (n = 81) was 40% African American, 39% white; 19% Latino; 65.4% female; 56% healthy weight, 23% overweight, 21% obese; and averaged 7.96 years of age (SD = 1.74).

Changes in Physical Activity

Table 1 describes changes in children's activity levels. The number of children who increased and decreased their physical activity was roughly equivalent; slightly more students maintained their activity levels. Table 2 reports the percentage of play time spent in MVPA.

Changes in Social Network Ties

Table 3 conveys changes in friendship status for all dyads. Children both formed and dissolved friendships. As is often observed in recently formed social networks, the amount of change over the first measurement period was greater than that of the subsequent period. This was reflected in the lower Jaccard coefficient (a measure of similarity in networks across time) for the first measurement period. Both periods satisfied the recommended guideline of Jaccard coefficient >0.30.[39] The overall network average degree (number of friendship ties) trended upward over the 3 waves of measurement, further illustrating that these friendship networks were evolving over the course of the study. On average, children nominated 3.7 (SD = 2.6) friends at wave 1, 5.25 (SD = 3.1) friends at wave 2, and 6.32 (SD = 3.5) friends at wave 3. Control variables are summarized in Table 4.

Results of SIENA Modeling

Results from the SIENA analysis are given in Table 5 and the Supplemental Information.

Selection Effect

The selection portion of the full model yielded large and highly significant parameters for rate of change in the friendship network, with changes in the first period (9.80, $P < .01$) greater than changes in the second period (4.95, $P < .01$). The outdegree parameter (odds ratio [OR] = 0.17, $P < .01$) indicated the general tendency away from having very large numbers of friendship ties in the network, which is a finding common to the vast majority of studies of this nature. The reciprocity parameter (OR = 1.99, $P < .01$) indicated the general tendency to reciprocate an incoming friendship tie. The transitive triplets term (OR = 1.32, $P < .01$), together with the term for 3 cycles (OR = 0.83, $P < .01$), indicated the general tendency for a friend of a friend to become a friend. Controls for similar age (OR = 2.40, $P <$ .01), attending the same school (OR = 1.78, $P < .01$), being the same gender

TABLE 1 Changes in Physical Activity by Period

	Up	Down	Same	Missing
From t1 to t2	26	19	29	7
From t2 to t3	16	34	17	14

TABLE 2 Mean Percentage of Play Time Spent in Moderate and/or Vigorous Activity by Wave

	t1	t2	t3
Mean, %	30.35	31.12	29.40
SD	15.62	15.59	18.94

TABLE 3 Changes in Friendships for Each Dyad by Period

	Tie Change				Jaccard Coefficient
	$0 \rightarrow 0$	$0 \rightarrow 1$	$1 \rightarrow 0$	$1 \rightarrow 1$	
From t1 to t2	5927	253	128	172	0.311
From t2 to t3	5874	181	95	330	0.545

Jaccard Coefficient, measure of similarity in networks across time.

TABLE 4 Actor Attributes Used as Control Variables

	Mean/Proportion	SD
Female, %	65.40	—
Age	7.96	1.74
Weight category		
Normal or Overweight	79.00	—
Obese	21.00	—
Dyads same race, %	34.30	—
Dyads same school, %	28.50	—
Dyads same household, %	0.08	—

TABLE 5 Parameter Estimates (PE) and SEs for the Basic and the Full Model

	Basic Model		Full Model	
	PE (SE)	OR (95% CI)	PE (SE)	OR (95% CI)
Selection: predicting the presence of ties				
Rate of change t1 to t2	7.76**(0.55)	—[a]	9.80**(0.82)	—[a]
Rate of change t2 to t3	4.54**(0.37)	—[a]	4.95**(0.40)	—[a]
Structural effects				
Outdegree	−1.17**(0.09)	0.31 (0.26–0.37)	−1.77** (0.09)	0.17 (0.14–0.20)
Reciprocity	1.00**(0.09)	2.72 (2.28–3.24)	0.69** (0.10)	1.99 (1.18–3.38)
Transitive triplets			0.28** (0.03)	1.32 (1.25–1.39)
3-cycles			−0.18** (0.04)	0.83 (0.74–0.95)
Dyadic effects				
Same race			0.25**(0.07)	1.28 (1.03–1.59)
Same household			0.02 (0.25)	1.02 (0.59–1.74)
Attend same school			0.58**(0.10)	1.78 (1.29–2.46)
Attribute effects				
Gender				
Alter			−0.05 (0.11)	0.95 (0.79–1.14)
Ego			−0.01 (0.09)	0.99 (0.81–1.22)
Similarity			0.44** (0.09)	1.56 (1.27–1.92)
Age				
Alter			0.02 (0.02)	1.02 (0.96–1.09)
Ego			0.02 (0.03)	1.02 (0.98–1.07)
Similarity			0.88**(0.19)	2.40 (1.18–4.91)
Obesity				
Alter			−0.00∼ (0.12)	1.00 (0.70–1.42)
Ego			0.02 (0.12)	1.02 (0.67–1.57)
Similarity			0.01 (0.12)	1.01 (0.76–1.36)
Activity level				
Alter	−0.03 (0.04)	0.97 (0.90–1.05)	0.04 (0.05)	1.05 (0.96–1.13)
Ego	−0.06 (0.04)	0.94 (0.87–1.02)	0.05 (0.04)	1.05 (0.95–1.16)
Similarity	1.82**(0.80)	6.17 (1.29–29.61)	0.02 (0.93)	1.02 (0.15–7.03)
Influence: predicting trends in behavior				
Rate of change t1 to t2	3.89**(0.21)	—[a]	3.94**(0.87)	—[a]
Rate of change t2 to t3	11.63+(6.34)	—[a]	16.45 (34.32)	—[a]
Linear shape	0.17 (0.20)	1.19 (0.80–1.75)	0.16 (0.19)	—[a]
Quadratic shape	0.00[b] (0.03)	1.00 (0.94–1.06)	−0.01 (0.04)	—[a]
Activity level				
Indegree	−0.04 (0.03)	0.96 (0.91–1.02)	−0.03 (0.05)	0.97 (0.87–1.08)
Outdegree	0.02 (0.04)	1.02 (0.94–1.10)	0.01 (0.04)	1.01 (0.94–1.09)
Average similarity	15.47**(3.74)	> 3.43E+03[c]	17.37**(4.88)	> 2.47E+03[c]
Attribute effects on behavior				
Gender (female)			−0.10 (0.14)	0.91 (0.69–1.19)
Age			−0.07+ (0.04)	0.92 (0.85–1.01)
Obesity			−0.41+ (0.22)	0.66 (0.43–1.01)
Program site			0.07 (0.33)	1.07 (0.56–2.06)

Two models, a basic and a full model, are presented, as is best practice in reporting SIENA results. The basic model included essential network selection and influence effects. The full model combined the effects from the basic model with all relevant control variables. Model parameters are described in 2 sections: selection effects (parameters that describe dynamics within the children's social network) and influence effects (parameters that relate to changes in activity behaviors). Parameter estimates divided by standard errors give *t* values for each effect. t values of at least 1.65 correspond to $P \leq .10$ (+), t values of at least 1.96 correspond to $P \leq .05$ (*), and t values of at least 2.58 correspond to $P \leq .01$ (**). CI, confidence interval; Outdegree, the tendency for actors to form ties within the network; Reciprocity, the tendency to reciprocate a received friendship tie; Transitive triplets, the tendency for a friend of a friend to become a friend; 3-cycles, a variant of transitive triplets; Ego, a given variable's effect on the propensity to initiate friendship ties; Alter, a given variable's effect on the propensity to receive friendship ties; Similarity, the propensity for individuals with similar covariate values to form ties; Activity level indegree, the effect of receiving friendship nominations based on level of activity; Activity level outdegree, the effect of initiating friendship ties on physical activity; Activity level average similarity, the tendency for a child to adjust their activity level to be more similar on average to the levels of their immediate friends.

[a] Rate and shape parameters do not have an odds interpretation.

[b] Coefficients that round to values <0.01.

[c] Due to space limitations only the lower bound for the 95% CI is given. See text for interpretation of this parameter.

(OR = 1.56, $P < .01$), and racial identification (OR = 1.28, $P < .01$), each increased the odds of forming a friendship tie. Obesity status was not related to friendship formation.

Research Question 1: The test of the hypothesized selection effect yielded nonsignificant activity level, alter, ego, and similarity terms. Thus, we found no support for the notion that children make or break friendship ties based on physical activity. Across all levels of physical activity, we found consistent patterns in the propensity to make and receive friendship ties with other children.

Additionally, there was no significant tendency for children of similar initial activity levels to choose each other as friends.

Influence Effect

The influence portion of the full model confirmed the rates of changes in activity for the first period (3.94, $P < .01$) but not the second period (16.45, $P = .63$), indicating that individual children significantly changed their activity levels over the first study period. The linear and quadratic shape terms remained nonsignificant, confirming that there was no upward or downward trend in activity level at the group level.

Research Question 2: The test of the hypothesized influence effect yielded nonsignificant terms for both activity level (indegree and activity level) outdegree terms. This indicated that activity level was not affected by a child's number of outgoing or incoming friendships. However, the activity level-average similarity term in the full model retained its sign, magnitude, and statistical significance ($\beta = 17.37$, $P < .01$), indicating that children were very likely to adjust their activity level to become more similar to the levels of their immediate group of friends. To illustrate the magnitude of this finding, consider a child with a MVPA level in the 20% decile category, whose friends all have an MVPA level in the 30% category. The average similarity term here expresses the log odds of making a maximally large adjustment in activity level (across the full range of the variable); our example supposes a 1 category change, or one-ninth of the maximum adjustment. The odds of making a 1 category increase in activity level (versus making no change) would thus be exp(17.37/9), or OR = 6.89 ($P < .01$). Although controls for the direct effect of age (OR = 0.92, $P < .10$) and obesity (OR = 0.66, $P < .10$) on activity were marginally statistically significant, they were relatively small in comparison with the effect of the activity level of a child's immediate friends. Neither gender nor program site had a direct effect on activity.

DISCUSSION

Main Findings

Children did not form or dissolve friendships based on physical activity levels, but existing friendships had tremendous influence on children's routine activity level after school: school-aged children assimilated to the activity level of their closest friends over the relatively brief period of 12 weeks.

Children did not select friends based on activity level. Active children did not have more (or fewer) friends than nonactive children, nor were they more (or less) likely to be chosen as friends. Friendships were more likely to be based on homophily in age, school, gender, and race. We did not find that children preferred children with similar weight status as friends, although other studies have.[14,20,22] A recent study suggests that adolescents were more likely to befriend peers who shared similar attitudes about physical activity than peers with similar activity levels.[42]

The activity level of a child's immediate circle of friends (typically 4–6 children) had a strong effect on the amount of time children spent in MVPA after school. Given the opportunity to either change activity level to match that of their friends, or keep activity level constant, children were >6 times more likely to adjust their activity level. Children became either more active or more sedentary as they emulated the behaviors of those in their immediate network. Another study using stochastic actor-based modeling has recently found that adolescents emulate the physical activity behaviors of their friends.[42] Our finding suggests that children's social networks may be as powerful as those of adolescents.

Implications

The finding that children exert considerable influence on other children's activity levels should be considered when structuring afterschool programs with the intent of increasing physical activity. An intervention that embeds inactive children with active peers may improve activity levels across the entire social network. Such a strategy could start with a group of very active children and implement a "rolling enrollment" of inactive children into the group. It would be critical that these inactive children form friendships with the active children for them to become more active themselves. Once the inactive children assimilate to their active friends, more inactive children would be brought into the group, while maintaining a favorable (albeit as of yet undefined) ratio of active to inactive children, and intentionally preventing the undesirable effect of active children adjusting their activity levels down to those of their sedentary peers.[16]

Limitations

Our study had several strengths and some limitations that have to be considered when interpreting the results.

Accelerometry as a Measure of Physical Activity

Strengths of the study include the use of an objective measure of physical activity. Accelerometers are considered the gold standard for measuring activity under free-living conditions,[43] but they do not adequately measure body movements of upper and lower extremities. To the best of our knowledge, this is the first study to analyze longitudinal social network data and activity measured by accelerometry, rather than by using self-reports, parental self-reports, or children's perceptions of the activity behaviors of friends, all of which are markedly less reliable.

Sample Size and Composition

Sample size was sufficient for determining the effects described above. A potential limitation stems from the fact that the data were drawn from 2 different afterschool environments, but our model controlled for the possible effect of program site on activity level and found no significant differences between these groups. Attempts were made to model these independently and compare differences, although this led to difficulties with model convergence. Additional work in this area would benefit from the selection of larger sample sizes and/or the collection of additional waves of panel data to tease apart social network effects versus shared environment effects. Afterschool networks may differ from other childhood friendship networks. We found that afterschool networks have a notably lower tendency toward reciprocity (OR = 1.99, $P < .01$) in comparison with most childhood friendship networks reported in the social network literature (OR = 7.4[23,25,26]). Despite this structural difference between afterschool networks and other childhood friendship networks, we found significant effects that are of real world importance, because many afterschool programs are trying to increase physical activity to meet state-level guidelines.[44,45]

Control variables

One of the strengths of this study is the inclusion of rigorous network, dyadic, and individual control variables in the modeling to rule out alternative explanations of our findings. The analysis controlled for the most important individual attributes associated with child physical activity (gender, age, and obesity) as well as program site, but cannot rule out the effects of other individual attributes, such as physical activity preferences, intention to be active, self-efficacy, parental overweight status, or healthy diet.[46,47]

CONCLUSIONS

This article showed that (1) friendship ties may play a critical role in setting physical activity patterns in children as young as 5 to 12 years and (2) a child's physical activity level can be increased, decreased, or stabilized depending on the activity level of his/her immediate social network during a 12-week afterschool program. These findings warrant the development of novel interventions that leverage the social influences of children's friendship networks to increase and maintain physical activity at a young age. Social network interventions after school hours hold the potential to produce clinically significant changes to children's physical activity.

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REFERENCES

1. Ogden CL, Carroll MD, Curtin LR, Lamb MM, Flegal KM. Prevalence of high body mass index in US children and adolescents, 2007-2008. *JAMA*. 2010;303(3):242–249
2. Trust for America's Health. *F as in Fat: How Obesity Policies are Failing in America*. Princeton, NJ: Robert Wood Johnson Foundation; 2010
3. Dietz WH, Robinson TN. Use of the body mass index (BMI) as a measure of overweight in children and adolescents. *J Pediatr.* 1998;132(2):191–193
4. National Task Force on the Prevention and Treatment of Obesity. Overweight, obesity, and health risk. *Arch Intern Med*. 2000;160 (7):898–904
5. Cornette R. The emotional impact of obesity on children. *Worldviews Evid Based Nurs*. 2008;5(3):136–141
6. Birch LL, Ventura AK. Preventing childhood obesity: what works? *Int J Obes*. 2009;33 (suppl 1):S74–S81
7. Ebbeling CB, Ludwig DS. Pediatric obesity prevention initiatives: more questions than answers. *Arch Pediatr Adolesc Med*. 2010; 164(11):1067–1069
8. Kamath CC, Vickers KS, Ehrlich A, McGovern L, Johnson J, Singhal V, Paulo R, Hettinger A, Erwin PJ, Montori VM. Clinical review: behavioral interventions to prevent childhood obesity: a systematic review and meta-analyses of randomized trials. *J Clin Endocrinol Metab*. 2008 Dec;93(12):4606–4615. Epub 2008 Sep 9. Review.
9. Borgatti SP, Mehra A, Brass DJ, Labianca G. Network analysis in the social sciences. *Science*. 2009;323(5916):892–895
10. Valente TW. *Social Networks and Health: Models, Methods, and Applications*. New York, NY: Oxford University Press; 2010
11. Christakis NA, Fowler JH. The collective dynamics of smoking in a large social network. *N Engl J Med*. 2008;358(21):2249–2258
12. Christakis NA, Fowler JH. The spread of obesity in a large social network over 32 years. *N Engl J Med*. 2007;357(4):370–379
13. Cohen S, Doyle WJ, Skoner DP, Rabin BS, Gwaltney JM Jr. Social ties and susceptibility to the common cold. *JAMA*. 1997;277(24): 1940–1944
14. Valente TW, Fujimoto K, Chou CP, Spruijt-Metz D. Adolescent affiliations and adiposity: a social network analysis of friendships and obesity. *J Adolesc Health*. 2009;45(2):202–204
15. Valente TW, Watkins SC, Jato MN, van der Straten A, Tsitsol LP. Social network associations with contraceptive use among Cameroonian women in voluntary associations. *Soc Sci Med*. 1997;45(5):677–687
16. Valente TW, Ritt-Olson A, Stacy A, Unger JB, Okamoto J, Sussman S. Peer acceleration: effects of a social network tailored substance abuse prevention program among high-risk adolescents. *Addiction*. 2007;102 (11):1804–1815
17. Trogdon JG, Nonnemaker J, Pais J. Peer effects in adolescent overweight. *J Health Econ*. 2008;27(5):1388–1399
18. Halliday TJ, Kwak S. Weight gain in adolescents and their peers. *Econ Hum Biol*. 2009; 7(2):181–190

19. Mednick SC, Christakis NA, Fowler JH. The spread of sleep loss influences drug use in adolescent social networks. *PLoS ONE*. 2010;5(3):e9775
20. de la Haye K, Robins G, Mohr P, Wilson C. Obesity-related behaviors in adolescent friendship networks. *Soc Networks*. 2010;32 (3):161–167. Available at: www.sciencedirect.com/science/article/pii/S0378873309000495. Accessed March 26, 2012
21. Bahr DB, Browning RC, Wyatt HR, Hill JO. Exploiting social networks to mitigate the obesity epidemic. *Obesity (Silver Spring)*. 2009;17(4):723–728
22. de la Haye K, Robins G, Mohr P, Wilson C. Homophily and contagion as explanations for weight similarities among adolescent friends. *J Adolesc Health*. 2011;49(4):421–427
23. Mercken L, Snijders TA, Steglich C, de Vries H. Dynamics of adolescent friendship networks and smoking behavior: social network analyses in six European countries. *Soc Sci Med*. 2009;69(10):1506–1514
24. Mercken L, Snijders TA, Steglich C, Vertiainen E, de Vries H. Smoking-based selection and influence in gender-segregated friendship networks: a social network analysis of adolescent smoking. *Addiction*. 2010;105(7):1280–1289
25. Kiuru N, Burk WJ, Laursen B, Salmela-Aro K, Nurmi JE. Pressure to drink but not to smoke: disentangling selection and socialization in adolescent peer networks and peer groups. *J Adolesc*. 2010;33(6):801–812
26. Knecht AB, Burk WJ, Weesie J, Steglich C. Friendship and alcohol use in early adolescence: a multilevel social network approach. *J Res Adolesc*. 2011;21(2):475–487
27. Summerbell CD, Waters E, Edmunds LD, Kelly S, Brown T, Campbell KJ. Interventions for preventing obesity in children. *Cochrane Database Syst Rev*. 2005;3:CD001871
28. de Vries SI, Bakker I, Hopman-Rock M, Hirasing RA, van Mechelen W. Clinimetric review of motion sensors in children and adolescents. *J Clin Epidemiol*. 2006;59(7): 670–680
29. Brage S, Wedderkopp N, Andersen LB, Froberg K. Influence of step frequency on movement intensity predictions with the CSA accelerometer: a field validation study in children. *Pediatr Exerc Sci*. 2003;15(3):277–287
30. Trost SG, Way R, Okely AD. Predictive validity of three ActiGraph energy expenditure equations for children. *Med Sci Sports Exerc*. 2006;38(2):380–387
31. Treuth MS, Schmitz K, Catellier DJ, et al. Defining accelerometer thresholds for activity intensities in adolescent girls. *Med Sci Sports Exerc*. 2004;36(7):1259–1266
32. Mattocks C, Leary S, Ness A, et al. Calibration of an accelerometer during free-living activities in children. *Int J Pediatr Obes*. 2007;2(4):218–226.
33. Puyau MR, Adolph AL, Vohra FA, Zakeri I, Butte NF. Prediction of activity energy expenditure using accelerometers in children. *Med Sci Sports Exerc*. 2004;36(9):1625–1631
34. Puyau MR, Adolph AL, Vohra FA, Butte NF. Validation and calibration of physical activity monitors in children. *Obes Res*. 2002; 10(3):150–157
35. Tudor-Locke C, Johnson WD, Katzmarzyk PT. Accelerometer-determined steps per day in US adults. *Med Sci Sports Exerc*. 2009;41 (7):1384–1391
36. Children's Hospital of Philadelphia. Body mass index and z-score calculation in children. 2010. Available at: http://stokes.chop.edu/web/zscore/. Accessed March 26, 2012
37. Pate RR, Almeida MJ, McIver KL, Pfeiffer KA, Dowda M. Validation and calibration of an accelerometer in preschool children. *Obesity (Silver Spring)*. 2006;14(11):2000–2006
38. Ripley R, Snijders T. Manual for SIENA version 4.0. 2011. Available at: www.stats.ox.ac.uk/~snijders/siena/s_man400.pdf. Accessed March 26, 2012
39. Snijders TAB, Van De Bunt GG, Steglich CEG. Introduction to stochastic actor-based models for network dynamics. *Soc Networks*. 2010;32(1):44–60
40. Snijders T, Steglich C, Schweinberger M. Modeling the co-evolution of networks and behavior. In: van Montfort K, Oud J, Satorra A, eds. *Longitudinal Models in the Behavioral and Related Sciences*. Mahwah, NJ: Lawrence Erlbaum; 2007
41. Steglich C, Snijders T, Pearson M. Dynamic networks and behavior: separating selection from influence. *Sociol Methodol*. 2010; 40(1):329–393
42. de la Haye K, Robins G, Mohr P, Wilson C. How physical activity shapes, and is shaped by, adolescent friendships. *Soc Sci Med*. 2011;73(5):719–728
43. Chen KY, Bassett DR Jr. The technology of accelerometry-based activity monitors: current and future. *Med Sci Sports Exerc*. 2005; 37(suppl 11):S490–S500
44. Beets MW, Rooney L, Tilley F, Beighle A, Webster C. Evaluation of policies to promote physical activity in afterschool programs: are we meeting current benchmarks? *Prev Med*. 2010;51(3-4):299–301
45. Beets MW, Wallner M, Beighle A. Defining standards and policies for promoting physical activity in afterschool programs. *J Sch Health*. 2010;80(8):411–417
46. Sallis JF, Prochaska JJ, Taylor WC. A review of correlates of physical activity of children and adolescents. *Med Sci Sports Exerc*. 2000;32(5):963–975
47. Van Der Horst K, Paw MJ, Twisk JW, Van Mechelen W. A brief review on correlates of physical activity and sedentariness in youth. *Med Sci Sports Exerc*. 2007;39(8): 1241–1250