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Modeling spatial segregation and travel cost influences on utilitarian walking: Towards policy intervention

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ABSTRACT

We develop an agent-based model of utilitarian walking and use the model to explore spatial and socio-economic factors affecting adult utilitarian walking and how travel costs as well as various educational interventions aimed at changing attitudes can alter the prevalence of walking and income differentials in walking. The model is validated against US national data. We contrast realistic and extreme parameter values in our model and test effects of changing these parameters across various segregation and pricing scenarios while allowing for interactions between travel choice and place and for behavioral feedbacks. Results suggest that in addition to income differences in the perceived cost of time, the concentration of mixed land use (differential density of residences and businesses) are important determinants of income differences in walking (high income walk less), whereas safety from crime and income segregation on their own do not have large influences on income differences in walking. We also show the difficulty in altering walking behaviors for higher income groups who are insensitive to price and how adding to the cost of driving could increase the income differential in walking particularly in the context of segregation by income and land use. We show that strategies to decrease positive attitudes towards driving can interact synergistically with shifting cost structures to favor walking in increasing the percent of walking trips. Agent-based models, with their ability to capture dynamic processes and incorporate empirical data, are powerful tools to explore the influence on health behavior from multiple factors and test policy interventions.

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1. Introduction

Walking for transportation is a feasible way to incorporate regular physical activity into daily life. Regular physical activity is important for maintaining a healthy weight and can reduce the risk for many chronic diseases (Department of Health and Services, 2008; Powell, Paluch, & Blair, 2011). However, only 6% of US adults routinely engage in walking for transportation (≥ 5 days/week for ≥ 30 min/day) and only about 18% of all trips in the US are made via walking (Pucher et al., 2011).

Americans primarily rely on private automobiles for transportation, which has enabled low-density development and contributed

to poor air quality (Frumkin, Frank, & Jackson, 2004; Marshall et al., 2005). At the same time, low-density urban development has encouraged further reliance on automobiles for mobility and has heightened the challenges of providing high-quality public transportation services. Inappropriate price signals are frequently invoked as a factor that skews travel toward the automobile and away from walking and public transit. For example, in the US, the cost of gasoline has declined since 1980 (after accounting for inflation and gains in fuel efficiency) and free, convenient parking is plentiful around residences, worksites, shopping and leisure destination (Auchincloss et al., 2014; Shoup, 1997, 2011). To date, the majority of work on transportation prices has focused on how it can reduce auto use or increase transit use (Guo, 2013; Marsden, 2006; Salon et al., 2012). Despite the importance of prices for people's travel choices, there is limited research examining how pricing automobile use can also have an impact on walking

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behaviors (Courtemanche, 2011; Hou et al., 2011). For example, one recent review (Martin, Suhrcke, & Ogilvie, 2012) claimed that financial incentives may have a larger role in promoting walking and cycling than is acknowledged generally although the conclusion was based on evidence predominantly involving free bicycles or local road pricing at specific locations and for specific groups.

It is well established that many health behaviors vary across socioeconomic groups. Walking for transportation is an atypical example in that, in contrast to many other behaviors, lower income groups tend to engage in healthier behaviors (i.e. walk more) than higher income groups (Kruger et al., 2008; Pucher & Renne, 2003). This is due in part to difficulties faced by low income households in assuming the costs of automobile ownership, operation, and maintenance. Compared to high income households, the well-being of lower income households has a higher dependence on proximity to health-promoting services, safe walking environments, and quality of public transit. Residential segregation by household income, a common feature of older post-industrial cities in the US, also has implications for walking behavior and differences in walking by income. In many older US cities, lower-income households tend to be located in or around the center of the city, while higher-income households locate on the city's outskirts. Density of residential and commercial land use also tend to be spatially patterned (Anas, Arnott, & Small, 1998). Spatially patterned proximity to destinations may also exert an important influence on walking behavior and income differences in walking behavior. Thus, in evaluating the impact of various policies (including pricing) on walking behavior it is important to evaluate their impact on income differences in walking in the context of various spatial segregation scenarios.

A major challenge in investigating the impact of various policies on walking behavior and its income differences at the population level is the need to account for the dynamic relationships among individuals (e.g. the behavior of one individual affecting others), between individuals and their built and social environments (e.g. the environment changing in response to the behaviors of individuals and vice versa), and among environmental characteristics (Cerin, Leslie, & Owen, 2009). However, data are often unavailable for examining these dynamic interactions and the interactions cannot be easily captured using traditional statistical methods. Agent-based models (ABM) are computational models that can be used to simulate the actions and interactions of agents as well as the dynamic interactions between agents and their environments in order to gain an understanding of the functioning of the system (Axtell & Epstein, 1994; Bonabeau, 2002). Several agent-based models (Batty, 2003; Haklay et al., 2001; Helbing et al., 2002; Ronald, Sterling, & Kirley, 2007; Turner & Penn, 2002; Willis et al., 2004) have been applied to study pedestrian behavior. However, these models largely focus on how people move around small areas or within buildings, and how people's movements are influenced by fine-level features such as design and layout of buildings and streets. Our model, by contrast, focuses mainly on the choice of travel mode without detail on route or fine-scale change in environment along the route. Only recently, ABMs have been used to study how the social and built environments shape travel mode choice, including walking and transit behaviors (Lu, Kawamura, & Zellner, 2008; Yang & Diez-Roux, 2013; Yang et al., 2011, 2012, 2014; Zhu et al., 2013).

We developed an ABM of utilitarian walking and use the model to explore questions relevant to understanding the factors affecting population-level patterns of walking to destinations (henceforth called utilitarian walking) and income variations in walking, and the plausible impacts of selected interventions. Specifically we explore utilitarian walking under various levels of residential segregation and spatial distributions of land uses and safety from crime. We investigate how travel cost can alter preva-

lence of walking and income differentials in utilitarian walking under various segregation scenarios. In addition we explore the synergistic effects of policies aimed at changing attitudes towards walking and driving (such as educational policies) with travel cost policies. Section 2 describes model design, scenarios analysis, and model validation. Results are presented in Section 3. Sections 4 and 5 discuss and conclude the findings, respectively.

2. Research method

2.1. Model design

The model simulates adults' daily utilitarian travel. Our intent was to capture the core elements and basic dynamics that could be relevant to our research questions regarding the impact of travel costs on utilitarian walking and the socioeconomic disparities in walking. For parsimony, the model includes only adults' travel behaviors on work days (no weekends). Seasonal variations and weather are ignored. The model assumes sidewalks are present and walkable.

The model is an extensive revision of a previously published model (Yang et al., 2011, 2012). The previous model had a simple mode choice algorithm (in which individuals chose to walk or travel by car) and four feedbacks. Travel cost was excluded from the travel mode choice function and public transit was not included as a travel mode in this earlier model. We modified the model to allow three travel modes (walking, car, and bus transit) and incorporated a number of theoretically and empirically justified feedbacks for each. We also adapted the model to make it more suitable to questions related to walking variation by income level. Fig. 1 shows the model's framework. It is a time-discrete model with each time step being one day. The model was developed in Java and Repast.

2.1.1. City, persons, and locations

The model represents a city of 64 km² (8 km by 8 km) with an 800 * 800 grid space, where each cell of size 10 m * 10 m is either occupied by a location (i.e. a place with a social function) or is empty. The city has 400 equal-sized neighborhoods, each composed of 40 * 40 cells.

Model agents are 100,000 adults grouped into 50,000 households (population density 1563/sq km). Each household includes two adults. Income quintiles are assigned to each household randomly from 1 (lowest) to 5 (highest). Following the US distribution of automobile ownership by income quintile, the percentages of households having no vehicle are 26.5%, 5.0%, 2.3%, 0.9% and 1.5% (Pucher & Renne, 2003) for the five income level groups (from the lowest to the highest), respectively. A person's social network includes the other household member and up to nine friends who are randomly selected from the same workplace (three), the same neighborhood (three), and people with the same income level in the city (three) (Carroll, 2004). At baseline, each individual is assigned an attitude value towards each travel mode (described below). These attitudes change over time as a function of various feedbacks.

The city has a number of residences and non-residential locations (workplaces, shops, social places and restaurants) with constant ratios to the total population (see Table 1 and Fig. 2). The city has a symmetrical transportation network centered in the city center. Three east–west bus lines and three north–south bus lines cross each other with 2 km of the interval distance among bus lines both east–west and north–south. Each bus route covers 4 km with bus stops at 400 m intervals to reflect that in US urban areas the distance between bus stops is in the range of 200–600 m (Ammons, 2001). Altogether, the city has 57 bus stops with higher

Fig. 1. Framework for an agent-based model for utilitarian travel.

Table 1
Locations in the city.

Location type	Total number	Probability of travel each day	Selection process
Residences	50 k	1.0 ^a	Randomly distributed over the whole city
Workplaces	10 k		At the beginning, one workplace is selected for each person by randomly drawing from all workplaces with weights derived from a distance decay function ^b .
Shops ^c	800	0.58	At the beginning, eight shops ^e are selected for each household as the choice set with weights derived from a distance decay function ^b . During the simulation, for each trip, one shop is randomly drawn from the pool.
All other places ^d	1200	0.93	At the beginning, forty places are selected for each household as the choice set with weights derived from a distance decay function ^b . During the simulation, for each trip, one place is randomly drawn from the pool.

^a Assuming that all persons travel to work every day.

^b Distance decay functions were estimated for trips for (1) work; (2) shops; and (3) all others. The functions were based on 2009 NHTS data for trips within urban area and no more than 10 miles (because the maximum distance in this model is 10 miles). Values of the decay parameters (β) are 0.268 for work, 0.455 for shops and 0.411 for others.

^c Travel for all categories of shopping are combined, and the probability value 0.58 is from 2009 NHTS data.

^d This includes all other travel purposes (e.g. social and recreational places), and the probability value 0.93 is from 2009 NHTS data.

^e Here, we assume each household has eight shops for daily shopping destination based on "Miller's Law", the theory about the human brain's capacity to process information (Miller, 1956) and specific evidence about shopping choice set (Pellegrini, Fotheringham, & Lin, 1997).

density in the central area. For evaluating what travel mode will be chosen for a given trip, the distance between the origin and the destination grid cells is calculated using Manhattan distance. The model uses a discrete time step of one day. Each day, each individual has a certain probability of traveling to work, to shop and to all other places (see Table 1). Except where noted, travel always occurs from the residence to the non-residential location and back to the residence (i.e., we ignore trip chaining).

2.1.2. Travel mode choices

Every day, individuals may travel to non-residential locations by one of the following: (1) private automobile, (2) public transportation, or (3) by walking. We assume that the travel mode selected is used for both the departing and the returning trip. The probability of selecting a certain travel mode, with walking (w) as example here, is computed by the following formula:

$$P(w) = \frac{A_w e^{-C_w}}{A_c e^{-C_c} + A_p e^{-C_p} + A_w e^{-C_w}} \quad (1)$$

where A_c , A_p , A_w are the attitude for car (private automobile), public transportation, and walking, respectively. C_c , C_p , C_w are the cost for car, public transportation, and walking, respectively. The selection probability is thus a function of the attitude towards each mode modified by the cost of each mode. Like many models used in transportation research, we model mode choice as an exponential function of cost (Domencich & McFadden, 1975; Ortuzar & Willumsen, 2001). Costs of each mode are computed for each individual prior to each trip. In selecting the mode, individuals both minimize the cost function and give higher probability to modes for which their

attitude value is higher. If an individual does not have a car, he/she can only choose between public transportation and walking.

We assume that the cost of driving is a function of the time it takes to drive and park the car, the cost of parking at the destination, the cost of the necessary fuel, and the car insurance and maintenance fee. The parking fee is halved in the calculation to avoid double counting parking at the destination, because the function applies to a one-way trip and residential parking is assumed to be free. The cost of using public transit is a function of the duration of ride, the time it takes to walk to and from the transit, the waiting time, and the fare. The time of walking to and from the transit and waiting are doubled, to reflect the fact that time out-of-vehicle is valued approximately at twice as much as the time of in-vehicle when traveling not for work (Barff, Mackay, & Olshavsky, 1982; Wardman, 2001). The cost of walking is a function of the time needed to walk, the distance, and the walking speed.

The formulas for the cost of various travel modes are as follows.

$$\text{Cost of driving} = \frac{R_s D}{S_d} + 0.5 F_p + F_i + R_g D \quad (2)$$

$$\text{Cost of public transit} = R_s \left(\frac{D_1}{S_t} + 2 \frac{D_2}{S_w} + 2 T_t \right) + F_t \quad (3)$$

$$\text{Cost of walking} = R_s \frac{D}{S_w} \quad (4)$$

R_s is the opportunity cost of an hour travel, and is assumed to be 50% of the value of the hourly wage (United States Department of Transportation, 2003); thus 4.5, 7, 9.5, 14, 23.5 dollars per hour for income levels 1–5, respectively, based on U.S.

Fig. 2. Spatial display of the typical scenario (top) and random scenario (bottom). Green dots are transit stations, gray dots are work places, red dots are shops, and blue dots are other places. As shows, three east-west bus lines and three north-south bus lines cross each other in the central area. In typical scenario, the density of non-residential locations decays outwards from the center of the city. In random scenario, all non-residential locations are randomly distributed across the city. In both scenarios, residences are randomly distributed, and they are not displayed here. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

cost of fuel per mile. For all above variables, we use dollars as unit for costs and fees, miles for distances, hours for durations. The default values for above variables are shown in Table 2.

2.1.3. Feedbacks

Feedbacks are implemented through updates to each person's attitude towards each travel mode, which vary with a person's past experience with that mode. Attitude towards a given mode, in turn, affects the likelihood that a person will choose that mode in the subsequent day. All attitudes are updated using a similar process.

Each day, the attitude towards each mode is updated using the following formula:

$$A^t = w_p A_p + w_a A^{t-1} + \sum_{i=1}^n w_i \frac{E_i^t}{\text{Max}(O)_i} \quad (5)$$

where A^t is the attitude on day t , A_p is an underlying, person-specific stable “predisposition”, which in part reflects prior long-term life course experience and is assumed to be constant over the simulation. A^{t-1} is the attitude on the prior day, E_i^t captures the persons prior exposure (both during the prior day and over a longer history, see below), and $\text{Max}(O)_i$ is the maximum value of each exposure attribute used for scaling purposes. w_p and w_a are weights of A_p and A^{t-1} , and each w_i (the weight for each relevant exposure, see below) is defined as $w_i = \frac{1-w_p-w_a}{N}$ to make sure all weights sum to 1. N is the number of relevant exposures and varies by each travel mode. Possible exposures include mode choices of other persons in the social network, the number of persons using the specific mode, the number of persons using other modes, and other supporting and experiential factors. Specifically, nine exposures are allowed (Table 3).

Each day, E_i^t is estimated as:

$$E_i^t = (1 - a) E_i^{t-1} + a O_i^{t-1} \quad (6)$$

where E_i^{t-1} is the value of E_i for the prior day, reflecting the exposure leading up to $t - 1$, and O_i^{t-1} is the observed exposure for the prior day. This allows E_i^t to reflect both the exposure from the prior day and the longer history of exposures. The weight a can be varied to give more or less weight to the more recent exposures.

For some exposures, the maximum value ($\text{Max}(O)_i$) can be derived from its definition. For example, the maximum of safety is 5 because the range of safety values used in the model is 1–5. For other exposures, such as walking density, simulations across various scenarios were used to derive maximum values. For exposures that negatively affect attitude (i.e., an increase in the exposure causes the attitude to drop), the term $\frac{E_i^t}{\text{Max}(O)_i}$ in Eq. (5) is replaced by $(1 - \frac{E_i^t}{\text{Max}(O)_i})$. Definitions of exposures and their maximum values for the nine feedbacks are listed in Table 4.

In order to begin the process, at initialization for each travel mode, each person is assigned a value for A_p and an initial attitude towards walking. At inception $A_p = A^0$, and is a random value from the uniform distribution ranging between 0 and 1. The attitude towards walking on day 1 is assigned by:

$$A^1 = \frac{w_p}{w_p + w_a} A_p + \frac{w_a}{w_p + w_a} A^0 \quad (7)$$

2.2. Scenarios analysis

2.2.1. Basic scenarios

Two scenarios were defined as “random” and “typical”. The random scenario is a scenario in which there is no income segregation, and both safety levels and non-residential locations are randomly distributed within the city. The typical scenario reproduces segregation patterns found in many older cities in the US, where households are segregated by income level such that lower-income

Bureau of Labor Statistics (Bureau of Labor Statistics, 2012). D is the distance from the residence to the destination for both driving and walking. For public transit, D_1 is the distance for the transit mode, and D_2 is the distance by foot (i.e., the sum of the distances from residence to transit stop and from transit stop to destination). S_d , S_t and are the speed of driving, public transit and walking, respectively. T_t is the waiting time for public transit. F_p and F_t are fees for parking at destination and using public transit. F_i is the car insurance and maintenance fees distributed to each trip. R_g is the

Table 2

Values of travel cost related parameters in various experiments: default, driving-optimized, walking-optimized, driving-extreme, and walking-extreme.

Parameter	Default	Driving-optimized	Walking-optimized	Driving-extreme	Walking-extreme
Car speed	25 miles per hour	30 miles per hour	20 miles per hour	30 miles per hour	20 miles per hour
Parking fee ^a (Auchincloss et al., 2014)	\$1	\$0.5	\$2	0	\$10
Insurance fee ^b	0.6 dollars per trip	—	—	—	—
Fuel price (20 miles per gallon) ^b	0.15 dollars per mile (3 dollars per gallon)	0.1 dollars per mile (2 dollars per gallon)	0.3 dollars per mile (6 dollars per gallon)	0.05 dollars per mile (1 dollars per gallon)	1 dollars per mile (20 dollars per gallon)
Public transit speed	15 miles per hour	—	—	—	—
Public transit fare ^c	1 dollar per trip	2 dollar per trip	0.5 dollar per trip	2 dollar per trip	0.5 dollar per trip
Waiting time for public transit	6 min per trip	12 min per trip	3 min per trip	12 min per trip	3 min per trip
Walking speed	3 miles per hour	—	—	—	—

—: the same value as default.

^a http://www.npapark.org/pdfs/2010_Parking_in_America_Report.pdf.^b <http://www.usatoday.com/story/news/nation/2013/04/16/aaa-car-ownership-costs/2070397/>.^c http://www.bts.gov/publications/national_transportation_statistics/html/table_03_18.html.**Table 3**

Names and underlying assumptions of the feedbacks for attitude towards driving, using public transit and walking.

	Attitude towards driving	Attitude towards public transit	Attitude towards walking
<i>Social network</i>	NetworkDriving, NetworkTransit, and NetworkWalking These feedbacks are based on that people's attitudes can be influenced by their social network including family members, friends and colleagues (Christakis & Fowler, 2007). Because attitudes may not be directly observable by other individuals and hence cannot themselves be sources of social influence (Mason, Conrey, & Smith, 2007), a person will update his attitude based on observations of the travel mode of her/his friends (rather than directly from their attitudes)		
<i>Number of persons using this mode</i>	Driving2Driving Because of traffic congestion, more people driving along the route decreases a person's attitude towards driving, and vice versa	Transit2Transit Higher comfort level on the transit increases a person's attitude towards using public transit, and vice versa	Walking2Walking More people walking increases a person's attitude towards walking, and vice versa
<i>Number of persons using other modes</i>	[Not considered] No feedbacks included. It is assumed that the # of persons using public transit or walking has no impact on the experience of driving	Driving2Transit More people driving decreases a person's attitude towards public transit, and vice versa	Driving2Walking More people driving decreases traffic safety and decreases attitude towards walking, and vice versa
<i>Other supporting and experiential factors</i>	[Not considered] Other important factors are not included in feedbacks because they are part of the cost function. For example, the cost function of driving considers the price of parking and the time necessary to find a parking space	[Not considered] Other factors such as uncertainty in public transit schedules and other comfort related factors on public transit are not yet included in this model	Safety2Walking Higher level of safety increases a person's attitude towards walking, and vice versa

households are located in the center of the city and higher-income households are located in the periphery (Berube, Katz, & La ng, 2003). At the same time, the safety from crime level decays inwards towards the center of the city, such that lower safety in the core and higher safety in the periphery. The density of non-residential locations also decays outwards from the center of the city, such that more non-residential locations are in the core and fewer non-residential locations are in the periphery. To be more specific, the city is divided into five concentric zones, and the density of non-residential locations decays outwards with the ratio of 0.5 from one zone to another. In previous work we found that the typical scenario (Yang et al., 2011, 2012) generated differences in walking by income level that are typically observed empirically.

2.2.2. Contribution of segregation to income differences in walking

To identify how income segregation interacts with the built environment (density of residential and non-residential land uses) and social environments (safety) to affect variations in walking for transportation by income level, we contrasted five scenarios: (1) no segregation (the random scenario), (2) segregation by income

(lower income households were located in the center of the city and higher income households are located in the periphery, while safety level was randomly distributed and the land uses were evenly distributed); (3) segregation by income + safety (safety also declines inwards towards the center of the city); (4) segregation by income + land use (non-residential land uses decline from the center of the city outwards); and (5) segregation by income, land use and safety ("typical"). For each scenario we described the percentage of walking trips among all trips for each income group.

2.2.3. Contribution of transportation cost policies to income differences in walking

To examine the contribution of transportation cost policies to the income differences in walking, four experiments were performed (see Table 2), with the rationale that lowering the cost of a desired travel mode (public transit) and raising the price of an undesired travel mode (driving) may be an effective strategy for motivating behavior change. Under the driving-optimized and extreme driving-optimized experiments, values of some cost-related parameters were changed to increase the competitive

Table 4

Exposures for feedback: feedback name, exposure definition, maximum value and direction.

Feedback name	Exposure definition	Maximum value	Direction
NetworkWalking	Ratio of walking trips from the network: the ratio of walking trips among all trips by all persons in the social network during the previous day	1	Positive
Walking2Walking	Walking density along walking path: The number of walkers crossing a cell during the day averaged across all cells along the walking route	Max walking density = 100 (this was determined based on the outcomes of exploratory model runs)	Positive
Driving2Walking	Driving along walking path	Max driving density = 400 (this was determined based on the outcomes of exploratory model runs)	Negative
Safety2Walking	The mean value of safety for all cells along the walking route for the day	5 (by definition)	Positive
NetworkTransit	Ratio of public transit trips from the network: similar to NetworkWalking	1	Positive
Transit2Transit	The mean value of the comfort index ^a of all the transit stations along the transit route during the day	1 (by definition); Transit station capacity: 500 (this was determined based on the outcomes of exploratory model runs)	Positive
Driving2Transit	Driving along transit path: The number of driving trips crossing a cell during the day averaged across all cells along the transit route	Max driving density = 400, see Driving2Walking	Negative
NetworkDriving	Ratio of driving trips from the network: similar to NetworkWalking	1	Positive
Driving2Driving	Driving along driving path: The number of driving trips crossing a cell during the day averaged across all cells along the driving route	Max driving density = 400, see Driving2Walking	Negative

^a Comfort index: The model does not include actual “buses”, and we track the total number of passengers who pass through a certain transit station over a day. We define a “comfort index” $\in (0, 1)$ for each transit station and assume that the comfort index is constant and at the highest value (=1) until the station is half full. When the passengers occupy the transit station at > 50% capacity, the trip becomes less comfortable. Each day, a comfort index is computed for each transit station. For a given day, the comfort index for that transit route is the mean value of the comfort index of all the transit stations along the transit route. For each transit station, the comfort index is computed as: If $n < 0.5 * C$, $I = 1$; Else $I = 2 - 2 * n/C$. Where n is the total number of passengers passing through the transit station over the whole day (total number of passengers, not unique passengers so that if the same person passes through the transit stop twice he will be counted twice) and C is the capacity of the station (the capacity is assumed to be 500 for all stations, this value is based on the observation from testing simulation).

advantage of driving as a travel mode. For example, compared to default values, car speed was increased, and time for parking, parking fee and fuel price were decreased. In addition, the fare and waiting time for public transit were increased because these changes decrease the competitive advantage of using public transit, and thus indirectly increase the competitive advantage of driving. Under the walking-optimized (or driving-constrained) and extremely walking-optimized experiment, the aforementioned car-related parameters were changed in the opposite direction. Again, the fare and waiting time for public transit were decreased because the use of public transit involves walking for transit. The four experiments were investigated for both the typical and random scenarios.

In addition to the four experiments described above, we selected two specific cost-related parameters for further exploration: (1) for fuel price, we set values between 0.05 dollar per mile and 1.0 dollar per mile (1 and 20 dollars per gallon, respectively), with step of 0.05 dollar; and (2) for parking fee, we set parking fee zero to 10 dollars (flat fee per trip), with step of 0.25 dollars. When one parameter was explored, all other cost-related parameters (as listed in Table 2) were set to default values. The impact of these cost changes were investigated in the typical and random scenarios.

For each scenario the model was run until the percentage of the three travel modes achieved stability which occurred after 100 steps. Stability was first determined visually and then via deviation

statistics that tested to what extent the observed curve deviated from a horizontal line. For each scenario and experiment, we report the mean percentage of trips by income for selected travel modes over 20 simulations. Walking trips include walking trips resulting from public transit use.

2.2.4. Synergistic effects of policies aimed at changing attitudes with transportation cost policies

We also examined the impact of changing attitudes towards walking and driving (though for example informational approaches to change knowledge and attitudes about the benefits of and opportunities for walking (Kahn et al., 2002) on walking and the synergistic effects changing attitudes towards different modes with each other and with transportation cost policies. We defined three interventions: A, decrease attitude towards driving (by reducing A_p for driving to be 0, see Formula 5); B, increase attitude towards walking (by increasing A_p for walking to be 0); and C, increase driving costs (walking-optimized cost experiment, see Table 2). We examined the impact of these three interventions separately and combined.

2.3. Model validation

We collected reasonable values and ranges for most parameters in the model (see Tables 1 and 2). We further evaluated the performance of the model by contrasting predictions of the model with

Table 5

Percentage of driving, public transit and walking trips, by distance and by income level, for the random scenario and typical scenarios.

		Random scenario			Typical scenario		
		Driving	Public transit	Walking	Driving	Public transit	Walking
By distance	<0.25 mile	39.7	0.0	60.4	37.5	0.0	62.5
	>=0.25 mile and <0.5 mile	55.6	0.1	44.3	50.0	0.3	49.8
	>=0.5 mile and < 1 mile	70.8	0.4	28.8	67.3	0.9	31.8
	>=1 mile and <2 miles	84.0	0.8	15.3	84.9	1.4	13.7
	>=2 miles	90.5	2.4	7.2	94.7	2.1	3.2
By income level	1	45.3	3.3	51.4	39.2	4.4	56.4
	2	69.7	0.8	29.4	68.5	2.4	29.2
	3	78.5	0.3	21.3	82.8	0.3	16.9
	4	85.6	0.1	14.3	91.5	0.1	8.4
	5	90.7	0.1	9.2	95.9	0.1	4.0

US national data. Because the model is for a very stylized hypothetical city there are no empirical data from a single city that can be used for model assessment. In addition available national level data are aggregated from a number of diverse urban and rural areas. We therefore validated the model by contrasting model predictions with the general qualitative patterns observed in national data.

First, we evaluated the percentage of walking trips by distance. As shown in Table 5, for both the random and typical scenarios the shorter the distance, the higher percentage of walking trips taken by walking. The patterns shown in Table 5 were roughly consistent with the modal split by distance in the US, that is, non-motorized trips are dominant only with distance less than 0.25 miles and the share of public transit is low in any distance (Schafer, 2000). Second, we evaluated variation of walking by income level. As shown

in Table 5 for both the random and typical scenarios, the percentage of walking trips was negatively related to income level. As indicated by National Health Interview Survey (NHIS) 2005 data (Kruger et al., 2008) and National Household Travel Survey 2001 and 2009 data (Pucher et al., 2011), lower income people were more likely to report walking for transportation. The percent of walking trips predicted by our model is slightly higher than the general pattern found from US national data because the hypothetical city in our model is relatively small so that there are less longer-distance trips (which are less likely to be walking trips).

3. Results

3.1. Contribution of segregation to income differences in walking

Fig. 3 shows income differences in walking trips (including transit) by segregation scenarios. As anticipated, the proportion of trips made by walking was negatively associated with income. The pattern of relationship was similar for the segregation by income and random scenarios, suggesting that segregation by income did not have a substantial impact on income differences in walking. In addition, safety did not appear to have a significant influence on income differences in walking regardless whether land use was also spatially patterned. Compared to the random scenario, segregation of land use showed a steeper income gradient in walking, primarily due to the lower proportion of trips walked by income levels 3, 4 and 5.

3.2. Contribution of travel cost to income differences in walking

As Fig. 4 shows, in the extremely walking-optimized experiment, walking represented 100% of all trips made by those with low incomes but a relatively low share of all trips made by those with higher incomes. The income differential was particularly steep under the typical scenario, where walking trips dropped from nearly 100% to 20% from the lowest to the highest income. In contrast, in the driving-optimized and extremely driving-optimized experiment, there are only slight differences in walking trips rela-

Fig. 3. Percentage of walking trips (including walk for transit) by income level, in various scenarios.

Fig. 4. Percentage of walking trips (including walk for transit) by income level, with default values, driving-optimized experiment, extremely driving-optimized experiment, walking-optimized experiment, and extremely walking-optimized experiment, for random and typical scenarios.

tive to the default experiment both for the random and typical scenarios.

An unexpected result was that for income level 1 in the typical scenario the percentage of walking trips under the extremely driving-optimized experiment was higher than in the driving-optimized and the default experiment. This is because under the extremely driving-optimized scenario, the number of driving trips increased significantly, and in the typical scenario the driving trips tended to be concentrated in the city center (which has a higher density of non-residential locations). Thus, persons with income level 1 who live in the city center are exposed to more driving trips, which, based on the feedbacks encoded in the model, decreases their attitude towards driving and leads to fewer driving trips.

3.3. Impact of specific pricing policies

Increases in fuel prices slightly exacerbated the income differential in walking trips: lower incomes added more walking trips

while higher incomes stayed roughly the same (Fig. 5 top two panels fuel price increased from 0.05 dollars per mile to 1.0 dollars per mile). This effect was slightly greater in the typical than in the random scenario. Increases in parking fees sharply increased walking trips for all incomes (Fig. 5 bottom panels) and the income differential in walking trips increased with increasing parking fees, with this effect being slightly greater in the typical than in the random scenario. In our experiments which used extreme but conceivable parameter values, the impact of increasing the parking fee was greater than the impact of increasing the fuel price.

3.4. Impact of educational interventions on attitudes and their synergistic effects

Increasing attitude toward walking (B) was the most effective intervention in terms of increasing the percentage of walking trips, and the cost intervention (C) was the second most effective. Decreasing the attitude towards driving (A) was the least effective,

Fig. 5. Percentage of walking trips (including walk for transit) by income level, for variation of fuel price (from 0.05 dollars per mile to 1.0 dollars per mile) and variation of parking fee (from 0 to 10 dollars), for random and typical scenarios.

Table 6

Percentage of walking trips (including walking for transit) by income level for the typical scenario, for three intervention strategies and their combinations: A, decrease attitude towards driving; B, increase attitude towards walking; and C, walking-optimized cost (see Table 2), and N is default typical scenario. The percent value in parenthesis is for the relative increase compared with the default typical scenario.

		Invention measures							
		N (default typical scenario)	A (decrease walking attitude)	B (increase walking attitude)	C (walking optimized cost)	AB	BC	AC	ABC
Income level	1	60.8	75.7 (25%)	78.8 (30%)	76.3 (25%)	81.7 (34%)	84.0 (38%)	99.9 (64%)	99.9 (64%)
	2	31.6	45.2(43%)	53.4 (69%)	50.3 (59%)	53.3 (69%)	61.2 (94%)	99.7 (216%)	99.8 (216%)
	3	17.2	24.2 (41%)	26.9 (56%)	25.2 (47%)	29.6 (72%)	32.6 (90%)	96.3 (460%)	97.2 (465%)
	4	8.5	11.6 (36%)	12.7 (49%)	12.0 (41%)	14.3 (68%)	15.5 (82%)	59.9 (605%)	63.2 (644%)
	5	4.1	4.9 (20%)	5.3 (29%)	5.1 (24%)	5.9 (44%)	6.3 (54%)	22.4 (446%)	24.1 (488%)

although differences between C and A were small (Table 6). Generally, for both absolute and relative increase, the impact of the interventions were greater for lower income level, with greatest value for income level 2 (may due to walking saturation in income level 1). The combinations of AB and BC were more effective than any single intervention, producing moderate increases in walking for all income levels. The strongest impact was seen for AC or ABC (all combined). In both cases, the percentages of walking for income levels 1, 2, and 3 were nearly 100%, and the percentage of walking increased 4.5–6 times for income levels 4 and 5 (for example, 644% relative increase for income level 4 under ABC). For all income levels, the increase produced by combining a reduction in attitude toward driving and walking optimization of the cost was larger than effects of each intervention separately.

4. Discussions

Using a stylized model that contrasted realistic and extreme parameter values, we were able to highlight some important determinants of mode choice and income differences in walking. The results indicate under what contexts income differentials in walking may be enhanced or attenuated. Contrasts in income differences across various segregation scenarios suggest that (in addition to differences in the cost of time) the separation of land uses, and the relative concentration of mixed land uses are important determinants of income differences in walking, whereas safety and income segregation on their own do not have large influences on income differences in walking. The importance of destinations for walkers has been shown elsewhere in empirical work (Ewing & Cervero, 2010; Hirsch et al., 2013; Rodriguez et al., 2009). In our model, destinations are important determinants of walking time, and thus of the attractiveness of walking.

We also found that, compared to the default scenario, very strong disincentives placed on driving and a few incentives offered for taking the bus (walking-optimized experiment) had the potential for greatly increasing walking trips. As expected, the effect of the walking-optimized experiment as a whole, as well as the effects of specific cost related parameters such as fuel prices and parking, were greater at lower income levels. In contrast, walking by the highest income group, especially in the typical (segregated) scenario, was insensitive to fuel price and had relatively low sensitivity to parking costs. The combination of decreasing attitudes towards driving and the walking-optimized cost intervention showed significant synergistic effects.

Lower income groups were more sensitive to changes in costs of fuel and parking, while higher income groups were unlikely to increase the percentages of walking trips even under the extremely walking-optimized experiment. Compared with the random sce-

nario, the income differential in walking was stronger in the typical scenario and land use was the main determinant of this outcome (density is higher inside city center). A key contributor to income differences in walking is encoded in our model because we assumed that the opportunity cost of an hour of local travel was equal to half of an hourly wage (States Department of Transportation, 2003). Thus the same time will cost more for people with higher hourly wages, that is, those who live outside the city center.

In contrast to walking optimization, the driving optimization experiments had much smaller impacts on walking that were approximately similar across income categories. This may reflect the existing orientation towards driving already built into the typical cost structure of transportation options. It may also reflect the relatively high fixed costs associated with driving (i.e., purchasing a vehicle and insurance) relatively to lower variable costs (i.e., fuel and parking), which have little effect when altered. For example, national level data show that the ownership of even one car dramatically transforms travel behavior: households with no vehicle take 41% of trips by walking compared with 12.5% trips by walking for households with one vehicle (Pucher & Renne, 2003). In a study (Hou et al., 2011) based on longitudinal data covering participants from 48 US states, \$0.25 per gallon increase was found to be associated with 17 min of additional walking each week. Another study based on Behavioral Risk Factor Surveillance System (BRFSS) data between 1984 and 2006 found that, in urban areas, a person walks 0.5 times more per week when the price of gas rises by \$1 per gallon (Courtemanche, 2011).

One counter-intuitive finding is that the lowest income group had a higher percentage of walking trips in the extremely driving-optimized experiment than in driving-optimized experiment. This is because of the influence of feedback on the attitude towards driving encoded in our model. In general the impact of the optimization schemes and fuel and parking fee changes were similar in the random and the typical scenarios. The difference is that higher income groups were less sensitive to the increasing cost of fuel and parking in the typical scenario than in the random scenario. This indicates, for the same income group, the effect of the same policy will vary by the context, in particular land use density.

Our results showed that increasing the parking fee was more effective at increasing walking than increasing the fuel price. This was likely because commutes were relatively short: in our model the maximum travel distance was 10 miles. The shorter the trip distance, the larger the proportion of the total cost attributable to the insurance and maintenance fee, parking time and parking fee, and the smaller the proportion attributable to fuel. A fixed parking fee per short trip means that parking fees will account for a larger share of costs per trip and thus have a higher contribution to income differentials in walking. For cities with longer trips

than the ones studied here, increasing fuel prices may play a more important role in decreasing driving.

Interventions at multiple levels may be particularly effective for behavioral change due to possible synergistic effects (McLeroy et al., 2003; Sallis, Owen, & Fisher, 2008; Stokols, Allen, & Bellingham, 1996; Weiner et al., 2012). We identified a synergistic effect between decreasing the attitude towards driving (for example through campaigns highlighting the adverse effects of driving) and modifying the cost structure to favor walking. This is just one example of synergies that likely operate in complex decision making that could impact travel mode choice. Clearly a diversity of interventions will be required to increase walking. Interventions targeted toward walking (educational campaigns, improved walkability) will be needed as well as interventions targeted toward reducing driving (parking policies).

A noteworthy attribute of this model is that agents changed their attitudes towards various travel modes based on a number of feedback mechanisms. This is in contrast to most model of travel mode choice, where attitudes to various modes do not vary over time in response to past experiences (Ortúzar & Willumsen, 2011). Another strength of our model is the use of empirical data to parameterize the model whenever possible.

Models cannot include all elements that are likely contributing to the behavior of a complex system, so this model includes only a few key elements that allow us to examine our study questions. For example, we restricted the model to factors directly related to travel mode choice, which is a short-term choice and does not represent medium-term choices (e.g., vehicle ownership) and long-term choice (e.g., residential and work location choices). Future work may incorporate other elements such as traffic safety, urban design, and feedbacks between behaviors and the features of the environments. For example, walking prevalence may influence land-use mix and safety, and increases in fuel price may result in higher income groups purchasing more fuel efficient (and costlier) vehicles, which would give them a better cost return on driving. Another potentially important factor the model did not include is habit: as daily travel mode may become a habitual behavior after repeating over a period and financial incentives may be insufficient to generate change (de Bruijn & Gardner, 2011; Martin et al., 2012; Murtagh et al., 2012).

Another limitation is that this study only examined scenarios of “random” and “typical”, and without a doubt, cities in reality are much more complex. Cities are different in a large number of dimensions. Our “typical” scenario may be not uncommon, but it is certainly not a representative of most US cities. Further, the variation within a city is too complicated to be represented by a certain pattern, that is, with a city various patterns may show at different scales or different part.

Ideally, an agent-based model explicitly describes the mode choice decision process at the individual level. Existing knowledge and data are not sufficient to justify this type of modeling, so we compromised by using knowledge and data at the population level (e.g. on how cost is associated with decisions at the aggregate level) as a substitute of the behavior rules operating at the individual-level. Additional research on individual-level decision-making will allow further refinements of agent-based models. For example, in this model we assume travel time could be transferred to be travel cost solely. However, evidence shows that uncertainty in time is a key determinant in attitude and travel mode choice (Mackie, Jara-Díaz, & Fowkes, 2001).

5. Conclusions

Our experiments with an agent-based model provided insight into three policy-relevant questions. The ability to capture dynamic processes and incorporate empirical data makes ABMs

powerful tools for exploring the influence of multiple interacting factors on behaviors, and for testing alternative policy interventions, despite several limitations including model's boundary, variation of contexts, and lack of knowledge on human's behavior at the individual level. The next step is to apply the model to specific real cities in order to further explore its potential and answer questions relevant to specific conditions in the real world.

6. Conflict of interest statement

No.

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References

- Ammons, D. N. (2001). *Municipal benchmarks: Assessing local performance and establishing community standards*. (2nd ed). Thousand Oaks, CA: Sage Publications.
- Anas, A., Arnett, R., & Small, K. A. (1998). Urban spatial structure. *Journal of Economic Literature*, 36(3), 1426–1464.
- Auchincloss, A. et al. (2014). Public parking fees and fines: A survey of US cities. *Public Works Management & Policy*. ePub March 14.
- Axtell, R., & Epstein, J. M. (1994). Agent-based modeling: Understanding our creations. *The Bulletin of the Santa Fe Institute* (Winter), 28–32.
- Barff, R., Mackay, D., & Olshavsky, R. W. (1982). A selective review of travel-mode choice models. *Journal of Consumer Research*, 8(4), 370–380.
- Batty, M. (2003). Agent-based pedestrian modelling. In P. A. Longley & M. Batty (Eds.), *Advanced spatial analysis: The CASA book of GIS*. Redlands, USA: ESRI Press.
- Berube, A., Katz, B., & La ng, R. E. (2003). Redefining urban and suburban America: Evidence from census 2000 (vol. 2). Washington, D.C.: Brookings.
- Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences*, 99, 7280–7287.
- U.S. Bureau of Labor Statistics (2012). Usual weekly earning of wage and salary workers. <<http://www.bls.gov/news.release/pdf/wkyeng.pdf>>.
- Carroll, J. (2004). Americans satisfied with number of friends, closeness of friendships. <<http://www.gallup.com/poll/10891/americans-satisfied-number-friends-closeness-friendships.aspx>>.
- Cerin, E., Leslie, E., & Owen, N. (2009). Explaining socio-economic status differences in walking for transport: An ecological analysis of individual, social and environmental factors. *Social Science & Medicine*, 68(6), 1013–1020.
- Christakis, N. A., & Fowler, J. H. (2007). The spread of obesity in a large social network over 32 years. *New England Journal of Medicine*, 357(4), 370–379.
- Courtemanche, C. (2011). A silver lining? The connection between gasoline prices and obesity. *Economic Inquiry*, 49(3), 935–957.
- de Bruijn, G.-J., & Gardner, B. (2011). Active commuting and habit strength: An interactive and discriminant analyses approach. *American Journal of Health Promotion*, 25(3), e27–e36.
- US Department of Health and Human Services, (2008). *Physical Activity Guidelines Advisory Committee Report*.
- Domencich, T., & McFadden, D. (1975). *Urban travel demand: A behavioral analysis*. Amsterdam: North Holland Publishing Company.
- Ewing, R., & Cervero, R. (2010). Travel and the built environment: A meta-analysis. *Journal of the American Planning Association*, 76(3), 265–294.
- Frumkin, H., Frank, L. D., & Jackson, R. J. (2004). *Urban sprawl and public health: Designing, planning, and building for healthy communities*. Washington, DC: Island Press.
- Guo, Z. (2013). Home parking convenience, household car usage, and implications to residential parking policies. *Transport Policy*, 29, 97–106.
- Haklay, M. et al. (2001). “So go downtown”: Simulating pedestrian movement in town centres. *Environment and Planning B: Planning and Design*, 28(3), 343–359.
- Helbing, D. et al. (2002). Simulation of pedestrian crowds in normal and evacuation situations. In *Pedestrian and evacuation dynamics* (pp. 21–58). Berlin: Springer.
- Hirsch, J. A. et al. (2013). Discrete land uses and transportation walking in two U.S. cities: The multi-ethnic study of atherosclerosis. *Health & Place*, 24, 196–202.
- Hou, N. et al. (2011). Longitudinal trends in gasoline price and physical activity: The CARDIA study. *Preventive Medicine*, 52(5), 365–369.
- Kahn, E. B. et al. (2002). The effectiveness of interventions to increase physical activity. A systematic review. *American Journal of Preventive Medicine*, 22(Suppl. 4), 73–107.
- Kruger, J. et al. (2008). Prevalence of transportation and leisure walking among U.S. adults. *Preventive Medicine*, 47(3), 329–334.

- Lu, Y., Kawamura, K., & Zellner, M. (2008). Exploring the influence of urban form on work travel behavior with agent-based modeling. *Transportation Research Record: Journal of the Transportation Research Board*, 2082, 132–140.
- Mackie, P. J., Jara-Díaz, S., & Fowkes, A. S. (2001). The value of travel time savings in evaluation. *Transportation Research Part E: Logistics and Transportation Review*, 37(2–3), 91–106.
- Marsden, G. (2006). The evidence base for parking policies—A review. *Transport Policy*, 13(6), 447–457.
- Marshall, J. D. et al. (2005). Inhalation of motor vehicle emissions: Effects of urban population and land area. *Atmospheric Environment*, 39(2), 283–295.
- Martin, A., Suhrcke, M., & Ogilvie, D. (2012). Financial incentives to promote active travel: An evidence review and economic framework. *American Journal of Preventive Medicine*, 43(6), e45–e57.
- Mason, W. A., Conrey, F. R., & Smith, E. R. (2007). Situating social influence processes: Dynamic, multidirectional flows of influence within social networks. *Personality and Social Psychology Review*, 11(3), 279–300.
- McLeroy, K. R. et al. (2003). Community-based interventions. *American Journal of Public Health*, 93(4), 529–533.
- Miller, G. A. (1956). The magical number seven, plus or minus two: Some limits on our capacity for processing information. *Psychological Review*, 63(2), 81–97.
- Murtagh, S. et al. (2012). Predicting active school travel: The role of planned behavior and habit strength. *International Journal of Behavioral Nutrition and Physical Activity*, 9(1), 65.
- Ortúzar, J. d. D., Willumsen, L. G. (2011). *Modeling transport*.
- Ortúzar, J. d. D., & Willumsen, L. G. (2001). *Modeling transport*. New York: John Wiley and Sons.
- Pellegrini, P. A., Fotheringham, A. S., & Lin, G. (1997). An empirical evaluation of parameter sensitivity to choice set definition in shopping destination choice models. *Papers in Regional Science*, 76(2), 257–284.
- Powell, K. E., Paluch, A. E., & Blair, S. N. (2011). Physical activity for health: What kind? How much? How intense? On top of what? *Annual Review of Public Health*, 32(1), 349–365.
- Pucher, J. et al. (2011). Walking and cycling in the United States, 2001–2009: Evidence from the national household travel surveys. *American Journal of Public Health*. [AJPH.2010.300067](https://doi.org/10.2196/ajph.2010.300067).
- Pucher, J., & Renne, J. L. (2003). Socioeconomics of urban travel: Evidence from the 2001 NHTS. *Transportation Quarterly*, 57(3), 49–77.
- Rodriguez, D. A. et al. (2009). Land use, residential density, and walking: The multi-ethnic study of atherosclerosis. *American Journal of Preventive Medicine*, 37(5), 397–404.
- Ronald, N., Sterling, L., & Kirley, M. (2007). An agent-based approach to modelling pedestrian behaviour. *International Journal of Simulation: Systems, Science and Technology*, 8(1), 25–39.
- Sallis, J. F., Owen, N., & Fisher, E. B. (2008). Ecological models of health behavior. In K. Glanz, B. Rimer, & K. Viswanath (Eds.), *Health behavior and health education: Theory, research, and practice* (pp. 465–482). San Francisco: Jossey-Bass.
- Salon, D. et al. (2012). How do local actions affect VMT? A critical review of the empirical evidence. *Transportation Research Part D: Transport and Environment*, 17(7), 495–508.
- Schafer, A. (2000). Regularities in travel demand: An international perspective. *Journal of Transportation and Statistics*, 3(3), 1–32.
- Shoup, D. (1997). The high cost of free parking. *Journal of Planning Education and Research*, 17(1), 3–20.
- Shoup, D. (2011). Free parking or free markets. *Cato Unbound*, 4.
- United States Department of Transportation (2003). *Revised departmental guidance for the valuation of travel time in economic analysis*. <<http://www.transportation.gov/regulations/revised-value-travel-time-2003>>.
- Stokols, D., Allen, J., & Bellingham, R. L. (1996). The social ecology of health promotion: Implications for research and practice. *American Journal of Health Promotion*, 10(4), 247–251.
- Turner, A., & Penn, A. (2002). Encoding natural movement as an agent-based system: An investigation into human pedestrian behaviour in the built environment. *Environment and Planning B: Planning and Design*, 29(4), 473–490.
- Wardman, M. (2001). A review of British evidence on time and service quality valuations. *Transportation Research Part E: Logistics and Transportation Review*, 37(2–3), 107–128.
- Weiner, B. J. et al. (2012). In search of synergy: Strategies for combining interventions at multiple levels. *JNCI Monographs*, 2012(44), 34–41.
- Willis, A. et al. (2004). Human movement behaviour in urban spaces: Implications for the design and modelling of effective pedestrian environments. *Environment and Planning B: Planning and Design*, 31(6), 805–828.
- Yang, Y. et al. (2011). A spatial agent-based model for the simulation of adults' daily walking within a city. *American Journal of Preventive Medicine*, 40(3), 353–361.
- Yang, Y. et al. (2012). Exploring walking differences by socioeconomic status using a spatial agent-based model. *Health & Place*, 18(1), 96–99.
- Yang, Y. et al. (2014). Examining the impact of the walking school bus using an agent-based model. *American Journal of Public Health*, 104(7), 1196–1203.
- Yang, Y., & Diez-Roux, A. (2013). Using an agent-based model to simulate children's active travel to school. *International Journal of Behavioral Nutrition and Physical Activity*, 10(1), 67.
- Zhu, W. et al. (2013). Agent-based modeling of physical activity behavior and environmental correlations: An introduction and illustration. *Journal of Physical Activity and Health*, 10, 309–322.