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Agent-Based Modeling of Physical Activity Behavior and Environmental Correlations: An Introduction and Illustration

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***Purpose*:** To introduce Agent-Based Model (ABM) to physical activity (PA) research and, using data from a study of neighborhood walkability and walking behavior, to illustrate parameters for an ABM of walking behavior. ***Method*:** The concept, brief history, mechanism, major components, key steps, advantages, and limitations of ABM were first introduced. For illustration, 10 participants (age in years: mean = 68, SD = 8) were recruited from a walkable and a nonwalkable neighborhood. They wore AMP 331 triaxial accelerometers and GeoLogger GPA tracking devices for 21 days. Data were analyzed using conventional statistics and high-resolution geographic image analysis, which focused on a) path length, b) path duration, c) number of GPS reporting points, and d) interaction between distances and time. ***Results*:** Average steps by subjects ranged from 1810–10,453 steps per day (mean = 6899, SD = 3823). No statistical difference in walking behavior was found between neighborhoods (Walkable = 6710 ± 2781, Nonwalkable = 7096 ± 4674). Three environment parameters (ie, sidewalk, crosswalk, and path) were identified for future ABM simulation. ***Conclusion*:** ABM should provide a better understanding of PA behavior's interaction with the environment, as illustrated using a real-life example. PA field should take advantage of ABM in future research.

***Keywords*:** GPS, mapping, environment, statistical modeling

The impact of the environment, especially built environment, on physical activity (PA) participation has been well documented.[1–4] While measuring and tracking individual PA participants, and their interactions with the environment is possible using a combination of PA, global positioning system (GPS), and Geographic Information System (GIS) measures, modeling the environmental factors or correlates and their impact using traditional statistical methods is still a challenge. There are several reasons for this:

1. It is very difficult to correlate travel-related PA with the environment because these activities extend over both time and space. In the end, PA must be assigned to individual subjects, not to specific locations. For example, a heavily used pedestrian bridge could be considered successful if it facilitated more walking; it would be less successful if it simply replaced an already heavily used crosswalk without having much effect on overall walking activity levels. The bridge is important only as a correlate of activity
2. It is difficult to quantitatively assess policy intervention strategies based on discovered correlates. For example, suppose that a survey reveals that both crossing major roads and lack of sidewalks are important inhibitors of pedestrians. In a typical urban setting with hundreds of dangerous road crossings and miles of thoroughfares with no or poor sidewalks, the question becomes which specific projects will produce the greatest yield in terms of increased pedestrian use. Commonly used correlational statistical methods are not appropriate because of the cluster nature of the data (ie, participants from a neighborhood are not independent of each other). As a result, Type I errors in statistical analysis are often heightened[5]
3. The statistical methods that can take clustered data into consideration in the data analysis (eg, the hierarchical linear model, HLM)[5] assume that PA participants are limited in macro units (eg, neighborhood) being studied. This assumption is often not true: a person who lives in walkable neighborhood in the suburb may walk very little if he/she spends most of their time in the city or a place where there are no sidewalks or it is not safe to walk

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4. The models that are appropriate for the clustered data usually require the data to be collected at multiple levels (eg, individual and neighborhood levels for the HLM); therefore, a large sample size is needed.

Clearly, a new modeling approach that can eliminate these limitations is needed. One tool often employed for spatial analysis is a GIS. Cities already use GIS to manage land and utilities; demographic researchers use it to understand area trends, and applications can be found in geology, geography, forestry, and environmental sciences, etc. However, addressing problems involving complex processes and events that occur in space and time presents an impossible challenge for a typical GIS. For these problems, a method and tool specifically designed to address events over time and space is more appropriate. Fortunately, agent-based modeling (ABM) can eliminate the above noted limitations of GIS and meet the challenges that evaluation of the impact of the environment on PA participation has.

Key Terms and Concepts of Agent-Based Model (ABM)

The hub of ABM is the "agent," the subject/individual with a set of characteristics or attributes. An agent's behaviors (eg, responses to the environment or interacts with other agents in the system) are determined by a set of rules governing its decision-making and protocols for communication. Agents are diverse, which matches the real world. ABM is a simulation technique. A simulation is a computer model of a phenomenon that occurs over time. Simulations are ubiquitous in the "hard sciences" and engineering––with uses ranging from the best design of air ducts in a luxury automobile to the probable state of the universe billions of years ago. A specific branch of simulation examines how objects interact with each other and the environment. The military was an early user of force-on-force simulations where the agents interacted with their environment and each other in battle. Since terrain is a key feature of military engagements, military simulations have grown to feature highly detailed terrain databases containing topography, road networks, waterways, foliage, building schematics, weather patterns, and ocean currents. Simulated objects interact with the environment and each other in increasingly complex manners. An agent-based simulation consists of a set of agents, a set of agent relationships, and a framework for simulating decisions and interactions. Unlike traditional modeling techniques, agent-based simulation begins and ends with the agent's perspective.[6]

A Brief History of ABM

In the 1960s, the U.S. Army developed a simulation called CARMONET that featured simple objects operating over low fidelity terrain. Human operators tightly scripted object's behaviors at the beginning of the simulation. They had no real behaviors during the simulation beyond a few, basic probabilistic events that ruled events such as target detection. This approach gave way in the 1970s to simulations that were operated by humans in real time. The first of these, Janus, developed by the Lawrence Livermore National Laboratory (LLNL), was soon adopted by the U.S. Army and other military services throughout the world. Janus permitted objects to be manipulated as the simulation progressed, thereby giving them the appearance of rationale behavior. Still, objects themselves possessed only the most rudimentary autonomic behaviors such as firing at a foe or slowing down when climbing up a hill. The requirement for more autonomous objects became apparent with the advent of the Defense Advanced Research Projects Agency (DARPA) networked training simulation called Simnet, which comprised a large number of manned simulators operating within a virtual environment. Manufacturing and manning hundreds of these systems was an expensive proposition, but it was still short of the tens of thousands of objects involved in the types of simulations of most interest. For this, DARPA explored a new type of simulation called a Semi-Automated Force (SAF). SAF models are distinguished by the largely autonomous behaviors of virtual objects such as vehicles, people, and aircraft. These objects are designed to react to battlefield conditions in a manner that would be reasonable for human operators, thereby greatly decreasing the cost of running large simulations with thousands of objects. SAF systems consume enormous amounts of computer resources and are constrained to run in real time. Thus, it is very difficult to examine large parameter spaces with SAF-like simulations. The research that developed these simulations has lead directly to Agent Based Modeling (ABM). ABM is a simulation methodology that couples software objects, called "Intelligent agents," with behaviors and rudimentary reasoning ability.[7] These simulations are used to study social patterns, military operations, and areas of interest in many other fields.[8–10]

Other parallel developments of ABM include the development of the cellular automata in the 1940s and the genetic algorithms by Holland in the 1970s. In 1984, the Santa Fe Institute was established with a focus on ABM. The concept of artificial life was developed/coined by Langton in a workshop held at Los Alamos in 1987.[11] In the 1990s, ABM was extended to artificial societies.[12] In 2002, Wolfram published a book called *A New Kind of Science* to describe the potential impact of ABM.[13] Today, ABM has been applied as a means of research in economics, organizations, supply chains, electric power market restructuring, transportation, human movements in emergency evacuation planning, societies/cultures, terrorism, military maneuvers, consumer markets, and biological processes.[8,10,14,15]

How ABM Functions

In contrast to traditional equation-based, top-down modeling, ABM grows a simulated complex adaptive system from the bottom-up; individual agents make up the system, and they interact among themselves and with the environment according to rules governing behavior and environmental interactions. ABM best addresses situations or problems with many interacting, intelligent objects. For example, an ABM applied to urban transportation activities would begin by defining the street grid (the environment) and driver agents with scenario guiding roles for the following agents—"9-5" commuters, students with flexible schedules, deliverymen, etc. Each agent would seek to accomplish its particular goal, such as arriving at work on time, by adjusting their driving patterns to accommodate the environment and other agents. A given agent will learn over time which route is the fastest and alter its behavior accordingly.

An ABM consists of several important components. These vary by application, but most all consist of

1. *The environment*. For walking behavior this must include a digital terrain elevation model (for computing the walking gradient), roads and their types, sidewalks, crosswalks, stoplights, ramps, railroads, water features, and ground cover (trees, fields, water, rocks, etc). At an intermediate level, this might include buildings and areas such as parks, malls, shopping areas, parking lots, bus/train routes, school grounds, and so forth. At a very high level we might identify high crime areas, socioeconomic status, ethnicity, weather, and neighborhood aesthetics. The ABM must implement interactions with the environment such as line-of-sight, automated route-planning, communication capabilities, automatic positioning, and elementary geometry. To limit the number of interactions between many thousands of agents, geographic hashing must be used (ie, agents are placed in buckets based on their location—they interact only with objects in only their bucket's neighborhood).
2. *Agents and their behaviors*. Agents are software embodiments of real world objects including objects that move or change in state: humans, cars, trucks, buses, stop lights, etc. Other agents (objects) are of a more abstract nature: road repairs, accidents, graffiti, and large events. This program must include interactions between objects: line-of-sight, communications, approach, and avoidance. Group behavior is a consequence of activity modeling on an individual basis rather than from a top-down direction. For example, a queue at a bank is caused by the agent's interaction with the environment (ropes and signs to direct formation) and other objects (in the case of humans not getting too close as to violate societal norms). At the lowest implementation level, we simulate agents moving through their environment at different velocities. Agents can be contained in other agents such as a human driving a car or taking a train. At a higher level, we simulate fine detail planning activities such as what route to take, and where to go. At the highest level, an agent has plans for the day such as going to work, going out to lunch, and heading home, etc.
3. *Scenario generation*. Though there may be many thousands of agents, there may be only a few different types. The scenario generation task creates the agents, places them in their initial positions in the environment, assigns their daily activities, and assigns various parameters. This can be as simple as completely random assignment to complex creations based on census and public health data.
4. *Parameters, multiple runs, randomness, collection of statistics, graphics*. Any number of parameters might influence simulation outcome. Parameters can be scalar values such as the time to run the simulation for, the number of agents to generate, or the random number seed to use. Other parameters might be distributions such as the range, mean, and standard deviation of walking speeds. The ABM implementation must be able to vary some of these, collect statistics for outcome analysis and perform multiple runs to encompass the variability. A graphical interface is necessary to provide some level of confidence. Since ABM is based on simulations, software is an important part of the development of an ABM application. Depending on users' preferences, the software application can be developed used traditional structured languages (eg, C, Pascal, etc.), objective languages (eg, Java, C++, etc.) or mathematics packages (eg, Mathematica, etc.). In addition, many ABM specific software have been developed; NetLogo (ccl.northwestern.edu/netlogo), Swarm (swaarm.org), and Repast (repast.sourceforge.net) to just name a few.

Key Steps of ABM

The key steps for an ABM are a) identifying the agent types and other objects (classes) along with their attributes; b) defining the environment the agents will live and interact in; c) specifying the methods by which agent attributes are updated in response to either agent-to-agent interactions or agent interactions with the environment; d) adding the methods that control which agents interact, when they interact, and how they interact during the simulation; and e) implementing the agent model in computational software.[16] Steps a–c are known collectively as the preparation of the "parameters of automated behavior" in ABM and are the key steps of an ABM application.

Advantages and Limitations of ABM

The major advantages of ABM, according to Gilbert and Troitzsch,[17] include a) the programming languages of ABM are more expressive and less abstract than most mathematical techniques; b) ABM deals more easily with parallel processes and processes without a well-defined order of actions than mathematical equations; c) ABM has a better "modularity" (ie, when new specification requirements are added, there is little need to modify pervious parts of ABM developed); d) it is easier to build a simulation which includes heterogeneous agents (eg, people with different ages, genders, etc.) and neighborhoods with different SES and walkabilities using ABM; e) it is possible to model "fluid" or "turbulent" conditions when modeled agents and their identities are not fixed or given, but susceptible to change using ABM; and f) it is possible to model agents and make related decisions under conditions with incomplete knowledge and information. Meanwhile, ABM has its own limitations. In fact, the limitations of ABM can be considered the tradeoff of its strength—better flexibility in modeling. Because of the modeling flexibility of ABM, it is sometimes difficult to judge if model results are a mere artifact of specific parameter configurations or really meaningful findings. In addition, ABM is often complex since there are typically huge numbers of model parameters and a massive amount of model-generated data for each parameter configuration. Therefore, ABM, like other computer simulation approaches, must be systematically observed and explored before they are understood and cross-validated constantly for its external validity using real world data.[18]

An Illustration

Walking has been proven to be a popular mode of PA because it can be done in many places and requires no special equipment.[19,20] Research studies have shown that walking, especially brisk walking, can help in the long-term maintenance of weight loss, increasing high-density lipoprotein, reducing blood pressure, and decreasing the risk of death from cardiovascular disease, cancer, and diabetes.[21–27] Compared with other forms of PA, walking is also known for its low injury risk.[28] Walking, in fact, may be the best form of PA for older adults because it is simple, inexpensive and safe. Health benefits of walking for older adults have also been confirmed.[29–31] However, older adults' walking activity has been moderated by street-crossing difficulty, poor vision, and difficulty hearing approaching vehicles.[32–37]

In general, accessibility, opportunities, and aesthetic attributes of the environment have been found to be associated with physical activity participation, while the attributes of weather and safety showed less-strong relationships.[38–43] According to a recent review by Saelens, Sallis, and Frank,[44] major neighborhood characteristics that are correlated with walking include population density, land-use mix, walking infrastructure, safety (eg, traffic, crime, animals), activity facilities, neighborhood aesthetics, and topography.[45–51] Due to technical difficulties and the cost constraints, most of the published studies are based on the "group/equation-based, top-down modeling," in which a group of subjects' walking behavior or perception is correlated with environmental measures. While this kind of study can identify some key environmental correlates associated with walking behavior, their exact roles in promoting walking behavior are not understood. Fortunately, this limitation can be addressed by ABM studies. Employing a case correlation study design, the purposes of this pilot study were to identify and prepare a set of "parameters of automated behavior" for a future ABM study of older adults' walking behavior.

Method

Neighborhoods and Subjects

Using the type of neighborhoods defined by Brower[52] and the information obtained from the US Census database and local GIS databases, 2 neighborhoods, 1 walkable (ie, the Broadmoor type) and 1 not walkable (ie, the Rolling Acres type) were identified (see Figure 1) in a Midwestern university town. The subject inclusion and exclusion criteria of the study were a) the inclusion was based on numbers needed and if there was someone who matched in the other neighborhood and b) the only exclusion was people who were housebound, since we were tracking walking behavior—the people chosen must have the physical option to walk outside of the house.

A series of efforts (eg, distributing information in targeted neighborhoods, community centers, fitness facilities, making e-mail announcement, flyers left in doors, etc.) were then made to recruit subjects in the targeted neighborhoods. Twenty-two participants responded to the recruiting but only 10 of them were qualified for the study (4 males and 6 females; 5 from the Rolling Acre neighborhood and 5 from the Broadmoor neighborhood). The most unqualified ones were those who did not live in the neighborhoods to be studied. The ages of the participants ranged from 60–82 years old (mean = 68, SD = 8); mean weight was 178 pounds (SD = 28) and their mean height was 65 inches (SD = 4). Five had at least a bachelors degree (2 of which had a graduate degree), 4 had a high school degree and 1 graduated from a technical school. All subjects provided written informed consent approved by the university institutional review board before participation in the study.

Data Collection

The participants were asked to wear an AMP 331 triaxial accelerometer (to measure steps taken; from when they got up in the morning to when they went to the bed at night), GeoLogger GPS tracking devices (to record their locations; only when they went outside) and Omron HJ-112 pedometer (to record their steps) at the same time for 21 consecutive days. Recruited subjects met with the project coordinator for an hour and were trained to use the devices. If participants had to remove the devices for a nonwalking activity (eg, showering or swimming) they were asked to record the time and reason in an activity log. They were also asked to record their daily steps on a chart/diary which was returned to the project coordinator when they completed their 21 days. The participants also completed questionnaires assessing demographics and background characteristics.

Figure 1 — Illustration of 2 selected neighborhoods: Broadmoor (walkable; shown at top) vs. Rolling Acres (nonwalkable; below).

Data Analysis

Collected data were first screened using descriptive statistics for typographical errors and outliers. Walking steps and information collected were then computed and summarized using descriptive statistics and compared using inferential statistics when appropriate. Collected GPS data were then analyzed using high-resolution geographic image analysis to help in understanding the interaction between older adults' walking behavior and the environment and to identify a set of parameters of automated behavior for an ABM of walking behavior. The major goal of the analysis was to identify the preferred walking surface to present to the ABM route planning algorithms. Specific steps are summarized below:

1. *Detailed map*. Neighborhoods studied had detailed maps built of them. Using 0.5 m resolution, orthorectified images of these areas, a high-resolution map of sidewalks, crosswalks, and footpaths was created:
   a. *Sidewalks*. A sidewalk is recognizable from the images as a number of pixels paralleling a street or meandering across open terrain to a structure, such as in a park. Sidewalks can also be inferred in some shopping malls. Points along the sidewalk and special nodes were marked where sidewalks intersect. Sidewalks were not extended to residences or small buildings
   b. *Crosswalks*. A crosswalk connects 2 sidewalks or paths across a recognizable street. A crosswalk can be inferred if at least 1 sidewalk extends perpendicular from the street near a street intersection. Crosswalks can also be inferred if a sidewalk extends to a street and is not connected to a residence
   c. *Footpaths*. A path can be inferred if there is no sidewalk alongside a street but walking will occur on the street edge. Footpaths also cross streets at intersections where no sidewalks exist and connect sidewalks where construction is occurring
2. *Distance matrix*. To correct GPS and registration errors, a distance matrix was built where each cell has the distance to the nearest entity (sidewalk, crosswalk, or path) and each reporting the type of the nearest entity
3. *Mapping subjects*. A subject's GPS position was mapped to the nearest entity and each reporting point was marked on the map with a circle for sidewalks, plus sign for crosswalks, and squares for paths. If the subject was not moving near a sidewalk, crosswalk, or footpath, (distance > 10 m) we used triangles to indicate cross country
4. *Examining GPS data*. The GPS data were examined to isolate walks using the following heuristics: a) a change of date starts a new walk; b) if the previous report time is over an hour in the past, a new walk is started; c) if the reported distance between 2 points is more than 200 m, a new walk is started. A reported point is discarded if its speed exceeds 4.47 m/second (10 miles/hour), the number of useful GPS satellites is less than 4, or its GPS position lies outside the study area. To arrive at these heuristics various point separations were tried and the number of paths generated counted. The horizontal axis shows the distance selected [heuristic (c) above] and the vertical shows the total number of paths generated. The number of walks per meter separation does not significantly change beyond 200 m
5. *Path analysis*. Considering that a "walk" often starts and ends at the same location, the distance between the walk start and end points should be minimal. Using the criteria presented, the start point of most walks is within 200–400 m of the end point
6. *Path analysis—walkability*. Paths were analyzed in both the neighborhoods by computing a) path length in meters, b) path duration, c) number of GPS reporting points, and d) distances and times on the 3 route classes. This was accomplished with the following operations:
   a. Compute the total path length
   b. Scribe the walk onto a blank matrix by drawing straight lines between each reporting point (these are usually about 3 m apart)
   c. For each matrix point, locate the nearest of the 3 classes and if it is less than some cutoff value (10 m), select that type and count each selected type. A value > 10 m is considered cross country. This is accomplished by a table lookup in the type and distance matrices (Figure 3 depicts what a distance matrix looks like) computed earlier rather than repeated computations
   d. Normalize the count to the total path length.

Results

Both large between- and within-subject variations were observed in walking steps per day. Average steps walked by the subjects ranged from 1810 steps–10,453 steps per day, with an overall mean = 6899 and a large SD of 3823. No statistical difference was found in the overall steps between the 2 groups: Walkable neighborhood with mean = 6710, SD = 2781 and Not walkable neighborhood with mean = 7096, SD = 4674. We conclude that this gross measure of walkability is not suitable for Agent Based Modeling suggesting that higher resolution details of human decision making need to be modeled.

The results of high-resolution geographic analysis were summarized according to the major steps employed, as follows.

1. Detailed Map

Detailed maps of the neighborhood and nearby areas were constructed; the most densely populated neighborhood is shown in Figure 2, in which wide black lines mark sidewalks, narrow lines crosswalks, and dashed lines paths.

Figure 2 — Constructed maps of the neighborhoods and nearby area.

2. Distance Matrix

Figure 3 shows the same neighborhood with distances to the nearest sidewalk, crosswalk or foot path depicted by a grayscale with the greatest distance in black shading to white shading for nearest. The greatest distance to any path is 270 m for this particular area though the average distance is a much lower 37 m. These matrices allowed quick determination of the subject's path type given the approximate positions provided by the GPS. Every matrix element contains the distance in meters to the nearest path element and its type—when this information is needed for the analysis, the lookup does not require repeated computation.

3. Mapping Subjects

Figure 4 shows a number of walks of one subject (only every 4th point is shown to eliminate clutter). In some cases, this allowed inference of a sidewalk near a shopping mall. The comparison neighborhood, Rolling Acres, has no sidewalks and there is a major paved road separating this area from the adjacent community (see Figure 5).

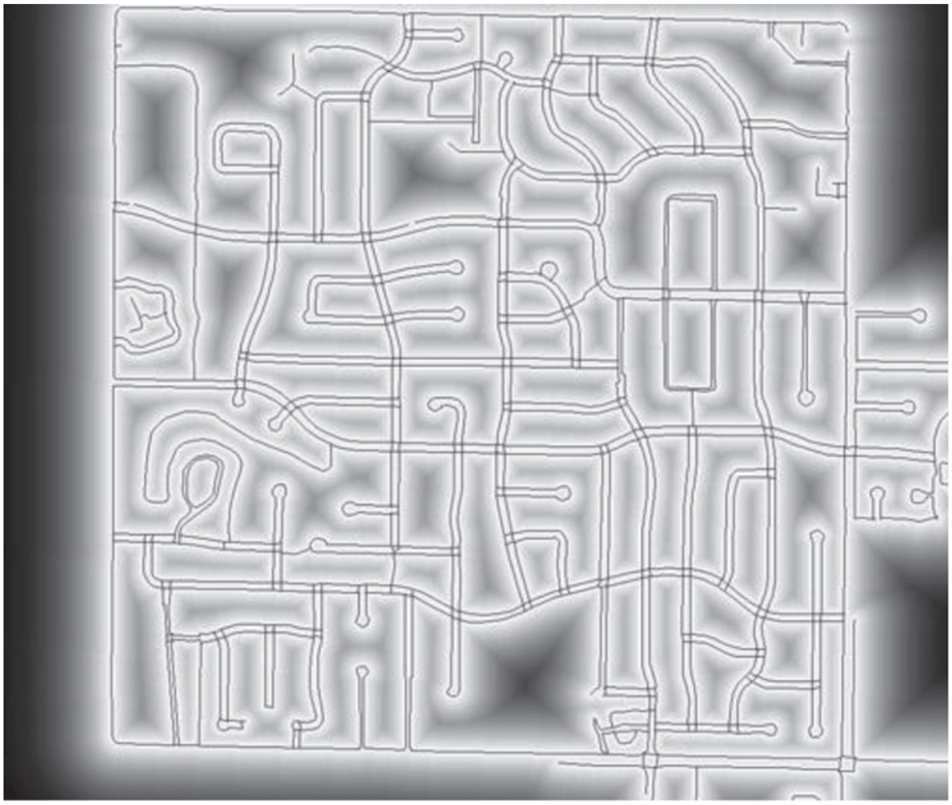

Figure 3 — Map with distances to nearest path.

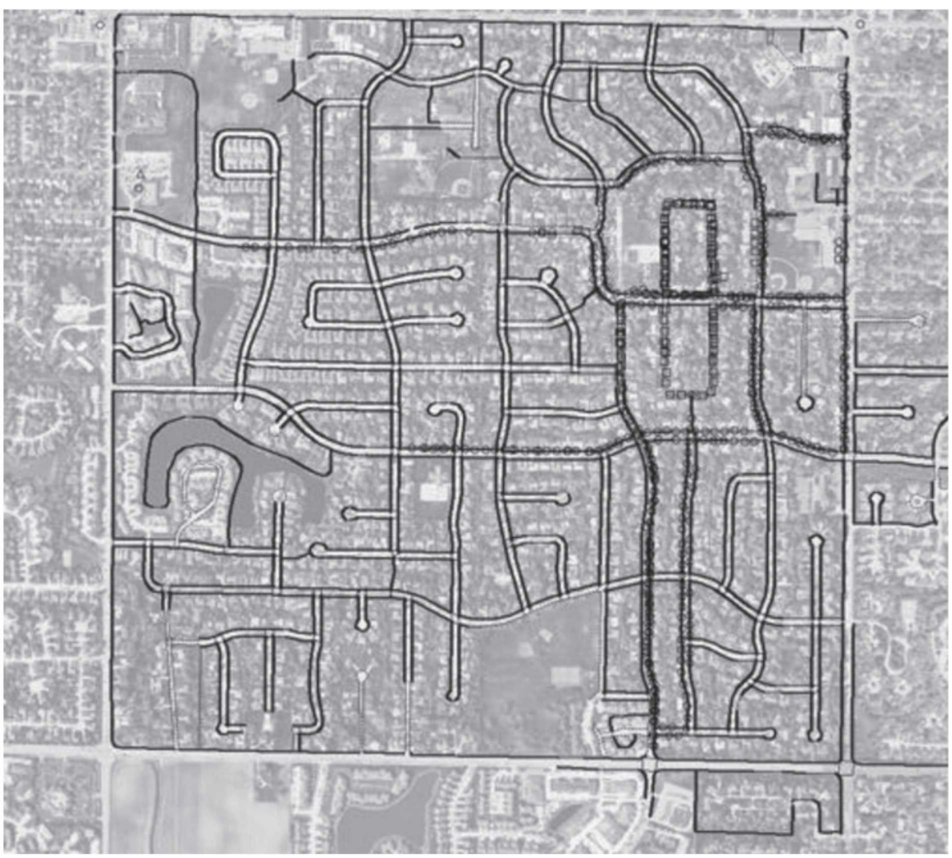

Figure 4 — Mapped information of a subject.

Figure 5 — Map of the comparison neighborhood.

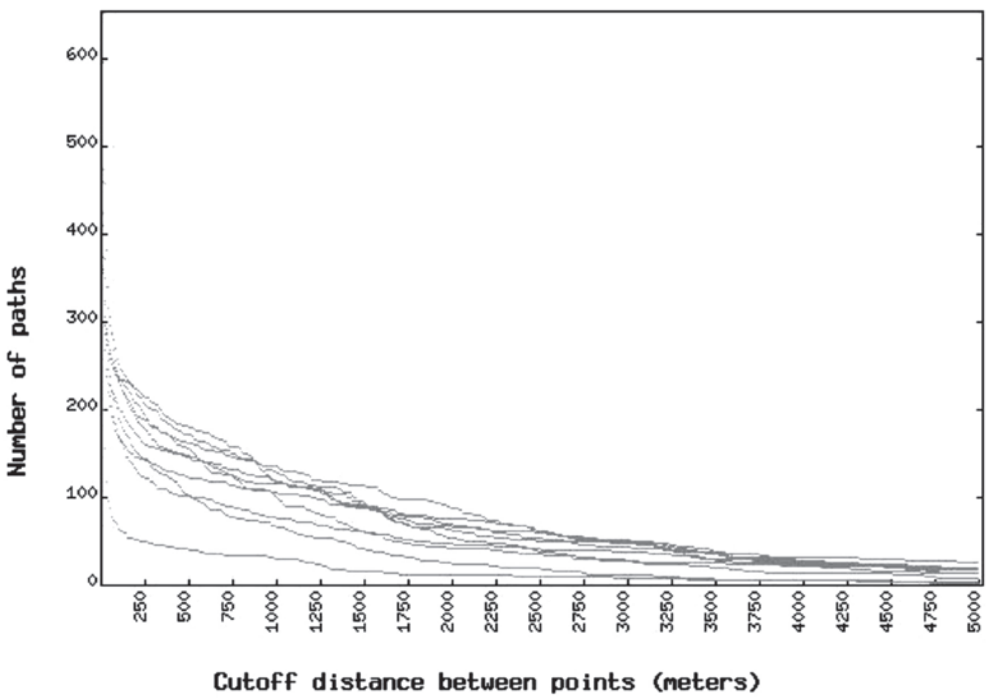

Figure 6 — Relationship between cutoff distances and number of paths.

4. Examining GPS Data

Separating GPS data streams into walks relies on differences in time and space between entries. We first consider separation in space—a new walk starts when the separation between 2 successive data points exceeds a specified distance. To generate Figure 6, we counted each subject's walks by varying the minimum separation distance. The distance required to make a new walk is the horizontal axis and the vertical axis is the total number of paths generated. Each subject is a separate line. The number of walks per meter separation does not significantly change beyond a separation distance of 200 m.

5. Path Analysis

Considering a "walk" to start and end at the same location, we computed the distance between the walk start and end points with a histogram for all subjects in Figure 7. Using the criteria presented, the start point of most walks is within 200 m of the end point.

6. Time Analysis

The times between successive GPS points that established when a new walk started were varied. As seen in Figure 8, increasing the cutoff time between points beyond about 1 hour has less effect, whereas very short times create many walks. Setting this value around 10 minutes allows for dropouts in urban canyons (streets running through dense blocks of structures/buildings, especially skyscrapers) or being indoors.

Recall that the goal is to identify the preferred walking surface to present to the ABM route planning algorithms. Data from all 10 subjects are presented in Table 1. The path number in Table 1 is an index that results from removal of short paths and single reporting points. The number of points in the path is listed and its total length in meters. Followed are distances spent on each type: sidewalk, a path, a crosswalk or far from any of these (Off path). The summary gives percentages of distances of each type.

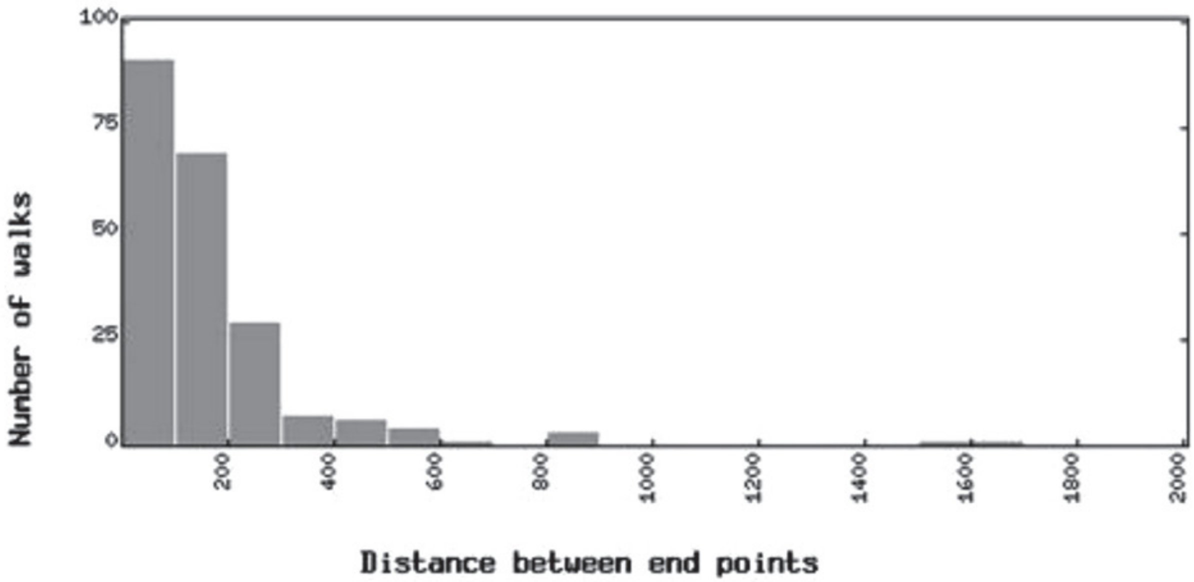

Figure 7 — Relationship between walks and end-point distances.

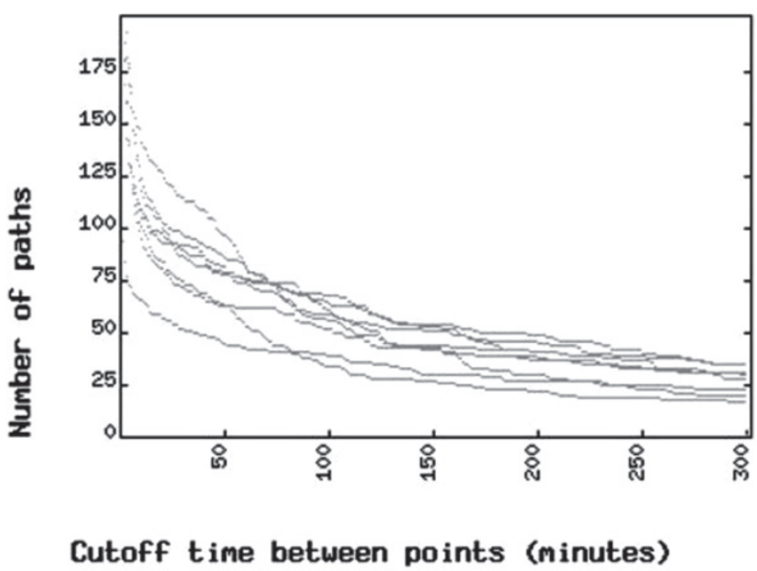

Figure 8 — Relationship between cutoff time and number of paths.

Table 1 Preferred Walking Surface by Subject

Path analysis of . . .	Points	Length	Sidewalk	On path	Crosswalk	Cross country
Subject 1						
Path 1	177	1227.2	227.3	954.5	0.0	45.5
Path 5	9	137.4	0.0	0.0	0.0	137.4
Path 9	282	2387.8	2014.4	267.6	68.5	37.3
Path 14	216	1531.7	555.3	964.0	0.0	12.4
Path 21	117	913.8	702.5	53.9	29.0	128.5
Path 22	12	206.2	184.4	0.0	21.8	0.0
Path 23	17	170.1	141.4	28.7	0.0	0.0
Path 26	370	2430.3	2032.0	304.8	61.0	32.5
Path 29	92	1309.6	791.9	444.0	14.3	59.3
Path 30	15	345.8	46.6	257.2	0.0	42.1
Path 34	9	150.4	0.0	0.0	0.0	150.4
Path 35	7	197.4	84.0	45.4	11.3	56.7
Path 39	205	1815.2	1524.0	104.2	70.1	116.9
Path 40	299	2116.5	1836.9	253.1	26.5	0.0
Path 41	103	1149.8	910.2	216.5	0.0	23.1
Path 43	38	777.7	554.6	99.9	19.1	104.1
Path 48	131	1375.8	1237.2	106.2	28.2	4.3
Path 52	99	847.9	787.0	26.4	34.5	0.0
Path 53	398	3649.6	2880.0	592.9	38.7	137.9
Total	2596	22740.3	16509.4	4719.2	423.1	1088.6
Percentage			72.6	20.8	1.9	4.8
Subject 2						
Total	3915	28301.1	6.3	27082.5	0.0	1212.3
Percentage			0.0	95.7	0.0	4.3
Subject 3						
Total	5979	43993.0	0.0	42234.7	0.0	1758.3
Percentage			0.0	96.0	0.0	4.0
Subject 4						
Total	3640	27939.3	24383.0	2109.3	922.7	524.3
Percentage			87.3	7.5	3.3	1.9
Subject 5						
Total	381	2848.6	2654.3	31.3	57.4	105.5
Percentage			93.2	1.1	2.0	3.7
Subject 6						
Total	1021	8153.4	5153.2	2620.5	228.4	151.2
Percentage			63.2	32.1	2.8	1.9
Subject 7						
Total	1919	15915.5	10874.5	934.4	512.6	3594.0
Percentage			68.3	5.9	3.2	22.6
Subject 8						
Total	438	2938.8	0.0	2938.8	0.0	0.0
Percentage			0.0	100.0	0.0	0.0
Subject 9						
Total	65	1618.4	161.4	555.8	0.0	901.2
Percentage			10.0	34.3	0.0	55.7
Subject 10						
Total	80	2509.3	0.0	1728.8	0.0	780.5
Percentage			0.0	68.9	0.0	31.1

Note. Only full results of Subject 1 are reported here; others are statistical summaries. Subjects 1 and 4–7 were from the Broadmoor neighborhood and Subjects 2, 3, and 8–10 were from the Rolling Acres neighborhood.

Discussion

While ABM has been widely used in other fields and has great potential in physical activity and environment research, little has been done in this area. To take full advantage of ABM, its utility and required conditions must be fully understood. Questions such as "What data and parameters are needed for an ABM of PA behavior?"; "What data granularity is appropriate for ABM?"; "What is the validity/utility of an ABM?"; "Which specific model is more appropriate to PA behavior?"; and "How much the existing software has to be modified for PA data?" have to be addressed before it can be applied. In addition, the concepts and methods of ABM have to be introduced to PA researchers to stimulate research and application of the new methods. Because the complexity of the research issues and expertise involved (eg, physical activity assessment, environment, transportation, GPS/GIS, ABM, and public health, etc), a multidisciplinary team is clearly needed. Furthermore, it is our belief that such a multidisciplinary should be able to bring many new insights of the impact on people's PA participation. With an interest in understanding neighborhood walkability and walking behavior of older adults, this study made an initial attempt to explore ABM's application in PA research.

The neighborhood has long been considered an important social-environmental factor for older adults' health.[53] The neighborhood is also an important factor for walking and other physical activity behavior of adults and older adults.[54,55] Walkability of a neighborhood, however, has not been found to be a consistent predictor of older adults' walking behavior.[56] This suggests that some aggregate measures of environment may not be suitable for use by ABM's—their emphasis on individual behavior will require measuring and using data at higher resolutions. Environmental information at this level includes road network traffic densities, high resolution geographic features (stop signs, cross walks, school zones, parks, shopping, theaters, restaurants, etc.), and topography. Using GPS and pedometers is the first step to collecting this information.

Although the sample size is small, the results of this study also suggest that the built environment may not be implicated in walking behavior of older adults. In this study, it was found that there is a large variation in the distances walked on and off paths in both neighborhoods; the neighborhood without sidewalks still allowed walks and not having sidewalks did not affect the average walk length (5.9 km in the neighborhood with sidewalks vs. 6 km in the neighborhood without). Thus, neighborhood walking characteristics did not significantly affect walking behaviors of older adults. Rather, their own preferences and walking habits seem to determine their walking behavior. This implies that ABM is the ideal mechanism for building PA computer models as individual humans and their behaviors are its basis.

Three walking environment parameters (ie, sidewalk, crosswalk, and path) were constructed in this study. As illustrated in the findings, by examining individuals' walking paths and their interaction with sidewalk and crosswalk parameters, walking patterns across neighborhoods can be examined and compared. With other associated parameters (eg, location and purposes of a walk), these parameters thus demonstrated as useful for future ABM of walking behavior.

While this study made an initial attempt to use the latest technology and applied a new method to understand individual walking behaviors and their interaction with specific features of neighborhood walkability, several limitations should be acknowledged. First, the sample size is small. While advanced technology could help in providing rich and detailed information, associated costs and inconvenience often become constraining. Exploring other inexpensive and convenient technology devices (eg, a smart phone), could help overcome this issue. Second, only 2 neighborhoods were studied. While they were selected according to traditional understanding of walkable and nonwalkable neighborhoods, other factors (eg, crime and unemployment rates) were not controlled for during neighborhood selection. Future studies should employ a greater number of neighborhoods to verify the findings of this study. Third, because of the model flexibility of ABM, exact role of these identified environment parameters should be examined and cross-validated in future ABM research. Finally, only a few features of walkability were examined in this study. As reported in the literature, many other features, such as dwelling density, street connectivity, land-use mix, etc., could have an impact on a neighborhood's walkability. They should all be included in future ABM based research.

Conclusions

ABM, an individual-based modeling method, has some great potential to help us understand the relationship between PA behavior and environment. This paper provides a detailed introduction to ABM, including its concept, brief history, mechanism, major components, key steps, advantages and limitations. Based on a small-sample of older adults' walking behavior and their neighborhood correlates, how to identify parameters for ABM study was then illustrated. The field of PA research should reexamine its current modeling approaches and start to systematically explore the advantage of ABM in its future research.

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