Reducing Income Inequalities in Food Consumption

Explorations With an Agent-Based Model

David J. Blok, MSc, Sake J. de Vlas, PhD, Roel Bakker, PhD, Frank J. van Lenthe, PhD

Introduction: Individual and environmental factors dynamically interact in shaping income inequalities in healthy food consumption. The agent-based model, Health Behaviors Simulation (HEBSIM), was developed to describe income inequalities in healthy food consumption. It simulates interactions between households and their environment. HEBSIM was used to explore the impact of interventions aimed at reducing food consumption inequalities.

Methods: HEBSIM includes households and food outlets. Households are characterized by location, composition, income, and preference for food. Decisions about where to shop for food (fruit/vegetable stores, supermarkets, or discount supermarkets) and whether to visit fast food outlets are based on distance, price, and food preference. Food outlets can close and new food outlets can enter the system. Three interventions to reduce healthy food consumption inequalities were tested: (1) eliminating residential segregation; (2) lowering the prices of healthy food; and (3) providing health education. HEBSIM was quantified using data from Statistics Netherlands, Statistics Eindhoven, and the GLOBE study (2011).

Results: The model mimicked food consumption in Eindhoven. High-income households visited healthy food shops more often than low-income households. Eliminating residential segregation had the largest impact in reducing income inequalities in food consumption, but resulted partly from a worsening in healthy food consumption in high-income households. Lowering prices and health education could also substantially reduce inequalities. Most interventions took 5–10 years to reach their (almost) full effects.

Conclusions: HEBSIM is a promising tool for studying dynamic interactions between households and their environment and for assessing the impact of interventions on income inequalities in food consumption.
(Am J Prev Med 2015;49(4):605–613) © 2015 American Journal of Preventive Medicine

Introduction

Dietary behavior is a major contributor to socioeconomic inequalities in health.[1,2] Lower socioeconomic groups are less likely to consume fruit or vegetables and have higher fat-intake than higher socioeconomic groups.[3–5] Initial research attributed socioeconomic inequalities in food consumption to differences in food-related knowledge, beliefs, and attitudes between socioeconomic groups.[6] However, there is growing evidence of the importance of characteristics of the obesogenic environment, such as access to healthy foods and fast food outlets, and the price of healthy food.[7–10]

Decisions on food consumption result from interactions between individuals or households and their environment.[11–14] An environment with healthy food outlets not only influences the choice for healthy food but is also shaped by the preferences of residents because shops prefer to be close to their customers.[15,16] As such, differential access to healthy food outlets may be the outcome of feedback. In addition, the outcome may depend on differences between individuals or households in, for example, income or location, causing some people

From the Department of Public Health, Erasmus MC, University Medical Center Rotterdam, Rotterdam, The Netherlands

Address correspondence to: David J. Blok, MSc, Department of Public Health, Erasmus MC, University Medical Center Rotterdam, P.O. Box 2040, 3000 CA Rotterdam, The Netherlands. E-mail: d.j.blok.1@erasmusmc.nl.

0749-3797/$36.00
http://dx.doi.org/10.1016/j.amepre.2015.03.042

to be more influenced by their environments than others.[12,17] Thus, people and their environment form an interactive "system".[14,18,19]

Research aimed at identifying the best interventions to reduce income inequalities in healthy food consumption is subject to challenges. Evaluating or predicting the impact of interventions is difficult because it takes (a long) time before an intervention may show an effect and, in some cases, evaluation is not even feasible.[13] Moreover, current statistical approaches simplify the complex interactions by neglecting or fixing features of the system, such as changes in the food environment due to interventions.[13,19] Failing to properly account for such interactions may result in underestimated or overestimated effects of interventions.[13]

A "systems-thinking" method that is able to overcome these limitations is the use of agent-based models (ABMs).[13,20] ABMs are simulation models describing a system of heterogeneous agents that influence each other over time.[21,22] An agent can be any entity, such as a household or food outlet, and is characterized by attributes (e.g., income) and follows behavioral rules, which together determine its behaviors. Behavioral rules, which are usually static, describe how an agent interacts with other agents and their environment. Agents can adapt their behaviors in response to changes in behaviors of other agents and to changes in their environment due to interventions, for example.[13,21,22] ABMs are therefore very suitable for exploring the impact of various interventions.[13,19,20]

ABMs are increasingly recognized in the fields of social epidemiology and health behavioral research.[23–26] Auchincloss et al.[23] were the first to use an ABM to understand income inequalities in diet. They modeled households' food shopping behavior in a hypothetical city and illustrated the importance of residential segregation, price, and food preference in shaping income inequalities in diet.

For this study, the agent-based model, Health Behaviors Simulation (HEBSIM), was developed by Erasmus MC. HEBSIM describes a real-world system explaining income inequalities in healthy food consumption in Eindhoven, The Netherlands. The model was quantified using empirical data and used to explore the impact of three (hypothetical) interventions aimed at reducing income inequalities in healthy food consumption: (1) eliminating residential segregation; (2) lowering prices of healthy food; and (3) health education.

Methods

Model

HEBSIM simulates the dynamic interaction between two types of agents: households and food outlets. It models households' food shopping behavior and the closures and openings of food outlets in a city. Time is represented in days. A simulation takes approximately 20 minutes to run. HEBSIM was programmed in Java using MASON and Magic-Tree, which are open-source Java libraries/tools for developing ABMs.[27,28] HEBSIM is available to researchers upon request.

In this study, the city of Eindhoven, The Netherlands was modeled. Initial conditions of the model were assigned using data about the population, obtained from Statistics Netherlands[29] and Eindhoven[30] and the 2011 wave of the Dutch prospective GLOBE study.[31] The GLOBE study includes a random sample of respondents between the ages of 15 and 75 years living in the city of Eindhoven. The 2011 wave consisted of 3,863 participants, of whom 2,398 had valid measurements on food behaviors.[31]

Environment

The city of Eindhoven is approximately 88 km^2 and includes 116 neighborhoods, 88 of which are residential neighborhoods (Figure 1A). A realistic grid was constructed using a GIS file of Eindhoven as input.[29] Each grid cell is 10 m X 10 m in size and can be occupied by a household and a food or vacant outlet. Unoccupied grid cells are considered "other areas" (e.g., parks). Household and vacant outlets were randomly distributed on the grid based on the number of households and vacant (food and non-food) outlets per neighborhood.[30] Food outlets were located on actual locations based on a search in the Yellow Pages in July 2012. In 2012, Eindhoven had 97,523 households, 12 fruit/vegetable stores, 33 supermarkets, 22 discount supermarkets, 160 fast food outlets, and 279 vacant outlets (Figure 1B and 1C).[30]

Attributes

Besides a location, each household is characterized by three other attributes: (1) household composition; (2) income level; and (3) preference for healthy food. Household composition was assigned following an empirical distribution per neighborhood and included single-person, single-parent, and multi-person with and without children.[30] Income was dichotomized into high and low. Low-income households were defined as those with a net household income <$31,777 per year and was assigned following the distribution of low-income households per neighborhood.[29] The preference for healthy food represents the attitude toward healthy food, ranging from 0 (prefers unhealthy food) to 1 (prefers healthy food). It was randomly assigned following a beta distribution. Based on results of Turrell and colleagues,[32] the mean preference for healthy food was 0.739 and 0.661 for high- and low-income households, respectively.

HEBSIM distinguishes four types of food outlets: fruit/vegetables stores, supermarkets, discount supermarkets, and fast food outlets. Besides a location, each type of food outlet has four other attributes: (1) quality of food; (2) price level; (3) monthly costs; and (4) capital. The quality of food refers to the level of healthy food sold in a food outlet, which is either mostly "healthy" or mostly "unhealthy." Fruit/vegetable stores and supermarkets were characterized as healthy, and discount supermarkets and fast food outlets as unhealthy. Studies have shown that people shopping at supermarkets eat and buy healthier food than those shopping at discount supermarkets.[33–35] Price levels were dichotomized into "cheap" and "expensive," because data only allowed quantification of households' behaviors for these categories. Fruit/vegetable stores and supermarkets were considered expensive, and discount supermarkets and fast food outlets were considered cheap.[33,34]

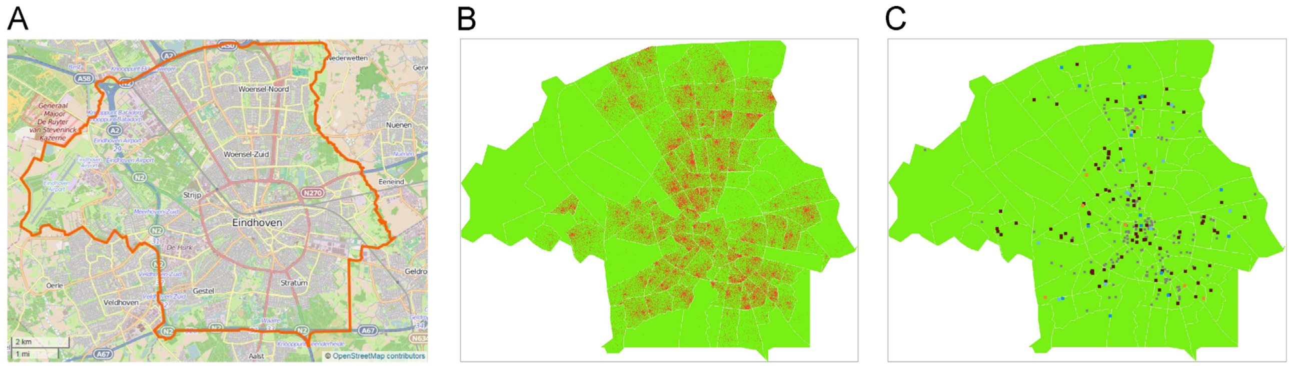

Figure 1. (A) Map of Eindhoven: the fifth largest city the Netherlands with 213,223 inhabitants and 97,523 households in 2012 (Source: OpenStreetMap.org); (B) Distribution of households on the grid at the start of the simulation: 97,523 households (red squares) in 88 neighborhoods; (C) Distribution of food outlets and vacant outlet on the grid at the start of the simulation: 12 fruit/ vegetable stores (orange), 33 supermarkets (dark blue), 22 discount supermarkets (light blue), 160 fast food outlets (brown), and 279 vacant outlets (grey).

Monthly costs, such as rent, remained unchanged during the simulation. Capital represents a food outlet's asset, which can increase or decrease during the simulation (Appendix A, available online).

Behaviors

Behavioral rules of households were based on the literature and quantified using data. Two behaviors of households were modeled: (1) food shopping and (2) fast food visits. The multi-attribute utility theory was used to guide interactions between households and food outlets and to determine behaviors.[36,37] It was assumed that each household does food shopping three times a week.[34] At each food shopping moment, each household selects a food outlet (i.e., fruit/vegetable store, supermarket, discount supermarket) by assigning a utility to each food outlet using a utility function. The food outlet with the highest utility is selected. The utility function includes determinants of food behavior and a random noise to account for bounded rationality.[38] Determinants for food behavior were based on literature and include distance, price of a food outlet, and preference for healthy food.[39] Each household assigns a score to each determinant based on its own attributes and that of the food outlet. Scores for price were derived from the GLOBE study,[31] assuming these scores differed between high- and low-income households. Scores for preference were determined by matching the quality of a food outlet with the preference for healthy food, which already incorporated income differences.

Fast food visits were considered daily. Here, each household assigns a utility to visiting fast food and to eating at home. Again, a utility function was used, but now including two determinants only: preference and price level.[39] Additionally, it was assumed that the availability of fast food in the neighborhood increases the preference for fast food.[40–43] Scores of determinants were assigned similarly to food shopping. A household only visits a fast food outlet when the utility of fast food is higher than the utility of eating at home. Finally, a fast food outlet was chosen based on distance only because fast foods only differ from each other in location (see Appendix B, available online, for technical details).

Food outlets respond to household decisions by either closing or opening a new food outlet. Closure is determined by a food outlet's capital, which increases with every customer (revenue) and decreases with monthly costs. If capital falls below zero, the food outlet closes and its location will become vacant. Every 30 days, new food outlets can be started at vacant locations. The number and type of new food outlets is determined by the monthly average number of new food outlets obtained from the Chamber of Commerce.[44] A location is randomly selected in the neighborhood with the highest expected revenue (see Appendix C, available online, for technical details).

Calibration

The model was fitted to data and ran until model outcomes reached a steady state (15,000 days). Model outcomes were based on the average results of 100 iterations. Parameters for which no data were available were calibrated against data about food shopping, fast food visits, and food outlets obtained from the GLOBE study and literature.[31,45] These parameters included relative importance of distance, price and preference of healthy food, the importance of bounded rationality, and monthly costs. Calibration was performed through an iterative process until the proportion of households that visited food outlets in the past week and the number of food outlets matched the data (Table 1, Appendix D, available online).

Outcome

Healthy food consumption was defined as the average proportion of times a household visited a healthy food outlet. Visits to fruit/ vegetable stores and supermarkets counted as healthy food consumption, whereas visits to discount supermarkets and fast food outlets counted as unhealthy food consumption. Income inequalities in healthy food consumption were defined as the difference between healthy food consumption of high- and low-income households.

Interventions

The impact of three (hypothetical) interventions, targeting potential upstream and downstream causes of income inequalities in food consumption, was explored. The first intervention assumed income inequalities in food consumption to be caused by differential access to healthy foods. The impact of eliminating residential segregation in neighborhoods on income inequalities in healthy food consumption was assessed. Households were relocated such that each neighborhood had the same proportion of high- and low-income households.

Table 1. Comparison of Model Outcomes With Empirical Data Obtained From the GLOBE Study

		Model outcomes[a] (90% CI)[b]	Data
Proportion of households that visited a fruit/vegetable store at least once in the past week			
Fruit/vegetable store	High-income household	0.427 (0.354–0.488)	0.250
	Low-income household	0.369 (0.300–0.419)	0.331
Supermarket	High-income household	0.886 (0.857–0.914)	0.883
	Low-income household	0.813 (0.781–0.845)	0.842
Discount supermarket	High-income household	0.393 (0.344–0.431)	0.412
	Low-income household	0.554 (0.510–0.600)	0.584
Proportion of households that visited a fast food outlet in the past week			
Never		0.252 (0.249–0.254)	0.249[c]
1–2 times		0.514 (0.512–0.517)	0.522[c]
>2 times		0.234 (0.230–0.236)	0.229[c]
Proportion of households that visited one type of food outlet		0.364 (0.329–0.405)	0.356
Average distance travelled for food shopping (meters)			
High-income household		2052 (1951–2157)	—
Low-income household		1775 (1695–1870)	—
Number of food outlets			
Fruit/vegetable store		12 (9–14)	12
Supermarket		34 (30–37)	33
Discount supermarket		23 (20–26)	22
Fast food		161 (158–163)	160

[a]Model outcomes in steady state (after 15,000 days).
[b]90% CI: 90% of the runs fall within this interval.
[c]Obtained from French et al. (2001).

The second intervention assumed higher prices of healthy food to be a main contributor of income inequalities in food consumption. Therefore, the impact of reducing the prices of healthy food by subsidizing all healthy food outlets was assessed. Expensive healthy food outlets were changed to "cheap" and the subsidy was reflected in lowering costs.

The third intervention featured health education. In different hypothetical scenarios, it was assumed that health education (e.g., through mass media campaigns) would increase the preference for healthy food by 2%, 4%, 6%, and 8% in the population. It was further tested whether these scenarios would differ when: (1) all households were exposed to the intervention or (2) only low-income households were exposed. It was assumed that the intervention was fully effective and that the effect was similar across all exposed households.

Results

Table 1 shows that all model outcomes were close to the data, except the proportion of high-income households that visited a fruit/vegetable store. Also, high-income households traveled further on average than low-income households for food shopping.

Figure 2 summarizes the impact of all interventions on income inequalities in healthy food consumption compared to no intervention. In the baseline scenario, the difference in the proportion of healthy food consumption between high- and low-income households was 14.8%. Eliminating residential segregation immediately reduced income inequalities in healthy food consumption to approximately 8.0%, which increased again to 10.4% in the long run because of adjustments of food outlets to the new household composition in neighborhoods. Lowering prices of healthy food decreased income inequalities in healthy food consumption to around 14.0% within 5 years and 13.4% in the long term. Health education targeting all households slightly widened income inequalities in healthy food consumption to 14.9%–15.4%, depending on the assumed level of increase in the preference for healthy food. By contrast, health education targeting only low-income households decreased inequalities to 12.2%–14.1%.

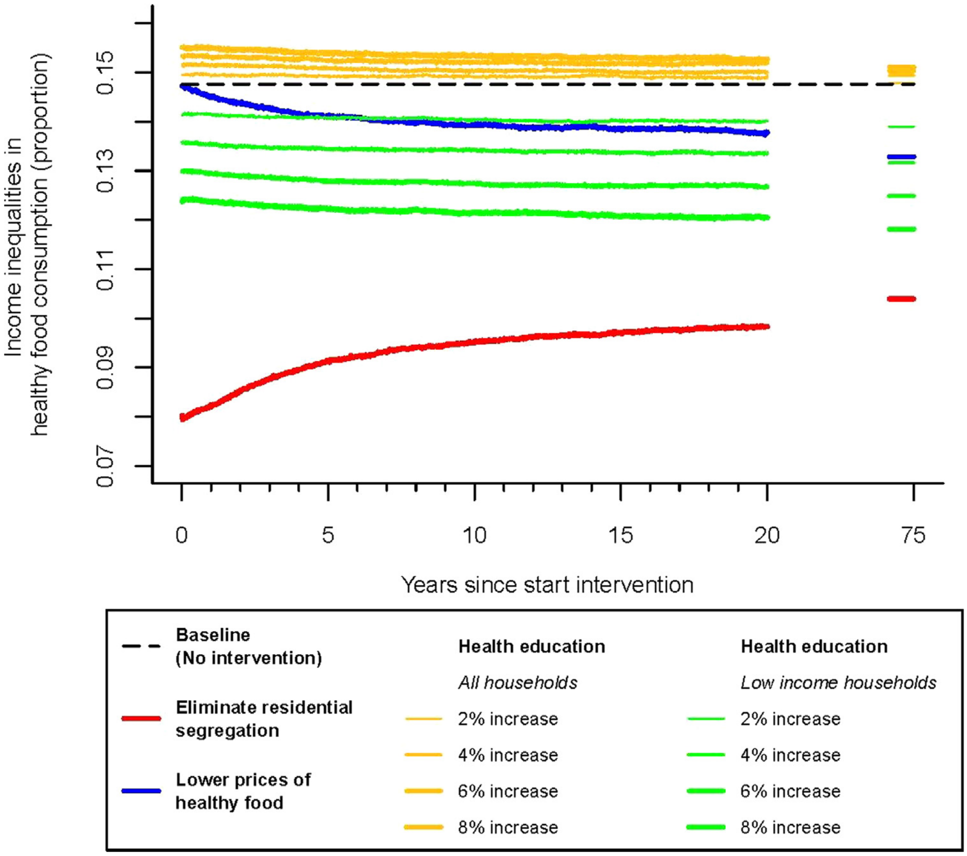

Figure 2. Impact of all interventions on socioeconomic inequalities in healthy food consumption. Model outcomes are the average of 100 runs. A new equilibrium was established after 75 years.

Figure 3 shows the impact of interventions on healthy food consumption of high- and low-income households separately. In the baseline scenario, healthy food consumption for high- and low-income households was 56.5% and 41.7%, respectively. Eliminating residential segregation increased healthy food consumption of low-income households to 44.9%, but decreased healthy food consumption of high-income households to 55.3% (Figure 3A). This was because a portion of high-income households moved to former low-income neighborhoods with relatively more unhealthy food outlets, resulting in fewer visits to healthy food outlets because of distance. Lowering prices of healthy food only affected low-income households by increasing healthy food consumption to 43.2% (Figure 3B). Health education targeting all households would increase healthy food consumption 57.3%–61.1% among high-income households and 42.5%–46.0% among low-income households (Figure 3C). Health education targeting low-income households only increased healthy food consumption in the low-income group (42.0%–44.7%) (Figure 3D). This increase is slightly lower than when all households are targeted, because overall more households visit healthy food outlets when all households are targeted, causing relatively more healthy food outlets to be opened. This change induced more low-income households to visit healthy food outlets.

Discussion

Eliminating residential segregation has the biggest impact on reducing income inequalities in healthy food consumption, but is partly the result of an unfavorable change in healthy food consumption among higher-income groups. Although it offers the biggest benefit, it is obviously not very likely that this intervention will be implemented in reality. Lowering prices of healthy food and health education targeting only low-income households also reduces inequalities. Most interventions would take at least 5–10 years to approximate their full effect.

This is the second study to develop an ABM for income inequalities in food consumption. It uses a conceptual framework similar to Auchincloss et al.[23] Both studies modeled food shopping behaviors of households and dynamics of food outlets. The present study, however, included fast food visits as a contributor to unhealthy food consumption, and based closures and openings of food outlets more on underlying business principles. Also, habit was excluded as a determinant of food shopping, because it did not contribute to food behaviors in the model.[34] Furthermore, this study drew more on available data and used a realistic grid to represent a city to make it useful for policymakers. Nevertheless, the model still needs to be regarded as "basic" and the results can at most be considered preliminary.

Results of this study showed, similar to Auchincloss and colleagues,[23] that residential segregation, prices, and preferences of food play an important role in shaping income inequalities in healthy diet. However, this study found a lower income inequality in healthy diet. This

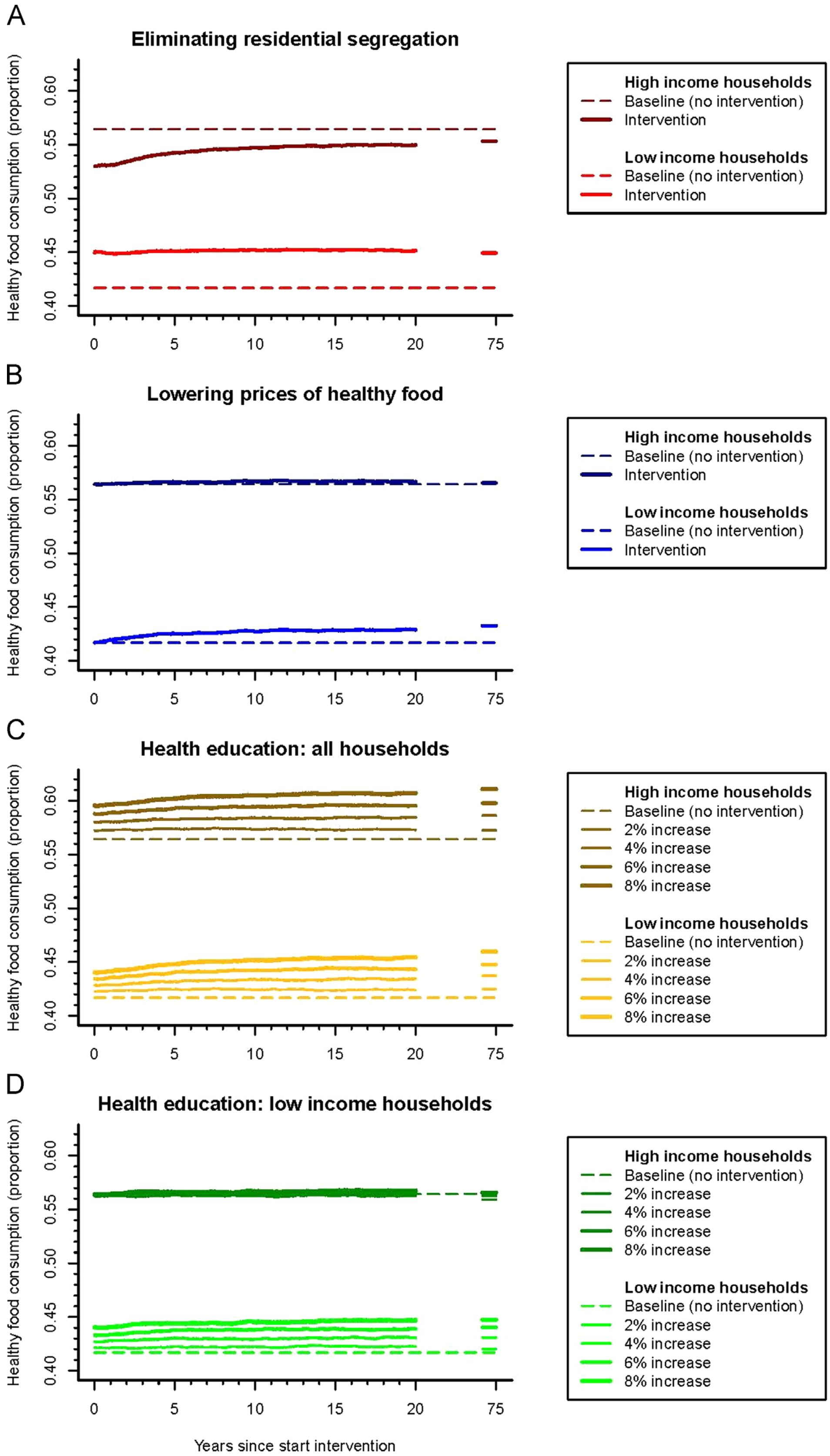

Figure 3. Impact of (A) eliminating residential segregation, (B) lowering prices of healthy food, (C) health education targeting all households, and (D) health education targeting low-income households on healthy food consumption among high- and low-income households. Model outcomes are the average of 100 runs. A new equilibrium was established after 75 years.

may be caused by the aforementioned differences between the models as well as the quantification of the model. In contrast to Auchincloss et al., HEBSIM was directly quantified from data on a real population.

Limitations

The application of ABM is still in its infancy, and comes with several limitations. First, the lack of data might affect results. For example, fast food data were not available for Eindhoven; therefore, data from U.S. literature were used.[45] It is likely that households in Eindhoven eat fast food less often, meaning that healthy food consumption might be underestimated.[11] The lack of data was also reflected in the model quantification. Household composition and age could not be quantified and therefore did not contribute to food behaviors, although they might play a role.[9,39] Secondly, households from surrounding villages were neglected. These households may occasionally shop for food in Eindhoven and to some extent influence the dynamics of food outlets.

Furthermore, the tested interventions are based on rather extreme assumptions and therefore not yet sufficient for policy recommendations. For example, it was assumed that each intervention had a perfect reach and was fully effective. In reality, interventions may only reach small or selective parts of the population, and their effectiveness may differ per household.[46,47] Also, an intervention such as eliminating residential segregation is a process that takes time and willingness of households, something the model did yet not take into account. The effect on healthy food consumption might therefore be overestimated in the short term. HEBSIM, however, will be able to accommodate such information in subsequent versions.

HEBSIM has substantial room for refinement. An important next step is to model food purchasing behaviors in more detail. This study determined healthy food consumption based on the type of food outlet visited. Obviously, households may still merely consume unhealthy food despite visiting food outlets that are considered healthy. It would be better to explicitly model the type of food households buy at each type of food outlet. This should, however, go hand in hand with data collection on food purchasing behaviors in different types of food outlets.

Another refinement is to allow household attributes, such as location, to change during the simulation. People may select a neighborhood based on safety, for example. Movements of people are associated with health inequalities and weakly with health behaviors.[48] Also, ethnicity that plays a role in explaining differences in food behaviors should be included.[49] Finally, it would be good to consider social environmental factors. Interactions with family or peers have an impact on food behaviors through, for example, social influence.[8,9,15]

Conclusions

This study illustrates that ABM is a promising method for studying dynamic interactions and assessing the impact of interventions to support decision makers. Despite the limitations, the findings of this study provide new insights on how various interventions affect healthy food consumption. With further refinements, HEBSIM will become more suitable for decision support.

This study was supported by a grant from the Netherlands Organization for Health Research and Development ZonMW (200400015). The GLOBE study is carried out by the Department of Public Health of the Erasmus University Medical Centre in Rotterdam, in collaboration with Municipal Public Health Service in the study region (GGD Brabant-Zuidoost). The study has been and is supported by grants of the Ministry of Public Health, Welfare and Sport, the Sick Fund Council, the Netherlands Organization for Advancement of Research, Erasmus University, and the Health Research and Development Council.

No financial disclosures were reported by the authors of this paper.

References

1. James WP, Nelson M, Ralph A. Leather S. Socioeconomic determinants of health. The contribution of nutrition to inequalities in health. *BMJ*. 1997;314(7093):1545–1549. http://dx.doi.org/10.1136/bmj.314.7093.1545.
2. Smith GD, Brunner E. Socio-economic differentials in health: the role of nutrition. *Proc Nutr Soc*. 1997;56(1A):75–90. http://dx.doi.org/10.1079/PNS19970011.
3. Giskes K, Avendano M, Brug J, Kunst AE. A systematic review of studies on socioeconomic inequalities in dietary intakes associated with weight gain and overweight/obesity conducted among European adults. *Obes Rev*. 2010;11(6):413–429. http://dx.doi.org/10.1111/j.1467-789X.2009.00658.x.
4. Irala-Estevez JD, Groth M, Johansson L, Oltersdorf U, Prattala R, Martinez-Gonzalez MA. A systematic review of socio-economic differences in food habits in Europe: consumption of fruit and vegetables. *Eur J Clin Nutr*. 2000;54(9):706–714. http://dx.doi.org/10.1038/sj.ejcn.1601080.
5. Giskes K, van Lenthe FJ, Kamphuis CB, Huisman M, Brug J, Mackenbach JP. Household and food shopping environments: do they play a role in socioeconomic inequalities in fruit and vegetable consumption? A multilevel study among Dutch adults. *J Epidemiol Community Health*. 2009;63(2):113–120. http://dx.doi.org/10.1136/jech.2008.078352.
6. Van Duyn MA, Kristal AR, Dodd K, et al. Association of awareness, intrapersonal and interpersonal factors, and stage of dietary change with fruit and vegetable consumption: a national survey. *Am J Health Promot*. 2001;16(2):69–78. http://dx.doi.org/10.4278/0890-1171-16.2.69.

7. Black C, Moon G, Baird J. Dietary inequalities: What is the evidence for the effect of the neighbourhood food environment? *Health Place*. 2014;27:229–242. http://dx.doi.org/10.1016/j.healthplace.2013.09.015.
8. Giskes K, van Lenthe F, Avendano-Pabon M, Brug J. A systematic review of environmental factors and obesogenic dietary intakes among adults: are we getting closer to understanding obesogenic environments? *Obes Rev*. 2011;12(5):e95–e106. http://dx.doi.org/10.1111/j.1467-789X.2010.00769.x.
9. Kamphuis CB, Giskes K, de Bruijn GJ, Wendel-Vos W, Brug J, van Lenthe FJ. Environmental determinants of fruit and vegetable consumption among adults: a systematic review. *Br J Nutr*. 2006;96(4):620–635.
10. Turrell G, Giskes K. Socioeconomic disadvantage and the purchase of takeaway food: a multilevel analysis. *Appetite*. 2008;51(1):69–81. http://dx.doi.org/10.1016/j.appet.2007.12.002.
11. Cummins S, Macintyre S. Food environments and obesity–neighbourhood or nation? *Int J Epidemiol*. 2006;35(1):100–104. http://dx.doi.org/10.1093/ije/dyi276.
12. Cummins S. Neighbourhood food environment and diet: time for improved conceptual models? *Prev Med*. 2007;44(3):196–197. http://dx.doi.org/10.1016/j.ypmed.2006.11.018.
13. Auchincloss AH, Diez Roux AV. A new tool for epidemiology: the usefulness of dynamic-agent models in understanding place effects on health. *Am J Epidemiol*. 2008;168(1):1–8. http://dx.doi.org/10.1093/aje/kwn118.
14. Diez Roux AV. Complex systems thinking and current impasses in health disparities research. *Am J Public Health*. 2011;101(9):1627–1634. http://dx.doi.org/10.2105/AJPH.2011.300149.
15. Story M, Kaphingst KM, Robinson-O'Brien R, Glanz K. Creating healthy food and eating environments: policy and environmental approaches. *Annu Rev Public Health*. 2008;29:253–272. http://dx.doi.org/10.1146/annurev.publhealth.29.020907.090926.
16. Moore LV, Diez Roux AV. Associations of neighborhood characteristics with the location and type of food stores. *Am J Public Health*. 2006;96(2):325–331. http://dx.doi.org/10.2105/AJPH.2004.058040.
17. Cummins S, Curtis S, Diez-Roux AV, Macintyre S. Understanding and representing 'place' in health research: a relational approach. *Soc Sci Med*. 2007;65(9):1825–1838. http://dx.doi.org/10.1016/j.socscimed.2007.05.036.
18. Resnicow K, Page SE. Embracing chaos and complexity: a quantum change for public health. *Am J Public Health*. 2008;98(8):1382–1389. http://dx.doi.org/10.2105/AJPH.2007.129460.
19. Luke DA, Stamatakis KA. Systems science methods in public health: dynamics, networks, and agents. *Annu Rev Public Health*. 2012;33:357–376. http://dx.doi.org/10.1146/annurev-publhealth-031210-101222.
20. Blok DJ, van Empelen P, van Lenthe FJ, Richardus JH, de Vlas SJ. Unhealthy behaviour is contagious: an invitation to exploit models for infectious diseases. *Epidemiol Infect*. 2013;141(3):667–669. http://dx.doi.org/10.1017/S0950268812000891.
21. Bonabeau E. Agent-based modeling: methods and techniques for simulating human systems. *Proc Natl Acad Sci USA*. 2002;99(Suppl 3):7280–7287. http://dx.doi.org/10.1073/pnas.082080899.
22. Macal CM, North MJ. Tutorial on agent-based modelling and simulation. *J Simulation*. 2010;4(3):151–162. http://dx.doi.org/10.1057/jos.2010.3.
23. Auchincloss AH, Riolo RL, Brown DG, Cook J, Diez Roux AV. An agent-based model of income inequalities in diet in the context of residential segregation. *Am J Prev Med*. 2011;40(3):303–311. http://dx.doi.org/10.1016/j.amepre.2010.10.033.
24. El-Sayed AM, Seemann L, Scarborough P, Galea S. Are network-based interventions a useful antiobesity strategy? An application of simulation models for causal inference in epidemiology. *Am J Epidemiol*. 2013;178(2):287–295. http://dx.doi.org/10.1093/aje/kws455.
25. Yang Y, Diez Roux AV, Auchincloss AH, Rodriguez DA, Brown DG. A spatial agent-based model for the simulation of adults' daily walking within a city. *Am J Prev Med*. 2011;40(3):353–361. http://dx.doi.org/10.1016/j.amepre.2010.11.017.
26. Yang Y, Diez-Roux AV. Using an agent-based model to simulate children's active travel to school. *Int J Behav Nutr Phys Act*. 2013;10:67. http://dx.doi.org/10.1186/1479-5868-10-67.
27. Luke S, Cioffi-Revilla C, Panait L, Sullivan K, Balan G. MASON: a multi-agent simulation environment. *Simulation*. 2005;82(7):517–527. http://dx.doi.org/10.1177/0037549705058073.
28. Bakker R, Busker T, White RG, Choenni S. Rapid weighted random selection in agent-based models of infectious disease dynamics using augmented B-trees. In: SIMUL 2013, The fifth international conference on advances in system simulation. Venice, Italy: IARIA; 2013.
29. Statsitics Netherlands (CBS). http://statline.cbs.nl/statweb/?LA=nl. Accessed May 18, 2015.
30. Statistics Eindhoven. http://eindhoven.buurtmonitor.nl/. Accessed May 18, 2015.
31. van Lenthe FJ, Kamphuis CB, Beenackers MA, et al. Cohort profile: understanding socioeconomic inequalities in health and health behaviours: the GLOBE study. *Int J Epidemiol*. 2014;43(3):721–730 http://dx.doi.org/10.1093/ije/dyt040.
32. Turrell G. Socioeconomic differences in food preference and their influence on healthy food purchasing choices. *J Hum Nutr Diet*. 1998;11(2):135–149. http://dx.doi.org/10.1046/j.1365-277X.1998.00084.x.
33. Chaix B, Bean K, Daniel M, et al. Associations of supermarket characteristics with weight status and body fat: a multilevel analysis of individuals within supermarkets (RECORD study). *PLoS One*. 2012;7(4):e32908. http://dx.doi.org/10.1371/journal.pone.0032908.
34. EFMI. Consumententrends 2011. Leusden: Centraal Bureau Levensmiddelenhandel, 2011.
35. Morland K, Wing S, Diez Roux A. The contextual effect of the local food environment on residents' diets: the Atherosclerosis Risk in Communities study. *Am J Public Health*. 2002;92(11):1761–1767. http://dx.doi.org/10.2105/AJPH.92.11.1761.
36. Keeney RL, Raiffa H. *Decisions with Multiple Objectives: Preferences and Value Tradeoffs*. New York: Wiley; 1976.
37. Dyer JS. Maut — Multiattribute Utility Theory. In: Figueira J, Greco S, Ehrogott M, eds. *Multiple Criteria Decision Analysis: State of the Art Surveys*. New York: Springer, 2005:265–292.
38. Kennedy WG. Modelling human behaviour in agent-based models. In: Heppenstall AJ, Crooks AT, See LM, Batty M, eds. *Agent-based models of geographical systems*. Springer; 2012:167–179. http://dx.doi.org/10.1007/978-90-481-8927-4.
39. Glanz K, Basil M, Maibach E, Goldberg J, Snyder D. Why Americans eat what they do: taste, nutrition, cost, convenience, and weight control concerns as influences on food consumption. *J Am Diet Assoc*. 1998;98(10):1118–1126. http://dx.doi.org/10.1016/S0002-8223(98)00260-0.
40. Reitzel LR, Regan SD, Nguyen N, et al. Density and proximity of fast food restaurants and body mass index among African Americans. *Am J Public Health*. 2014;104(1):110–116. http://dx.doi.org/10.2105/AJPH.2012.301140.
41. Chou SY, Grossman M, Saffer H. An economic analysis of adult obesity: results from the Behavioral Risk Factor Surveillance System. *J Health Econ*. 2004;23(3):565–587. http://dx.doi.org/10.1016/j.jhealeco.2003.10.003.
42. He M, Tucker P, Gilliland J, Irwin JD, Larsen K, Hess P. The influence of local food environments on adolescents' food purchasing behaviors. *Int J Environ Res Public Health*. 2012;9(4):1458–1471. http://dx.doi.org/10.3390/ijerph9041458.
43. Dunn RA, Sharkey JR, Horel S. The effect of fast-food availability on fast-food consumption and obesity among rural residents: an analysis by race/ethnicity. *Econ Hum Biol*. 2012;10(1):1–13.
44. Chamber of Commerce. Brancheinformatie. www.ondernemersplein.nl/brancheinformatie/. Accessed May 18, 2015.
45. French SA, Story M, Neumark-Sztainer D, Fulkerson JA, Hannan P. Fast food restaurant use among adolescents: associations with nutrient

intake, food choices and behavioral and psychosocial variables. *Int J Obes Relat Metab Disord*. 2001;25(12):1823–1833. http://dx.doi.org/10.1038/sj.ijo.0801820.
46. Pomerleau J, Lock K, Knai C, McKee M. Interventions designed to increase adult fruit and vegetable intake can be effective: a systematic review of the literature. *J Nutr*. 2005;135(10):2486–2495.
47. Ammerman AS, Lindquist CH, Lohr KN, Hersey J. The efficacy of behavioral interventions to modify dietary fat and fruit and vegetable intake: a review of the evidence. *Prev Med*. 2002;35(1):25–41. http://dx.doi.org/10.1006/pmed.2002.1028.
48. van Lenthe FJ, Martikainen P, Mackenbach JP. Neighbourhood inequalities in health and health-related behaviour: results of selective migration? *Health Place*. 2007;13(1):123–137. http://dx.doi.org/10.1016/j.healthplace.2005.09.013.
49. Brug J, van Stralen MM, Chinapaw MJ, et al. Differences in weight status and energy-balance related behaviours according to ethnic background among adolescents in seven countries in Europe: the ENERGY-project. *Pediatr Obes*. 2012;7(5):399–411. http://dx.doi.org/10.1111/j.2047-6310.2012.00067.x.

Appendix

Supplementary data

Supplementary data cited in this article is available online at, http://dx.doi.org/10.1016/j.amepre.2015.03.042.