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Grocery shopping behavior in Detroit neighborhoods experiencing disinvestment and decline: An empirically grounded agent-based model of data-scarce communities

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Abstract: This paper presents a data-driven agent-based model that simulates the weekly grocery shopping behavior of disadvantaged consumers in highly segregated lower eastside neighborhoods of Detroit, Michigan. We focus on neighborhoods experiencing severe disinvestment to analyze the shopping behavior of residents after all major regional and national supermarket chains abandoned the city. The presented model is unique in that it utilizes detailed shopping behavior data collected to examine travel in marginalized communities, specifically among residents in severe poverty who are often overlooked in the travel behavior literature. The research shows that in extreme socio-economic decline, sociodemographic variables (such as class) can become more relevant than the built environment (land-use mix, density, and street connectivity) in determining access and influencing mobility. After identifying unique groups of household agents, we design rules that utilize probability distributions generated from survey responses. The decision-making of agents that emulate households is habitual rather than utility driven. Modeled behavior is designed based on stated preferences, which may contradict premises such as the "shortest distance to the nearest shop" approach, a common assumption in the literature. We also report on three what-if scenarios to evaluate how major population changes would affect the results.

Keywords: agent-based modeling, food travel, urban systems

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1 Introduction

In studying the evolving nature of development patterns within metropolitan centers experiencing disinvestment and local population vulnerabilities—and especially among the disadvantaged, considerable interest has been placed on the relationships between access, mobility, and resulting public health impacts associated with uneven

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neighborhood food environments (Robles et al., 2019; Rojas et al., 2016; Swinburn et al., 2015). Past research has established links between marginalized neighborhoods with limited healthy food options, dietary intake, and adverse public health outcomes, such as obesity, diabetes, cardiovascular disease, and poorer mental health. Within this research, a robust discussion has emerged regarding the best ways to conceptualize and measure access to various urban amenities, most notably exemplified in the food access and built environment literature.

In examining access to healthy food options, much research has focused on the concentration of neighborhood stores, especially supermarkets, or the distance between residences and the closest shopping destination. While useful, such geospatial analysis has been criticized over the past decade. As Shannon et al. (2021) have noted, spatial access is more than physical proximity, and by overly focusing on physical environments, researchers not only obscure the social, cultural, economic and political factors that determine food inequities but also minimize other variables that play essential roles in explaining and understanding how people navigate their surroundings and obtain their daily food provisions. Likewise, an individual's choice of travel can take on much more complex patterns based on income, household characteristics, urban versus rural locations, time constraints, and varying destination preferences while also being shaped by a diverse set of mobility constraints, including whether they have access to a vehicle or an effective public transit system (Li et al., 2024; Losada-Rojas, 2021; Mahmoudi et al., 2019; Omer & Kaplan, 2017; Socharoentum & Karimi, 2016; Widener, 2017). In research on marginalized communities, the complexity of travel for food shopping in areas with limited access to stores is evident in the choice of destinations, frequency, and mode of travel. In part, this is a result of not only the more limited healthy food options within the neighborhoods but also the transportation options, including the availability of an automobile or public transit (LeDoux & Vojnovic, 2013; Vojnovic, Lee, et al., 2013; Vojnovic, Kotval-K, et al., 2014; Widener et al., 2015). A similar concern is also seen in the built-environment literature.

Solely focusing on physical proximity in determining food access can lead to an overemphasis on the role of the built environment in shaping access, including food shopping, and overlooking the role of larger processes of uneven development and the conditions of neighborhoods in severe decline. This includes the impact of racial segregation and disinvestment on neighborhoods, as well as how such processes hinder the urban built environment's ability to reduce access and travel constraints.

Consequently, existing research on the built environment and travel, in its emphasis on urban form, tends to overlook how patterns of disinvestment negatively shape the built environment and the characteristics of the land-use mix (Day, 2006; Figueroa et al., 2019; Ghimire & Bardaka, 2023; Lee et al., 2022). A small but growing body of research indicates that built environments in low-income neighborhoods influence access to certain types of activities, including walking as a means of reaching destinations, in ways that differ from those found in more affluent neighborhoods (Adkins et al., 2017). Ignoring how relationships between land uses, the built environment, and travel vary by socioeconomic disparities and levels of disinvestment can lead to policy prescriptions and infrastructure projects that do not produce improved access or greater pedestrian activity in low-income neighborhoods. Complicating such debates and concerns in the literature are the often-overlooked discussions on how to best capture travel and mobility data and how to utilize such data to model access to resources, services, and amenities.

While offering valuable insights, past studies in the food environment literature have focused heavily on distance-based and cumulative opportunity approaches. A second wave of food environment mobility research has critiqued these approaches. As an alternative data collection method, this food mobility research often incorporated GPS using cell phones and other passive sensors to trace precisely how people navigate the built environment to obtain food.

Despite the promise of these methods to better understand food environments and travel, significant challenges remain. Using GPS to track people's movements is challenging to scale due to the high costs of the technology. While appealing, such data often misses crucial demographic information for travel and mobility studies. There is also the issue of sample bias. Not everyone carries a cell phone, and in places where laws limit the use of cell phones while driving, the potential for such data declines (Rojas et al., 2016; Scully et al., 2017). Collecting detailed information in marginalized communities is also difficult because of the limited cell phone access, combined with distrust of tracking, limiting the potential of such methods. As a result, such methods must still rely heavily on travel diaries and surveys.

Tools that can augment existing research on grocery shopping travel in disadvantaged communities include complex systems models, which provide a venue for generating what-if scenarios where specific characteristics of communities in decline are significantly altered. Then, the results are compared to the baseline. One approach is to use agent-based models (ABMs) to model travel behavior, which we adopt in this study.

In this research, we utilize a modified food access agent-based model (fABM), originally developed by Vojnovic et al. (2020), to examine the specific dynamics of grocery shopping travel. The model's primary novelty lies in its focus on understudied populations in the travel behavior literature, specifically low-income residents in highly segregated neighborhoods experiencing severe disinvestment. It is built from detailed survey data that defines the shopping behaviors of these communities, and critically, it utilizes residents' habitual behavior information on their preferred stores, which are not necessarily the closest ones to their homes. This empirical grounding directly challenges the classic shortest-distance store selection mechanism, which remains prevalent in many food access models. Our focused approach contrasts with comprehensive, general-purpose models, such as TASHA (Miller & Roorda, 2003), which are designed for large-scale regional planning by simulating complete 24-hour travel schedules from conventional travel diaries. Whereas TASHA provides a "wide-angle lens" to forecast system-wide demand, our fABM acts as a "high-powered microscope," allowing us to conduct in-depth analyses of uncertainty, sensitivity, and "what-if" scenarios for grocery shopping exclusively. This targeted focus is essential because, as our results reveal, within a context of extreme socio-economic decline, sociodemographic variables such as class, race, and ethnicity can become more relevant than the built environment in defining food access.

Data for the fABM was collected in 2008 and 2009, during which there was not a single major national/regional supermarket chain in the city, making it an ideal period to study marginalized neighborhoods with limited access to healthy food options. For low-income disadvantaged communities, significant issues related to grocery shopping include the frequency of trips, the selection of store destinations, and the mode of travel (Lee et al., 2018; Widener et al., 2013). All are constrained by the limitations of motorized mobility. Hence, we concentrate on the following questions that guide the research reported in the following sections:

For households grouped by age and income, and given their store selection, what mode of transportation—motorized (automobile/bus) versus non-motorized (walk/bike)—do residents use to access their stores of choice given their mobility constraints and the built environment characteristics?

How do simulated structural changes in age and income (i.e., what-if analysis) modify the patterns of grocery shopping trips?

2 Literature review on agent-based models of food shopping behavior

To date, few studies have sought to examine how ABMs can contribute to our understanding of food access and travel in urban areas, especially when applied to low-income populations living in highly segregated communities in decline. Existing models can be grouped into two classes: those that are non-spatial or utilize abstract space (Armendáriz et al., 2015; Auchincloss et al., 2011) and those that are spatially explicit (Abel & Faust, 2020; Giabbanelli & Crutzen, 2017; Widener et al., 2013). These models focus on a variety of aspects of urban food systems—from gaining a deeper understanding of the problems of healthy food access and utilization (Armendàriz et al., 2015; Auchincloss et al., 2011; Blok et al., 2015; Calisti et al., 2019), to evaluating policy interventions (Abel & Faust, 2020; Giabbanelli & Crutzen, 2017; Salvo et al., 2022; Widener et al., 2013), to shopping behaviors under pandemic restrictions (Smith et al., 2022).

Most of the published models concentrate on (the barriers to) healthy food consumption and related policy interventions. For example, Blok et al. (2015) introduced policies aimed at eliminating residential segregation, reducing the prices of healthy food, and providing health education to increase healthy food consumption in low-income communities. While their studies focused on disadvantaged communities, their primary goal was to increase access to healthy food, not considering the travel component to shop for food.

We identified a few limitations within the reported literature. First, many models assume that the shortest distance primarily drives store choice (Koh et al., 2019; Leischow & Milstein, 2006; Maglio & Mabry, 2011), often simplified to a straight line distance between the home and the store (Sturley et al., 2018). Giabbnelli and Crutzen (2017) refer to this modeling assumption as the "proximity hypothesis," which posits that the closer the store, the more likely the agent is to select it. However, numerous studies have demonstrated that this assumption requires empirical support (Alkon et al., 2013; Caspi et al., 2012; LeDoux & Vojnovic, 2013). Instead, the agent's store choice should first be driven by disaggregate habitual behavior derived from empirical data (Abel & Faust, 2020; Giabbanelli & Crutzen, 2017). Giabbanelli and Crutzen (2017), among others, noted that the foremost hurdle to developing policy-relevant public health models is the "lack of data that precisely captures how individuals navigate the food environment and the ability to derive an insight from this data" (Giabbanelli & Crutzen, 2017, p. 2). The model presented in this paper is a step in this direction.

Second, agent choice behavior is often simplified and based on theoretical frameworks, such as utility maximization (Blok et al., 2015; Rice, 2012) or random selection (Yang et al., 2011, 2012). Most researchers utilize secondary data, such as censuses or loyalty cards (Sturley et al., 2018). Custom-built interviews, focus groups, or surveys could be more varied in their design. A notable exception is research by Koh et al. (2018), who conceptualized their ABM to study food insecurity using participatory modeling.

Most importantly, published modeling studies focus primarily on the urban population as a whole, largely overlooking the unique conditions of low-income minority communities that inhabit neighborhoods experiencing severe disinvestment and decline, with large proportions of derelict, unclaimed buildings located on abandoned land, resulting in unhindered ecological succession. A notable example is the research by Widener et al. (2013), who studied access to fruit and vegetables for low-income households. Their model relied on secondary sociodemographic census data to build a population of agents, assuming an agent will visit the nearest store using an inverse sigmoid function to calculate a weighted straight-line distance to a store. The novelty of their study was to introduce dynamics between consumers and mobile markets, where the latter periodically changed their locations, affecting access to fresh produce for individual households. A similar approach to simulating dynamic retailers who change their geographic locations and close/open during model execution was implemented in a model by Blok et al. (2015), Abel and Faust (2020), and Calisti et al. (2019).

What sets fABM apart is that it utilizes data reflecting habitual grocery shopping behavior, based on information obtained from a detailed survey conducted in marginalized and highly segregated communities experiencing severe disinvestment (Section 3.4). Specifically, unlike the study by Widener et al. (2013), our model selects a store from a set identified by respondents. Many of these stores are located outside the case study neighborhoods, requiring long travel distances (LeDoux & Vojnovic, 2013). Moreover, unlike Widener et al. (2013), we utilize a road network to calculate distances between stores and households. Finally, to ensure a methodologically sound empirical ABM, we followed one of the structured parameterization sequences developed by Smajgl, Brown et al. (2011) and Smajgl, Barreteau et al. (2014) described in section three.

3 Study area and data

Our empirically grounded model was informed by household (HH) survey data and extrapolated to all HHs in the area using the 2006-2010 five-year American Community Survey estimates (U.S. Census Bureau, 2010). The survey data collected for this research were gathered during a unique period in the City of Detroit's history. Despite a population of well over 700,000 residents at the time of the survey, following A&P's decision to close all metro Detroit Farmer Jack stores, this was a period in Detroit's history during which there was not a single major regional/national supermarket chain within the city's jurisdiction boundary. This period makes it ideal for studying food shopping, including store selection and travel, among residents living in Detroit's socioeconomically marginalized neighborhoods.

The neighborhood area (Figure 1) covers 25 km², comprising 24 census tracts, with ~41,000 people, 14,700 households, 11,800 single-family houses, and 290 multi-family apartments. The building vacancy is about 10%. The area is predominantly African American (~94% of the total population), with high-density, high connectivity, and mixed land uses. Most grocery trips are made by automobile to independent, full-service supermarkets across Metro Detroit (~1,650 25 km²). The 2000 Census defined the neighborhoods based on the population densities of these lower eastside Detroit neighborhoods, which averaged 16,353 people per square kilometer. By the 2010 Census, these neighborhoods averaged only 10,173 people per square kilometer, illustrating the scale of disinvestment and abandonment over the preceding decade.

The neighborhoods within the study site are generally low-income, with some households classified as lower-middle-income. Approximately half of the survey respondents reported an annual household income of less than $20,000 (U.S. Census Bureau, 2010). However, moving from neighborhood to neighborhood—and even street to street—within the study site, there is variability in the quality of housing and income levels. Some 22% of the survey respondents maintain household incomes of $40,000 or higher. Moreover, it is essential to acknowledge the persistent disinvestment in these neighborhoods. The poverty rate for the entire study area in 2010 was 42.29%; by 2020, it had only reduced to 40.5%. The neighborhoods continue to be characterized by high concentrations of poverty.

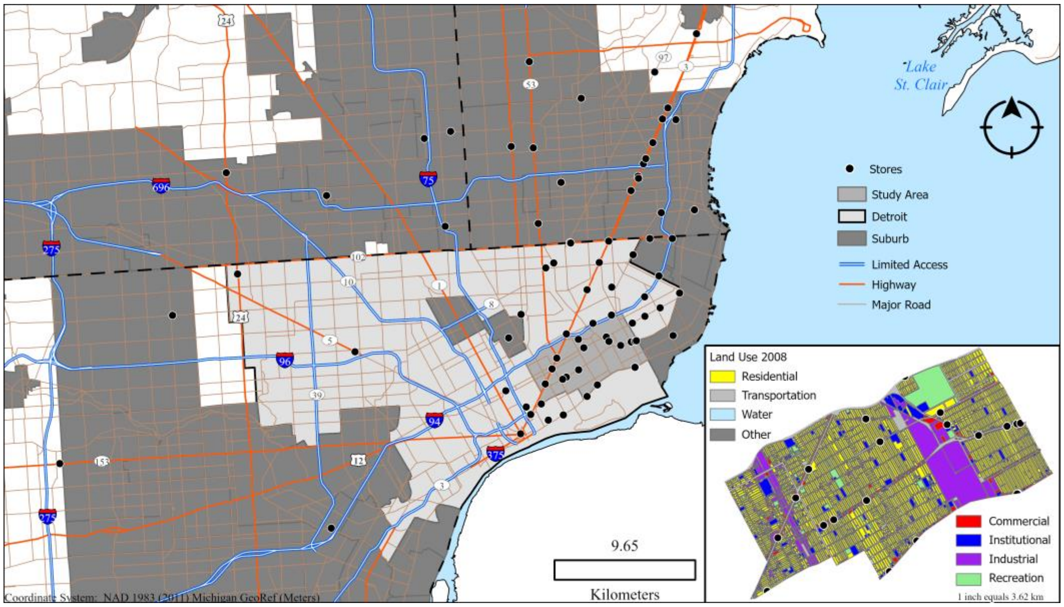


Figure 1. The study area is represented as follows: light grey represents the city of Detroit, dark grey represents the suburbs, and medium grey represents the neighborhoods. The black dots are stores identified by the respondents. Lower right corner: land use in the study area in 2008.

We used sample N = 202, reported by LeDoux and Vojnovic (2013), as a baseline. The initial sample was further adjusted to include only those respondents who indicated the number of trips per mode of transportation. We also deleted spatially ambiguous entries, i.e., where a particular individual did not provide sufficient data about a store they visited. The final sample size was reduced to N = 188.

3.1 Stratification

Our analysis focuses on two sociodemographic dimensions that influence travel for food shopping: age and income, which are among the most important variables shaping retail travel. Even within neighborhoods confronting disinvestment and decline, where the population is generally of lower socioeconomic standing, higher incomes increase the chances of owning a vehicle, which tends to encourage longer travel distances (Lee et al., 2018). Age, in contrast, has a reverse relationship with travel. Aging populations tend to make fewer trips and travel shorter distances (Boschmann & Brady, 2013; Yang et al., 2018).

We used household income (INCOME) and householder age (AGE) to stratify the survey data into eight classes (Table 1). We used the same classes to organize agents into INCOME-AGE groups (called "agent groups"). This stratification was necessary to account for correlations between some variables and to prevent implausible agent definitions. For example, based on the analysis of the survey data, young people with low incomes typically owned a smaller number of vehicles, usually one or none per household, compared to the middle-income population, which owned approximately two automobiles per family. Leaving the data unclassified could generate many HH agents characterized by unlikely cases, like a low-income family owning three automobiles.

The respondent/agent groups are defined based on combinations of three INCOME and three AGE groups. Annual INCOME was divided into: [1] less than $20,000 (core low income), [2] $20,000 to $49,999 (low income), and [3] greater than $50,000 (medium income). Second, AGE was aggregated into three categories: [1] 18-44 (young), [2] 44-64 (middle-aged), and [3] 65+ years (old). Consequently, we identified nine combinations of age and income, ranging from householders aged 18-44 with an annual income below $20,000 to householders over 65 with an annual income of $50,000 or more. Due to the small size of two classes, i.e., "medium income middle age" and "medium income old," we re-grouped them into one class, "medium income middle age and old." Table 1 shows the final bivariate classification of respondents.

Table 1. Strata for different combinations of age and income are used to define respondent and agent groups (sample size is given in parentheses). Group names are built from abbreviated group descriptions: a bold name followed by a description in italics.

		AGE		
		18-44	45-64	65+
INCOME	< $20,000	(33) CoLwInYg Core Low Income Young	(43) CoLwInMiAg Core Low Income Middle Age	(15) CoLwInOld Core Low Income Old
	$20,000-$49,999	(23) LwInYg Low Income Young	(28) LwInMiAg Low Income Middle Age	(11) LwInOld Low Income Old
	> $50,000	(13) MeInYg Medium Income Young	(22) MeInMiAgOld Medium Income Middle Age and Old	

3.2 Frequencies of weekly trips

Each agent must make a specific number of trips per week. Therefore, for every group, we plotted the count of agents per number of weekly trips (Figure 2). Note that all distributions are positively skewed, indicating that there is a large frequency of fewer trips made weekly (~2-4), and a small frequency of many trips made weekly (> 4).

3.3 Other data

We utilized residential, commercial, and transportation land-use data, which included houses, stores, and a road network. Land and building surveys collected data on land uses (residential, commercial, retail, and industrial) and building types (such as single-family, duplexes, apartments, and factories). Abandoned buildings, residential and non-residential, were also recorded. The store data was generated from a travel survey. Each respondent was asked about the grocery stores they regularly visit for food shopping. The addresses were geocoded and matched with existing store locations. The road network was derived from the Michigan Geographic Framework v17a and obtained from the Michigan GIS Open Data portal as an ESRI shapefile (State of Michigan, 2023). This dataset was used to calculate the origin-destination (OD) distance cost matrix, where the origins were the houses and the destinations the stores. We used ArcGIS ArcMap v10.5.1 network analyst to generate the OD matrix (ESRI, 2017).

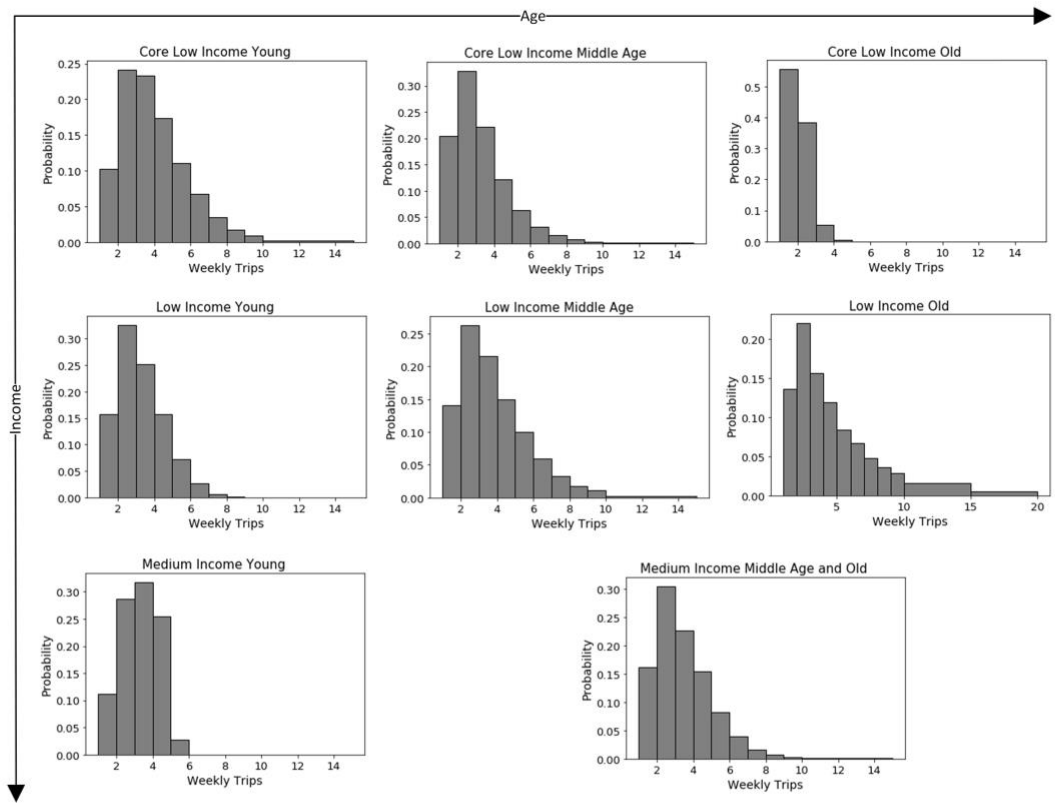


Figure 2. Distributions of weekly shopping trips by respondent groups (organized as in Table 1).

3.4 Survey data processing

The analyses presented here relied on the built environment and survey data to study the relationship between land uses, access, and shopping travel behavior in Detroit neighborhoods experiencing extreme disinvestment. The data collection and analysis were at the neighborhood scale. Survey data used here on low-income neighborhoods in decline is usually challenging to collect because minoritized communities experiencing disinvestment have little trust in institutional structures, including universities.

Details on the survey can be found in Vojnovic et al. (2020) and LeDoux and Vojnovic (2013). While the respondents were asked to report the perceived distances between their homes and shopping locations, they were also asked to record the names and exact addresses, or the closest major intersections, of the stores they visited throughout the week. All the stores were found through mapping programs and site surveys. The surveys also contained household addresses. Thus, all trips' start and end points were known, recorded, and geocoded.

A total of 258 households responded to the survey, yielding a 10.3% response rate. Seventy surveys were removed because of insufficient travel and shopping data, with a small number also eliminated as outliers. In the end, 188 household surveys were used to build the fABM database for the lower eastside Detroit data-scarce communities. While the overall number of responses may raise concerns about non-response bias, it is essential to consider several key factors.

First, the rates are within expectations in socially and economically marginalized communities (Siegel, 2002). Second, there are mixed results regarding whether higher response rates reduce nonresponse errors or whether low numbers of hard-to-survey respondents yield findings that differ sharply from those of efforts with larger responses (Yan et al., 2004). Moreover, the relationship between low responses and data quality varies by survey type and indicators (Fricker & Tourangeau, 2010). Third, more extensive and robust travel surveys and databases commonly used in the United States are not suitable for studying travel disparities in marginalized communities. As Landis (2022) notes, US Census Bureau travel surveys are often limited to work trips, and their data cannot be easily disaggregated by travel mode. Other travel surveys, such as the Federal Highway Administration's National Household Travel Survey, systematically undercount minority households. Lastly, there is a paucity of research, both within and outside the United States, that examines the travel behavior of marginalized households living in communities experiencing disinvestment (Adkins et al., 2017; Figueroa et al., 2019; Ghimire & Bardaka, 2023; Lee et al., 2022). Hence, there is a strong need for data collection efforts and analysis within neighborhoods of extreme poverty that face disinvestment and decline, to better understand the travel constraints imposed upon marginalized communities.

4 Agent-based model

We adopted a rigorous approach to empirical model development for fABM using the case two Characterization and Parameterization (CAP) framework by Smajgl, Brown et al. (2011) and Smajgl, Barreteau et al. (2014). The procedure is appropriate when the agent population is high (the generated population equals ~14,700 census HH counts). While the sample is representative of the population (LeDoux & Vojnovic, 2013), which would better fit CAP one, CAP two was selected as the survey data was not designed to capture agent decision-making diversity (section 4.2). Following the CAP, we first utilized expert knowledge to develop and conduct the survey, subdivided agents into groups (section 3.1) based on previous studies (LeDoux & Vojnovic, 2013), used census data to upscale the survey data to the whole agent population (section 5.1.1) and then built agent profiles (Table 2, Figure 3). Agent behavioral rules were developed by the research group, which has conducted previous studies on travel within socioeconomically marginalized communities in the City of Detroit (Lee et al., 2022; Li et al., 2024; Vojnovic, 2006; Vojnovic, Lee et al., 2013; Vojnovic, Kotval-K et al., 2014). We used Monte Carlo sampling (section 5.3) and GIS-based agent allocation to initialize the agents. Finally, since fABM is empirically driven, it requires extensive data verification and outcome validation (uncertainty and sensitivity analysis), especially given the data-scarce community under investigation (Bruch & Atwell, 2015; Ligmann-Zielinska et al., 2020; Smajgl & Barreteau, 2014).

We describe fABM using an adapted visual ODD (Szangolies et al., 2024). Note that our model is limited to household agent-environment relationships and does not explicitly model feedbacks, for example, from retailers. As such, it is a hybrid between an ABM and microsimulation (Bae et al., 2016; Birkin & Wu, 2012). Bae et al. (2016) identify interactions as a core feature of ABM, but they also point to other ABM characteristics like explicit modeling of habitual behaviors.

Our ABM is not strictly a microsimulation, as it is not built from large datasets but rather from upscaling a sample to a population. It does not use classic utility-based decision-making, and (unlike microsimulation), its purpose is not future projection based on observed patterns (Bae et al., 2016). On the other hand, it is not strictly ABM, as it does not directly model agent-agent interactions, given that the HH agent decides to go grocery shopping independently from another agent. However, interactions are concealed in the probability distributions, which capture cases of sharing cabs, carpooling, walking, and/or cycling to stores.

4.1 Process overview

Figure 3 depicts the conceptual flowchart of fABM. At the beginning of the week, an HH agent from a specific agent group decides to make a predefined number of trips to buy groceries. Then they need to decide on which store to visit and how to get there. This includes: (a) the choice of a store from a pool of stores identified by respondents belonging to a given agent group and (b) the mode of travel. The choice is based on the probability with which the respondent group nominated a store as their preferred one (every store has a survey-based selection probability – mapped, for example, in Figure 4). After the agent makes the trip, we register the store visited, the mode of transportation, and the distance traveled. This procedure is repeated every week.

The number of trips, the pool of stores to choose from, and the frequency of visiting a particular store are all determined based on the probability distributions generated from the survey (Figures 2 and 4, Table 2). Unfortunately, the survey was not designed, and data were not collected solely for the fABM. Therefore, certain steps, like agent decision rules, had to be theorized.

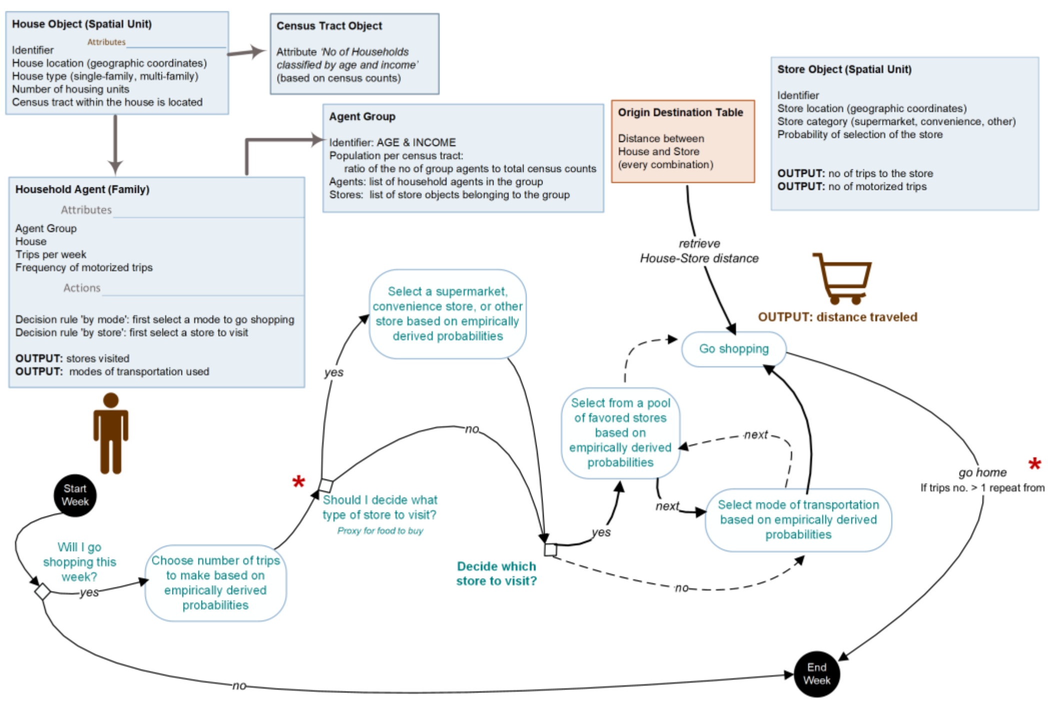
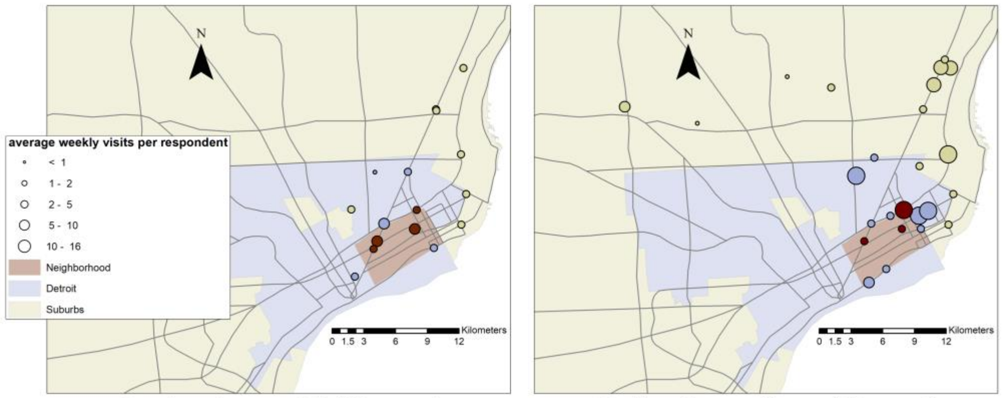


Figure 3. The conceptual diagram of fABM, including entities with their attributes and actions of agents, their collectives, and environment objects (listed in the boxes), as well as the agent decision-making process presented as a flowchart. The temporal unit is one week. The Agent Groups are described in Table 1. The first decision point is based on distributions in Figure 2. The shopping decision rule (Section 4.2) is plotted, starting with the decision point, "Decide which store to visit?" The selection of stores is based on the pool of stores and their frequency of visits

for each group (an example is provided in Figure 4). The mode choices are triggered by sampling the empirical distributions in Table 2, which are unique for each agent group.



Core Low Income Old (16 stores) Medium Income Young (25 stores)

Figure 4. A map with an example collection of stores for two selected groups, together with their visit frequencies represented as graduated circles. Similar data was created for the other groups.

4.2 Shopping decision rule

The most uncertain element of our model is also the most critical: how do the agents decide which store to go to and how to get there? Does store selection define the trip, or is a mode the primary driver of the choice of destination? We refer to this as the agent shopping decision rule or, more generally, agent shopping behavior. We identified three alternative behaviors: [1] the selection of a store followed by the selection of travel mode, [2] the selection of travel mode followed by the selection of a store, and [3] the selection of a store and a mode simultaneously, having a store always associated with a particular mode of travel. We describe these rules using three imaginary stories in which we combine the survey outcomes with model assumptions. Because the latter is simulated rather than observed, we perform a comprehensive sensitivity analysis of the results (section 6.2.2) to evaluate the contribution of our agent decision-making assumptions to the overall variability of the outcomes.

In the first option, the agent decides on which store to visit and then selects the travel mode:

Samantha Noble is a 41-year-old woman and a mother of two. She strongly believes in supporting local businesses and places a high value on exercise. Samantha likes to walk to her favorite nearby local supermarket almost daily to purchase fresh produce. However, suppose the market has a sale on bulkier or heavier packaged goods (when she might buy two or three cases of pop or multiple packages of paper towels or toilet paper). In that case, Samantha will drive to the market with her automobile and stock up on sale products.

The second option is the inverse of the first, i.e., the selection of travel mode is followed by the selection of a store:

William Smith is a fit 27-year-old single man. He is unemployed for most of the year and relies on SNAP benefits and financial aid from other resources to get by. He often shops for groceries on foot or by bike to minimize gas and vehicle maintenance expenses on his 1986 Bronco. He goes shopping many times per week. While he does have his *favorite stores in the suburbs, he mainly visits nearby convenience stores for essential items, such as milk and bread.*

In the third option, the agent associates a particular store with a travel mode:

Tiara Anderson is 51 years old and a mother of three. She is an accountant and lives in the city. She regularly shops in the smaller retail outlets around her home, walking to the local bakery and neighborhood market. Tiara also shops one or two times a week by automobile in the suburbs, with the major weekly shopping trip typically at a supermarket or big-box store, approximately 9 miles from her home. Due to the larger purchase and the distance to her favorite big-box supermarket, Tiara always drives to the suburbs to shop.

In all decision-making variants, we utilized distributions of stores identified by a given group of respondents (as shown in Figure 4), distributions of all trips and motorized trips (Table 2), and the number of respondents versus the number of trips (Figure 2). The final agent choices should, therefore, reflect data derived from the survey. Since we had no other data to support the three decision rules, we assigned them an equal probability of selection during model initialization.

Note that agents do not explicitly consider distance in their decision-making – trips are based solely on the mode of transportation and preferred stores. Studies suggest that people select stores with the best prices, quality, and wide availability of culturally acceptable products and services, as well as stores where they feel welcomed, rather than shops close to their homes (Hill, 2021; Shannon, 2016; Widener, 2018). Low-income shoppers, in particular, make significant sacrifices to bypass nearby stores to seek out such options (LeDoux & Vojnovic, 2013). Moreover, our assumption of excluding distance from decision-making was based on the specific design of the survey instrument. The respondents were asked about the frequency of grocery shopping and the stores they chose to visit. The formulated questions did not prioritize distance over store and mode, quite the opposite. Thus, when formalizing fABM, we assumed that distance is the derivative property of the system and the core output of the simulations.

5 Model implementation and verification

Our fABM was developed using Python Programming Language ver. 3.10 (Python Software Foundation, 2022). The core model code comprises the main executable script and a package with modules for the HH agent, the agent group, the store object, and the house object. Auxiliary code handles input and output. Data is stored in a separate directory. We performed standard model verification, including debugging, unit tests, test runs, assertions, and extreme combination tests (An et al., 2005; Gilbert, 2007; Graebner, 2018) followed by data verification (section 6.2.1).

5.1 Model setup

The fABM was initialized as follows. First, the number of agents in each group was initialized based on the input table of population counts per census tract, using the ACS variable "age of householder by household income in the past 12 months in inflation-adjusted dollars" (ACS COUNT TABLE), which had been previously reclassified into cohorts from Table 1. Second, store selection frequency tables were loaded and assigned to agent groups. Third, spatial data (buildings, census tracts) and the OD matrix were loaded to generate other objects (Figure 3). Fourth, agents were assigned to houses. Finally, agents' attributes were populated with data described in the following section.

5.1.1 Upscaling the sample to the population in the study area

We employed disproportionate upscaling to construct the synthetic population (Smajgl et al., 2011). While we could have used proportional scaling (cloning) as the survey sample is representative of the population (LeDoux & Vojnovic, 2013), we decided to generate probability distributions (Table 2) from sample data (separate for each agent group) due to the small survey sample size (~1.4% of the HH population). Since we previously established the number of agents in a group using the ACS COUNT TABLE, we could then draw values from their group's distributions (Table 2) to assign specific values to agents' attributes in that group. For example, suppose Census Tract has 900 HHs falling into the low-income young category. In that case, that tract will have 900 agents of that group with attribute values derived from PDFs for that group, which, in turn, were obtained by fitting survey data into probability density functions (Table 2).

To place agents within houses, the upscaled AGE-INCOME groups were proportionally assigned to houses within census tracks, thereby avoiding a completely random allocation across the entire study area. Consequently, while every agent group is present in every census tract, there are regions where that group is more common. For example, the core low-income young cohort is most prevalent in tracts in the northeast corner of the study area.

Table 2. Probability density functions (PDFs) of all trips and motorized trips per agent group derived from survey data. These PDFs were used to draw values for agent attributes: trips per week and frequency of motorized trips. Logistic: logistic distribution (parameters: mean and standard deviation), Genextreme: generalized extreme value distribution (parameters: shape, location, and scale), Genlogistic: generalized logistic distribution (parameters: shape, location, scale), Genpareto: generalized Pareto distribution (parameters: shape, location, scale), Gamma: Gamma distribution (parameters: shape, location, scale).

Group	Motorized trips PDF (parameters)	All trips PDF (parameters)
CoLwInYg	Logistic (2.3415,1.4303)	Genextreme (0.22045, 1.8859, 2.3644)
LwInYg	Genextreme (0.21475, 1.2176, 1.6466)	Genlogistic (0.37177, 2.9389, 1.7342)
MeInYg	Genextreme (0.59605, 1.6466, 1.892)	Genextreme (0.69787, 1.9163, 2.2241)
MeInMiAgOld	Genlogistic (0.24957, 2.7529, 1.2117)	Gamma (1.845, 0, 2.116)
CoLwInMiAg	Genlogistic (0.43359, 1.5369, 1.2814)	Genextreme (0.20191, 1.8466, 2.6024)
LwInMiAg	Genlogistic (0.55813, 2.1045, s1.575)	Genextreme (0.45444, 1.9705, 2.6648)
CoLwInOld	Genextreme (0.08086, 0.35604, 0.61504)	Genpareto (-0.60246, -0.35359, 2.1611)
LwInOld	Genpareto (0.12562, -0.52271, 3.1573)	Genlogistic (0.37186, 2.41, 1.5433)

5.1.2 Design of experiments

Unfortunately, some data was unavailable, so we introduced uncertain inputs (factors) into the model. These include [1] three variants of the decision rule (*store first – mode second*, *mode first – store second*, and *store and travel mode selected simultaneously*) that are equally likely to be selected (discrete uniform distribution, section 4.2), [2] a binary decision of whether or not to include store type in the choice process (discrete uniform distribution), [3] a scaling factor that reduces the initial population of agents, representing 14,688 census HHs, to reduce the computation time, and [4] a random seed that controls the variability of other uncertainties like agent-house allocation. As output, we recorded every trip per agent, along with its mode and distance traveled, for each model run.

We performed four simulation experiments: lower eastside baseline, and three extreme case scenarios: i) Aging Population, ii) Increasing Poverty, and iii) Gentrification (increasing middle-class population). The model was also evaluated using sensitivity analysis, which is rarely present in food access ABM. Notable examples include Abel and Faust (2020), Koh et al. (2019), and Salvo et al. (2022). None of these studies, however, utilized variance-based global sensitivity analysis (Saltelli et al., 2008), which decomposes the variance of a distribution of a given output and apportions it to model inputs, generating sensitivity indices. The most efficient sampling method for calculating these sensitivities is the Sobol quasi-random. Through trial and error, we determined that for the four factors in our model, the minimum number of runs required for the sensitivity index to converge is 2560 (Lorscheid et al., 2012). Hence, our final experiments involved M=2560 independent model executions, each comprising five time steps corresponding to five weeks (approximately one month of grocery shopping). This temporal resolution corresponds to the temporal units of the survey data. The model was run on a Lenovo ThinkPad with a Windows 10 Pro 64-bit operating system, with an Intel Core i7-8550U CPU @ 1.8 GHz, and 26 GB of RAM, with an average execution time of 30 seconds per run.

6 Results

We report the results in three sections: i) overview (the baseline scenario) to address the first research question, ii) model verification and validation using uncertainty and sensitivity analysis, and iii) what-if scenario analysis to address research question two. All results are averages from all M model runs.

6.1 Overview

Figure 5 shows the results of the lower eastside baseline scenario. We plotted the change in the ratio of motorized trips to non-motorized trips with distance. Given the dominance of motorized travel in the US, particularly private automobile travel, motorized travel outweighs non-motorized travel over the entire distance traveled. These travel patterns reflect a context where disinvestment in Detroit resulted in limited store options within the lower eastside neighborhoods. At the time of the survey, the City of Detroit did not have a single major regional or national supermarket chain within its jurisdictional boundaries. Only smaller independent and discount supermarkets were located within the city.

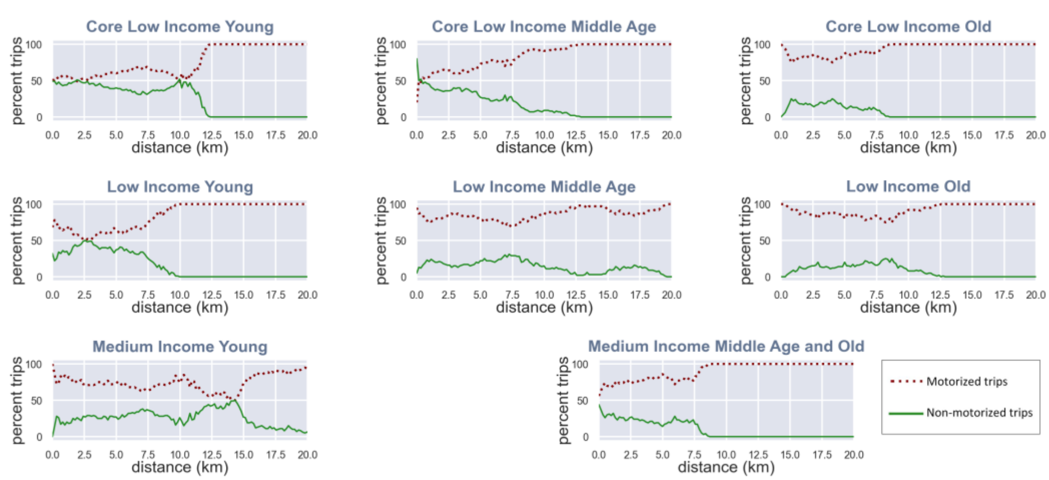


Figure 5. Percentage of trips by distance and mode for agent groups – baseline scenario. Green line – non-motorized travel, red dotted line – motorized travel.

Regarding Figure 5, non-motorized travel over considerable distances is unique to the U.S. There are a few important issues to consider when examining active travel. Non-motorized travel includes walking and cycling, and many of these long distances covered for food shopping are by bike. One of the project's important findings, however, was the extensive distances that respondents who did not have access to an automobile were willing to walk, especially evident among the core poor young (Figure 5, top right). This included some who might walk one way to the supermarket but take a taxi back home. The degree to which Detroit residents walk extreme distances received international coverage in a 2015 Detroit news story about James Robertson, a 56-year-old Detroiter, who walked 21 miles daily to work, a total of 42 miles in both directions (Laitner, 2015).

These extreme non-motorized travel distances are reflective of the unique burdens associated with Detroit's population living in neighborhoods of extreme disinvestment and decline. It should be recognized, however, that similar conditions are evident in the neighborhoods of other Michigan cities characterized by segregation, with minority populations whose communities within the urban core are experiencing disinvestment. The Lansing Capital Region provides another example (Vojnovic et al., 2013).

There is yet another dimension to these long travel patterns among different Detroit socio-demographic groups, perhaps most evident among the medium-income young. The population that has been moving into the City of Detroit over the last two decades has generally been an "alternative population subgroup," including many artists, hipsters, and activists. As the title of a 2014 Los Angeles Times article recognizes, "Detroit [is] evolving into a haven for artists" (Bender, 2014). The Detroit school system is considered to have the worst quality schools among large U.S. cities, and as a result, while the city has been on a steep decline throughout the 21st century, it has not been successful in attracting the typically mainstream nuclear family (Vojnovic, 2009; Vojnovic, et al. 2014). Initially attracted to Detroit by its rapidly declining property values, many singles and a more progressive population have been moving into the City, including those with a stronger focus on broader public and community issues, such as social, racial, and gender justice, as well as greater environmental and health awareness. Many are young, Black university-educated progressives—including schoolteachers, chefs, artists, and municipal employees—who made a conscious decision to move into the City of Detroit and not one of its wealthier suburbs (Conlin, 2011; Bender, 2014). While the automobile is still dominant in Detroit, there are those among this younger cohort—including some who are part of our medium-income young group captured in our surveys—who choose not to purchase or drive a car, but rather, use transit or simply elect to walk and cycle, including over long distances.

Even though the model predicted that the number of motorized is larger than that of non-motorized, specific patterns can be observed. Generally, as age increases (along the horizontal axis), households tend to travel more by automobile/bus. Over the entire distance range, the number of motorized trips remains high for the older population, regardless of income (box plot IQR in Figure 6, lower left).

There is no such clear correlation regarding income (along the vertical axis). Core low-income and low-income young agent populations are more likely to make trips using non-motorized modes. For these groups, the number of motorized trips is relatively close to that of non-motorized trips within a specific distance (up to 11 and 2 km, respectively). The younger population tended to make more trips by walking and cycling for shopping, even over relatively longer distances. However, regarding the number of trips, these younger groups exhibited more heterogeneous behavior, i.e., a mix of motorized and non-motorized travel, and traveling throughout the city for food shopping (box plot IQR in Figure 6, lower left). The core low-income elderly individuals compensate for the cost of motorized trips by taking fewer weekly trips to supermarkets. Some groups exhibit multiple maxima (e.g., medium-income young adults), indicating that households skip stores to travel longer distances to preferred shopping locations. This trend is also a consequence of the largest number of favorite stores identified by this cohort (see Figure 4). Note that this mode-distance may be contingent on the pool of stores identified by respondents in particular cohorts, where some groups reported many favorite stores outside of the neighborhood (Vojnovic et al., 2020).

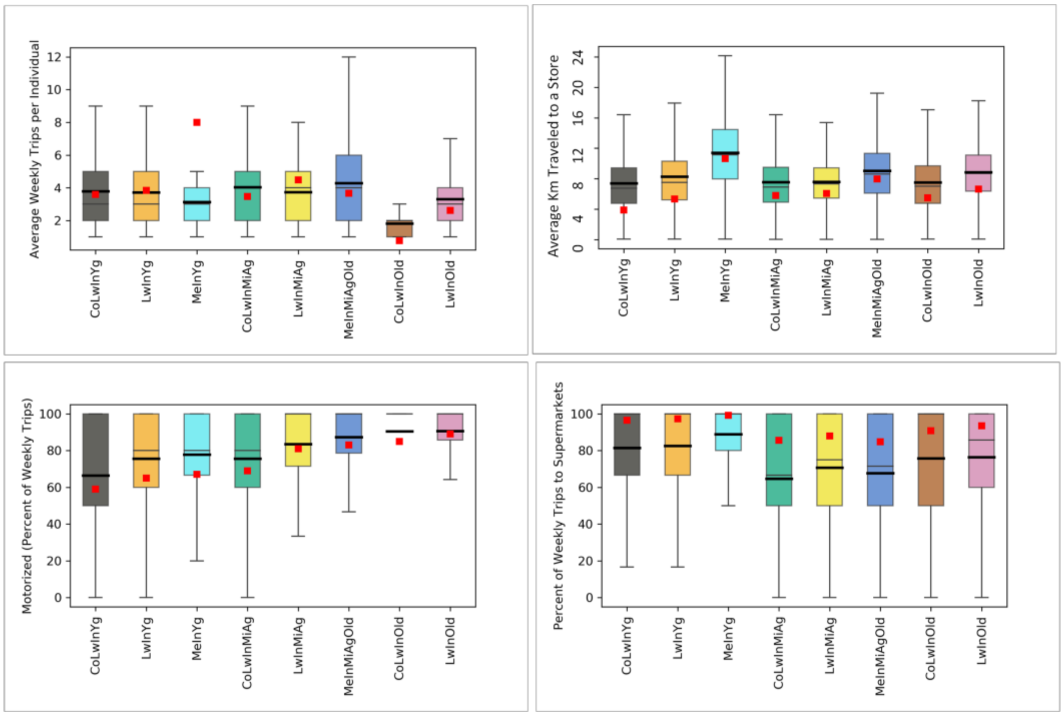


Figure 6. Selected output statistics for uncertainty analysis of the baseline scenario. The red squares are averages from survey data used for comparison in validation.

6.2 Verification and validation

Given the empirical nature of fABM, we first apply output verification (Belfrage et al., 2024; Windrum et al., 2007), in which we assess the extent to which the model replicates existing data (Graebner, 2018). We adopt the concept of in-sample comparison, where the goal is to replicate the statistical properties of the observed data (Windrum et al., 2007). Since the empirically derived probability distributions (Table 2) were used to inform the model, values of the variables in the output (i.e., simulated) should align with the values obtained directly from the survey (observed).

Second, we perform statistical validation using uncertainty and sensitivity analysis (Railsback & Grimm, 2019), which enables us to identify the essential components that affect the variability of the results. These drivers of variability reduce the model's accuracy in relation to the system and require revision to improve model validity and reliability.

6.2.1 Data verification

Table 3 summarizes the selected outputs and compares them to the summaries from the observations. All variables are controlled inputs except for the average distance traveled (DISTANCE). For TRIPSAVG, all but one group differ (from the empirical data) by one or fewer trips per week. The outlier is medium-income young (~4.9 trips difference). This discrepancy can be easily explained. Note that the sample sizes are relatively small (Table 1), and any outlier can significantly affect the averages.

On the contrary, TRIPSAVG obtained from the model is calculated from millions of records and initialized using probability distributions. Hence, we can conclude that the model's average is more robust than the survey's average. DISTANCE exhibits behavior similar to TRIPSAVG. The range of differences falls from 0.8 to 3.5 km. Note that the sample has a fixed spatial distribution, whereas the population of 10,000+ agents is distributed over the entire study area, introducing variability to the weekly distance traveled due to the uncertainty of spatial allocation. We obtained a relatively similar value between the observed and simulated data for the percent of motorized trips. However, the model slightly overestimates the values of all groups (by up to 11%). These differences are to be expected. The young population tends to use a mixture of transportation modes, which introduces more stochasticity in fABM, making it more likely to generate differences between the observed and simulated values.

The choice of supermarkets over other stores is higher in the simulated data (up to 21% difference). These differences can be attributed to the uncertainty in the decision rules used in the model (section 4.2). The variables SUBURBS, CITY, and NEIGHBOR represent the fraction of trips to the suburbs, within Detroit, and in the neighborhood. Note that these variables are derivatives of DISTANCE. We hypothesize that the underlying cause of the differences between the simulated values and the survey data is the variability in house versus store locations.

Table 3. Selected fABM output variable values compared with survey data: survey average, simulation average.

Variable Name	Description	CoLwInYg	LwInYg	MeInYg	MeInMiAgOld	CoLwInMiAg	LwInMiAg	CoLwInOld	LwInOld
TRIPSAVG	Avg. No. of trips per individual	3.6, 3.8	3.8, 3.7	8, 3.1	3.7, 4.3	3.5, 4.0	4.5, 3.7	0.8, 1.8	2.6, 3.3
DISTANCE	Average distance traveled (km)	3.93, 7.47	5.37, 8.32	10.7, 11.5	8.01, 9.11	5.84, 7.6	6.11, 7.66	5.52, 7.58	6.66, 8.9
MOTORIZD	Percent of motorized trips	59, 66	65, 76	67, 78	83, 87	69, 76	81, 84	85, 90	89, 91
SUPER	Percent of trips to supermarkets	96.5, 81.5	97.2, 82.5	99.1, 88.9	84.8, 67.7	85.5, 64.7	87.9, 70.7	90.8, 75.7	93.6, 76.4
SUBURBS	Percent of trips to the suburbs	3.5, 17.8	20.5, 36.1	47, 52.77	46.6, 41	13, 28.3	31.2, 34.7	32.9, 39.8	46.2, 52.3
CITY	Percent of trips in the city	55.3, 56.8	46, 36.7	40.3, 35.8	24.1, 28.5	51.4, 51.6	50.3, 42	32.3, 34.8	38.7, 32.8
NEIGHBOR	Percent of trips in the neighborhood	41.2, 25.4	33.5, 27.2	12.7, 11.5	29.3, 30.5	35.6, 20.1	18.5, 23.3	34.8, 25.4	15.1, 14.9

6.2.2 Validation using uncertainty and sensitivity analysis

Figures 6 and 7 show the results of the uncertainty and sensitivity analyses. The former is depicted using distribution diagrams and the latter using input sensitivity indices.

The uncertainty analysis verification in Figure 6 and Table 3 show a high level of convergence in several aspects. First, regardless of household income and age, respondents tend to shop at supermarkets outside their immediate neighborhood rather than at stores in their proximate food environment (Figure 6, bottom-right and top-right). For example, even low-income elderly households shop at supermarkets outside the immediate neighborhood food environment. Second, wealthier households frequent more trips to suburban stores than low-income households. However, low-income households also shop in the suburbs, albeit at lower rates than high-income households. Third, most travel to stores is by motorized vehicle (Figure 6, bottom-left). The rate of motorized travel increases with household income and age. Last, when leaving their neighborhood, lower-income groups tend to make shorter trips confined to stores in Detroit rather than the higher-income population subgroups, which tend to shop in the suburbs. Overall, we conclude that the model reflects the observed data and is adequate for what-if analysis.

Using sensitivity analysis, we can evaluate if more data is needed to fine-tune the model so that it better reflects the target system. In addition, we want to evaluate whether there is a need to use a complete enumeration of the population or whether we can use its sample (Figure 7 "Scale Factor"). The number of agents used in fABM was initially set to the total HH population estimates (~14,700). Scaling down these counts has practical implications as the number of agents in the model affects its execution time. Finally, we had to capture the stochasticity of the empirical distributions used in the model and agent assignment to the buildings (Figure 7, "Random Seed").

Figure 7. Sensitivity analysis of percent of motorized trips: STORE (select store type – yes/no), DRULE decision rule (one of the three variants described in section 4.2), SF scale factor, SEED random seed.

Because this study aims to evaluate the percentage of motorized trips per distance, we focus on the motorized results, Figure 7. The box plots reveal three major conclusions. First, there is considerable variability among groups in the influence of the four inputs on the results. Store Type and Decision Rule equally influence motorized for the young populations, both singly and in interactions. In contrast, the variability of motorized for the old groups is equally influenced by all four inputs, especially when analyzed in interactions. Second, fABM proves to be a highly nonlinear model. For the motorized output, all factors noticeably interact with each other for all groups. Finally, the sensitivity of the motorized variable correlates with age. For the young agent populations, the percentage of motorized trips is driven by Store Category and Decision Rule. For the older agent groups, all four inputs have a relatively equal influence on the variability of this output.

In sum, the model results are predominantly sensitive to the choice of store type and the decisions made. These two inputs were not derived from the survey but were theorized. The sensitivity analysis suggests that future data collection requires survey instruments that specifically ask about the decision processes leading to grocery shopping, especially focusing on the question of shared modes of transportation to reduce the travel costs.

6.3 Extreme case scenario analysis

We performed a what-if analysis using three amplified sociodemographic profile scenarios (Figure 8): “Aging Population,” “Increasing Poverty,” and “Gentrification.” The objective here was not to explore policy interventions but rather to simulate alternative futures using extreme-case configurations. All scenarios were generated by tripling the population of the old, core low-income, and medium-income groups, respectively. There are some commonalities but also significant differences between scenarios (Figure 8). In general, these configurations solidified the trends in the tripled agent groups. For example, the same trends can be observed for all core low-income groups in both the “baseline” and the “Increasing Poverty” scenarios (top row in Figure 8). Instead, the three scenarios allowed for emphasizing the patterns for the remaining groups, with certain observable differences discussed below.

In the Detroit survey, questions were asked about why the residents chose to live in these neighborhoods. Many respondents did so because they could afford the housing, with several indicating that they inherited their properties from their families. These were not necessarily their neighborhoods of choice, but due to their income levels, with many unemployed, they could not afford to move. Within this context, the first scenario assumes residents are staying in place and getting older.

In the “Aging Population” scenario, aside from some minor variability, there is not much of an impact on the elderly, who consistently remain reliant on motorized travel, and the core low-income population, who generally continue to walk and cycle over long distances to reach their shopping destinations. The most notable changes in the choice of non-motorized versus motorized travel are observed among the low-income young and middle-age populations (the left and center columns in Figure 8) and the medium-income young population (the bottom left column of Figure 8). First, the behavior becomes more volatile for these groups, which is to be expected given that their relative population sizes have decreased. Second, under this scenario, the low-income young population, in general, becomes more reliant on non-motorized travel to reach stores, particularly those located up to 7 km away, which enforces the shopping behavior evident in the baseline. Third, under the “Aging Population” scenario, the low-income, middle-age cohort becomes more reliant on non-motorized travel to reach stores at shorter distances, particularly up to about 3 km, but then begins to depend on motorized modes to reach more distant locations, in cases where stores are located 6 km or more from home.

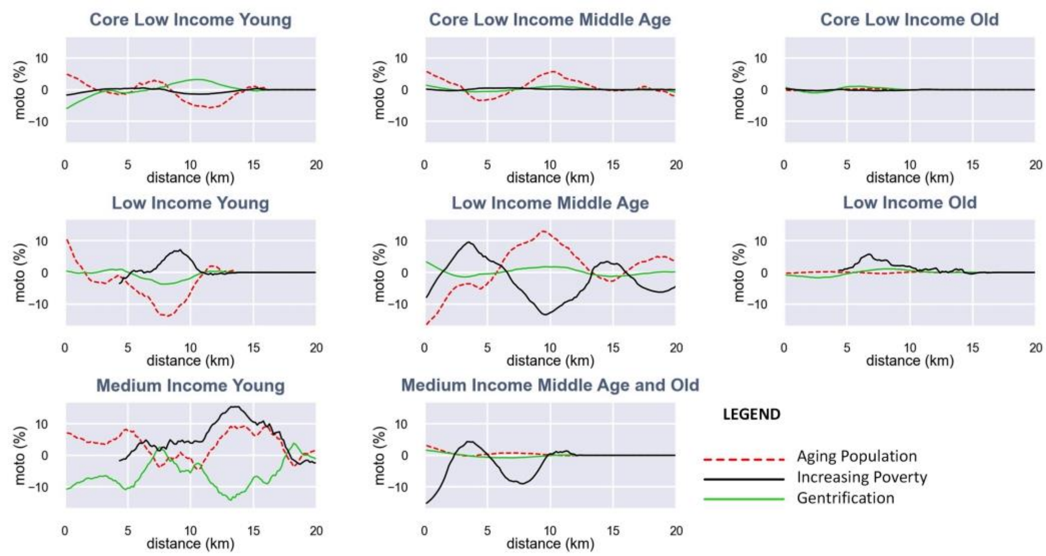


Figure 8. Motorized percentage of trips by distance for three extreme case scenarios for all agent groups, shown as deviations from the baseline scenario: aging population (dashed line), increasing poverty (black line), and gentrification (light green line). A line starts at a minimum average motorized distance for a particular agent group across all runs. For example, ~ 5 km for Low-Income Young in the Increasing Poverty scenario means that the agents, on average, use non-motorized transportation up to a distance of ~ 5 km. This pattern results from a relatively small number of favored stores identified by a selected cohort (Vojnovic et al, 2020).

Finally, for the medium-income young, given the lower constraints of this cohort—and their generally expansive selection of stores across Detroit and its surrounding suburbs—they exhibit considerable deviation from the baseline, with generally increased motorized travel to a wide range of shopping destinations. This increased motorized travel is evident in stores up to 5 km away, and then again, at an even more pronounced pattern in travel to stores from 12 to 18 km away. Overall, in the "Aging Population" scenario, there is a sizeable component of residents who continue with similar levels of reliance on motorized and non-motorized travel to reach shopping destinations, when compared to the baseline, and a notable component that becomes more reliant on the car and bus to travel, which in general, is to be expected in the cultural context of Michigan. The low-income young, on the other hand, accentuate their reliance on non-motorized travel.

Our subsequent two scenarios stand out because of two ongoing patterns of economic change being experienced across the City of Detroit. Over the last decade, a narrative of economic recovery and gentrification has emerged, particularly evident in Detroit's Downtown and Midtown Areas. At the same time, a stalling out, or ongoing decline, has been recognized in many of the other neighborhoods throughout the city (Reese et al., 2017; Vojnovic & Darden, 2013). Using the 2006-2010 and 2016-2020 ACS 5-year estimates, our study area had a poverty rate of 42.29% in 2010 and 40.50% in 2020. The lower eastside neighborhoods explored in this analysis also lost approximately 12,000 people between 2010 and 2020, illustrating the ongoing process of disinvestment and abandonment in the study area. The lower eastside neighborhoods have and continue to experience concentrated poverty and disinvestment, making the relevance of scenario 2 (increasing poverty) a feasible future condition. At the same time, with all the discussion of recovery, resilience, and the influx of creatives to Detroit, we also offer scenario 3 (the case of gentrification), where more medium-income households invest in the neighborhoods, and average incomes increase.

With both the "Increasing Poverty" and "Gentrification" scenarios, for the elderly and the core low-income poor cohorts, one immediate pattern that becomes evident is their similarity to the "Aging Population" scenario. Aside from some minor fluctuations from the baseline, there is generally little impact on these groups from either the "Poverty" or "Gentrification" scenarios. The elderly continue to rely consistently on automobile travel, while low-income groups largely rely on non-motorized travel to reach their shopping destinations.

With the "Increasing Poverty" scenario, there are several cohort deviations from the baseline that are evident. First, the low-income young cohort becomes more reliant on motorized travel between about 7 and 11 km. There are several major supermarkets along Gratiot Avenue, which has a bus line, stretching along this retail strip into the northeast suburb of Eastpointe and beyond, which effectively match these distances. Second, the low-income, middle-age group does more shopping by non-motorized modes in stores close to home, and then increases reliance on motorized travel for shopping from about 2 to 7 km. The low-income, middle-age group also increases non-motorized travel in the 7 to 13 km range. Under the "Increasing Poverty" scenario, for this 7 to 13 km range, the low-income, middle-age cohort might be cycling more to supermarkets further into the northern suburbs—stores of preference for this group in the baseline scenario—in areas with limited bus routes and connections.

Third, under the "Increasing Poverty" scenario, what is most prominent for the medium-income young is that they travel even longer distances to reach shopping destinations, relying more on motorized travel. Once again, given their income levels and access to private automobiles, if the case study neighborhoods are experiencing further decline, it is not surprising that they would choose to shop in stores located in wealthier suburbs. Finally, with increasing poverty in the neighborhoods, for the "medium-income, middle-age and old" group, there is, in general, much greater reliance on shopping by non-motorized means. This cohort walks and cycles to stores closer to their homes, up to about 2 km, and then again to stores within a range of 5 to 9 km, likely driven by the middle-age group of this cohort. This cohort maintains somewhat greater reliance on motorized travel within the 3 km to 5 km distance, a likely imprint of those who own an automobile.

Finally, for the "Gentrification" scenario, the only discernible difference compared to the baseline is evident with the medium-income young cohort. As the neighborhood gentrifies, the medium-income young population walks and cycles more to reach their shopping destinations. They not only utilize non-motorized modes of travel to reach stores within their neighborhoods and the City of Detroit, but also to access stores in the suburbs, particularly those within a 10- to 17-km distance. As the quality of the case study neighborhoods improves, with the neighborhood reinvestment that accompanies gentrification, given the greater environmental and health consciousness among some within this cohort, we would expect them to rely more on non-motorized travel, with an even greater dependence on walking and biking to reach shopping destinations. It is worth noting that for an intermediate cyclist, a 14-kilometer bike ride would take approximately 45 minutes, while a skilled cyclist could reduce this trip by another 10 minutes.

7 Discussion

Our fABM demonstrates that most trips are motorized, predominantly by an automobile (Figures 5 and 8). Based on the results presented here, the number of motorized trips increases with age (Figures 6 and 8). The younger sociodemographic groups, particularly those with medium incomes, have the least constraints regarding resources or physical mobility limitations within the lower eastside Detroit neighborhoods. Their shopping patterns cover a vast area across the Detroit region. They tend to shop at the more distant suburban locations at a high frequency while minimizing shopping within their neighborhood. They have unique mobility freedom associated with having money, being young, and being willing to travel extensive distances for food shopping, whether by motorized or non-motorized means. Within the broader context, these findings are not necessarily surprising, given that most shopping trips, regardless of cohorts, are outside their neighborhood or in the suburbs (LeDoux & Vojnovic, 2014; LeDoux et al., 2017; Widener, 2018).

The average number of weekly trips is similar across the AGE-INCOME groups (3-4 trips, Table 3) except for the low-income elderly, who average 2 trips per week (Figure 6, top-left). This can be attributed to reduced mobility, but, at the same time, a small number of weekly trips allowed for a high percentage of motorized travel (Figures 5 and 8, top right). In summary, our study has uncovered significant differences in the tolerance threshold for non-motorized travel. Younger and poorer residents, as revealed in the scenario analysis, are much more willing to walk and cycle long distances to shop for food. This finding is crucial for understanding the dynamics of food access in disadvantaged communities. The generally wealthier households, on the other hand, travel the greatest distances and the highest number of times per week to shop at major national/regional supermarkets at their preferred locations, mainly in Detroit suburbs (Table 3 and Figure 6). The elderly, in contrast, travel the least for food shopping, and when they do, they travel considerable distances using motorized means.

Research has consistently shown that higher densities, mixed land uses, and well-connected street networks are conducive to non-motorized travel and shorter travel distances. However, our analysis reveals that these fundamental planning and design principles can falter in neighborhoods grappling with severe disinvestment and decline. The departure of urban amenities and the loss of major supermarket chains force residents to travel significantly longer distances by automobile to access basic destinations, including food shopping. This trend persists even as the population becomes wealthier, assuming no new major supermarkets open within the lower eastside neighborhoods. The impact of disinvestment on travel distances is a significant challenge that warrants further investigation and potential solutions.

The additional dimension of high poverty rates and associated lower levels of vehicle ownership and limited public transit lines in the city, partly due to disinvestment (limiting motorized travel even for longer shopping trips, such as to major suburban supermarket chains), adds yet another dimension to mobility restrictions due to the extreme socioeconomic conditions within neighborhoods experiencing decline. In neighborhoods experiencing disinvestment, despite the higher densities, mixed land uses, and high connectivity, travel to reach basic destinations is considerable. In addition, for the poorest, due to limited vehicle access and a city under extreme financial stress with limited public transportation, what becomes evident, especially among the young, is that they are forced to travel long distances, even by non-motorized means, to access food and other daily necessities.

The results of this study, with a mixture of non-motorized and motorized travel at shorter to longer distances, can be attributed to corridors (Figure 9) with bus lines (including Gratiot, Warren, Mack, and Jefferson Avenues) which become key shopping destinations, whether they are located within the case study neighborhoods, the rest of the City of Detroit, and/or extending into the suburbs. The importance of these retail and service corridors is observed across all income and age groups, as they enable a wide array of travel options, including non-motorized (bicycles and pedestrians) and motorized (private automobiles and buses), while also accommodating the convenience of regular and frequent shopping alternatives.

As an example, Gratiot Avenue, which comes in from the southwest and extends northeast through the lower eastside neighborhoods, provides access to pharmacies, discount, dollar, and convenience stores, as well as popular Detroit independent supermarkets within the city, such as Sav-Mart Marketplace, still open, and former Food Town, currently closed. As one enters the suburbs, the Gratiot Avenue corridor also features major national/regional supermarket chain destinations, including a Meijer, a Sam's Club, and two Kroger supermarkets, all of which have emerged as important shopping destinations for residents of the lower eastside of Detroit. The multi-modal transportation options and the concentration of retail and commercial activity along these corridors reinforce and support each other despite the extensive scale of disinvestment throughout the city, including in neighborhoods directly adjacent to these major retail strips. The transportation options and the concentration of shopping destinations along these Detroit corridors have also likely helped ensure that these retail outlets have remained financially viable, open, and continue to provide services to the community, even under conditions of extreme disinvestment.

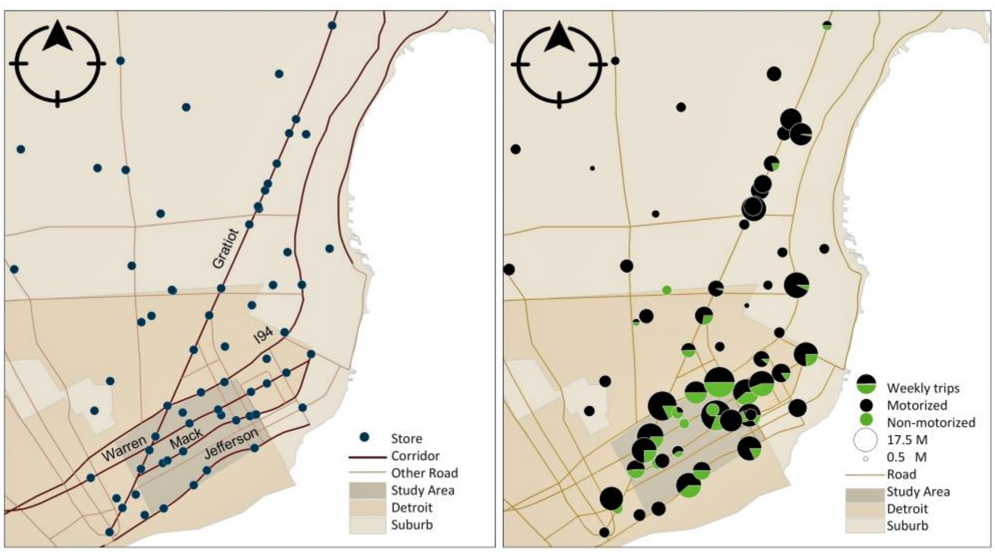


Figure 9. Major shopping corridors near case study neighborhoods with stores identified by the respondents (left) and the stores' ABM simulated motorized and non-motorized weekly trips (right).

Despite the importance of these retail corridors in accommodating various modes of travel, many basic design elements that promote walking and cycling are missing from these streetscapes (Vojnovic, 2006). These corridors have long distances between street crossings, which, when reached, usually require you to cross six vehicle lanes. There are no designated bike lanes, and these streets lack many features that urban designers recognize as promoting a high-quality and inviting pedestrian streetscape, from trees to street furniture. Nevertheless, in a landscape of severe disinvestment, the convenience of regular and frequent shopping alternatives makes these retail corridors important and necessary shopping destinations within the lower eastside neighborhoods. In addition, as one might expect, within and in the proximity of the case study neighborhoods, walking and cycling play a more significant role among residents in reaching the stores of choice along these corridors, while private automobiles and buses dominate the transportation options for reaching suburban store locations.

7.1 Limitations

The fABM presented is primarily an exploratory tool, designed to analyze distance-mode relationships within the specific communities studied. Due to its reliance on probability distributions from local survey data, the model's generalizability is limited to the study area or similar core poverty populations in declining US Midwest cities. We acknowledge these limitations and are committed to further research to enhance the model's explanatory power.

Second, based on the sensitivity analysis results, the three decision rules we introduced into the model (section 4.2) substantially influence the variability of the ratio of motorized to non-motorized trips and the median distance from home to the selected store. To enhance the model's explanatory power, we advocate further research that specifically asks householders about how they grocery shop, to what extent they rely on each other when commuting to grocery stores, and how their behavior changes over time with the changing store landscape (the number and the location of stores). This would enable more empirically grounded agent behavior, a deeper understanding of the complex dynamics of food access in disadvantaged communities, and informed policy recommendations based on well-targeted models.

We acknowledge our 10.3% survey response rate is low, though not unexpected for travel surveys in marginalized urban communities (Groves & Couper, 2012; Siegel, 2002; Zimowski et. al., 1997). While the small sample size risks overrepresenting rare behaviors (Smajgl & Barreteau, 2014), the data's uniqueness—capturing geocoded weekly trips with travel modes for communities in decline—justifies its use and underscores the need for more research on grocery shopping decision-making.

It should be noted that the retail landscape in the City of Detroit has undergone changes since this survey was conducted. The Great Recession (2007) led to extensive foreclosures in the city and the closing of the last major supermarket chain, A&P's Farmer Jack. It would be some five years before a major chain supermarket would open in the city again, with both Meijer and Whole Foods opening in 2013. The Meijer supermarket (1301 W. Eight Mile Road) is located far from our neighborhoods, approximately 21 kilometers away. There are other relatively far Meijer locations in the Detroit suburbs. Whole Foods is closer, about 9 kilometers from the neighborhoods, but the outlet is a smaller store than normal, only about 2,007 square meters, and maintains higher prices than traditional supermarkets. It will likely appeal to only middle-income respondents.

In October 2021, an urban Meijer opened on E. Jefferson in Detroit, Meijer Rivertown Market. It is located about 8 kilometers from our neighborhood, but it is a much smaller store, at 3,900 square meters. In addition to groceries, it also focuses on providing "grab-and-go" items. Being an urban Meijer, the focus of Rivertown Market is quite different from that of the suburban Meijers, which are typically anywhere from 4 to 6.5 times larger. For example, the Eight Mile Road Meijer, which opened in 2013, spans 17,745 square meters.

More relevant to our neighborhoods is a store that has been around since the time of the survey and which respondents relied upon extensively: a suburban Kroger supermarket located approximately 7 km from our neighborhoods. It is closer to our neighborhood respondents than the new Meijer Rivertown. In our case study, neighborhood residents are also closer to several independent supermarkets located within the neighborhoods. Given the new supermarkets' characteristics and locations, shopping patterns have likely remained largely unchanged in our case study neighborhoods. Overall, these stores are not expected to significantly alter shopping behavior among lower eastside residents.

Other aspects that may influence the conclusions derived from fABM are race/ethnicity and gender. Studies suggest that race and ethnicity play a role in describing grocery shopping and the nature of food consumption in general (Eckert & Vojnovic, 2017). Since the selected neighborhoods are racially relatively homogeneous, with about 94% African American (LeDoux & Vojnovic, 2013), we disregarded race as a descriptor of food shopping behavior. We also anticipate that the shopping behavior of females is different from the population (Lee et al., 2018), which may also affect the results. For example, women may prioritize crime and safety more when selecting a store and mode of travel. Likewise, the number of trips per day may be higher for women compared to the entire sample. Finally, future model improvements should include observed travel time (rather than calculated distance) as the impedance value in road network traversal (a more common unit in transportation decision-making, e.g., "five minutes driving" instead of "four kilometers away") and split mode travel (e.g., walk to store but take a bus back home).

8 Conclusions

In this paper, we demonstrate how empirically grounded agent-based modeling of urban food systems can shed light on the grocery shopping behavior of disadvantaged communities. Research on travel, particularly non-motorized travel, has generally focused on dynamic urban centers, examining non-motorized travel (walking and cycling) in the urban cores of cities such as Boston, New York, San Francisco, and Seattle. Travel behavior research in communities experiencing extreme disinvestment and decline, focusing on the core poor, is recognized as underrepresented in the planning literature. Examining neighborhoods characterized by high densities, mixed land uses, and highly connected street networks, this research shows that basic tenets in planning and design can break down within communities experiencing extreme economic distress. The fABM reported here exemplifies an attempt to develop a model from data collected within neighborhoods experiencing extreme disinvestment, combined with theory on land use and travel. The model development, evaluation, and application process follow a strict protocol (section 5), allowing for a comprehensive sensitivity analysis of the most uncertain factors.

This research demonstrates that low-income, highly segregated communities employ diverse and complex mechanisms of grocery shopping behavior in response to major national/regional supermarket chains leaving the city. Specifically, the model presented here rejects the proximity hypothesis (Giabbanelli & Crutzen, 2017) since store selection is based on real-world people's stated preferences rather than simplified assumptions. The travel decisions directly affect the change in the mode of transportation with distance, as the results of ABM suggest.

Due to the decades of disinvestment, the loss of urban amenities in the city illustrates the unique mobility burdens faced by populations living in communities characterized by decline. As noted earlier, the disinvestment and abandonment in these lower eastside Detroit neighborhoods have continued into the 2020s. Despite the high densities, mixed land uses, and street connectivity—all assumed as requirements to promote accessibility—the residents must travel extensive distances to reach something as basic as healthy food options. While there are prevailing shopping patterns across these neighborhoods, there is considerable diversity in how and where population subgroups access stores based on their sociodemographic characteristics, as seen here with age and income. For example, there are significant differences in the tolerance threshold for non-motorized travel, with younger and poorer residents being much more willing to walk and cycle long distances to shop for food. In addition, the generally wealthier travel the greatest distances and the highest number of times per week—utilizing motorized and non-motorized travel—to shop at major national/regional supermarkets at their preferred locations, mainly in Detroit suburbs. The elderly, in contrast, travel the least weekly for food shopping, and when they do, they primarily use motorized means to travel to stores, regardless of distance. In light of our observations, we would encourage researchers to employ tools that explicitly quantify the dynamics between space and residents' purchase patterns when studying declining communities.

Data Availability

Some access restrictions apply to the data underlying these analyses and findings for approved reasons. The Detroit surveys collected information at the household level. These surveys contain confidential data, including household and personal income, employment, educational attainment, gender, age, race/ethnicity, number of dependents, marital status, automobile ownership, travel destinations, and dietary habits (including alcohol consumption). All these attributes are tied to addresses, which are considered sensitive and potentially harmful if exposed. The IRB approval to collect this data was given on the condition that any information from the survey would only be provided to the public in the aggregate, which we included in Tables 2 and 3. All other datasets mentioned in the paper are sourced from public online repositories, with citations included in the references.

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Author contribution

The authors confirm contribution to the paper as follows: funding acquisition, oversight, and mentorship: I. Vojnovic; conceptualization: A. Ligmann-Zielinska and I. Vojnovic; methodology and figure preparation: A. Ligmann-Zielinska and T. F. LeDoux; data processing: T. F. LeDoux; model implementation: A. Ligmann-Zielinska; results analysis, drafting, review, and editing: A. Ligmann-Zielinska, I. Vojnovic, T. F. LeDoux.

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