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Food Acquisition And Shopping Patterns And Associations With Body Mass Index

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FOOD ACQUISITION AND SHOPPING PATTERNS AND ASSOCIATIONS WITH BODY MASS INDEX

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Dedication

This dissertation is dedicated to my brilliant, loving, and supportive husband, and to my always encouraging and ever faithful parents and brother. Without your love and support, I could never have accomplished so much.

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Abstract

Background: Obesity is a big public health concern in the US. Previous studies examined its association with food shopping practices measured by distance to the food store, shopping frequency, and type of store selected. However, not much is known about the actual food acquisition and shopping habits integrating multi-dimensional aspects. The purpose of this study was to identify distinct food acquisition and shopping patterns in populations primarily residing in food deserts in South Carolina (SC) and a general population in the US and characterize these patterns with respect to socioeconomic status (SES), nutritional knowledge, and perceptions and store selection reasons, and then examine the association between the identified patterns with body mass index (BMI).

Methods: Two datasets were employed, including a sample of 522 participants from two SC counties and 4826 households from a national representative survey. Food acquisition and shopping habits measures including travel distances between residential location and each of the used stores, shopping frequency, store type, transportation, and utilization of community food resources, such as food banks or pantries and church or social services were used. Latent class analysis was employed to explore the acquisition and shopping patterns. Multivariable linear regression was used to assess the association between the identified patterns and BMI adjusting for sociodemographic information.

Results: Three classes were identified among the SC low-income population, defined by distance, frequency, transportation and community resources utilization. Among the national population, three classes among urban households and two classes among rural households (with similar attributes as two classes that identified among urban households) were identified, which were defined by distance, travel time, transportation, and farmers' market utilization. SES factors, nutritional knowledge, perception of food environment, and store selection reasons were associated with the identified patterns. No significant associations were found between the identified patterns and BMI.

Conclusions: Different patterns were identified among general and low-income populations, and among urban and rural populations. Future interventions on increasing healthy food access and intake should take into consideration the different food acquisition and shopping patterns and factors that impact those patterns.

Table of Contents

List of Tables

List of Figures

Chapter 1. Introduction

Background

Rapidly increasing rates of overweight and obesity are a public health crisis in the United States. Significant disparities in overweight and obesity and related chronic diseases exist and are related with individual socioeconomic status (SES) and with race/ethnicity. [1-4] African Americans with average lower SES have higher rates of obesity than other groups such as Non-Hispanic Whites. [3] For example, the prevalence was higher in women, among middle-age group (40-59 years old), and among non-Hispanic Black adults. [5] Obesity occurs within a complex framework of interrelated factors. The prevalence of preventive behaviors to achieve energy balance, such as regular physical activity and a healthy diet, lags far behind the Healthy People 2010 objectives for the nation as a whole and for people of lower SES. [6] Neither medical nor educational and behavioral approaches have been sufficient to stem the rapid rise in population obesity, nor has significant progress been achieved in eliminating health disparities in obesity[7] In light of the modest and short-term successes of individually focused strategies, [8-13] built environment has drawn increasing attention. In epidemiological studies, associations have been studied between healthy food access and obesity. [12,14-18] A review of neighborhood food access in the US found that in general, neighborhood residents who have better access to supermarkets and limited access to convenience stores have healthier diets and lower levels of obesity. [19] However, not all studies have found an association between food environment and body weight. [20]

Previous studies often focused on food access, which is the potential food shopping behavior based on the availability in the residential food environment. [12,14-18] A recent improvement over previous studies is that studies are able to capture the real food shopping by measuring shopping behaviors conducted in utilized grocery stores. [21-31] These newer studies have included a focus on distance to the food store, shopping frequency and type of store selected etc. However, these measures only reflect one aspect of food shopping at a time. A recent study incorporating multiple additional aspects of shopping behaviors (including fruit and vegetable purchases, frequency of shopping, type of purchasing location and food and beverage purchases) identified food shopping patterns among college students. [32] Despite these improvements, other aspects that influence food shopping, such as food price in selected stores and specific reasons for store selection, have not been included in the study. Thus, there remain gaps in this area, primarily in the need for a better measure of food shopping patterns among general populations.

Need for the Study and Significance

The proposed research is relevant to both policy and practice in multiple ways. First, to the best of our knowledge, there is no literature that explores and defines food shopping patterns by taking multiple factors—such as price, reasons for shopping, nutritional consideration and personal shopping behaviors—into account together among general populations. Second, if an association between food shopping patterns and weight status exists, the results of the proposed study can inform how obesity prevention efforts could be tailored to incorporate different domains of food shopping patterns. Third, the USDA is responsible for food assistance programs in the US, including considerations of eligibility criteria and benefit levels. Using a latest nationally representative data, this study will inform policymakers about the presence and magnitude of any shopping-related challenges faced by food assistance program (e.g., SNAP) recipients in reducing obesity. Also, the federal Healthy Food Financing Initiative (HFFI) spends over $167 million in 2015 [33] to address healthy food access problems in underserved communities. Results from the proposed study will lend support to the government to improve interventions to increase food purchase for disadvantaged group.

Conceptual Framework

Food shopping is a complex behavior that likely has multiple domains. **Figure 1.1** shows the conceptual framework for the association between food shopping and obesity, and the factors that are related to food shopping. First of all, personal factors could influence store selection. These individual characteristics include socio-economic status such as food assistance program participation, food security status, income, and education; nutrition domains, such as nutritional awareness and diet knowledge; personal consideration of store selection and their perception of food in store and its environment; and the demographic factors such as individual's age, gender, race/ethnicity, marital status, and health status. [34] On the other hand, the surrounding food environments could influence whether a store would be selected by individuals or not. Because the proposed study focused on food shopping by surveying shopping behaviors in the utilized grocery stores, we conceptualize the food environment as having two parts, which are the utilized food environment and the unutilized but still potentially to be utilized food environment.

As food shopping in a utilized store represents an interaction ("interaction" not meant in a statistical sense here) between an individual and a store, we frame an overlapping area between utilized food environment (including food price in utilized store, shopping frequency, store accessibility, shopping frequency, store type, competitive store characteristics, and community food resources, food desert/non-healthier retailer tract, urbanicity) and individual characteristics. Moreover, this overlapping part is our main interest in this proposed study, which is described by multi-dimensional aspects of food shopping behaviors, and is related with characteristics from other domain such as SES, nutrition, and psychological domains. We believe that there is an underlying pattern that distinguishes different types of shoppers using Latent Class Analysis to classify the different components in different domains. The identified patterns will then be related with body weight via the nutrients intakes.

Objectives

By employing the above conceptual model, the goal of the proposed research is to identify food shopping patterns with multiple dimensions and to evaluate how food shopping patterns are related with obesity.

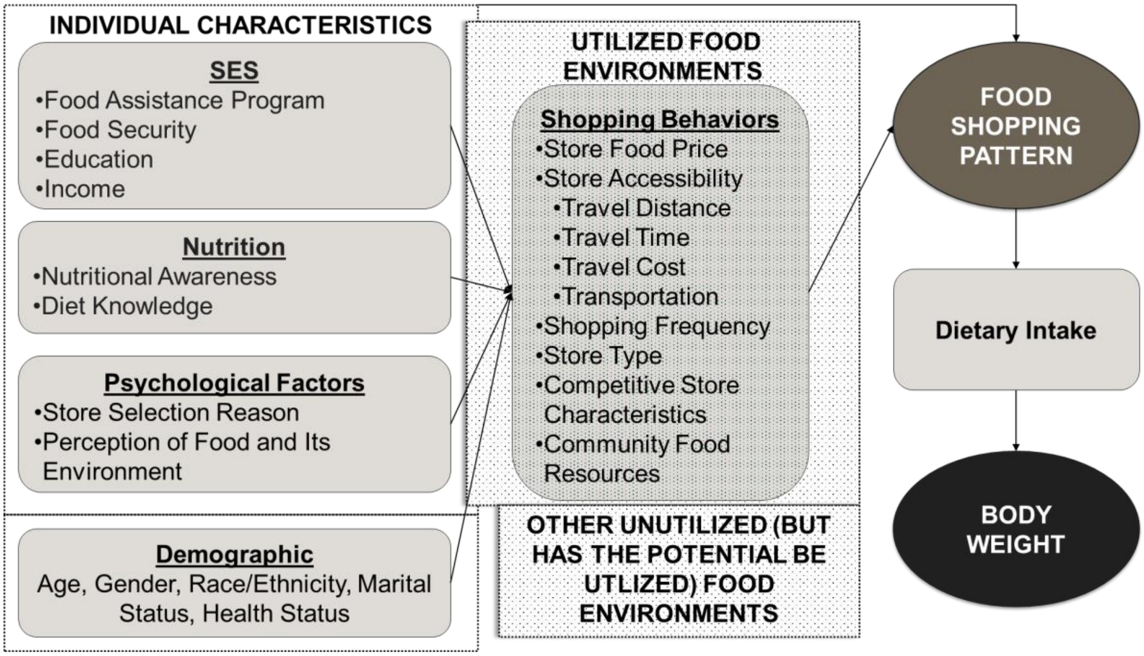

Figure 1.1 Conceptual Model of Association between Food Shopping and Body Weight

Chapter 2. Literature Review

Adults Obesity Disease Burden

Overweight and obesity rates increase rapidly. [35,36] In 2014, World Health Organization reported that more than 1.9 billion adults (39%) were overweight worldwide, of which over 600 million (13%) were obese. Moreover, most population in the world lives in countries that overweight and obesity could lead severe health outcomes for more people than underweight. [37]

In the United States, obesity is a public health crisis as well. During 2009 -2010, about 78 million or more than one-third people were obese (defined as body mass index [BMI] ≥30 kg/m^2). [38] In 2011-2012, studies found that non-Hispanic blacks had the highest age-adjusted obesity rates (47.8%) and other groups such as Hispanics (42.5%), non-Hispanic whites (32.6%), and non-Hispanic Asians (10.8%) followed after. [5] The obesity prevalence was found to be higher in women and among the middle-aged group (40-59 years old). [5] In the United States, the regions with the highest self-reported obesity prevalence are Midwest (30.7%) and South (30.6%) from the Behavioral Risk Factors Surveillance System (BRFSS) in 2014. [39]

Overview of Risk Factors for Obesity

Obesity occurs within a complex framework of interrelated factors. Neither medical nor educational and behavioral approaches have been sufficient to stem the rapid rise in population obesity, nor has significant progress been achieved in eliminating health disparities in obesity and chronic diseases. [7] In light of individually-focused strategies, which achieved modest and short-term successes, socio-ecological and systems models have received increasing attention. [8-13] The model in **Figure 2.1**, which is a simplified version of a causal framework of obesity, was adapted from Gordon-Larsen et al. [8] Different levels of factors were conceptualized to affect body weight, including policy environment, environmental behavior setting, individual socioeconomics, individual psychosocial factors, individual-level behavior, individual- level biological factors. Though researchers have not fully confirmed the potentially complex interrelationships among the depicted levels, the previous literature provides evidence for significant associations between the levels and obesity. Such systems or socio-ecological models conceptualize the behaviors that affect body weight as occurring within overlapping policy and environmental contexts. Changes in one or more levels may affect health-related behaviors and outcomes.

Individual-level Risk Factors for Obesity

The association between obesity and socioeconomic status has already been well documented. Studies have found that obesity rates were inversely associated with income and education among women. [35,36,40-44] However, the relationship among men was not consistent. [41,43] As the disparities appeared regarding with SES, the relationship of obesity with food assistance program participation has become an area of interest for policy makers. [45-50] For example, a study focused on low income populations found an association between Food Stamp Program participation (FSP, now named Supplemental Nutrition Assistance Program [SNAP]) and obesity using data from National Longitudinal Survey (NLS) of Youth 1979. [45] However, the association was different by gender among the participants. Compared with youths from the households that did not participate in the FSP, FSP participants have been associated with a 42.8% increase for girls and a 28.8% decrease in boys of overweight. [46] As food security status is closely related with individual's income, studies have also focused on food security status and its relationship with obesity. The food insecurity concept was initially adopted from Food and Agriculture Organization of the United Nation. It is defined by examining the access to food by low-income households. [51] In 1995, food insecurity was formally defined by USDA as "limited or uncertain availability of nutritionally acceptable or safe foods". [52,53] Food insecurity and obesity also appear to be associated, that is subjects from food-insecure households were more likely to be overweight or obese. [54-56]

Body weight and composition and the storage of energy ultimately are affected by changing the long-term energy balance between energy intake and expenditure. [57] Physical activity is one of the key interventions that affect the energy expenditure. Intervention studies have found that increasing physical activity prevents or helps on weight loss. [58-60] Disease Control and Prevention and the American College of Sports Medicine also make recommendations of physical activity to encourage participation and improve public health. [61,62] Diet has been found to be associated with energy intake, which has been identified as another key area of obesity intervention as well. [63,64] However, the long-term intervention effect with combination of diet and exercise was modest. [65] Besides the methodological issues such as inadequate study duration and drop-off, changing individual's behaviors and habits could be difficult to maintain long-term. Also, individual SES could affect the intervention effectiveness. It affects food purchases and diet quality. [44,66,67] Given the issues observed in intervention studies, researchers have indirectly focused on a more broad level of intervention, they examined the association between food environment and food retail access and obesity.

Food Environment and Food Retail Access and Obesity

Disparities in Food Retail Access

There is a large body of research examining healthy food access around the residential neighborhood. [12,14-18,20,21,27,68,69,69-75] Research has measured the presence of a grocery store such as supermarket [28,68,70,76-83] or density of healthy and unhealthy food sources in a given area [21,27,69,72-75] using Geographic Information System (GIS) approach. These measures cannot depict a real food shopping picture, but they are a measure of food access in the residential food environment.

Studies have found that residents in low-income or predominantly African American neighborhoods are less likely to have access to supermarkets compared to high-income or white predominant neighborhoods. [72,84-86] The disparities may due to the disparities in the distribution of supermarkets such that most of the supermarkets are operated in wealthier areas. [72,87,88] Also, a regional study in rural areas consisting of food deserts in South Carolina found that almost 75% of rural food retail outlets were convenience stores, where produce products are limited. [89] Another study of Detroit and the metropolitan Detroit area, which consisted of food desert tracts as well, found that only 8% food retail outlets were small, medium or large grocery stores compared with 92% fringe locations such as liquor and party stores. [90] Half the population in the city lived in the area where the travel distance to the closest grocery store was twice as far as the closest fringe food locations. [90] Residents in low-income, minority, or disadvantaged neighborhoods have been reported to be at greater distance from full-service supermarkets and from grocery stores with more healthful food choices. [19,70,81,87,91-96]

Food Retail Access and Dietary Intake

Many observational studies have shown that local food environments are associated with residents' diets. [21,72,76,80,97-103]. This association was studied in several natural experimental studies as well. [104] However, not all results have been consistent in this study area. [103,105-107] Several studies found that supermarket availability was significantly associated with fruit and vegetable intake. [72,76,98-101,104] However, Liese et al. [21] did not find any direct association between supermarket availability and fruit and vegetable intake using a path analysis among residents in eight counties in South Carolina. They found that presence of supermarkets in the residential neighborhood had significantly indirect effects via shopping distance in the path model. Additionally, they also found a significant direct association between shopping frequency at a primary utilized grocery store and fruit and vegetable intake. [21]

To evaluate whether low-income households have physical access to supermarkets, recent studies have focused on the physical distance to a supermarket, but the findings between distance and fruit and vegetable intake or overall diet quality are mixed. Studies found that closer distance to the nearest supermarket was linked with higher consumption of fruits and vegetables and higher overall diet quality. [18,80,103,108,109] In contrast, some studies found a null association. [110,111] Furthermore, studies have found that fruit and vegetable intakes or overall diet quality were associated with type of grocery store (such as better access to supermarket and limited access to convenience store) [27,28,85,103] and the cost of a healthy diet [34,79,112].

Food Retail Access and Obesity

Some studies have found an association between the presence of supermarkets or other indicators of healthy food access and obesity. [12,14-18,68-71,107] Especially, for the residents who are living in low-income neighborhoods, poorer healthy food access is associated with higher rates of obesity. [12,14-18,35,68-72,96,107,113] For example, a study found that residents living in urban Massachusetts with a supermarket within their zip code area were 11% less likely to be obese. [68] Another study analyzed 10,763 residents, and found that the availability of supermarkets within their residential tracts was related with 9% lower prevalence and 24% lower prevalence of overweight and obesity respectively; while, the availability of a convenience store was associated with a higher prevalence of obesity. [69] Powell et al. conducted a study among adolescents, and they found a relationship between limited access to chain supermarket and higher BMI. [70] The above association was also confirmed by a national study among 60775 women using a density measure of the store availability. [71] They found that lower supermarket density within a 0.5 mile buffer from residential location was related with higher BMI. [71]

However, not all studies have found an association between presence of a supermarket or other indicators of healthy food access and obesity. [20,107] For example, a study by Budzynska et al. reported that there was no difference in BMI between residents living in food deserts and those who were not living in a food desert area, after adjusting for demographics, disease status, shopping and eating behaviors, dietary intakes and diet knowledge. [107] Another two longitudinal studies focused specifically on fruit and vegetable access and its relationship with obesity. [74,114] However, their findings also did not support the relationship between limited physical access to fruit and vegetables and higher obesity rates.

Distance to Stores and Obesity

One commonly used measure is the network or straight line distance to the food retail outlet in the neighborhood, which can be derived from a gravity model. It measures the average distance from centroid of a neighborhood to all grocery stores within the neighborhood. [22,115,116] This measure can be used if there is no exact information on residential addresses of participants, or the utilized store information is missing. This measure of distance is actually a measure of accessibility to food resources in a certain food environment instead of a real travel distance from home to a utilized store. Another commonly used measure of shopping distance is the network distance between residential location and food shopping location (utilized or not utilized) by employing GIS technique. For example, some studies simply measured the network distance to the nearest food store, [21,103,114,117,118] some to the utilized store. [21,23-25,30,31,103,119-121] Given the obvious drawback of nearest distance in the neighborhood or to the nearest store, network distance to the utilized store is viewed as an improvement in measurement.

The findings on the association between distance to food retail outlets and obesity are mixed. Some studies found that distance to a grocery store (whether utilized or not) might be a risk factor of obesity. [15-18,69,70,72,76,77,79,87,108,122-126] However, studies also found a null association between distance and BMI, [31,119] even between distance to utilized primary store and BMI. [23,25,120,121]

When estimating the association between distance and obesity, transportation mode of food shopping may play an important role. The mixed finding of previous studies could be due to the failure to consider the role of transportation mode, because participants who were able to shop by car may not be limited by physical distance between home and grocery store. [23] Moreover, studies showed that grocery store type and shopping distance are reported to be varied by transportation mode. [28,116,127] However, the information on transportation mode is only available in the survey of food shopping behavior in utilized store. Due to limited literature focused on food shopping in utilized stores, the role of transportation between shopping distance and obesity is still not well-documented.

Store Type and Obesity

Food retailers are often classified as supermarkets, supercenters, large grocery stores, medium grocery stores, small grocery stores, specialty stores, and corner/convenience stores, according to the number of employees, the size of the retail outlets, and the food they served. In-store environment and a store's neighborhood environment are viewed as important factors that affect food shopping. Previous studies have found that shopping at a discount store has been associated with higher BMI after adjusting for confounders. [25,102] Moreover, shopping at a store located in a low-SES neighborhood is associated with higher BMI as well after adjusting for confounders. [24] The findings focusing on store type and in-store environment and their association with obesity are not consistent. Lear et al. and Hartley et al. have found that there is no association between in-store characteristics (i.e. summary score of quality, food availability, and food price; availability of fruit and vegetables) and BMI. [120,128]

Shopping Frequency and Obesity

Studies that have reported grocery shopping frequency at the primary store, suggest that people usually shop 1-3 times if measured in month in some studies, [28,31] and 1 -2 times if measured in week. [21,27,129] Given that the majority of previous studies that reported shopping frequency have constrained their survey to the primary grocery stores, these frequencies can be under-estimates. To date, only one USDA survey that focused on food acquisition and purchase behaviors has studied more than the primary store, but the survey does not query the shopping frequency in each of the stores. [127] Thus, the accurate frequency of shopping is still not available in the literature.

Few studies have examined the association between food shopping frequency and obesity rates. Jilcott Pitts et al. have reported a lack of an association between shopping frequency and BMI. [119] Although shopping frequency was not associated with obesity, another study has found a positive association between shopping frequency and sugar-sweetened beverage consumption. [27] Another study by Yoo et al. has found that African Americans shopped for groceries least frequently and Asian Americans shopped most frequently. [129] Shopping frequency is a factor that could be largely influenced by household size, nutritional needs in the family, employment status of household members, and type of household (single mother or married). [129,130] Moreover, Jilcott Pitts et al. found that shopping frequency and distance were inversely correlated. [119] Liese et al. have found that shopping frequency at primary store was directly associated fruit and vegetable intake through a path analysis. [21]

Food Prices and Obesity

Economic constraints and coping strategies such as bulk or coupon using, and food storing placed on households have been shown to influence food shopping in recent literature. [131] Market basket food price of a certain number of commonly consumed food items is the commonly used measurement of a store's food price in the food shopping literature. Some studies have found that high food basket prices of store are a barrier for residents living in low-income neighborhoods to access, especially to access healthy foods. [132-134] Compared with other types of food stores such as convenience stores, grocery stores and supermarkets were more likely to be offering a large variety of high-quality, healthy food with lower food prices. [108,135]

Recently, several studies have started considering both spatial and economic access. For example, a Canadian study took surveys on adults who shopped at several selected supermarkets. [120] They found that market basket food prices were inversely associated with self-reported BMI. [120] One study conducted in Seattle in the United States simultaneously measured the network distance to the supermarket and basket food prices of the supermarket where the participants primarily shopped, and studied their relationships with obesity. [23] They found that network distance to the primary supermarket was not significantly associated with obesity after adjusting for individual level socio-demographic information. [23] However, customers who shopped at a high-price supermarket had obesity rates of 9%, versus customers of low-price supermarket had higher obesity rates of 27%. [23] Moreover, Ghosh-Dastidar et al. also examined the above association in an urban food desert area in Pittsburgh, Pennsylvania in the United States. [124] They measured the network distance between residential location and primary shopping store. They also surveyed store price by using store audits approach. They found that both distance to store and food prices were associated with obesity when analyzed separately. However, when jointly modeling the two indicators, only store price was significantly and inversely associated with obesity. [124] This finding was also consistent with another study in Paris, France using Residential Environment and Coronary heart disease (RECORD) study. [25]

Studies of Low-Income Populations

A large body of research has focused on a particular low-income group, such as Food Stamp Program ([FSP], now called Supplemental Nutrition Assistance Program [SNAP]) recipients. [98,136-139] Generally, the main interest of those studies is to identify food shopping behaviors of the low-income population and to use the evidence to inform policy. Specifically, they have found that FSP recipients often use a supermarket as their main sources of grocery shopping; [138] FSP recipients shop further beyond the nearby store around their residential area, because they face the barrier of limited food sources in the neighborhood or the food prices sometimes are high in the nearby store; [137] and more than half of FSP recipients cannot drive themselves for food shopping due to a lack of vehicles. [138]

Food security is another widespread problem among low-income population. Studies have examined the association between household food security status and food access, and the findings are not consistent. [140,141] Kirkpatrick et al. found that food security status was not associated with proximity to food retail outlets in Canadian families. [140] However, another Canadian study by Sadler et al. found that food-insecure participants lived significantly closer to nutritious food sources and grocery stores than food-secure respondents. [141] Of note, both studies measured the accessibility of retail outlets in the neighborhood instead of actual network distance to a utilized store. [140,141] Thus, living closer to nutritious food sources does not guarantee shopping at the nutritious store. Due to the limited number of studies examining the food security and real shopping behaviors, the real shopping behaviors could be different by taking into consideration the economic constrains or other characteristics.

Several qualitative studies have described the factors that influence food shopping or store choices. Thompson and his colleagues conducted survey on 26 participants. [142] They investigated shopping behaviors of residents living in low-income neighborhoods and whether in-store food choices were influenced by supermarket environments. [142] They identified four strategies of conducting food shopping: 1) little planning activities but heavily rely on supermarket environment; 2) rely on familiarity and repetitive food purchases; 3) grocery list shopping or intended purchases; and 4) more planning on money allocation and health concern. Another qualitative study explored the reasons of store choice in-depth. [143] They identified those characteristics such as proximity to home or work, store food prices and personal financial status, variety/quality/availability of produce products and meat, and store characteristics were the main concerns when selecting the grocery store. Additionally, store knowledge and time availability for shopping were also found to impact food shopping. [144]

Food Shopping-Interaction of the Individual with Their Environment

As mentioned previously, availability of food retail outlets or accessibility to the retail outlets that offer healthy foods do not guarantee that people will really shop there. Studies have shown that residents often travel outside of their neighborhood for grocery shopping, which is especially true for residents of low-income neighborhoods. [23,25,29,30,103,145] This finding was also confirmed by a national survey on food acquisitions and purchases survey. [127] Thus, focusing on shopping behaviors in a utilized store and health outcomes is an important new area of study in this field.

A few previous studies have focused on food shopping in the utilized store in relation to obesity [23,25,102,120,121,124,128] and dietary intake [21,32]. Network distance between residential location and grocery store, basket food price of utilized store, and shopping frequency were often measured in those studies, and mixed findings were shown among those studies in relation to obesity. A recent study has been conducted by VanKim et al. on food shopping patterns among college students in relation to dietary intake. [32] They found that those who were conscientious regarding fresh food and who shopped primarily in supermarkets had better dietary intake, compared to those who are not conscientious about fresh food purchase. [32] They applied multi-dimensional information to identify food shopping patterns among the college students, which sheds light on characterizing food shopping.

Multi-dimensional Approaches to Study Food Shopping

Almost all of the previous studies have focused on a single aspect of food shopping (e.g. shopping distance, store type, shopping frequency etc.) and examined its association with obesity, nutrients intake, or diet patterns, except VanKim et al. [32] As the proceeding review has shown, many factors that are related with food shopping, and almost all of them are examined separately in relation to obesity. Many mixed findings have been reported in the previous studies, so it is likely that factors that influence food shopping and obesity are interrelated.

The limitation in characterizing food shopping with a single factor was overcome by VanKim's study (as mentioned before) which incorporated multiple components, including fruit and vegetable purchasing, frequency of shopping, type of grocery store, beverage purchasing etc. [32] They identified 8 different shopping profiles among college students using latent class analysis methods (see section 3.6.2 for detailed explanation). These included traditional shoppers who mainly shopped at supermarket (14.9%), fresh food and supermarket shoppers who shopped more fresh food and shopped mainly in a supermarket (14.1%), convenience shoppers (18.8%), conscientious convenience shoppers (13.8%), conscientious, fresh food, conveniences shoppers (11.8%), conscientious fresh food shoppers (6.6%), conscientious nonshoppers (10.2%), and nonshoppers (9.8%). The classifications were based on higher probabilities of one or two items response probabilities, for example, traditional shoppers showed a high probability of shopping at supermarket and bought a beverage on campus. Finally, VanKim et al. reported that "convenience shoppers", "conscientious convenience shoppers" and "non-shoppers" have worse dietary intake for soda, calcium, dairy, fiber, and fat than the "traditional shoppers". [32]

As discussed previously, food shopping could be determined with multiple domains and many components. Thus, the existing literature that only focuses on one or two aspects may not reflect the whole picture of the food shopping. The approach by Van Kim et al., a latent class analysis, will serve as the model for this dissertation's approach to characterizing multi-dimensions.

One of the multi-dimensional grouping approaches is well-known as a cluster analysis, and it is mainly applied in the area of economics (e.g. to analyze consumer's behaviors). Carlson et al. employed cluster analysis to group consumers using information on where consumers' got their food to describe their shopping and eating habits. [146] This analysis grouped percentage of food coming from different food sources and used variables in the same scale (percentage). One recent study by Stern et al. used amount of packed food shopped at different types of stores to identify mutually exclusive clusters. The clusters were trying to minimize the heterogeneity of the mean proportion of packed food purchased in a given cluster and maximize the heterogeneity between clusters. [147] Both of the applications employed several variables in the same scale in one domain (such as different type of retailer sources in Carlson's study, and different store types in Stern's study).

Factor analysis is another grouping method, which is different from cluster analysis in that it groups attributes or variables, not people. It uses information collected on multiple attributes, such as Likert-type preference questions or food groups, and then derives so called factor scores from these variables that are linear combinations of the underlying attributes, with the added benefit that the derived factors are entirely uncorrelated. The derived weights associated with each variable/component of the factor scores determines which variables are considered to be contributing most strongly to a given factor score, which in turn determines the interpretation of a given factor score. [148,149]

As introduced previously, VanKim et al. have used Latent Class Analysis (LCA) to identify food shopping profiles with information on different shopping behaviors (including fruit and vegetable purchases, frequency of shopping, type of purchasing location and food and beverage purchases) among college students. [32] All these applications provide possibilities to identify shopping pattern using a multi-dimensional approach. Detailed comparisons on different statistical approaches were provided in the methods section.

Besides the multi-dimensional approaches, the dimensions that have been studied to identify shopping patterns are different depending on the study of interest. The above mentioned studies are mainly focused on the shopping behaviors that including type of shopping location, type of food purchased, and frequency of shopping. [32,146,147] Studies on food shopping using a grouping strategy are often conducted in marketing research. [150-153] Only Stern's and VanKim's studies are placed in public health research and target on identifying shopping patterns and health disparities concerns. [32,147]

The food shopping patterns of interest in our study are mainly focused on the similarity within a group of people who have similar probability in one or more given characteristics from domains of shopping behaviors, and then examine whether characteristics from SES, perception factors, and nutrition knowledge are related with the food shopping patterns. Because the characteristics of food shopping behaviors are from different aspects such as shopping frequency, distance, and store type etc., the scales are very disparate. Also, we want to maximize the heterogeneity between different shopping patterns.

Food Shopping Research beyond the Scope of Our Research

There are many domains that influenced food shopping, but are beyond of the scope of the current study. Each domain is worthy of an in-depth investigation to understand the role that it plays in determining food shopping pattern. For example, household expenditures are one of the domains that are found to be associated with food shopping patterns. [154] Other domains like eating behaviors are associated with food choices, and then can be related with food shopping. [155,156] Additionally, shopping behaviors are likely to be distinctive depending on stage of life and life circumstance. Our study will only focus on identifying adults' household food shopping patterns at one time point of their life for general population in the United States and among low-income population living in two counties in South Carolina. We will not study the food shopping pattern in terms of changes over time, or among some youth group or a subset of particular population such as college students.

Research Gaps

The findings of the association between food shopping and obesity are mixed, and more studies have focused on food environment or food access versus utilization. One reason could be that the current measures focus on single aspects of food shopping (e.g. shopping distance, food prices etc.). This single dimensional approach does not represent the complexity of the food shopping behaviors in nature. Food shopping can be influenced by many factors, such as socio-economic factors (e.g. SNAP participation, food security, education, and income), nutrition factors (e.g. nutritional awareness, and diet knowledge), perception factors (e.g. store section reason, and perception of food and its environment), and shopping behaviors (e.g. travel distance and time, transportation, shopping frequency, store type, competitive store characteristics, community food resources, food desert, and urbanicity) and so on. Future studies should consider incorporating this complexity into the definition of shopping patterns. [132,157-159]

VanKim's study does shed light on using multi-dimension of shopping behaviors (including fruit and vegetable purchases, frequency of shopping, type of purchasing location and food and beverage purchases).[32] Their study does not, however, measure economic access such as food prices in utilized stores and reasons for store selection, which have been shown to influence food shopping. They focused on the college students, which limits the generalizability of the finding. The complexity in defining a food shopping pattern requires more sophisticated methods and the study by VanKim et al.[32] is an excellent example as it used a latent class approach. Such a multi-dimensional approach has not been applied, to the best of our knowledge, to a general population. Thus, there remain gaps in this research area, primarily in the need for a better measure of food acquisition and shopping patterns among other population and a general population.

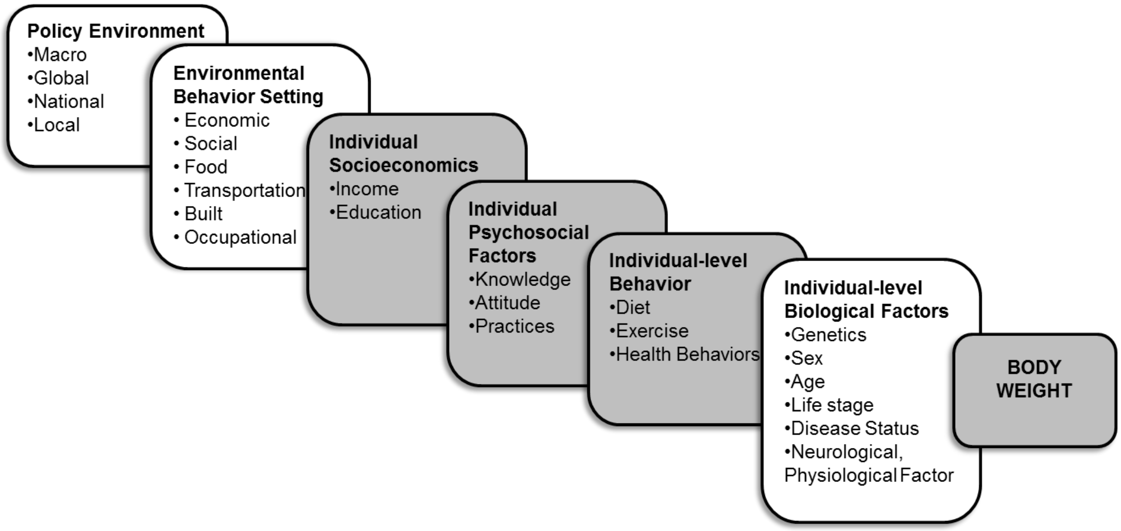

Figure 2.1 Obesity Systems, adopted from Gordon-Larsen 2011

Chapter 3. Methods

Specific Aims

The goal of the current research was to identify food acquisition and shopping patterns, and evaluate how the identified food acquisition and shopping patterns are related with obesity in a local low-income population, and then to identify food shopping patterns in a nationally representative population. Two readily available data sources were used, a local study of 522 South Carolina residents (Food Access and Family Food Shopper Study) participants, and the US Department of Agriculture (USDA)'s National Household Food Acquisition and Purchase Survey (FoodAPS), to address the following specific aims:

<u>Specific Aim 1</u>: To identify distinct food acquisition and shopping patterns among residents living in low-income and low-access communities in SC using latent class analyses; and to examine whether SNAP participation, food security, education, income, nutrition knowledge, and perception of healthy food access factors were associated with the identified patterns;

<u>Specific Aim 2</u>: To identify distinct food acquisition and shopping patterns among US population; and to examine whether SNAP participation, food security, education, income, employment, nutrition awareness and knowledge, and store selection reasons were associated with the identified patterns.

Specific Aim 3: To examine the association between the identified food acquisition and shopping patterns and BMI in the same national US population.

Hypotheses

Hypothesis 1

Given that LCA is an empirical exploratory method, it is not possible to predict the total number and type of classes that the procedure will identify in a given dataset. However, it is possible to hypothesize which shopping behaviors would probably play important roles. First, store-type conscious shoppers are hypothesized, as the previous cluster analysis by Stern et al. found some patterns regarding store type clusters in the US [147]. Second, the impact of travel distance on health outcomes is not clear. Yet previous studies have shown the disparities in food retail access between low- and high- income population, thus, it is reasonable to assume that the shopping behavior in some sub-groups might be driven by distance from home to food retails. Third, shopping frequency could also be used to differentiate shopper types such as frequent shoppers. Moreover, food shopping features can also be combined with shopping frequency, store type, frequent shoppers at a range of store types. Thus, besides the three types, the combinations of these key features of food shopping are also expected.

As for components in other domains such as SES, nutrition, and perceptions, we hypothesized that either SNAP participation or food security in SES domain would be a significant and predominant predictor of latent class membership, because of their close relationship with SES, a key determinant of food shopping. Nutrition knowledge might be a weak predictor in food shopping pattern, as it is more relevant to which type of food purchased in store, instead of deciding a food shopping trip. Store selection reasons were assumed to be associated with latent class membership, because these factors determined the location and type of store being chosen, as well as the shopping frequency.

Hypothesis 2

The identified food acquisition and shopping patterns would be associated with obesity.

Data Sources

South Carolina-Specific: Food Access and Family Food Shopper Study Data

The Food Access and Family Food Shopper Study were funded by the National Institutes of Health (NIH). Five hundred and twenty-two participants were recruited and interviewed from November 2013 to May 2014 in two South Carolina counties in the context of a quasi-experimental evaluation of an intervention to increase access to healthy food, in which individuals (or clusters of individuals) exposed to the experimental and control conditions are determined by nature or by other factors outside the control of the investigators. Sampling frame focused on seven census tracts (six of which were United States Department of Agriculture (USDA)-designated food deserts) [160] with a combined population of 19,117 individuals and 6,459 households. [161] After obtaining written informed consent, interviewers conducted in-person interviews to obtain baseline measures of sociodemographic, attitudinal, behavioral and health-related information. Interviews took place at the research field offices or local community centers, and within two weeks after the in-person interview, a single telephone-based 24-hour dietary recall interview was also conducted. At the end of the in-person interview, interviewers gave each participant a list of community resources, including contact information for emergency sources of food and food assistance benefits. Participants received a $15 gift card for the in-person interview and another $15 gift card for the dietary recall interview.

After quality control checks of the interview forms, a staff person scanned the data using Teleform software. This study was approved by the Institutional Review Board of the University of South Carolina.

The targeted enrollment was 560 individuals, which was determined on the pre-specified hypotheses, statistical power analysis, and assumptions about retention rates over time. Letters were mailed to the "family primary food shopper" within the recruitment area using a purchased address lists from a survey sampling firm. After the initial letter, multiple recruitment strategies including in-person, printed and electronic were followed. Finally, 527 participants prior to the food hub's opening were finally included in the in-person interview. The average age of participants in the South Carolina-specific study was 52 years. Approximately 93% were black; 80% were females; and about 65% of the participants received SNAP. All the data collection had completed and baseline data were used for current study.

National data: Food Acquisition and Purchase Survey (FoodAPS)

The FoodAPS was a national survey conducted by USDA and included 4,826 households (with 14,317 members) surveyed between April 2012 and January 2013. [127,162] FoodAPS is a nationally representative sample with multiple stage sampling strategies. A stratified sample of 50 primary sampling unites (PSUs, defined as counties or groups of contiguous counties) were selected from 948 PSUs, including 34 metro PSUs, 10 non-metro PSUs, and 6 mixed PSU [163]. The study population contains both SNAP and non-SNAP recipients. The overall study response rate was 45.6 percent. [162]

Primary Respondent (PR), also the primary shopper or the meal planner for the household, was asked to participate into five interviews (two in-person interviews at the start (day 0) and the end (day 8) of the survey week and three telephone interviews to report the household's food acquisitions for day 2, 5, and 7) regarding food acquisition events during the data collection period. Additionally, household members aged 11 years or older were asked to record and report all their food acquisition during the data collection period. For members less than 11 years old, the PR was asked to record food acquisitions for them. Barcodes on foods were required to scan when food items were bought outside. PR was also asked to keep and save the receipts of grocery purchases and restaurants eating. This way of data collection is advantageous in providing in-depth food acquisition information, including accurate and precise information on food items purchased, thereby minimizing ambiguity and recall errors.

The average age of the FoodAPS sample was 32 years. Approximately 52% were non-Hispanic white, 16% non-Hispanic black, 26% Hispanic, and 7% non-Hispanic others. Also 74% of the sample were females. About 33% of FoodAPS participants receive SNAP. The FoodAPS data collection was completed and the data were publicly accessible after removing personal identifiers and geographic information. (e.g. geographic locations and home addresses' tracts information).

Geocoding Addresses

<u>South Carolina-Specific: Food Access and Family Food Shopper Study Data</u>

Residential addresses of participants were verified during the in-person interview to confirm that geographic eligibility (i.e. residence in geographically-defined study area) criterion was met. Addresses were then entered and geocoded using ArcGIS 10.2.

Participant-reported names and addresses of utilized food stores were incorporated into GIS analyses, using the utilized stores' GPS locations (which had been obtained in a separate on-the-ground verification effort of the study area) if contained within the study area or a geocoded location if the utilized store was situated outside the study area.

Addresses for stores and participant homes were geocoded according to Topologically Integrated Geographic Encoding and Referencing (TIGER) road files for 2013. We calculated the shortest street network distance from each participant's home address to each food outlet utilized.

National: Food Acquisition and Purchase Survey (FoodAPS) Data

The geocoding process in FoodAPS was completed by FoodAPS staff and the data were public accessible by providing the final computed measures and removing the original geographic location information. The detailed geocoding process were described below. The FoodAPS Study employed an Address-Based Sampling (ABS) method. The commercial list from the United States Postal Service Delivery Sequence File was used for sampling. Addresses were matched with a SNAP recipients' address to make sure the sample consisting both SNAP and non-SNAP household. As the sampling of FoodAPS started identifying residential addresses in each defined sampling units, the residential address of each household was available at the beginning of interview, but removed for public release version because of confidentiality concern.

PR was asked to report the store where they did most food shopping, as well as less most frequent food shopping store. Most large food stores information such as name and addresses were saved in the computer. If a store was not saved in the system, the PR was asked to report the store's information including store name, address, and type, which can be used to identify the store later.

Both residential and store addresses were geo-coded in google map. If an address cannot be geocoded in google map, ArcGIS was used to geocode. Coordinates could be obtained in ArcGIS and imported to google map to calculate travel distance or travel time. Specifically, the straight-line distances were obtained using SAS software, and driving and walking distances and time were calculated in Google map. We used driving distance in current study to reflect the travel distance. The geographic variables were already calculated by FoodAPS group and were available in public use dataset.

Study Design

Study Area

For **Specific Aim 1**, the study area focused in two counties in South Carolina, which were Florence and Spartanburg. Figure 3.1 presented the study area, which marked with number 1 and 2 are the study areas. For **Specific Aim 2 and 3**, the study area covered the whole area of the United States, because the FoodAPS survey was conducted nationwide.

Study Design

Food Access and Family Food Shopper Study is designed as a longitudinal survey to examine the effectiveness of increasing healthy food access by operating a Food Hub in the intervention site. However, for the **Specific Aim 1** of this dissertation, we only aimed to identify shopping patterns among this low-income population at the baseline sample, so a cross-sectional analysis was applied. Because the nature of FoodAPS survey is cross-sectional, the designs and analyses (**Specific Aim 2 and 3**) based on this survey were cross-sectional.

Description of Variables

Detailed information on key variables from the two data sources that were used in this proposed study were provided in **Appendix A**. Also details about data cleaning processes on these variables were also described in the same appendix.

BMI was calculated by using self-reported weight (kg)/height (m^2). Obesity was defined as BMI greater and equal to 30kg/m^2 according to World Health Organization (WHO) standard.[164]

Socio-demographic variables were measured very similar in the two datasets, including, age, gender, race/ethnicity, education, income, marital status, health status. Those variables were also the confounding variables that determined from previous studies.

Descriptive Analyses

Demographic and socioeconomic characteristics of PRs in SC studies and FoodAPS were tabulated. Descriptive statistics were presented for both samples.

Latent Class Models

To explore food shopping patterns in **Specific Aim1 and 2**, Latent Class Analysis (LCA) was used, in which subjects were assumed to belong to one of a set of T latent classes, with the number and size of classes unknown. LCA examines the pattern among a set of observed categorical variables, and groups individuals with similar characteristics into latent classes. [165] The LCA model contains two types of categorical variables (that is, observed or manifest and unobserved or latent variables) and two types of parameters, which are latent class and conditional probabilities. The LCA assumes that the relationship between any two observed variables is accounted by the unobserved (latent) variable; this is commonly known as *axiom local independence*. Thus, for a basic LCA model including one latent variable (X) and N manifest variables, the LCA model can be formally expressed as the product of the latent class probabilities and conditional probabilities:

$$\pi_{ijk\ldots m\,t}^{123\ldots\,NX} = \pi_t^X \pi_{it}^{1|X} \pi_{jt}^{2|X} \pi_{kt}^{3|X} \ldots \pi_{mt}^{N|X}$$

Where the latent class probability (π_t^X) is the probability that a randomly selected observation in the sample is located in latent class t, and the conditional probabilities (e.g.$\pi_{it}^{1|X}$) are the probabilities that a member of latent class *t* is at specified level of an observed indicator variable.

Within the LCA, hypotheses are tested by imposing restrictions and determining how these restrictions affect the fit of the model to the data. For the basic LCA with a single latent variable (X_t) and N observed indicator variables ($1_i, 2_j, \ldots, N_m$), we can express the restrictions as $\sum_t \pi_t^X = \sum_i \pi_{it}^{1|X} = \sum_j \pi_{jt}^{2|X} = \cdots = \sum_m \pi_{mt}^{N|X} = 1.0$.

The above restriction requires that the probabilities of all latent classes sum to 1.0, which means there is a latent class for each of the possible response patterns observed in the data. Each of the indicator variables sums to one within each of the T classes.

In current study, the above LCA model was fitted to identify homogenous, mutually exclusive groups of individuals based on information in food acquisition and shopping habits. First of all, the measures of food acquisition and shopping habits in **Appendix A** (first sets of variables) for each dataset were included in the model, and correlations of variables were checked. High correlations between variables and low endorsement (low possibility to predict the pattern) of a variable were dropped from the LCA model. Then, all key variables were used to fit the LCA model. Standard criteria were applied (e.g. Akaike Information Criteria [AIC], Bayesian Information Criteria [BIC], Bootstrap Likelihood Ratio Test [BLRT], separation and entropy, class size and interpretability) to select the best-fitting model. Probabilistic parameterization and maximum likelihood estimation were used in this model fitting. Item response probabilities and probability of latent class membership were presented to show the final latent classes. Item response probabilities can be interpreted as, for example, the probability of answering "yes" to the given item, given that you belong to a particular class. Probability of latent class membership provided the probability that the person belongs to each class, and the highest probability was selected to assign a subject to a certain class. Number of classes can be determined via comparing the AIC or BIC model fit statistics.

In our study, we have a large set of variables that we hypothesized to be associated with food shopping patterns. Because of the computation loading and the interpretation issues, it was very difficult to put all variables in the conceptual framework into one latent class model and identify the latent class. One option is that we put several variables (e.g. variables in shopping behaviors domain) into LCA model simultaneously, and treat all other variables in other domains (e.g. SES, nutrition knowledge, perception of food environment, and store selection reasons) as covariates. However, these covariates may slightly change the definitions of clusters. Also, it is difficult to perform an exploratory analysis with a large set of covariates in LCA model. [166]

An alternative is three-step modeling approach, which was employed in our analysis but with an innovation improvement by correcting some errors in the third step. [166] We first identified latent classes with information in food acquisition and shopping measures (**Figure 1.1**), then assigned individuals to latent class using their posterior class membership probabilities, and subsequently investigated the association between the assigned class membership and other variables in other domains (e.g. SES, nutrition knowledge, perception of food environment, and store selection reasons). The detailed analysis process was followed as shown in **Figure 3.2**. The LCA models and step-3 analyses were fitted in LatentGOLD version 5.1. Two-tail $p<0.05$ was set as the significance level.

Strengths, Limitations and Alternate Approaches

LCA and Other Clustering Analyses

LCA is closely analogous to cluster analysis and it is often used to discover groups or types of cases based on observed data, and possibly to also assign cases to groups. As noted, LCA can be applied to categorical covariates, a reason why all shopping-related variables in **Appendix A** were categorized. Another similar approach called Latent Profile Analysis (LPA) employs a similar theory but is often applied to continuous variables. In the proposed study, many variables of interest in identifying food shopping patterns are categorical. Also we are interested the item response probability, so we choose LCA. LCA is theoretically a Finite Mixture Model (FMM). The FMM provides a natural representation of heterogeneity in a finite number of latent classes. It concerns modeling a statistical distribution by a mixture, or weighted sum of other distributions. The main difference between FMM and other clustering algorithms is that FMM uses a "model-based clustering" approach, which derives clusters using a probabilistic model based on data distribution. Thus, instead of finding clusters with some arbitrarily chosen distance measure between clusters, as used in traditional cluster analysis (which maximizes distance between clusters and minimizes distance between each case's attributes and the cluster's mean), LCA uses a model that describes the distribution of the data itself with multiple variables, and based on this model we can assess probabilities that certain cases are members of certain latent classes. [165] In other words, LCA is a top-down approach, which starts with describing the distribution of the data; while other clustering algorithms are rather bottom-up approaches that start with finding similarities between individuals.

Another difference is that LCA is more flexible than clustering. Clustering algorithms just do clustering, while the LCA model allows one to conduct confirmatory, between-group analysis, combine Item Response Theory (and other) models with LCA, and include covariates to predict individuals' latent class membership.

<u>LCA and Factor Analysis</u>

LCA is often called a categorical-data analogue to factor analysis. In factor analysis, the underlying unobserved variables are continuous, but LCA is categorical. Thus, LCA is a person-centered method, concerned with identifying the underlying category a person belongs to, in contrast to factor analysis, which is variable-centered in which the main interest is to find an underlying variable (or set of variables) that could explain the variability of all the observed variables. [167]

Still, some methodological similarities between LCA and factor analysis are worth noting. First, both are useful for data reduction. Second, latent classes, like factors, are unobserved constructs, inferred from observed data, and hence need to be given descriptive names by the investigator. Third, determining the number of latent classes is analogous in certain respects to that of determining the number of factors: as the number of clusters/factors increases, fit of the latent class/factor model to the observed data becomes better, but one seeks a balance between fit to the data and number of latent classes/factors required.

To sum up, we are interested in identifying patterns from a set of variables of shopping behaviors domain and describing key attributes of food acquisition and shopping from both South Carolina Food Access and Family Food Shoppers Study and FoodAPS. Instead of grouping participants themselves we care more about how the underlying latent variables can be predicted with the observed food acquisition and shopping measures and whether the underlying patterns are associated with predictors from other domains, and how many distinct patterns we can identify. Item response probability is very helpful to construct those patterns. Thus, we prefer the LCA approach to identify the food shopping pattern.

Multiple Linear Regression Models

To examine the association between identified shopping patterns and BMI in **Specific Aim 3**, a series Multivariate Linear Regression Models (MLRM) were fitted adjusting for age, gender, race/ethnicity, marital status, education, income, SNAP participation status, food security status, and healthy status.

The expression of the model was as follows:

$$Y = \beta_0 + \beta_1 X_1 + \cdots + \beta_P X_P + \epsilon$$

Where *Y* is the outcome, which is continuous BMI, we assumed that BMI follows the normal distribution. X_1 represents the food acquisition and shopping patterns that were identified from **Specific Aim 2** with multiple categories representing multiple patterns from latent class analysis, and X_{2-p} represent other covariates; β_0 is the intercept, β_1 was the coefficient of shopping patterns, and β_{2-p} were the coefficients for other covariates.

Multinomial Logistic Regression Model

BMI will be classified as a categorical variable with three categories. They are underweight or normal (if BMI<25.00 kg/m^2), overweight (if 25.00 kg/m^2≤BMI<30.00 kg/m^2), and obese (if BMI ≥30.00 kg/m^2). Because of these multiple categories of the outcome, multinomial Logistic Regression Model will be employed to examine the association between identified shopping patterns and obesity adjusting for age, gender, race/ethnicity, marital status, education, income, and health status. It is an extension of logistic regression, which analyzes dichotomous (binary) dependents.

For an outcome with 3 categories in our analysis, this requires the calculation of 3 equations, one for each category relative to the reference category, to describe the relationship between the outcome and the exposures.

Hence, if the underweight or normal BMI category is the reference, then, for m = 2 and 3:

Overweight Y=2 compare to underweight or normal weight (Y=1):

$$logit(Y = 2) = \log(\frac{p(Y = 2)}{1 - p(Y = 2)}) = \beta_0 + \beta_1 X_1 + \cdots + \beta_P X_P$$

Where X_1 would be the variable that identified from the above latent class analysis (Aim 1), while X_{2-p} are the socio-demographic variables that we want to adjust to control for the confounding.

Overweight Y=3 compare to underweight or normal weight (Y=1):

$$logit(Y = 3) = \log(\frac{p(Y = 3)}{1 - p(Y = 3)}) = \beta_0 + \beta_1 X_1 + \cdots + \beta_P X_P$$

The interpretation of the multinomial logistic regression model is the same as logistic regression model. The odds ratio of interest is to e^{β_1}.

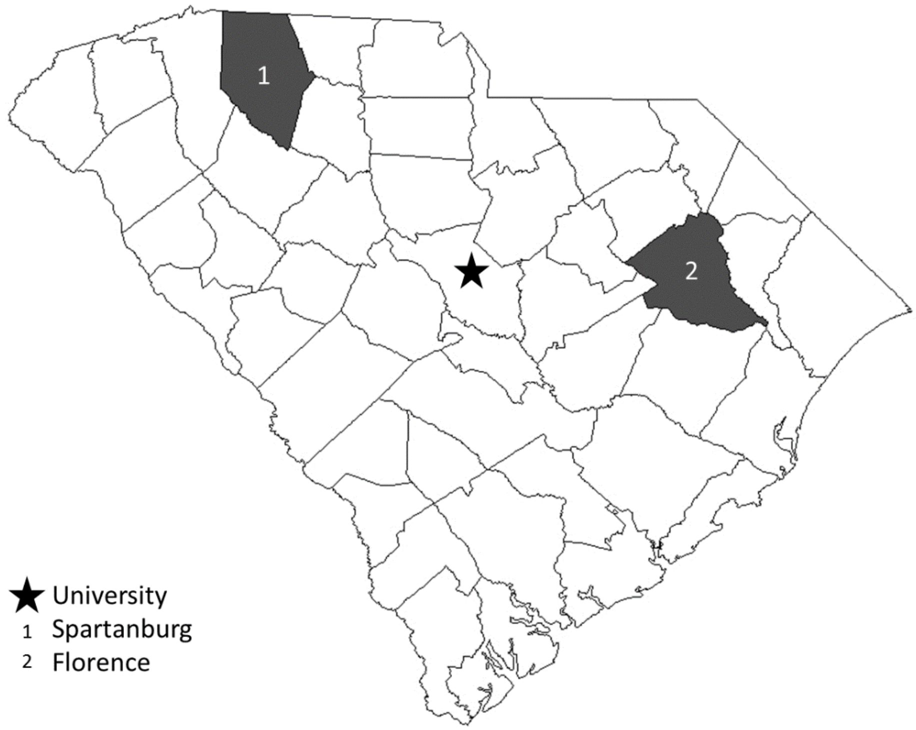

Figure 3.1 Study Areas for Specific Aim 3

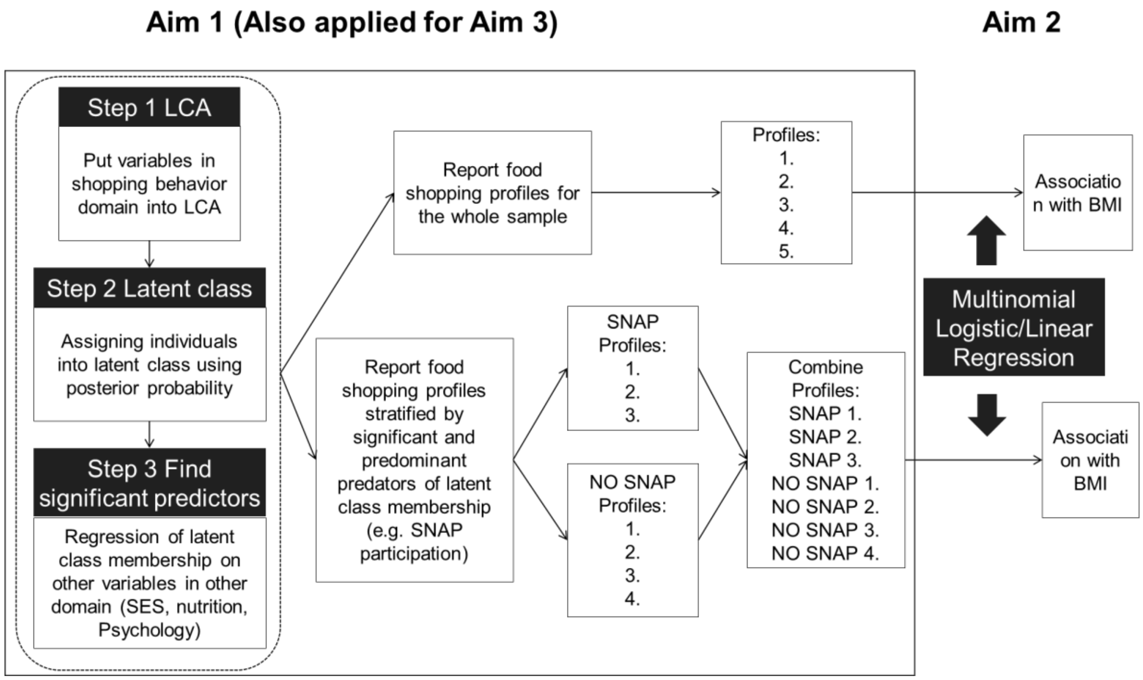

Figure 3.2 Analysis Process for Each Specific Aim

Chapter 4. Food Acquisition and Shopping Patterns among Residents of Low-income and Low-access Communities in South Carolina[1]

[1] Ma, X., Sharpe, P.A., Bell, B.A., Liu, J., White, K., and Liese, A.D. Submitted to *The Journal of Academy and Nutrition Dietetics, 11/8/2017*.

Abstract

Background: Food deserts, as defined by the US Department of Agriculture, are low-income areas in which residents have poor access to healthy foods. Residing in a food desert limits a resident's spatial access to supermarkets and grocery stores. However, not much is known about the actual food acquisition and shopping habits of residents living in food deserts. The purpose of this study was to identify distinct food acquisition and shopping patterns or profiles among residents of two South Carolina counties, 81% of whom lived in food desert census tracts, and characterize these patterns with respect to the residents' socioeconomic status (SES), nutritional knowledge, and perceptions of their food environment.

Methods: 527 participants were recruited between November 2013 and May 2014 from two SC counties. Participants were interviewed about their food acquisition and shopping habits at their three most frequently used stores. Thirteen measures of food acquisition and shopping habits (i.e., travel distances between residential location and each of the used stores, shopping frequency, store type, transportation mode (most frequented store only), and utilization of community food resources such as food banks or pantries and church or social services) were used in the food acquisition and shopping patterns analysis. Latent class analysis was employed to explore the acquisition and shopping patterns. In addition, associations between acquisition and shopping patterns and various factors such as SNAP participation, food security, education, income, nutrition knowledge, and perceptions of the food environment were examined using multiple logistic regression models.

Results: Three classes were identified, including those who use community food resources, are infrequent grocery shoppers, and use someone else's car or public transportation when shopping [Class 1] (35%), those who use community food resources, are more frequent and proximal shoppers [Class 2] (41%), and those who do not use community food resources and are distal shoppers [Class 3] (24%). Store type used and whether an individual shopped at a farmers' market did not differ between the classes. Compared to Class 3, individuals in Class 1 had comparatively lower SES, including higher proportions of SNAP participation, being food insecure, having lower levels of education and annual household income; individuals in Class 2 also had comparatively lower SES attributes except for income. Individuals in Class 2 were not significantly different from those in Class 1 except that a higher proportion in Class 1 saw food access as a problem.

Conclusions: Food shopping frequency, utilization of free community food resources, transportation, and food shopping distance were the key factors that defined distinct food acquisition and shopping patterns among the residents living in food deserts. Future interventions to increase healthy food access in underserved areas should consider community food resource utilization. More investigations are needed to examine the association between these acquisition and shopping patterns and dietary intake and health outcomes.

Introduction

Eliminating nutrition-related health disparities is an ongoing challenge. In addition to economic challenges, low-income populations may additionally be disadvantaged by living further away from a grocery store selling healthful foods. [21,76,85,98,116,138,168] Therefore, the US government has made efforts to increase healthy food access among low-income and low-access populations through a number of policy initiatives. [169,170]

Incentivizing the opening of a large grocery store or supermarket is one approach to improving healthy food access in disadvantaged areas, because supermarkets are the major grocery resources for US households. [12,14-18,127] It is assumed that the presence of or proximity to a full-service supermarket in a disadvantaged area will increase the opportunity for residents to purchase healthy food and thereby reduce obesity or other chronic diseases. However, natural experiments suggest that establishing a new full-service supermarket in a low-income and low-access area does not necessarily increase utilization of such a store or influence dietary intake. [105,171-175] Studies have also shown that residents often travel outside of their neighborhood for grocery shopping. [23,25,29,30,103,132-134,137,145] A better understanding of food acquisition and shopping habits in low-income populations residing in food deserts would allow federal policies and local interventions to be more tailored to this population's specific needs.

Public health–oriented research on food shopping behaviors is a relatively new area of inquiry. A major gap in food access studies is lack of data on where people actually shop for food. Food shopping is an interaction of the individual with his/her food environment and thus has a multidimensional nature. [34] Furthermore, US households may not rely only on supermarkets for their grocery shopping, especially low-income households. A recent nationally representative study [147] using Nielsen's National Consumer Panel data found that food shopping involves a mixture of multiple store types, including grocery chain stores, non-chain grocery stores, ethnic and specialty stores, mass merchandisers, convenience stores, warehouse club stores, and others. Although US households primarily shop at grocery chain stores (50%) or mass merchandisers (23%), 27% of households split their food purchases among the different store types listed above.

The availability of farmers' markets and other types of local food systems (such as food bank or pantry, food from church or social services) have been increasing in recent years. [176] In line with these growing local food systems, research has focused on strategies to increase food access through local food systems. [177] Larsen and colleagues found that a new farmers' market opened in a low-income area increases healthy food access. [19] High satisfaction and positive changes in eating behaviors and physical activity have also been reported as a result of introduction of a farmers' market. [178] Thus, an understanding of how food is acquired from the local food system is needed, which will further inform policy to determine intervention strategies in improving healthy food acquisition among low-income populations.

Although some previous studies have described the real food shopping behaviors in terms of individual attributes, e.g., the actual travel distance to the primary shopping store, shopping frequency, and store type used, [21,23-25,30,31,103,119-121] very few studies incorporated multiple dimensions of shopping behaviors together. [32,147] The study by Stern employed cluster analysis and found three classes, including primarily grocery shoppers, primarily mass-merchandiser shoppers, and shoppers who use a mixture of different store types.[147] VanKim and colleagues employed information on fruit and vegetable purchases, frequency of shopping, type of purchasing location, and food and beverage purchases to identify food shopping patterns using a latent class analysis and defined eight shopping patterns among a sample of college students.[32] These new applications of pattern techniques in epidemiological studies are promising tools to describe the complex nature of food shopping behaviors.

The purpose of the current study is two-fold. First, to identify distinct food acquisition and shopping patterns among residents living in low-income and low-access communities in SC using food shopping behavior information and latent class methods. Second, to examine whether SNAP participation, food security, education, income, nutrition knowledge, and perception of healthy food access factors were associated with the identified patterns.

Methods

This cross-sectional analysis is secondary analysis using baseline data from a quasi-experimental study. The study has been described previously.[179-181] In brief, the study evaluated the impact of a food hub to increase healthy food access with a longitudinal, quasi-experimental design among a low-income population. Baseline data were collected between November 2013 and May 2014 in two South Carolina counties. Recruitment focused on seven census tracts (six of which were US Department of Agriculture [USDA]-designated urban food deserts, defined as a low-income population with low access to a supermarket or supercenter).[160] Low-income tract was defined by a poverty rate of at least 20%. Low-access tract was defined as ≥33% of the tract population residing > 1 mile from a supermarket in an urban tract.[110,182] However, food desert status was not a requirement, and inclusion boundaries were extended to one mile beyond the contiguous core tracts' boundaries into adjacent tracts if those tracts had a poverty level at least as high as the state of SC (16%). Using purchased address lists from a survey sampling firm, letters addressed to the "family food shopper" were mailed to all residential addresses in the recruitment area inviting them to call for information about a study of food access and food shopping. Multiple recruitment strategies (in-person, printed, and electronic) followed this initial letter and resulted in 527 participants. Interested participants were screened for eligibility by phone or in person with the criteria of 1) doing at least half of food shopping in the household; 2) age 18 and older; 3) speaking and understanding English; 4) not planning a move outside the area within next year; 5) address being within geographic study area and having lived there at least 3 weeks out of a typical month; 6) not living in institutional setting (i.e. controls food choices); 7) no cognitive impairment that would prevent understanding and responding to the interview. Eligible and interested persons completed an in-person interview. The interview included sociodemographic, attitudinal, behavioral, food shopping, and health-related questions. The study was reviewed and approved by the Institutional Review Board of the University of South Carolina.

Food Acquisition and Shopping Habits Measures

Store-specific food shopping behaviors were queried for each participant's three most-frequented stores (i.e., "what is the name of the store or market where you shopped the most often [store 1], the second most often [store 2], and the third most often [store 3] for food?"). Participants were queried about the type of stores 1 to 3 (convenience store, drugstore/pharmacy, dollar variety store, farmers' market, food bank or food pantry, supermarket, supercenter, smaller grocery store, specialty store, warehouse club, or other type of food store, such as a military commissary). Shopping frequency at each was queried (i.e. “over the past year, how often did you usually shop at [name of store answered before])?” Respondent could answer in their preferred units of times per day, week, month, or year. All responses were converted to times per week. Transportation mode used (i.e., drive your own car, van, truck, or motorcycle; ride in the car, van, truck, or motorcycle of family or friends; ride the bus; take a taxi; walk; or ride a bicycle) to store 1 only was queried too. Participants also reported whether they shopped at a farmers’ market or whether they acquired food from a food bank or pantry or from a church, which were the key elements of food acquisition in this study.

To fit the latent class model, continuous variables were dichotomized. Shopping distances to stores 1-3 were dichotomized using the store-specific mean (2.7 for store 1, 2.8 for store 2, and 4.0 for store3). Prior to this step, the extreme values of shopping distances to stores 1–3 were Winsorized (transformation of statistics by limiting extreme values in the statistical data to reduce the effect of possibly spurious outliers) [183] at a reasonable value (99th percentile for store 1 and 3, no extreme value for store 2). Shopping frequency was dichotomized using store-specific cutoff points according the distribution, including once per week for store 1, twice per month for store 2, and once per month for store 3. Store type was classified into supermarkets (including supercenters and warehouse clubs) and other (including smaller grocery stores, convenience stores, dollar variety stores, drug/pharmacy stores, and specialty stores). Transportation mode was regrouped into two categories: own vehicle (driving their own car/van/truck/motorcycle), using someone else’s car or others (riding in a car/van/truck/motorcycle of family or a friend, taking a bus, riding in a taxi, walk, or riding a bicycle).

Stores' and participants' home addresses were geocoded per Topologically Integrated Geographic Encoding and Referencing (TIGER) road files for 2013 using ArcGIS 10.2. [184] Network distances from participants' homes to stores 1 to 3 were calculated using ArcGIS 10.2. [184]

Socioeconomic Characteristics, Nutrition Knowledge, and Perceptions of Food Access

Socioeconomic characteristics included SNAP participation, food security, education, and income. Food security was assessed via the validated 18-item USDA US-Household Food Security Survey Module. [185] Participants were classified as having high food security (0 affirmative responses), marginal food security (1 to 2 affirmative responses), low food security (3 to 7 affirmative responses), or very low food security ($\geq$8 affirmative responses). [186] Education level was reported in seven levels and was regrouped into three categories including below high school, high school (which included GED and high school diploma), and above high school. Annual household income including government assistance was reported by participants in a 10,000-increment. It was dichotomized using $20,000 as a cutoff as only 21% of participants exceeded that level. Household size information was collected during the in-person interview. The nutrition knowledge was assessed by the question "How many servings of fruits and vegetables should a person eat each day for good health?" Participants who responded "Five servings or more per day" were recoded as having nutritional knowledge and all other responses were recoded as not having nutritional knowledge. Perception of food access was examined with the question “How much of a problem would you say that lack of access to adequate food shopping is in your neighborhood?” The responses ranged from 1 (very serious problem) to 4 (not really a problem). It was reclassified into two categories. One category indicated that accessing to adequate food shopping was somewhat a problem (category 1-3), and the other category indicated not a problem (category 4).

Statistical Analyses

Of the 527 participants, 61 were excluded because of missing data on food shopping and acquisition, sociodemographic, nutrition, or perception information; the final analysis included 466 participants. Descriptive analyses of the sample characteristics were performed using SAS version 9.4. [187] Subsequently, latent class analysis was used to identify mutually exclusive, homogenous groups based on the 13 measures of food acquisition and shopping habits selected including distance to store 1-3, frequency and type of store 1-3, transportation for store 1, and using of farmers’ market, food bank or pantry, church or social service originations. Standard criteria such as Bayesian Information Criteria (BIC), entropy, classification errors, the bootstrap likelihood ratio test, and class size were used to select the best-fitting model. Practical meanings of the identified patterns were also used as criteria for model selection. We started with fitting a 2-class model, and stopped when the class size was less than 10%. The probability of latent class membership was obtained via the maximum likelihood approach. Step-3 approach was used to examine the association between the identified pattern and other factors, because it is a bias-adjusted and intuitive approach. [188] The first step is to identify latent classes with information in the acquisition and shopping measures, and then assign individuals to a latent class using their posterior class membership probabilities. Subsequently, a separate multinomial logistic regression model was employed to investigate the association between the assigned class membership and other factors (e.g., SES, nutrition, perception).

The data management and cleaning and descriptive analyses were conducted in SAS 9.4 version. [187] The latent class analysis model and step-3 model were fitted in LatentGOLD 5.1.[189]

Results

Sociodemographic characteristics of participants and measures of food acquisition and shopping habits are summarized in **Table 4.1**. The study population was mostly African American (92.5%) and female (80.3%). The majority of participants had very low socioeconomic status: 65.2% participated in SNAP; 61.8 % were food insecure; only 68.4% had completed high school or a lower level of education; and 79% had an annual household income less than $20,000.

The mean shopping distance between residential addresses and utilized store increased from store 1 to store 3 (2.7, 2.8, and 4.0 miles, respectively), whereas shopping frequency decreased from store 1 to store 3 (1.2, 0.6, 0.3 times/week, respectively). The proportion of participants who shopped at a supermarket or a supercenter ranged from 81% (store 3) to 89% (store 1). Nearly half of participants shopped at a farmers' market or acquired food from a food bank or pantry or from church or social services.

Model fit statistics for the latent class analysis are presented in **Table 4.2**. The three-class model was selected because of a smaller BIC value, less classification errors, and relatively higher entropy R^2. Although other statistics (i.e., AIC and bootstrap likelihood ratio test) suggested that models with more classes fit better than the three-class model, certain classes had a very small size. In addition, compared to the two-class model, the three-class model further differentiates patterns that were grouped into one class in the two-class model. Thus, the three-class model was used as the final model.

Food acquisition and shopping patterns are presented in **Figure 4.1**. Overall, 35% of participants were classified into Class 1 (individuals who used community food resources, shopped infrequently, and used someone else's car or public transportation to store 1). Forty-one percent of participants were classified into Class 2 (individuals who used community food resources, shopped more frequently, and more proximally). Twenty-four percent of participants were classified in Class 3 (individuals who did not use community food resources and were distal shoppers). The proportion of participants who shopped above the mean distance for store 1 were highest in Class 3 (70.1%), and followed by Class 1 (41.4%) and Class 2 (35.1%). Similar patterns were found in store 2 and store 3 distances. However, the proportion of participants who shopped more frequent (once per week or greater) for store 1 was the highest in Class 2 (56.6%), followed by Class 3 (46.3%) and Class 1 (14.1%). The distribution of the store type across different classes was very similar with that of shopping distance, with highest proportions of shopping at a supermarket for store 1-3 in Class 3 (86.2%-98.3%), followed by Class 1 (82.6%-92.4%), and Class 2 (75.6%-79.7%). The proportion of participants traveling to store 1 using their someone else's car/taking bus/taxi/riding bicycle/walk was the highest in Class 1 (74.1%), and followed by Class 2 (56.4%) and Class 3 (22.7%). The proportion shopping at a farmers' market was lowest in Class 1 (35.3%), and was similar in Class 2 (50.1%) and Class 3 (50.6%). The proportion of participants acquiring food at a food bank/pantry or church/social services was highest in Class 2, whereas very few participants in Class 3 acquired food at a food bank/pantry or church/social services organizations. Detailed distribution of acquisition and shopping measures can be found in **Appendix B**.

Differences in socioeconomic characteristics, nutrition knowledge, and perceptions of food shopping access between identified acquisition and shopping pattern classes are shown in **Table 4.3**. After adjusting for the age, gender, and race/ethnicity, compared to those in Class 3, Class 1 had a higher proportion of SNAP recipients, marginal, low and very low food-insecure households, less than high school education participants, and participants with less than $20,000 household annual income. Class 2 also had a higher proportion of participants with low SES, including a higher proportion of marginal, low and very-low food-insecure households, and having less than high school education, and Class 2 had a lower proportion of participants who perceived a lack of access to adequate food shopping in their neighborhood, compared to Class 3. Compared to Class 2, Class 1 individuals were not significantly different on any of the SES attributes; however, there was a significantly higher proportion of participants who perceived a lack of access to adequate food shopping in their neighborhood in Class 1. There was no significant difference across the classes in terms of their nutrition knowledge of fruit and vegetable intake, and household size.

Discussion

Our latent class analysis identified three distinct classes among a population primarily residing in low-income and low-access areas including: 1) Class 1, those who use community food resources, are infrequent shoppers, and use someone else's car or public transportation when shopping (35%), 2) Class 2, those who use community food resources and are more frequent and proximal shoppers (41%), and 3) Class 3, those who do not use community food resources and are distal shoppers (24%). Thus, food shopping frequency, utilization of community food resources, food shopping distance, and transportation were the key attributes that jointly defined the acquisition and shopping patterns among this population. Store type and farmers' market utilization did not differ between the acquisition and shopping patterns.

In addition, compared to Class 3, individuals in Class 1 had comparatively lower SES, including higher proportions of participating in SNAP, being food insecure, having lower level of education and annual household income; individuals in Class 2 also had a comparatively lower SES attributes. Individuals in Class 2 were not significantly different from those in Class 1, except that a higher proportion in Class 1 saw food access as a problem.

These results indicate that SES attributes, nutrition knowledge, and perceptions of food shopping access co-vary with an array of acquisition and shopping behaviors among low-income and low-access populations. Both individuals in Class 1 and Class 2 were characterized by utilization of community food resources; however, individuals in Class 1 perceived more difficultly in food shopping and reported more lack of transportation than those in Class 2. And consistently, this group shopped far less frequently. This finding mirrors previous research on the relationship between the perception of ease of food shopping access and shopping frequency that has suggested a positive, although not statistically significant relationship. [21]

Transportation issues seem to be a barrier to those who use community resources and have poorer perception of food shopping access (class 1). This finding is consistent with emerging literature that access to a vehicle or public transportation is increasingly associated with greater access to healthy food choices, especially in low-income communities. [178,190,191] The importance of the role of transportation in acquisition and shopping patterns may be relevant to a broad audience, including the food-insecure population. [180] Policy interventions aimed at increasing healthy food access should take transportation issues into consideration.

Both individuals in Class 2 and Class 3 shop more frequently, but the two groups differ in their SES attributes. The high proportion of food-insecure, and very low education participants in Class 2 means that individuals in this class are characterized by a high probability of utilizing food support from the community, i.e. at food banks/pantries or churches/social services, in addition to shopping at farmers' markets, which offer SNAP incentives and vouchers through federal food assistance programs. [176] Surprisingly, the relevant low SES group (i.e. Class 2) perceived a greater ease of food shopping access compared to the comparatively higher SES group (i.e. Class 3). This contradicts previous findings that a low SES group (i.e. food-insecure) had lower odds of reporting easy access to adequate food shopping. [192] However, the high proportion of participants who participated in SNAP program in current study may modify the perceptions of that group. Additionally, the perception of healthy food access is also impacted by the geographic measures (i.e. distance to stores). [193] Participants in our study lived in very similar neighborhoods of low-income and low-access, which may lead to the different patterns of perception regarding their food environment. Our finding suggests a link between perceived ease of food shopping access and actual proximal shopping distance, which is consistent with previous path analyses. [21] Also, people who are proximal shoppers and use community resources may be more likely to shop where it is convenient for them, reflecting a lack of other nearby resources.

Interestingly, community resource utilization is one of the key factors that defined the acquisition and shopping patterns among this low-income and low-access population. Although the majority of US households shop at a supermarket or large grocery chain store, [12,14-18,127] current findings suggest that many low-income households acquire food from community resources. As suggested by Stern et al., 27% of US households split their purchases among different store types. [147] Building a new supermarket in a low-access area has been advocated and viewed as a strategy to increase healthy food access and improve dietary intake. However, evidence has shown that supermarket establishment in underserved neighborhoods does not necessarily translate into use of that resource or improve health food like fruit and vegetable consumptions. [105,171-175] It is possible that low-income populations have a high reliance on food support from the community, which is why they do not use a new grocery store in their neighborhood.

We described acquisition and shopping patterns based mainly on the participants' actual acquisition and shopping attributes at different food shopping locations. We did not investigate the underlying reasons participants chose these stores. We found that the SES attributes and participants' perception of lack of access to adequate food shopping in their neighborhood were significantly different among the three classes. This finding suggests that financial barriers and perceptions of the food shopping environment drove households to form different acquisition and shopping patterns, although reverse causality cannot be excluded in this cross-sectional study. Other reasons such as food preference, store food price, and food expenditures may also determine store choice and should be investigated in future studies.

In terms of the application of latent class analysis of acquisition and shopping patterns, our study differs from previous work in that we employed multidimensional aspects of food shopping. VanKim's study included information on fruit, non-processed food, and organically grown foods purchase, store type, on-campus location beverage purchase, and near campus restaurant or store food and beverage purchases [32]. Stern's study focused on the different type of store [147]. While the current study included information on food shopping distance, frequency, store type, transportation mode, and community resource utilization, to study complex acquisition and shopping patterns among residents of low-income communities. Pattern techniques allow researchers to group participants based on similarities of responses to several variables, and to the best of our knowledge, this is the first study that included acquisition and shopping attributes to identify patterns.

With respect to study limitations, the current findings might not be generalizable to other areas of the US or different time periods, geographic and demographic configurations. Furthermore, it was assumed that all shopping trips originated from home, although some of the grocery shopping trips may have commenced at work or from other points of origin. Also, all the information was obtained from the primary shopper's response. Nevertheless, the results underscore the potential of defining acquisition and shopping patterns with multidimensional attributes of food acquisition and shopping and profiling complex food shopping behaviors.

Conclusions

The low-income and low-access population studied here showed different patterns of food acquisition and shopping. Food shopping frequency, utilization of community food resources, food shopping distance, and transportation were the key factors that defined the acquisition and shopping patterns among this population residing in low-income and low-access areas. Future interventions to increase healthy food access in underserved areas should consider community food resource utilization and relieve transportation barrier. More investigations are needed to examine the association between these acquisition and shopping patterns and dietary intake and health outcomes.

Table 4.1 Demographic characteristics and measures of food acquisition and shopping habits of 466 participants from disadvantaged communities in a study of food access, food shopping, and food security in South Carolina (2013/2014)

Characteristics	n=466
Age (y), mean (SD)	51.6 (14.5)
Female, %	80.3
African Americans, %	92.5
SNAP participation, %	65.2
Food security[1], %	
High food security	18.0
Marginal food security	20.2
Low food security	32.8
Very low food security	29.0
Education, %	
Less than high school	30.0
High school	38.4
Some college and above	31.6
Annual household income, %	
$0–9,999	46.6
$10,000–19,999	32.4
$20,000–29,999	11.8
$30,000 or more	9.2
Household size, mean (SD)	2.3 (1.4)
Nutrition knowledge about F&V serving per day	3.6 (2.0)
Above or equal than 5 servings per day, %	23.8
Perception of lack of access to adequate food shopping in neighborhood, %	
A very serious problem	29.4
A somewhat serious problem	21.0
A minor problem	17.6
Not a problem	32.0
Store 1	
Distance in miles, mean (SD)	2.7 (2.4)
Frequency (per week), mean (SD)	1.2 (1.2)
Supermarket/Supercenter, %	88.6
Transportation to store 1, %	
Drive own vehicle	44.7
Ride in a friend's/family member's car	35.8
Take a bus or taxi	9.3
Walk or bicycle	10.1
Store 2	
Distance in miles, mean (SD)	2.8 (1.7)
Shopping frequency (per week), mean (SD)	0.6 (0.6)
Supermarket/Supercenter, %	85.4

Characteristics	n=466
Store 3	
Distance in miles, mean (SD)	4.0 (12.0)
Frequency (per week), mean (SD)	0.3 (0.3)
Supermarket/Supercenter, %	81.1
Community resources[2]	
Shop at farmers' market, %	45.1
Acquire food at bank or pantry, %	52.2
Acquire food from church or social services, %	53.2

[1] Food secure=High and Marginal food security; and Food insecure=Low and Very low food security.

[2] Community resources in this paper refer to food bank/food pantry and food acquired from church/social services. The distribution of these and other types of community resources and association with food insecurity level has been reported previously.

Table 4.2 Fit statistics for unconditional latent class analysis model of 13 measures of food acquisition and shopping habits of 466 participants from disadvantaged communities in a study of food access, food shopping, and food security in South Carolina (2013/2014)

No. of classes	Likelihood	Bayesian Information Criteria	Akaike Information Criteria	Entropy R^2	No. Parameter	Classification Errors	Bootstrap likelihood ratio test*
2	-3602.70	7371.30	7259.41	0.77	27	0.07	--
3	-3535.83	7323.57	7153.66	0.75	41	0.11	<.001
4	-3504.00	7345.94	7118.01	0.74	55	0.14	<.001
5	-3476.07	7376.09	7090.14	0.76	69	0.15	<.001

Test didn't go beyond 5 classes, because less than 10% of participant was classified in one class.
*P value for k-class vs. (k+1) - class solution

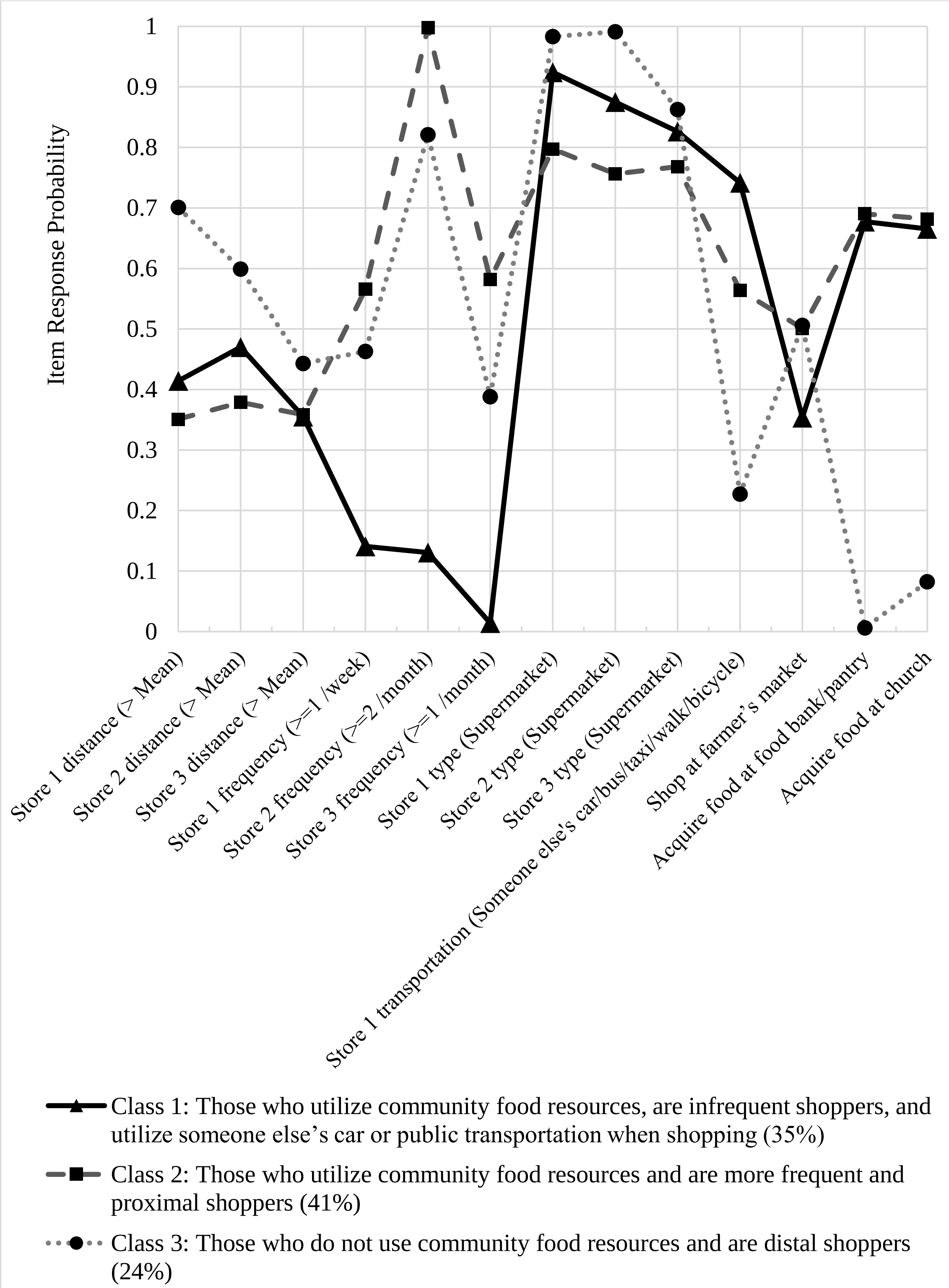

Figure 4.1 Probability of latent class membership and item-response probabilities of retained unconditional three-class solution of 466 participants from disadvantaged communities in a study of food access, food shopping, and food security in South Carolina (2013/2014)

Table 4.3 Differences in socio-economic, nutrition knowledge, and perceptions of food access between identified food acquisition and shopping patterns of 466 participants from disadvantaged communities in a study of food access, food shopping, and food security in South Carolina (2013/2014)

Characteristics	**Class 1:** Those who use community food resources, are infrequent shoppers, and use someone else's car or public transportation when shopping **n=163**	**Class 2:** Those who use community food resources and are more frequent and proximal shoppers **n=191**	**Class 3:** Those who do not use community food resources and are distal shoppers **n=112**
SNAP participation, % [b]	77.1	68.6	41.9
Marginal food security, % [bc]	21.6	20.8	17.1
Low food security, % [bc]	34.9	34.4	27.1
Very low food insecurity, % [bc]	35.0	33.0	13.1
High school education, %	35.8	40.9	37.9
Less than high school education, % [bc]	39.6	35.7	6.2
Less than $20,000 household annual income, % [bc]	91.1	82.4	55.3
Mean households size	2.4	2.3	2.3
Nutrition knowledge in fruit and vegetable intake amount of less than 5 servings per day, %	77.8	78.4	70.1
Perception of lack of access to adequate food shopping in neighborhood	75.7	59.0	72.4

as a problem, % [ac]	

Model adjusts for age, gender, and race/ethnicity. Detailed parameter estimation can be found in **Appendix C.**

[a] is for significant difference in the prediction of class membership between Class 1 and Class 2 using multinomial logistic regression;

[b] is for significant difference in the prediction of class membership between Class 1 and Class 3 using multinomial logistic regression;

[c] is for significant difference in the prediction of class membership between Class 2 and Class 3 using multinomial logistic regression.

Chapter 5. Food Acquisition and Shopping Patterns in the United States: Results from FoodAPS[2]

[2] Ma, X., Bell, B.A., White, K., Liu, J., and Liese, A.D. To be submitted to *American Journal of Public Health.*

Abstract

Background: Public health–oriented research on food shopping habits is a relatively new area of inquiry. Food shopping is an interaction of the individual with her/his food environment and thus has a multidimensional nature. A previous study identified different shopping patterns among residents living in food desert areas in South Carolina. Here, we are interested in exploring food acquisition and shopping patterns in a national sample of households in the United States.

Methods: The US Food Acquisition and Purchase Survey recruited 4,826 households between April 2012 and January 2013. Participants were interviewed about their food acquisition and shopping habits at their primary and alternative stores during an in-person interview. Eight measures of food acquisition and shopping habits (i.e., travel distances between residential location and each of the stores used, perceived travel time to primary store, store type, transportation mode (primary store only), and utilization of community food resources, such as food banks or pantries) were used in the food acquisition and shopping pattern analysis. Latent class analysis was employed to explore food acquisition and shopping patterns. In addition, associations between acquisition and shopping patterns and various factors such as socioeconomic status, nutrition knowledge, and store selection reasons were examined using multinomial logistic regression models. All the analyses were stratified by urbanicty.

Results: Overall, 65.2% households were located in an urban tract, and 34.8% were located in a rural tract. Among urban households, we identified three distinct classes: Class 1 (Household that shopped more proximally but perceived longer travel time, used their own vehicle, and were more likely to use a farmers' market [41%]); Class

2 (Households that shopped more distally but perceived shorter travel time, used their own vehicle, and were more likely to use a farmer's market [40%]); and Class 3 (Household that shopped distally and perceived longer travel time, shopped more proximally for their alternative store, used someone's car, and were less likely to use a farmers' market [20%]). Among rural households, we identified two classes: 49% were Class 1 and 51% were Class 2 (Class 3 was used for urban households only). Moreover, among urban households, Class 3 was characterized by lower SES attributes and participants reporting that they considered store food price and proximity as their major reasons when choosing stores compared to Class 1 or Class 2; Class 2 had higher SES attributes (lower proportion participating in SNAP and reporting food insecurity) and considered store food prices more but store proximity less than Class 1. No significant differences were observed between Class 1 and Class 2 among rural households, except for the proximity concern when selecting stores.

Conclusion: Food shopping distance, perceived travel time to primary store, and transportation were the key factors that defined distinct acquisition and shopping patterns. Additionally, the patterns differed between rural and urban populations. Future interventions to increase healthy food access should consider geographic differences and transportation barriers.

Introduction

Public health–oriented research on food shopping habits is a relatively new area of inquiry. Food shopping is an interaction of the individual with her/his food environment and has a multidimensional nature. [34] Although some previous studies have described food shopping with respect to the actual distance traveled to the primary store, shopping frequency, and store type utilized, [21,23-25,30,31,103,119-121] very few studies have incorporated multiple dimensions of shopping habits simultaneously. [32,147] Food shopping is a complex behavior that can be characterized by various factors. Stern et al. employed cluster analysis and found three classes using Nielsen's national consumer panel data, including those who shop primarily at grocery chain stores, those who shop primarily at mass-merchandiser shoppers, and those who use a mixture of different store types. [147] VanKim and colleagues used information on what items were purchased (e.g., fruits and vegetables), as well as frequency of shopping, type of purchasing location, and food and beverage purchases on or off of campus or from vending machines to identify food shopping patterns using latent class analysis and defined eight classes among a sample of college students in Twin Cities area of Minnesota. [32] These new applications of pattern techniques are promising tools to describe the complex nature of food acquisition and shopping habits in epidemiological studies.

We previously used latent class analysis to explore shopping profiles among residents living in food desert areas in South Carolina to understand food acquisition and shopping patterns among disadvantaged populations (Chapter 4). Three classes were identified, including those who use community food resources, are infrequent grocery shoppers, and use someone else's car or public transportation when shopping (35%);

those who use community food resources and are more frequent and proximal shoppers (41%); and those who do not use community food resources and are distal shoppers (24%). A limitation of our study was that it was situated exclusively in two counties in South Carolina, which limits the generalizability of the findings.

To the best of our knowledge, there is no research describing patterns of food acquisition and shopping habits among a general population of US households using similar multidimensional measures of food shopping and acquisition habits. VanKim's study focused on college student Twin Cities area of Minnesota; while Stern's study only investigated the store type of where the packed food were purchased nationwide. [32,147] The USDA's National Household Food Acquisition and Purchase Survey (FoodAPS) conducted between April 2012 and January 2013[162] presents an opportunity to describe food acquisition and shopping patterns in a nationally representative sample, including comprehensive information on food acquisition and shopping. Thus, the purpose of the current study was to identify distinct patterns in food acquisition and shopping habits in a nationally representative sample of US households using latent class analyses and subsequently examine whether socioeconomic status (SES), nutritional factors, and reasons underlying store choice were associated with the identified patterns.

Methods

Study Population and Settings

We conducted a cross-sectional analysis of the 2012-2013 Food Acquisition and Purchase Survey (FoodAPS) public use data, which includes 4,826 households (with 14,317 members). [127,162] FoodAPS collected comprehensive data about household food purchases and acquisitions for consumption at home and away from home and is the first nationally representative survey of American households on this topic via in-person interview. The FoodAPS sample of households was selected using a multistage sample design. First, Primary Sampling Units (PSUs) defined as counties or groups of contiguous counties were selected before sampling, Then, within each of the PSU, eight secondary sampling units (SSU) (comprised a census block group (CBG) or a group of contiguous block group if CBG was expected to contain fewer than 50 survey-eligible household) were selected. Finally, 20,084 commercial list of addresses paired with a list of SNAP addresses were selected to be screened. This selected list of addresses was further screened via a two-phase sampling approach to reduce the potential non-response bias. The Phase 1 screening removed the addresses that appeared to be occupied but did not respond after at least eight attempt by field interviewer. Phase 1 screening left 4,814 households. For Phase 2 screening, 138 randomly selected addresses were released, and ten additional contact attempts were made. The effort resulted in 12 completed case that were added to the 4,814 addresses. Finally, 4,826 households were selected for following two in-person and three telephone interviews. [163] . Surveys were completed between April 2012 and January 2013. The study population was sampled from households receiving assistance from the Supplemental Nutrition Assistance Program (SNAP), low-income households not participating in SNAP, and higher-income households. [163] FoodAPS also aimed to investigate how the local food environment affects food spending patterns in the US, so the study included a geographic component. The urbanicity of each household's residential location was decided according to participant geographic location in relation to the census tract using the Census Bureau's urbanized area definitions. A census tract was defined as urban if the geographic centroid of the tract was in an area with more than 2,500 people; all other tracts were considered rural. [194] The weighted average of responses in Phases 1 and 2, the FoodAPS screener response rate was 70.9%, and the overall study response rate was 41.5%.

Socioeconomic Characteristics, Nutrition Knowledge and Awareness, and Reasons for Store Selection

Socioeconomic characteristics of interest in the study included participation in a food assistance program (such as SNAP), food security, education, household annual income, and employment. Because the sampling of the households was based on a stratification of participants on SNAP and total household income, SNAP participation status could be determined from the designated sampling eligibility. The SNAP participation was further grouped into three categories according to the distribution, including the SNAP participation, non-SNAP participation with income less than 185% federal poverty guideline (FPG), and non-SNAP participation with income greater or equal with 185% FPG, following the FoodAPS sampling scheme. Food security was assessed by in-person interview using the validated 10-item USDA US-Household Food Security Survey Module. [185] Participants were classified as having high food security (0 affirmative responses), marginal food security (1 to 2 affirmative responses), low food security (3 to 7 affirmative responses), or very low food security (≥8 affirmative responses) [163] and were further grouped into food secure (including high food security and marginal food security) and food insecure (including low food security and very low food security) in the Step-3 analysis. Education was assessed by the question "what is the highest level of school (you/NAME) completed or the highest degree (you/NAME) received?" [195] and was recoded as less than high school, high school, and above high school. Monthly household income was assessed by a variety of questions and included income from work, unemployment compensation, welfare, child support or alimony, and retirement and disability income [196] and was categorized into three levels using $20,000 and $50,000 as cutoffs, according to the distribution. Employment status was queried by the question "which of the following (working at a job or business, with a job or business but not at work, looking for work, not working at a job or business, refused, or unknown) (were you/ was NAME) doing last week" [196] and was recoded into employed (including "working at a job or business (52.1%)" and "with a job or business but not at work (3.3%)") and unemployed (the remaining categories(44.6%)). Nutrition knowledge was assessed by whether a participant tried to search for nutrition information or received nutrition-related education in the past year or whether a participant had heard of MyPlate or MyPyramid. [196] The question on reasons for selecting their primary store queried whether a participant thought lower price, proximity, produce selection, meat department, variety of food (general), variety of special foods(such as gluten free), loyalty/frequent shopper program, or other was a reason. [196] Only low price and proximity were used in current study as they were the predominant reasons reported by participants.

Measures of Food Acquisition and Shopping Habits

Primary and alternative store information was queried with the questions "where (do you /does your household) do most of your food shopping?" and "in a typical month, where else (do you /does your household) shop for food?".[195] Most information on large grocery stores (i.e., name, address, and type) had been pre-stored in the query system and could be matched with what the primary respondents reported. If a store could not be matched during the interview, the primary respondent was asked to report the store's name, address, and type, and the store was identified later. Stores were classified into: supermarket, supercenter, large, medium, and small grocery store, specialty-meat/poultry, convenience store, non-profit cooperative, combination grocery/other, military commissary. Both residential and store addresses were geocoded in Google Maps. Driving distances were calculated using Google Maps API. [194] The perceived one-way travel time in minutes to the primary store was queried during the interview by the question "how long does it take to go one way from home to the primary store?". [195] Transportation mode to the primary store was determined by the question "how do you usually get to the store where you do most of your food shopping?". [195] Options included driving own car, using someone else's car, walk, bus, taxi, riding bicycle or others. Food acquisition habits were also queried, including utilization of farmers' markets with the question "when in a season, do you ever get food from a farmers' market or farm stand?"[195] and utilization of food banks or pantries with the question "during the past 30 days, did (you/ anyone in your household) go to a food pantry or food bank for groceries?".[195] FoodAPS did not include a question on the frequency of shopping at the primary and alternative stores.

To fit the latent class model, continuous variables were dichotomized. Because of the inherent spatial differences between urban and rural areas, shopping distances to the primary and alternative stores and the perceived travel time to the primary store were dichotomized using urban- or rural-specific medians (urban: 1.8 miles, 2.1 miles, and 6.2 minutes, respectively; rural: 7.4 miles, 7.8 miles, and 14.0 minutes, respectively). Store type was classified into supermarkets (including supermarkets and warehouse clubs), supercenters (i.e., Walmart, Target, etc.), and other (including grocery stores, convenience stores, dollar variety stores, drug/pharmacy stores, military commissary, delivery route, and specialty stores). Transportation mode to primary store was grouped into three categories: own vehicle (drive their own car/van/truck/motorcycle)), someone else's car or public transportation (ride in a car/van/truck/motorcycle of family or a friend, take a bus, or ride in a taxi), and walk or ride a bicycle.

Statistical Analyses

Of the 4,826 total households, 316 were excluded because of missing data on travel distance to primary store, 1,099 were further excluded because of missing information on travel distance to alternative stores, and 32 additional households were excluded because of missing information on farmers' market utilization, sociodemographics, nutrition knowledge, or the reasons for primary store selection. The final analysis included 3,379 households. As a large number of households were excluded from the current analyses, the sociodemographic characteristics were compared between those who were excluded from the study and those who were included in the study. No significant difference were observed between excluded and included households except a significant higher proportion of female in the included sample. Detailed distributions can be found in the **Appendix D**. We examined the missing patterns between the missing data and the observed data. The correlations between missing and observed variables were -0.02-0.67. The moderate correlation of 0.67 pertains to the pair of variables: missing on alternative store distance and alternative store type. The majority of participants missing the alternative store distance were for supercenter or supermarket, for which participants only reported the store name. Given that no further information was available, we could not determine the store address from participants' report. The correlation between missing and observed value were between -0.09-0.11, which were weak. Given the large missing of alternative store characteristic, we also examined the pattern removing the alternative store characteristics.

Descriptive analyses of the sample characteristics were performed using SAS version 9.4. [187] To take into consideration the complex sampling scheme of FoodAPS, the SURVEY procedure and a domain analysis of urbanicity differences were used to appropriately maintain the sampling structure and generate weighted frequencies and averages. All the analyses were also conducted separately in urban and rural households.

Latent class analysis was used to identify mutually exclusive, homogenous groups based on the eight food acquisition and shopping attributes selected including the distance to primary and alternative store, type of the primary and alternative store, perceived travel time to the primary store, transportation mode to the primary store, use of farmers' market or food bank or pantry. The standard criteria Bayesian information criterion (BIC), classification errors, the bootstrap likelihood ratio test, and class size were used to select the best-fitting model. The best-fitting model should have the lowest BIC and classification errors, with none of the classes comprising less than 10% of the data and a significant bootstrap likelihood ratio test showing that the bootstrap model with k+1-class solutions fits better than that with k-class solutions. Practical interpretations of the identified patterns were also considered for model selection. The probability of latent class membership was obtained via the maximum likelihood approach. The complex sampling scheme was incorporated by adding weights to different response patterns, which can be done using LatentGold software. Thus, the weighted item-response probability from the latent class analysis and proportions from the Step-3 analysis (described below) are reported.

The Step-3 approach was used to examine the association between the identified pattern and other factors. The Step-3 approach is similar to the commonly used three-step approach but is more advanced in that it corrects for bias from classification errors in the third-step parameter estimation. [188] The first step is to identify latent classes with information from the acquisition and shopping measures and then assign individuals to a latent class using their posterior class membership probabilities. Specifically, we first identified latent classes with information from the food acquisition and shopping measures among all the households. Then we stratified our sample by urbanicity and repeated the process in order to explore the food acquisition and shopping patterns in-depth because of the inherent spatial differences between urban and rural areas. Subsequently, separate multinomial (for the urban population) and ordinary (for the rural population) logistic regression models were employed to investigate the association between the assigned class membership and other factors (e.g., SES, nutrition knowledge, store selection reasons).

The data management and cleaning and descriptive analyses were conducted in SAS 9.4 version. [187] The latent class analysis model and step-3 model were fitted in LatentGOLD version 5.1.[189]

Results

Characteristics of the households' primary food shoppers and of the food acquisition and shopping measures are summarized in **Table 5.1**. Weighted averages and frequencies are reported. Overall, 65.2% households were located in an urban tract, and

34.8% were located in a rural tract. The study population was 50 years old on average and mostly female (70.4%); the majority were white (75.6%), and 12.8% were Black. 13.4% of households participated in SNAP, and 17.3% were low-income households not participating in SNAP; 16% of households were food insecure; 65.9% of primary food shoppers had more than a high school education, and 44.6% were not employed; and the mean annual household income was $57,604. Only 6.7% of primary food shoppers had participated in any events, lectures, or demonstrations about how to shop for or prepare nutritious food and meals, 32.4% had searched for nutrition information on the internet, 26.7% and 56.0% heard of MyPlate or MyPyramid, respectively, and 55.5% and 50.9% considered price or proximity, respectively, as main reason for selecting their primary store. In addition, compared to rural households, respondents in urban households were significantly younger and were more likely to be African American, come from a food-insecure household, and be highly educated and employed.

Overall, the average shopping distances to the primary and alternative stores were 5.1 and 5.4 miles, respectively. The proportions of households that shopped at a supermarket or a supercenter were 95% (primary store) and 90% (alternative store). Over half of the households shopped at a farmers' market. Only 3.4% acquired food at a food bank or pantry. Moreover, compared to urban households, rural households traveled significantly farther to their primary (urban: 2.8 miles; rural: 9.6 miles) and alternative (urban: 3.0 miles; rural: 10.0 miles) stores, perceived significantly longer time to travel to their primary stores, and had lower proportions of respondents utilizing a supermarket or supercenter for their primary food shopping and relying on someone else's car or on public transportation.

Model fit statistics for the latent class analysis of all households in FoodAPS are presented in **Table 5.2**. The three-class model was selected because of a smaller BIC value and bootstrap likelihood ratio test. Although other statistics (i.e., classification errors, entropy R^2) suggested that the two-class model fits better than the three-class model, the three-class model could further differentiate patterns that were grouped into one class in the two-class model. Thus, the three-class model was used as the final model.

Food acquisition and shopping patterns of all the households are presented in **Figure 5.1**. Overall, 45% of households were categorized as Class 1 (Household that shopped more proximally but perceived longer travel time, used their own vehicle, and were more likely to use a farmers' market). Forty-two percent of households were categorized as Class 2 (Households that shopped more distally but perceived shorter travel time, used their own vehicle, and were more likely to use a farmer's market). Thirteen percent of households were categorized as Class 3 (Household that shopped distally and perceived longer travel time, shopped more proximally for their alternative store, used someone's car, and were less likely to use a farmers' market).

As the food acquisition and shopping patterns were largely distinguished by distance and perceived travel time, as shown in **Figure 5.1**, we further explored food acquisition and shopping stratified by urbanicity. Model fit statistics for the latent class analysis by urbanicity are presented in **Table 5.3**. The three-class model for urban households and two-class model for rural households were selected by optimally balancing the model fit statistics, including the lowest BIC statistics, significant bootstrap likelihood ratio test (for urban households), and small classification errors (for rural households).

Food acquisition and shopping patterns by urbanicity are presented in **Figure 5.2** (urban) and **Figure 5.3** (rural). The patterns identified among urban households were very similar to those among the overall sample of households. Among urban households, 41% of households were categorized as Class 1 (Households that shopped more proximally but perceived longer travel time, used their own vehicle, and were more likely to use a farmers' market). Forty percent of households were categorized as Class 2 (Households that shopped more distally but perceived shorter travel time, used their own vehicle, and were more likely to use a farmer's market). Twenty percent of households were categorized as Class 3 (Households that shopped distally and perceived longer travel time, shopped more proximally for their alternative store, used someone's car, and were less likely to use a farmers' market). Among rural households, 51% were Class 1 and 49% were Class 2. Class 3, as shown in urban households and in households overall, was not identified among rural households because the two-class model was used for these households, as the three-class model solutions did not fit better for rural households.

In general, for urban households, Class 2 had the highest proportion of households that shopped farther away from home, traveled to their primary store by their own vehicle/bike or walked, and shopped at a farmers' market. Class 3 had the highest proportion of households reporting longer travel time to their primary store, shopping at a supercenter or other type of stores, and acquiring food at a food bank or pantry. For rural households, Class 2 has the highest proportion of households for almost all the characteristics, expect for shopping at other types of stores and at a farmers' market. Detailed distributions of characteristics are presented in **Appendix E**.

We further examined whether the food shopping and acquisition pattern was influenced by the missing on alternative store information, we then examined the food shopping and acquisition pattern restricted with primary store characteristics, which allowed us adding about 1,000 observations back to our analysis. Our results of removing alternative store characteristics show very similar patterns (**Appendix F**) with very slightly changes in class prevalence.

Differences in socioeconomic characteristics, nutrition knowledge and awareness, and reasons for store selection between the acquisition and shopping patterns identified are shown in **Table 5.4**. For urban households, after adjusting for age, gender, and race/ethnicity, compared to Class 1, Class 2 had a significantly lower proportion of households participating in SNAP, being food insecure, and considering proximity in store selection. Compared to Class 1, Class 3 had a significantly higher proportion of households participating in SNAP, non-SNAP households with incomes under 185% of the federal poverty guidelines (FPG), having less than high school education, being unemployed, smaller household size, and considered store food price but a lower proportion of respondents considering proximity in their store selection. Moreover, compared to Class 2, Class 3 had a significantly higher proportion of households participating in SNAP, food-insecure households, respondents with less than a high school education, unemployed respondents, small household size, and lower proportion of respondents considering proximity in their store selection. There was no significant difference across the classes in terms of household annual income or nutrition awareness or knowledge. For rural households, Class 2 had a significantly smaller household size, and lower proportion of households that considered proximity when selecting stores compared to Class 1. However, no significant difference was observed for SES characteristics or nutrition knowledge or awareness.

Discussion

Our latent class analysis identified three distinct classes among urban households and two classes in rural households. In urban households, 41% were categorized as Class 1, 40% were categorized as Class 2, and 13% were categorized as Class 3. Among rural households, 51% were Class 1 and 49% were Class 2. No Class 3 group was identified among rural households. The general pattern of characteristics in Class 1 and Class 2 was similar in rural and urban households. Travel distance and perceived travel time were key factors for both urban and rural households that differentiated acquisition and shopping patterns. Transportation and farmers' market and food bank/pantry utilization were key factors that further differentiated acquisition and shopping patterns among urban households only.

Households in both Class 1 and Class 2 were characterized by being more likely to use their own vehicle/bike or walk to a store and to shop at farmers' markets. However, those in Class 1 shopped mainly proximally (i.e., below the median distance to their primary grocery store), whereas those in Class 2 shopped more distally. In our analysis of predictors in urban households, Class 1 was characterized by a higher proportion of people who consider proximity important for store selection and a lower proportion considering store price. This finding is interesting in that the empirically identified pattern based on shopping habits reflects the reasons for store selection reported by the respondents, and this was true for both urban and rural respondents. No significant difference was observed between Class 1 and Class 2 for rural households, except for the proximity concern when selecting stores.

Our results also highlight interesting ways in which SES attributes, nutrition knowledge, and reasons for store selection co-vary with an array of food acquisition and shopping measures in the US. For instance, Class 3 households (urban) differed in almost all acquisition and shopping attributes from urban Class 1 and Class 2 households, except in the store type utilized. Class 3 households also differed in their SES attributes, except income, compared to Class 1 and Class 2 households. Because Class 3 households are characterized by a high proportion of SNAP-receiving households, non-SNAP households with income lower than 185% FPG, food-insecure households, and respondents with very low education, it is not surprising that households in this class are also characterized by a low probability of traveling to their store using their own vehicle/bike or walking.

Current results are consistent with a previous study on food stamp recipients [138] and a recent national report [127] that low-SES households (i.e., food-insecure households or food stamp recipients) are less likely to drive a car of their own to do their primary food shopping and more likely to get rides from someone else. [180] Transportation issues seem to be a barrier to low-SES households, which comparatively more often utilize a food bank or pantry and perceive longer travel time to their primary store (i.e., urban Class 3 households). Additionally, urban Class 3 households had a significantly higher proportion of respondents concerned about food price when selecting stores. Energy-dense foods usually cost less than healthy foods, [197] so those foods may be the best choice for low-SES households with a very limited budget for life expenses.

Households in Class 1 shopped more proximally but perceived longer travel time, whereas Class 2 households shopped farther away but perceived shorter travel time. The discordance between real travel distance and perceived travel time to the same type of location is more obvious among urban than rural households. This finding is consistent with literature showing that the difference between objective and perceived distance to a specific destination decreases as the objective distance increases. [198] Thus, further studies focusing on perception measures should consider urbanicity differences.

There are few studies to which we can directly compare our findings. In a previous South Carolina study, we found three classes that were characterized by shopping frequency, utilizing a food bank/pantry or church/social services, transportation, and shopping distance. The food acquisition measures (food bank/pantry or church/social services) were key factors that defined the acquisition and shopping patterns; in the current study, these factors do not define the patterns. One reason for this difference is that the current study had a very low proportion of respondents reporting that they shop/acquire food at a food bank or pantry (3.4%), whereas in the South Carolina study, nearly half of the participants shopped/acquired food at a food bank/pantry. Also, the racial composition and SES characteristics of the study population were very different, with the South Carolina study including about 90% African Americans and recruiting from very disadvantaged neighborhoods. Additionally, the food bank–related survey questions were framed differently between the two studies. In FoodAPS, participants were asked to report whether they went to a food bank or pantry for groceries in the past 30 days, whereas the South Carolina survey queried about the past year. The FoodAPS survey was completed in each household during a one-week period from April 2012 to

January 2013. It is possible that the monthly basis of the question frame could be easily affected by the season or the time when the survey was conducted such that it underestimated the food bank or food pantry utilization among the study population.

This study has some limitations. We have a large set of missing values for alternative store characteristics. The missing patterns were not at random with more missing of alternative store's distance on supercenter or supermarket. Besides a higher proportion of male participants were excluded due to restriction our analysis with completed information. Those missing may result in unrepresentativeness of current survey in terms of our pattern analysis. However, when we added those missing back to our sample and focused on the food shopping and acquisition patterns for primary store, the pattern was very similar with very slightly changes in class prevalence. Also, although FoodAPS is surveyed to represent the whole nation, it may not represent the food acquisition and shopping patterns of a different time period. The FoodAPS survey did not explicitly query food shopping frequency for the primary and alternative stores, which is a significant factor that differentiates the food acquisition and shopping patterns in the SC study. Thus, we are unable to determine what role food shopping frequency plays in this general population and how that factor influences the patterns. Other limitations pertain to the public version of the FoodAPS dataset. We are unable to link the FoodAPS participants with census tract–level information, such as food desert status. Although residence in a food desert is not an attribute of the food acquisition and shopping habits, it influenced the habits via grocery store availability and accessibility. [22] In addition, we were unable to link a subset of the participants whose utilized primary and alternative stores were surveyed by IRI with information from the Thrifty Food Price

Index in the publicly released FoodAPS data. Thus, the role of food price at the utilized store was unknown. However, we included information on store selection reasons (i.e., price or proximity), which could indirectly suggest the important role of store food price in food acquisition and shopping patterns.

Strengths of our study are that we identified food acquisition and shopping patterns among a survey with large sample size. Thus, our study differs from previous work in that we employed multidimensional aspects of food acquisition and shopping, such as food shopping distance, perceived travel time, store type, transportation mode, and community resource utilization, to study complex food acquisition and shopping patterns among the general population. Pattern techniques allow researchers to group participants based on similarities of responses to several variables.

Conclusion

The general population studied here showed different patterns of food acquisition and shopping. Food shopping distance, perceived travel time to primary store, and transportation mode to primary store were the key factors that defined distinct acquisition and shopping patterns. Additionally, the food acquisition and shopping patterns differed between rural and urban populations. Future interventions to increase healthy food access should consider geographic differences and transportation barriers. More investigations are needed to examine the association between these acquisition and shopping patterns and dietary intake and health outcomes.

Table 5.1 Demographic and socioeconomic characteristics and food acquisition and shopping habits by urbanicity of 3,379 participants in the 2012-2013 interview from the Food Acquisition and Purchase Survey (FoodAPS)

Characteristics	**All n=3,379**	**Urban n=2,443**	**Rural n=936**
Age, mean (SD)*	49.9 (0.6)	48.1 (0.7)	53.1 (0.9)
Female, %	70.4	69.1	73.0
Race/Ethnicity*, %			
White	75.6	68.3	89.2
Black	12.8	15.9	6.9
American Indian/Alaska native	0.5	0.6	0.4
Asian/Native Hawaiian/Other Pacific islander	4.5	6.7	0.4
Others/Multiple race	6.6	8.5	3.0
SNAP participation, %			
SNAP household	13.4	14.4	11.5
Non-SNAP household, income <100% FPG	4.8	5.2	4.0
Non-SNAP household, income >=100% and <185% FPG	12.5	11.8	13.9
Non-SNAP household, income >=185% FPG	69.3	68.5	70.6
Food security*, %			
Very low food security	6.4	7.2	5.0
Low food security	9.6	10.3	8.3
Marginal food security	14.8	16.3	12.0
High food security	69.2	66.2	74.7
Education*, %			
Less than high school	34.1	30.8	40.3
High school and above	65.9	69.3	59.7
Annual household income, %			
$0–9,999	13.1	14.1	11.3
$10,000–19,999	13.0	12.8	13.4
$20,000–29,999	10.8	10.0	12.4
$30,000–39,999	8.9	8.1	10.5
$40,000–49,999	8.0	7.1	9.7
$50,000 or more	46.2	47.9	42.8
Mean (SD)*	$57,604 (2,685)	60,266 (3,371)	52,625 (2,834)
Being employed*, %	55.4	59.0	48.7
Nutrition education, %	6.7	7.0	6.0
Nutrition information searching, %	32.4	33.7	30.2
Heard of MyPlate, %	26.7	25.6	28.9
Heard of MyPyramid, %	56.0	58.2	51.8
Reason of selecting primary store			
Price, %	55.5	55.4	55.9
Proximity, %	50.9	51.5	49.9
Primary Store			
Travel distance in miles*, mean (SD)	5.1 (0.6)	2.8 (0.1)	9.6 (1.1)
Perceived travel time in minutes*, mean (SD)	11.0 (0.6)	8.7 (0.2)	15.4 (1.0)
Type of primary store utilized*, %			
Supermarket	49.1	54.4	39.3

Characteristics	All n=3,379	Urban n=2,443	Rural n=936
Supercenter	46.0	42.0	53.5
Other	4.9	3.7	7.2
Transportation mode*, %			
Own vehicle	88.7	85.9	94.2
Someone else's car/public transportation/bicycle/walk	11.3	14.1	5.8
Alternative Store			
Travel distance in miles, mean (SD) *	5.4 (0.5)	3.0 (0.2)	10.0 (1.0)
Type of alternative store utilized, %			
Supermarket	43.9	44.9	42.1
Supercenter	46.0	46.2	45.7
Other	10.1	8.9	12.2
Community Food Sources			
Shop at a farmers market*, %	57.4	54.2	63.4
Acquire food at food bank or pantry, %	3.4	3.7	2.9

*Indicates significant difference by urbanicity. Continuous variables were analyzed via ANOVA, and categorical variables were analyzed via chi-square test. FPG: Federal Poverty Guidelines.

FPG: Federal Poverty Guidelines.

Table 5.2 Fit statistics for unconditional latent class analysis model of eight food acquisition and shopping measures of 3,379 participants in the 2012-2013 interview from the Food Acquisition and Purchase Survey (FoodAPS)

No. of classes	Likelihood	Bayesian Information Criteria	Akaike Information Criteria	Entropy R^2	No. Parameter	Classification Errors	Bootstrap likelihood ratio test*
2	-16236.97	32644.58	32515.95	0.81	21	0.04	--
3	-16152.36	32564.73	32368.72	0.65	32	0.12	<0.01
4	-16121.06	32591.50	32328.12	0.61	43	0.19	0.41
5	-16094.35	32627.47	32296.70	0.58	54	0.24	0.59

*P value for k-class vs. (k+1) - class solution

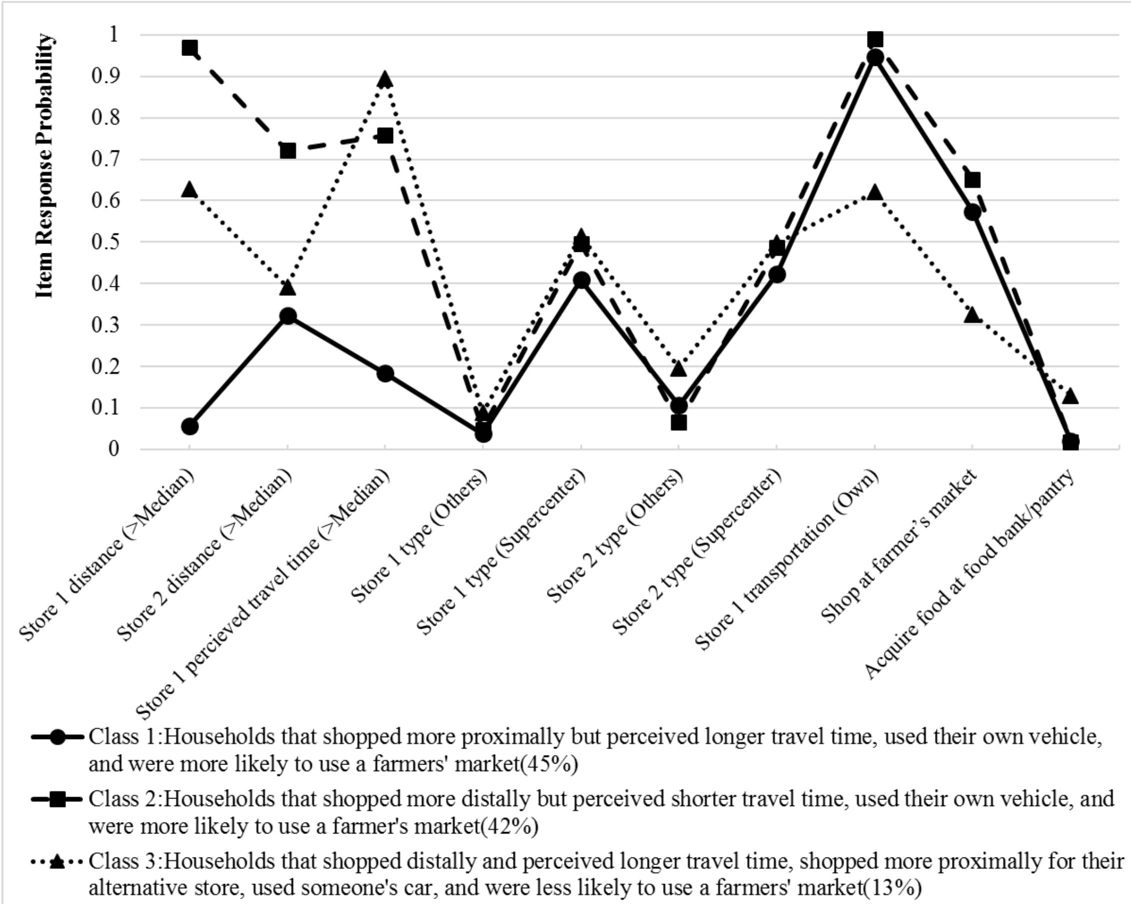

Figure 5.1 Probability of latent class membership and item-response probabilities of retained unconditional three-class solution of 3,379 participants in the 2012-2013 interview from the Food Acquisition and Purchase Survey (FoodAPS)

Table 5.3 Fit statistics for unconditional latent class analysis model of eight food acquisition and shopping measures by urbanicity of 3,379 participants in the 2012-2013 interview from the Food Acquisition and Purchase Survey (FoodAPS)

No. of classes	Likelihood	Bayesian Information Criteria	Akaike Information Criteria	Entropy R^2	No. Parameter	Classification Errors	Bootstrap likelihood ratio test*
Urban							
2	-11906.65	23977.11	23855.29	0.92	21	0.01	--
3	-11815.88	23881.39	23695.76	0.65	32	0.14	<0.01
4	-11784.52	23904.48	23655.04	0.57	43	0.21	0.37
5	-11764.04	23949.32	23636.07	0.58	54	0.20	0.76
Rural							
2	-4237.65	8618.97	8517.30	0.84	21	0.04	--
3	-4196.72	8636.38	8481.45	0.85	32	0.05	0.39
4	-4165.72	8642.11	8433.92	0.78	43	0.10	0.06
5	-4147.06	8663.58	8402.13	0.78	54	0.12	0.12

*P value for k-class vs. (k+1) - class solution

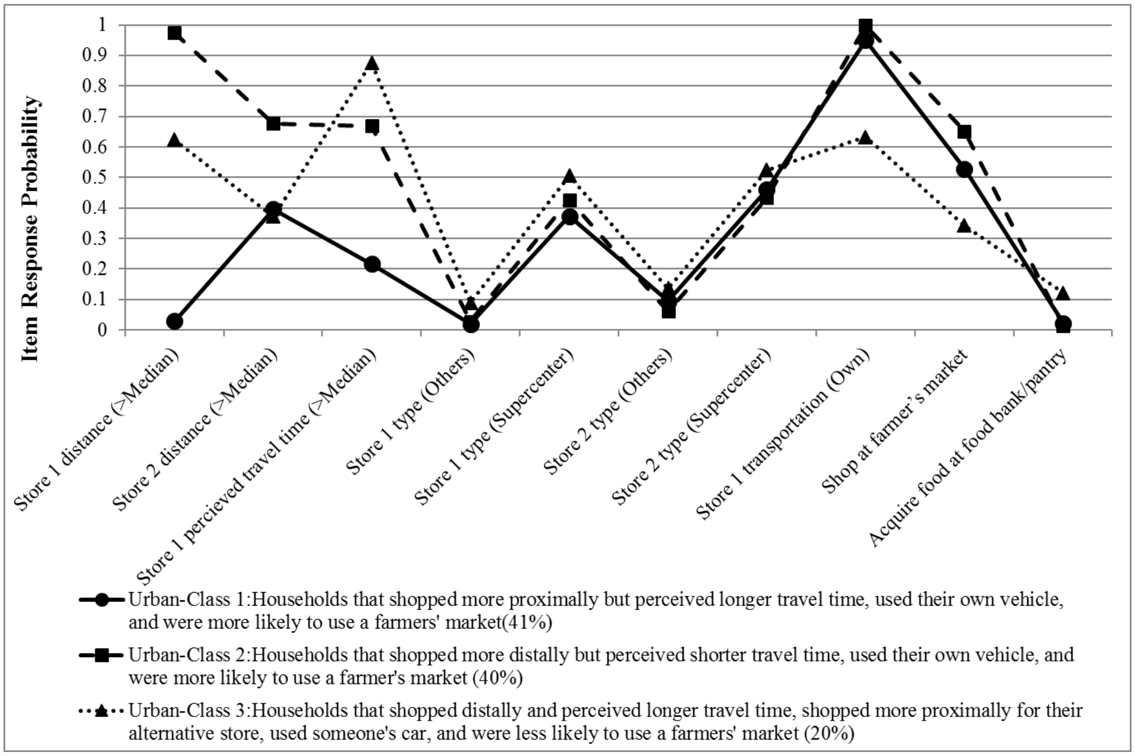

Figure 5.2 Probability of latent class membership and item-response probabilities of retained unconditional three-class solution for urban and two-class solution for rural of 3,379 participants in the 2012-2013 interview from the Food Acquisition and Purchase Survey (FoodAPS)-Urban

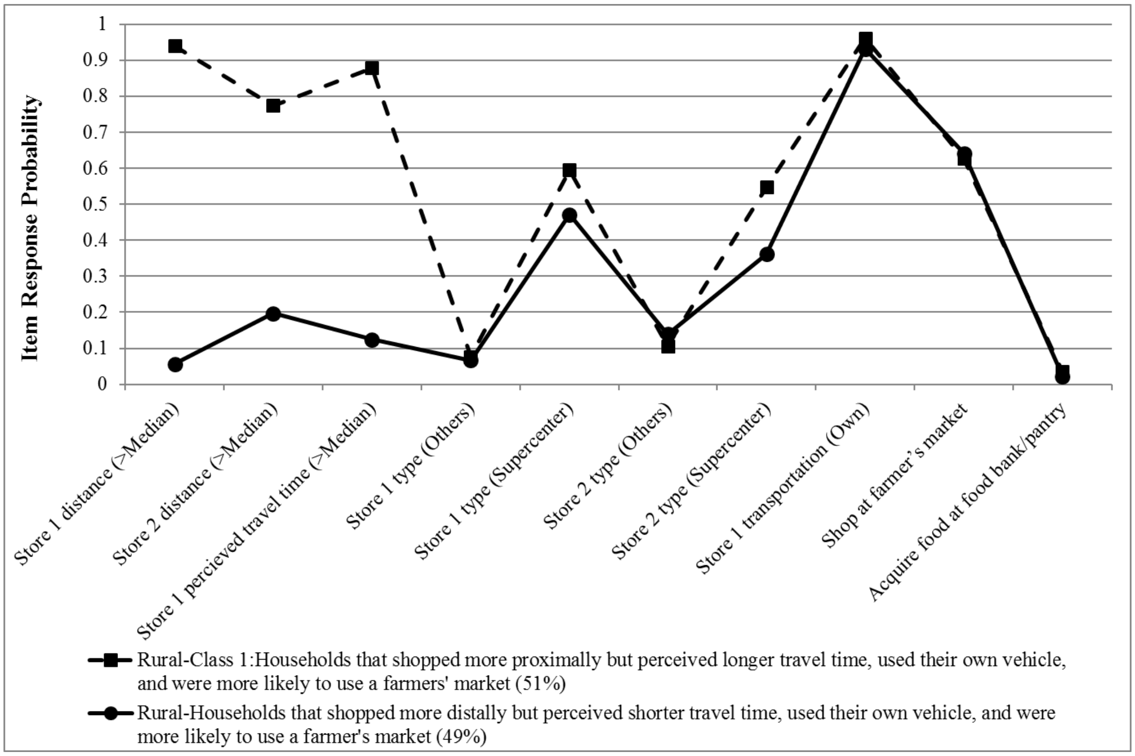

Figure 5.3 Probability of latent class membership and item-response probabilities of retained unconditional three-class solution for urban and two-class solution for rural of 3,379 participants in the 2012-2013 interview from the Food Acquisition and Purchase Survey (FoodAPS)-Rural

Table 5.4 Differences in socioeconomic characteristics, nutrition knowledge, and store selection reasons between identified food acquisition and shopping patterns by urbanicity of 3,379 participants in the 2012-2013 interview from the Food Acquisition and Purchase Survey (FoodAPS)

Characteristics	Urban Class 1	Urban Class 2	Urban Class 3	Rural Class 1	Rural Class 2
SNAP participation status[+]					
Non-SNAP, income <185% FPG, % [Ub]	12.2	12.1	36.7	15.7	19.9
SNAP participation,% [Uabc]	12.7	5.8	35.2	13.1	10.1
Food insecure,% [Uac]	15.3	7.4	42.1	15.0	11.6
Education[+]					
High school education,%	19.8	16.9	2.9	26.1	36.9
Less than high school education, % [Ubc]	8.9	2.5	31.2	11.1	6.5
Annual household income[+]					
Between $20,000 and $50,000,%	30.0	23.0	19.8	35.1	30.1
Less than $20,000, %	19.8	16.7	61.6	24.2	25.0
Unemployed, % [Ub]	36.2	33.1	66.8	48.8	53.7
Household size, mean[Ubc; Ra]	2.6	2.7	2.1	2.3	2.4
No nutrition knowledge[*],%	34.3	37.7	46.5	42.8	42.2
No nutrition awareness[*],%	59.2	58.3	83.3	66.2	67.7
Store selection-price,% [Ub]	44.4	57.9	72.5	55.6	56.2
Store selection-proximity,% [Uabc; Ra]	69.3	46.4	25.5	56.1	43.9

[+] Reference of SNAP participant status is "non-SNAP, income ≥185% FPG"; reference of education is "above high school"; reference of income is "≥50,000 annual household income".

[*] No nutrition knowledge or awareness is defined by only measures included in the current study. Model adjusts for age, gender, and race/ethnicity. Detailed parameter estimation can be found in **Appendix G**.

[U] stands for urban; [R] stands for rural.

[a] is for significant difference in the prediction of class membership between Class 1 and Class 2 using multinomial logistic regression for urban and ordinary logistic regression for rural;

[b] is for significant difference in the prediction of class membership between Class 1 and Class 3 using multinomial logistic regression;

[c] is for significant difference in the prediction of class membership between Class 2 and Class 3 using multinomial logistic regression.

Chapter 6. Association between Food Acquisition and Shopping Patterns and BMI: Results from FoodAPS[3]

[3] Ma, X., Bell, B.A., Liu, J., White, K., and Liese, A.D. To be submitted to *American Journal of Public Health.*

Abstract

Background: The prevalence of obesity increased rapidly during the last decades of the 20^{th} century and continues to be high, but the rate of increase has recently slowed in the US. Previous studies examined the association between food shopping habits and obesity with a focus on distance to the food store, shopping frequency, and type of store selected. No study examined the association using an integrated measure of food acquisition and shopping habits. Thus, the purpose of the current study was to use an integrated measure of food acquisition and shopping habits and examine its relationship with body mass index (BMI).

Methods: The US Food Acquisition and Purchase Survey (FoodAPS) recruited 4,826 households between April 2012 and January 2013. Participants were interviewed about their means of food acquisition and shopping habits at their primary and alternative stores during an in-person interview. From LCA, three classes for urban households and two classes for rural households were identified using eight measures of food acquisition and shopping. Multivariable linear regression was used to assess the association between the identified patterns and BMI by urbanicity adjusting for sociodemographic information.

Results: Overall, 65.2% (weighted percentage) households were located in an urban tract, and 34.8% (weighted percentage) were located in a rural tract. Forty-four percent of urban households were categorized as Class 1 (Households that shopped more proximally but perceived longer travel time, used their own vehicle, and were more likely to use a farmers' market). Forty-four percent of urban households were categorized as Class 2 (Households that shopped more distally but perceived shorter travel time, used

their own vehicle, and were more likely to use a farmer's market). Twelve percent of urban households were categorized as Class 3 (Households that shopped distally and perceived longer travel time, shopped more proximally for their alternative store, used someone's car, and were less likely to use a farmers' market). Among rural households, 49% were Class 1 and 51% were Class 2 (Class 3 was not identified among rural households). Among rural households, the proportion of participants in Class 2 was higher in the obese group than the non-obese group. For urban households, participants in Class 3 has significantly higher BMI (b=1.23, *p*-value=0.03) than those in Class 1 before adjusting for other covariates. However, after adjusting for sociodemographic variables and self-reported health status, the association was not statistically significant. No significant association was found for rural households.

Conclusion: Food acquisition and shopping patterns were not associated with BMI among this large sample after adjusting for sociodemographic characteristics. However, the current study contributes to the literature in that it documents the association between food acquisition and shopping patterns and BMI by urbanicity. Future studies should also investigate how store food prices and shopping frequency interact with the current food acquisition and shopping patterns and their relationship with BMI.

Introduction

The prevalence of obesity increased rapidly during the last decades of the 20th century and continues to be high, but the rate of increase has recently slowed in the US. [35,36,199] Obesity occurs within a complex framework of interrelated factors. The prevalence of preventive behaviors to achieve energy balance, such as regular physical activity and a healthy diet, lags far behind the Healthy People 2010 objectives for the nation as a whole. [6] Neither medical nor educational and behavioral approaches have been sufficient to stem the rapid rise in population obesity, nor has significant progress been achieved in eliminating health disparities in obesity. [5,7,200] In light of the modest and short-term successes of individually focused strategies, [8-13] the influence of the built environment has drawn increasing attention. In epidemiological studies, associations have been studied between healthy food access and obesity.[12,14-18] A review of neighborhood food access in the US found that in general, neighborhood residents who have better access to supermarkets and limited access to convenience stores have healthier diets and lower levels of obesity. [19] However, not all studies have found an association between the food environment and body weight. [113]

Public health–oriented research on food shopping habits is a relatively new area of inquiry. Food shopping is an interaction of the individual with his/her food environment and has a multidimensional nature. [34] Although some previous studies have described food shopping with respect to the actual distance traveled to the primary store, shopping frequency, and store type utilized, [21,23-25,30,31,103,119-121] very few studies have incorporated multiple dimensions of shopping habits simultaneously. [32,147] Food shopping is a complex behavior that can be characterized by various factors. Stern et al. employed cluster analysis and found three classes, including those who shop primarily at grocery chain stores, those who shop primarily at mass-merchandiser shoppers, and those who use a mixture of different store types. [147] VanKim and colleagues used information on what items were purchased (e.g., fruits and vegetables), as well as frequency of shopping, type of purchasing location, and food and beverage purchases on or off campus or from vending machines, to identify food shopping patterns using LCA and defined eight classes among a sample of college students. [32] These new applications of pattern techniques are promising tools to describe the complex nature of food acquisition and shopping habits in epidemiological studies.

We previously identified food acquisition and shopping patterns by the application of pattern techniques using the national Food Acquisition and Purchase Survey (FoodAPS) data and found three patterns in urban households and two in rural households. Here we aimed to examine the relationship of these food acquisition and shopping patterns with obesity.

Methods

Study Population and Settings

We conducted a cross-sectional analysis of the 2012-2013 FoodAPS data, which includes 4,826 households (with 14,317 members). [127,162] FoodAPS collected comprehensive data about household food purchases and acquisitions for consumption at home and away from home and is the first nationally representative survey of American households on this topic via in-person interview. The FoodAPS sample of households was selected using a multistage sample design. First, Primary Sampling Units (PSUs) defined as counties or groups of contiguous counties were selected before sampling, Then, within each of the PSU, eight secondary sampling units (SSU) (comprised a census block group (CBG) or a group of contiguous block group if CBG was expected to contain fewer than 50 survey-eligible household) were selected. Finally, 20,084 commercial list of addresses paired with a list of SNAP addresses were selected to be screened. This selected list of addresses was further screened via a two-phase sampling approach to reduce the potential non-response bias. The Phase 1 screening removed the addresses that appeared to be occupied but no response after at least eight attempt by field interviewer. Phase 1 screening left 4,814 households. For Phase 2 screening, 138 randomly selected addresses were released, and ten additional contact attempts were made. The effort resulted in 12 completed case that were added to the 4,814 addresses. Finally, 4,826 households were selected for following two in-person and three telephone interviews. [163] Surveys were filled out between April 2012 and January 2013. The study population was sampled from households receiving assistance from the Supplemental Nutrition Assistance Program (SNAP), low-income households not participating in SNAP, and higher-income households. [163] FoodAPS also aimed to investigate how the local food environment affects food spending patterns in the US, so the study included a geographic component. The urbanicity of each household's residential location was decided according to participant geographic location in relation to the census tract using the Census Bureau's urbanized area definitions. A census tract was defined as urban if the geographic centroid of the tract was in an area with more than 2,500 people; all other tracts were considered rural. [194] The weighted average of responses in Phases 1 and 2, the FoodAPS screener response rate was 70.9%, and the overall study response rate was 415%. [162]

Exposure: Food Acquisition and Shopping Habits Measures and Identified Patterns

Detailed information about the food acquisition and shopping habit measures has been described previously. [201] In brief, eight measures of food acquisition and shopping habits (i.e., travel distances between residential location and primary and alternative stores, perceived travel time to primary store, store type, transportation mode to primary store, and utilization of farmers' markets and food banks or pantries) were used in the food acquisition and shopping pattern analysis using LCA in LatentGOLD version 5.1. All food acquisition and shopping information was collected during two in-person interviews at the beginning and end of the data collection week. Three classes were identified for urban households and two for rural households [201], with the first two classes being very similar between the urban and rural groups. Class 1 comprised households that shopped more proximally but perceived longer travel time, used their own vehicle/bike or walked, and were more likely to use a farmers' market, and Class 2 comprised households that shopped more distally but perceived shorter travel time, used their own vehicle/bike or walked, and were more likely to use a farmers' market. Class 3 comprised households that shopped distally and perceived farther travel to their primary store, shopped more proximally for their alternative store, utilized someone else's car or public transportation, and were less likely to utilize a farmers' market. Class 1 was used as the reference group for both urban and rural households.

Outcome: Body Mass Index (BMI)

BMI was calculated by dividing self-reported body weight in kilograms by height in meters squared. BMI was categorized into underweight or normal (if $BMI<25.00$ kg/m^2), overweight (if $25.00\ kg/m^2 \leq BMI < 30.00\ kg/m^2$), and obese (if $BMI \geq 30.00$ kg/m^2) according to the World Health Organization (WHO) standard. [164]

Covariates

Demographic information was queried during the two in-person interviews at the beginning and end of the data collection week, including age, gender, and race/ethnicity. Self-reported health status was reported during the in-person interview, including five categories (excellent, very good, good, fair, and poor). Socioeconomic characteristics of interest in the study included participation in a food assistance program (such as SNAP), food security, education, household annual income, and employment. Because the sampling of the households was based on a stratification of participants on SNAP participation and total household income, SNAP participation status could be determined from the designated sampling eligibility. Food security was assessed by in-person interview using the validated 10-item USDA US-Household Food Security Survey Module. [185] Participants were classified as having high food security (0 affirmative responses), marginal food security (1 to 2 affirmative responses), low food security (3 to 7 affirmative responses), or very low food security (≥8 affirmative responses) [163] and were further grouped into food secure (including high food security and marginal food security) and food insecure (including low food security and very low food security). Education was assessed by the question "what is the highest level of school (you/NAME) completed or the highest degree (you/NAME) received?" [195] and was then regrouped into three classes in the current analysis, including high school and below, high school, and above high school. Monthly household income was queried by a variety of questions and included income from work, unemployment compensation, welfare, child support or alimony, and retirement and disability income. [196] Employment status was queried by the question "which of the following (working at a job or business, with a job or business but not at work, looking for work, not working at a job or business, refused, or unknown) (were you/ was NAME) doing last week?" [196] and was recoded into employed (including "working at a job or business (52.1%)" and "with a job or business but not at work (3.3%)") and unemployed (the remaining categories (44.6%)).

Statistical Analyses

Descriptive analyses were performed by urbanicity and obesity status. Food acquisition and shopping patterns were developed previously via LCA using LatentGOLD software. [201] In brief, latent classes were identified using measures of food acquisition and shopping habits, and then participants were assigned to latent classes using their posterior class membership probabilities. Finally, three classes in urban households and two classes in rural households were identified by comparing model fit statistics (i.e., Bayesian information criterion (BIC)). [201] The covariates were adjusted in the analysis including age (continuous), gender (categorical), race/ethnicity (categorical), marital status (categorical), education (categorical), income (continuous), SNAP-receiving status (categorical), food security (categorical), and health status (categorical). For the continuous BMI, multiple linear regression models (MLRM) were fitted first. For categorical BMI, multinomial logistic regression models were fitted. The detailed model adjustments for both MLRMs and multinomial logistic regression models were: 1) adjusting for age, sex, and race/ethnicity; 2) additionally adjusting for marital status, education, income, and employment; 3) additionally adjusting for SNAP-receiving status and household food security status; and 4) additionally adjusting for health status. Descriptive and regression analyses were run in SAS version 9.4. [187] Survey procedures were used which took into consideration of the complex sampling scheme. Domain analysis were employed to maintain the sampling structure when stratify by urbanicity.

Results

Characteristics of the household primary food shoppers by obesity status and urbanicity are summarized in **Table 6.1**. The prevalence of obesity among this population was 33% (weighted percentage) in urban households and 36% (weighted percentage) in rural households. For urban households, most of the primary shoppers were female (69%), non-African American (84%), reported good health status (excellent, very good, or good) (83%), and were 48 years old on average, and 44% were currently married. Most of these shoppers had above a high school level of education (69%) and were employed (59%), and nearly half had an annual household income more than $50,000 (48%). Fourteen percent participated in SNAP, and 5% had an income level less than 100% of the federal poverty guidelines (FPG) but were not participating in SNAP. Ten percent experienced low food security, and 7% experienced very low food security. Additionally, the obese group had a higher proportion of respondents who were African American (23% vs. 13%), had self-reported poorer health (29% vs. 12%), participated in SNAP (21% vs. 11%), and experienced food insecurity (24% vs. 14%) compared to the non-obese group.

For rural households, most of the primary shoppers in the households were female (73%), non-African American (93%), reported good health status (excellent, very good, or good) (84%), and were 53 years old on average, and 48% were currently married. Most of these respondents had more than a high school level of education (60%), and 43% had an annual household income more than $50,000. Twelve percent participated in

SNAP, and 4% had an income level less than 100% of the FPG but did not participate in SNAP. Eight percent were low food security, and 5% were very low food security. Additionally, the obese group had a higher proportion of respondents who were African American (12% vs. 4%), had an annual household income below $50,000 (64% vs. 53%), had self-reported poorer health (24% vs. 13%), and participated in SNAP (16% vs. 9%) compared to the non-obese group.

The distribution of food acquisition and shopping patterns are additionally shown in the **Table 6.1**. Forty-four percent of urban households were categorized as Class 1 (households that shopped more proximally but perceived longer travel time, used their own vehicle/bike or walked, and were more likely to use a farmers' market). Forty-four percent of urban households were categorized as Class 2 (households that shopped more distally but perceived shorter travel time, used their own vehicle/bike or walked, and were more likely to use a farmers' market). Twelve percent of urban households were categorized as Class 3 (households that shopped distally and perceived longer travel time, shopped more proximally for their alternative store, utilized someone else's car or public transportation, and were less likely to utilize a farmers' market). The proportion of urban respondents categorized as Class 1 or Class 3 was slightly higher in the obese group than in the non-obese group. Among rural households, 49% were Class 1 and 51% were Class 2 (Class 3 was not identified among rural households). The proportion of respondents in Class 2 was higher in the obese group than in the non-obese group.

Table 6.2 presents results from a sequential set of linear models relating food acquisition and shopping patterns to BMI. For urban households, participants categorized as Class 3 had significantly higher BMI (b=1.23, *p*-value=0.03) than those in Class 1 before adjusting for other characteristics. However, after adjusting for age, gender, and race/ethnicity, the association was not significant. The association remained insignificant after adjusting for sociodemographic variables and self-reported health status. No significant associations were found between Class 2 and Class 1 for urban or rural households in terms of BMI outcome.

From the least squares means, BMI was generally lower among respondents in Class 2 (households that shopped more distally but perceived shorter travel time, used their own vehicle/bike or walked, and were more likely to use a farmers' market) than those in Class 1 (households that shopped more proximally but perceived longer travel time, used their own vehicle/bike or walked, and were more likely to use a farmers' market), but this difference was not statistically significant; BMI was generally higher among respondents in Class 3 (households that shopped distally and perceived longer travel time, shopped more proximally for their alternative store, utilized someone else's car or public transportation, and were less likely to utilize a farmers' market) than those in Class 1, except in model 4. BMI become more and more similar across classes after adjusting for sociodemographic information and health status. For rural households, BMI was higher among respondents in Class 2 than those in Class 1, but this difference was not statistically significant.

Table 6.3 shows the association from a sequential set of multinomial logistic regression model between the identified food acquisition and shopping patterns and categorical BMI. Also, we did not find any significant associations between the identified patterns and categorical BMI in unadjusted and multivariate analyses.

Discussion

This study examined the association between BMI and an integrated measure of food acquisition and shopping habits separately among urban and rural households in a nationally representative sample. Overall, this association was not significant for either urban or rural households after adjusting for sociodemographic characteristics.

To our knowledge, there is no study with which we can directly compare our results. However, when we break down the current food shopping and acquisition patterns into their determinants, we are able to compare our findings with some previous literature. [23,25,121] Shopping distance, perceived travel time to stores, transportation (for urban households only), and use of a farmers' market (for urban households only) were key factors that defined the food acquisition and shopping patterns of this nationally representative population. For shopping distance, all three classes differ in terms of travelling distance to the primary and alternative stores, and the null associations with BMI were consistent with previous literature. [23,25,121] Considering our findings with the additional the role of transportation, our study is consistent with that of Fuller et al., [121] who found that shopping distance was not significantly associated with BMI for any mode of transportation (car, public transit, or multiple modes). [121] The interaction between shopping distance and transportation explored in that study is, to some extent, similar to the idea we used to develop the food acquisition and shopping patterns. Thus, our findings add evidence to the obesity literature that confirms the null relationship with shopping distance, even when adjusting for transportation mode (own vehicle/bike or walk, or use someone else's car or public transportation). The relationship between utilization of a farmers' market and BMI was mixed. Our null findings between the food acquisition and shopping patterns and BMI are consistent with the study by Jilcott Pitts et al. (2014), who reported that shopping at a farmers' market was not associated with BMI; [202] however, our findings are contrary to the findings of an inverse association between access to a farmers' market and obesity in an ecologic study [203] and among eastern North Carolina children from rural and urban areas [204].

The prevalence of obesity was 33% and 36% among urban and rural households in this study, respectively. Befort et al. previously reported obesity prevalence of 33% (the same as FoodAPS) and 40% (higher than FoodAPS) in urban and rural populations using the NHANES survey. [205] Compared to the food acquisition and shopping habits among urban households, rural households traveled farther for both their primary (9.6 miles for rural vs. 2.8 miles for urban) and alternative (10.0 miles for rural vs. 3.0 miles for urban) shopping and perceived a longer travel time to their primary store (15.4 minutes for rural vs. 8.7 minutes for urban). [201] The shopping distance in urban FoodAPS households was similar to that in a study conducted in an urban setting in a Pittsburgh food desert (3.0 miles); [124] no rural study was found with which to compare our results. However, the difference in shopping distance between urban and rural households did not translate to different associations with BMI. There was no previous study using a nationally representative dataset exploring a similar association to which we can compare. Compared with previous regional studies, our study is consistent with Jilcott Pitts et al., which found no association between shopping distance and BMI in a small urban area of eastern North Carolina, [119] but is counter to Dubowitz et al., which found that farther shopping distance was associated with higher BMI in an urban food desert in Pittsburgh. [206] We found no previous studies to with which to compare our association between shopping distance and BMI in a rural population. Thus, our study by urbanicity contributes to the literature in this theme.

This study has some limitations. The FoodAPS survey did not explicitly query food shopping frequency for the primary and alternative stores, which was a significant factor that differentiated the food acquisition and shopping patterns in a study we conducted in South Carolina. [207] Thus, we are unable to determine what role food shopping frequency plays in this general population and how that factor influences the patterns and association with BMI. In addition, BMI were calculated using self-reported weight and height, these measures could result in social disability bias. In our analysis, we excluded those who have missing values, and the majority of missing was from missing of alternative store information when developing the food acquisition and shopping patterns. We compared the characteristics between those included and those excluded. The only significant difference was the current analytical sample had a significant higher proportion of females. The prevalence of obesity was high among women [3,36], thus, including more males would not change the current null association between food acquisition and shopping patterns. However, deleting those missing could influence the representativeness. Other limitations pertain to the public version of the FoodAPS dataset. We were unable to link a subset of the participants whose utilized primary and alternative stores were surveyed by IRI with information from the Thrifty Food Price Index in the publicly released FoodAPS data. Literature has pointed to store food price being significantly associated with obesity. [23,120,124] The role of food price at the utilized store was unknown and was not taken into account when defining the patterns in current study; thus, we were unable to examine its relationship with BMI.

There is a methodological issue in classifying participants into classes that should be noted. The parameter estimates of the association between food acquisition and shopping patterns and BMI could be biased because of classification errors when assigning participants to classes. [188] Specifically, the predicted latent scores (random variables) were used as observed variables (constants), which results in underestimation of the true standard errors of the parameters. [208] However, we prefer this approach because it is more intuitive and allows us to run any complex analysis needed using other software such as SAS.

A strength of our study is that we examined identified food acquisition and shopping patterns and BMI among a nationally representative population. Thus, our study differs from previous studies [207] in that we used multidimensional aspects of food acquisition and shopping and integrated them into one condensed measure to describe complex food acquisition and shopping habits among the general population, and further explored the pattern by urbanicity.

Conclusion

Food acquisition and shopping patterns were not associated with BMI or obesity defined by BMI among this nationally representative sample after adjusting for sociodemographic characteristics. However, the current study contributes to the literature in that it documents the association between food acquisition and shopping patterns and BMI by urbanicity. Future studies should investigate how store food prices and shopping frequency interact with the current food acquisition and shopping patterns and their relationship with BMI as current study was unable to investigate.

Table 6.1 Demographic and socioeconomic characteristics and food acquisition and shopping habits by obesity and by urbanicity of 3,379 participants in the 2012-2013 interview from the Food Acquisition and Purchase Survey (FoodAPS)

	Urban				Rural			
Characteristics	**All n=2,443**	**Non-obese n=1,539**	**Obese n=904**	**p**	**All n=936**	**Non-obese n=575**	**Obese n=361**	**p**
Age, mean (SD)	48.1 (0.7)	47.5 (0.9)	49.5 (0.8)	0.12	53.1 (0.8)	52.9 (0.8)	53.4 (1.4)	0.74
Female, %	69.1	69.1	69.0	0.95	73.0	73.9	71.4	0.65
Race/Ethnicity, %				<.01				--
White	68.3	70.8	63.1		89.2	92.6	83.3	
Black	15.9	12.5	22.9		6.9	4.1	11.8	
American Indian/Alaska native	0.6	0.4	0.9		0.4	0.1	1.1	
Asian/Native Hawaiian/Other Pacific islander	6.7	8.4	3.3		0.4	0.6	0.0	
Others/Multiple race	8.5	7.9	9.7		3.0	2.5	3.8	
Marital status, %				0.54				0.91
Ever married	27.4	26.4	29.5		31.8	31.4	32.6	
Married	44.3	44.6	43.6		48.3	48.1	48.8	
Never married	28.4	29.0	27.0		19.9	20.6	18.6	
Self-reported health status, %				<.01				<.01
Excellent	14.4	18.5	6.0		13.9	17.2	8.0	
Very good	32.2	36.2	24.0		37.3	41.5	29.9	
Good	36.2	33.5	41.5		32.3	28.9	38.3	
Fair	14.7	10.2	23.7		13.1	10.5	17.7	
Not good	2.6	1.5	4.8		3.5	2.0	6.2	
Education, %				<.01				0.28
Below high school	10.4	9.5	12.2		8.7	7.6	10.7	
High school	20.4	17.6	26.1		31.6	31.0	32.7	
Greater than high school	69.2	73.0	61.7		59.7	61.4	56.5	
Annual household income, %				<.01				0.11
$0–9,999	14.1	14.9	12.6		11.3	11.1	11.5	
$10,000–19,999	12.8	11.6	15.1		13.4	13.0	13.9	
$20,000–29,999	10.0	8.6	12.7		12.4	9.2	17.8	
$30,000–39,999	8.1	6.7	11.0		10.5	9.7	12.0	
$40,000–49,999	7.1	7.4	6.5		9.7	10.4	8.3	
$50,000 or more	47.9	50.8	42.1		42.8	46.5	36.3	
Mean income (SD)	60,266 (3,343)	64,180 (4,310)	52,275 (2,850)	0.01	52,625	57,196	4,4527	<.01

Characteristics	Urban All n=2,443	Urban Non-obese n=1,539	Urban Obese n=904	Urban p	Rural All n=936	Rural Non-obese n=575	Rural Obese n=361	Rural p
					(2,739)	(3,419)	(2,864)	
Employment				0.95				0.76
Not employed	41.0	41.1	40.9		51.4	51.6	50.8	
Employed	59.0	58.9	59.1		48.7	48.4	49.2	
SNAP participation, %				<.01				<.01
Non-SNAP household, income <100% FPG	5.2	5.5	4.6		4.0	3.6	4.7	
Non-SNAP household, 100% =<income <185% FPG	11.8	11.6	12.3		13.9	13.6	14.3	
Non-SNAP household, income >=185% FPG	68.5	71.7	62.0		70.6	73.7	65.1	
SNAP household	14.4	11.2	21.1		11.5	9.1	15.9	
Food Security				<.01				0.08
Food security	66.2	71.3	55.8		74.7	77.3	70.1	
Marginal food security	16.3	14.4	20.2		12.0	9.7	16.2	
Low food security	10.3	8.2	14.6		8.3	8.9	7.1	
Very low food security	7.2	6.1	9.4		5.0	4.1	6.6	
Food shopping pattern, %				<.01				0.23
Class 1 (Households that shopped more proximally but perceived longer travel time, used their own vehicle, and were more likely to	43.9	43.4	44.8		48.7	50.4	45.5	

Characteristics		Urban All n=2,443	Urban Non-obese n=1,539	Urban Obese n=904	p	Rural All n=936	Rural Non-obese n=575	Rural Obese n=361	p
	use a farmers' market)								
Class 2	(Households that shopped more distally but perceived shorter travel time, used their own vehicle, and were more likely to use a farmer's market)	44.4	45.8	41.5		51.3	49.6	54.5	
Class 3	(Households that shopped distally and perceived longer travel time, shopped more proximally for their alternative store, used someone's car, and were less likely to use a farmers' market)	11.8	10.8	13.7		--	--	--	

Table 6.2 Associations between identified food shopping pattern and obesity from the linear regression model by urbanicity of 3,379 participants in the 2012-2013 interview from the Food Acquisition and Purchase Survey (FoodAPS)

Food acquisition and shopping pattern	**Urban n=2,443**					**Rural n=936**				
	b	**SE**	**P**	**LS-Means (Kg/m²)**		**b**	**SE**	**P**	**LS-Means (Kg/m²)**	**R^2**
Raw Model					0.006					0.001
Class 1	Ref.			27.99		Ref.			28.15	
Class 2	-0.37	0.38	0.33	27.62		0.37	0.6	0.55	28.52	
Class 3	**1.23**	**0.54**	**0.03**	29.22		--	--	--	--	--
Model 1					0.036					0.019
Class 1	Ref.			27.98		Ref.			28.09	
Class 2	-0.47	0.35	0.19	27.51		0.55	0.57	0.35	28.64	
Class 3	0.85	0.57	0.15	28.98		--	--	--	--	--
Model 2					0.046					0.043
Class 1	Ref.			28.17		Ref.			28.29	
Class 2	-0.38	0.36	0.29	28.69		0.44	0.54	0.43	28.74	
Class 3	0.51	0.66	0.44	27.79		--	--	--	--	--
Model 3					0.082					0.070
Class 1	Ref.			28.68		Ref.			28.88	
Class 2	-0.21	0.36	0.27	28.47		0.45	0.58	0.45	29.33	
Class 3	0.05	0.69	0.94	28.74		--	--	--	--	--
Model 4					0.168					0.136
Class 1	Ref.			28.73		Ref.			28.94	
Class 2	0.02	0.31	0.95	28.75		0.43	0.5	0.4	29.38	
Class 3	-0.16	0.67	0.81	28.57		--	--	--	--	--

Detailed labels of classes can be found in **Table 6.1**.

Model 1 adjusted for age, gender, and race/ethnicity;
Model 2: Model 1+ adjusted for marital status, education, income, employment;
Model 3: Model 2 + adjusted for SNAP, food security;
Model 4: Model 3 + adjusted for health status.

Table 6.3 Associations between identified food shopping pattern and obesity from the multinomial logistic regression models by urbanicity of 3,379 participants in the 2012-2013 interview from the Food Acquisition and Purchase Survey (FoodAPS)

	Urban						**Rural**					
	Overweight vs. Underweight/Normal			**Obese vs. Underweight/ Normal**			**Overweight vs. Underweight/Normal**			**Obese vs. Underweight/ Normal**		
	OR	**95%CI**	**P**	**OR**	**95% CI**	**P**	**OR**	**95%CI**	**P**	**OR**	**95% CI**	**P**
Raw Model												
Class 1	Ref.			Ref.			Ref.			Ref.		
Class 2	1.06	0.74-1.52	0.75	0.90	0.67-1.20	0.47	0.86	0.53-1.40	0.52	0.76	0.47-1.24	0.25
Class 3	1.28	0.83-1.97	0.26	1.37	0.92-2.05	0.12	--	--	--	--	--	--
Model 1												
Class 1	Ref.						Ref.			Ref.		
Class 2	1.05	0.73-1.49	0.80	0.84	0.63-1.12	0.22	0.89	0.53-1.47	0.62	0.71	0.46-1.08	0.10
Class 3	1.15	0.72-1.85	0.55	1.15	0.71-1.87	0.55	--	--	--	--	--	--
Model 2												
Class 1	Ref.			Ref.			Ref.			Ref.		
Class 2	1.05	0.73-1.51	0.79	0.86	0.65-1.14	0.28	0.93	0.56-1.56	0.78	0.70	0.46-1.05	0.08
Class 3	1.03	0.62-1.70	0.91	1.03	0.60-1.79	0.90	--	--	--	--	--	--
Model 3												
Class 1	Ref.			Ref.			Ref.			Ref.		
Class 2	1.07	0.74-1.55	0.70	0.91	0.67-1.23	0.53	0.91	0.54-1.53	0.70	0.71	0.47-1.06	0.09
Class 3	0.87	0.53-1.43	0.58	0.93	0.53-1.63	0.80	--	--	--	--	--	--
Model 4												
Class 1	Ref.			Ref.			Ref.			Ref.		
Class 2	1.10	0.78-1.56	0.56	1.02	0.73-1.43	0.90	1.05	0.59-1.87	0.86	0.71	0.46-1.09	0.11
Class 3	0.81	0.48-1.36	0.41	0.88	0.49-1.58	0.66	--	--	--	--	--	--

OR: Odds Ratio; 95%CI: 95% confidence interval. Detailed labels of classes can be found in **Table 6.1**. Model 1 adjusted for age, gender, and race/ethnicity; Model 2: Model 1+ adjusted for marital status, education, income, employment; Model 3: Model 2 + adjusted for SNAP, food security; Model 4: Model 3 + adjusted for health status.

Chapter 7. Summary

In summary, for **Specific Aim 1**, we found three classes of food acquisition and shopping patterns among residents of low-income and low-access communities in South Carolina. Shopping distance, shopping frequency, transportation to primary store, and community food resources such as food bank/pantry, or church/social services are the key factors that define food acquisition and shopping patterns. In the nationally representative population, for **Specific Aim 2**, we found food acquisition and shopping patterns to differ between rural and urban households. Three classes among urban households and two classes among rural households were found in FoodAPS dataset. Shopping distance, perceived travel time to primary store, transportation, and farmers' market utilization (not applicable for rural households) are the key factors that define food acquisition and shopping patterns among this national representative population.

We tried to use similar information to explore food acquisition and shopping patterns among the two distinct datasets which represent a low-income and a general population. Consistent among the two studies is that both shopping distance and transportation play important roles among the two populations in differentiating the food acquisition and shopping patterns. Policy efforts have focused on increasing healthy food access by increasing accessibility, availability, and affordability. However, the role of transportation that interacts with food access should also be considered. Another consistency is that the store type in both datasets did not differentiate food acquisition and shopping patterns. This finding is inconsistent with previous study by Stern et al. [147] which found three clusters using store type information. However, the finding is not comparable with Stern's study in terms of the classification of store type. The current study generally grouped store type into supermarket, supercenter, and other type of stores, while Stern's study focused on the more detailed classification of the store type, and explored the cluster based on store type only.

The inconsistency between **Specific Aim 1** and **Specific Aim 2** is the role of communities' resources and farmers' market utilization. Communities' resources play key roles in shaping food acquisition and shopping patterns among low-income and low-access populations who need more supports from nutrition. In contrast, shopping at a farmers' market seems important in defining the patterns among general urban population. However, the class that was less likely to shop at a farmers' market was characterized by comparatively lower levels of SES among a general population. The seasonal operation of farmers' market or acceptance of food assistance voucher could influence how low SES population uses this food resource. Shopping frequency is another important feature that defined the food acquisition and shopping patterns among the low-income population, while this information is not available in the FoodAPS dataset. Thus, we were unable to compare the role of shopping frequency among the two populations.

Results in both studies suggest that the SES attributes, perceptions, and store selection reasons were associated with distinct food acquisition and shopping patterns among both low-income and general populations. It provides new insights for future intervention aimed at increasing healthy food access.

In **Specific Aim 3**, we examined the association between food acquisition and shopping patterns and BMI among the nationally representative population. No significant association was found. The food and shopping patterns among the FoodAPS population was mainly defined by shopping distance and perceived travel time. In other words, it could be translated into the null association between shopping distance and BMI controlling for sociodemographic covariates and other features of food acquisition and shopping. This finding is consistent with previous studies. [23,25] They suggested economic factor such as store food price could be significant factor that associated with BMI. [23,25] Given the current study's lack of this information, we were unable to determine the role of economic factors in relation with BMI. This limitation provides new insight for future studies. Economic factors need to be included in defining food acquisition and shopping patterns. In addition, how this improvement would influence the association between food acquisition and shopping patterns and BMI should be investigated in future.

Current application of pattern techniques (i.e. LCA) in **Specific Aim 1** and **Specific Aim 2** provides new insights in food acquisition and shopping studies, as well as in epidemiological studies. The technique helps to condense information and finds similarities from a variety of different variables. We demonstrated the possibility of using pattern technique in defining empirical patterns within two datasets, especially in one sample with complex sampling scheme (**Specific Aim 2**). Moreover, we used an innovative step-3 approach to correct systematic bias which could result in underestimating the standard errors in parameter estimation in **Specific Aim 1** and **Specific Aim 2**. However, to run multivariate linear regression models adjusting for covariates using SAS version 9.4 (outside of LatentGOLD software) in **Specific Aim 3**, we used the traditional three-step approach which suffered from bias when assigning participants into classes using the posterior probabilities. We prefer to explore the association using this scenario because it is more intuitive to first build a latent class model (**Specific Aim 2**), and then relate it to BMI (**Specific Aim 3**) with more flexibilities.

The current study has some limitations. First, the cross-sectional nature of design limited the causal inference and it is difficult to establish temporality. Although there are limitations of the nature our study design, a cross-sectional study is still best choice for this early stage of investigation to understand the association with both a low-income and a nationally representative samples. It is extremely labor intense, expensive, and time consuming to conduct a time series study (e.g. cohort) at a national scale. However, because the two datasets are of different scope, composition and started with different aims when designed, it is not surprising that some inconsistency could occur. The South Carolina study results provide information focused only on low-income household, most of whom lived in food desert areas, which is useful for future policy intervention. Moreover, some measurements in the current study have limitations. The frequency measure in the FoodAPS dataset was omitted and measures of food acquisition and shopping patterns only focused on a specific week when the survey conducted. It is possible that the measures are not representative for a normal food and shopping acquisition habits. In addition, the lack of the basket price index data limits our ability to explore food acquisition and shopping patterns with this economic information and to examine its association with BMI.

The present study was the first study, to our knowledge, to identify food shopping patterns using a national dataset. In the current study, we targeted food acquisition and shopping habits measures that were collected on multiple utilized stores, which captured the actual behaviors. Also, we used techniques such as ArcGIS to calculate the travel distance to shopping locations, which provides us a chance to measure real shopping distance. We used a multi-dimensional approach with different information to identify the patterns and characterized the patterns with many other predictors. Moreover, the application of a data-driven approach, latent class analysis, provides ways to classify different kinds of shoppers objectively. This approach is not a priori approach, so it is an empirical measure of food acquisition and shopping patterns. By identifying predictors that influence food acquisition and shopping, it could provide evidence to policy makers and intervene accordingly to increase healthy food access, and increase the chance of consuming those healthy foods. By identifying the subgroup of population with similar food acquisition and shopping habits, and characterizing the population using SES attributes, it will lend support to improve interventions to the most vulnerable population.

Current study has pointed out that considering the store food price was one of the key factors characterized the patterns, especially the class of low-SES. Future studies could improve the current food acquisition and shopping pattern by including the actual store food price information. Current analysis of relationship with food acquisition and shopping patterns focused on obesity, other health outcomes should be considered in future studies. Also, interventions studies on healthy food access could focus on communities' resources' availability, accessibility and affordability among disadvantaged population.

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Appendix A. Variable description

Variables	National Food Acquisition and Purchase Survey (FoodAPS)			South Carolina-specific Food Access and Family Food Shopper Study		
	Variable name	**Measurement**	**Description**	**Variable name**	**Measurement**	**Description**
Food acquisition and shopping habits measurements						
Store 1						
Travel distance	primstoredist_d	Name and address of household's primary food store. Geocoded, and get travel distance using Good Maps API	Continuous: **Dichotomize** into two categories using urban or rural specific median as cutoff points.	sb_dist_store1_t1	What's the name of the store or market where you shopped the most for food?—store 1 Name and address were recorded during the interview. Geocoded, and get travel distance using ArcGIS	Continuous: **Dichotomize** into two categories using mean as cutoff points after winsorizing the varaible.

Travel time	Pirmstore time_d	Name and address of household's primary food store. Geocoded, and get travel distance using Good Maps API	Continuous: **Dichotomize** into two categories using median as cutoff points.	NA	NA	NA
Transportation	primstoretravelmode	Usual means of getting to primary food store	Categorical: 1=Drive own car; 2=Use someone else's car; 3=Someone else drives me; 4=Walk; 5=Bus; 6=Taxi; 7=Ride bicycle; 8=Others **Regroup into**: 0=By car (1,4,7 in above category); 1=Rely on others (2-3, 5-6, 8).	t1store1_tansport	For most of your trips to your most frequent store to shop for food in the past year, what type of transportation did you use most often?	Categorical: 1=Drive your own car, van, truck, or motorcycle; 2=Ride in the car, van, truck, or motorcycle of family or friends; 3=Ride the bus; 4=Take a taxi; 5=Walk; 6=Ride a bicycle. **Regroup into**: 0=By own (1,5-6 in above category); 1=Rely on others (2-4).
Shopping frequency	primstorefreq	How many shopping events happen during the survey week?	Continuous: **Dichotomize** according 1 per week	T1store1_times	Over the past year, how often did you usually shop at store 1?	Continuous: **Dichotomize** according 1 per week

			Among those who shopped in the data collection week.			
Store type	primstoretype	Primary store type classification based the assortment (depth and breadth) of food products available in each store and the range of nonfood items commonly sold in each store grouping.	Categorical: 102=Combination grocery/other; 103=Convenience store; 105=Direct marketing farmer; 106=Dollar store; 107=Farmers market; 111=Grocery store, large; 112=Grocery store, medium; 113=Grocery store. Small; 114=Grocery store, not further specified; 116=Meat /poultry specialty; 117=Military commissary; 118=Non-profit food buying co-op;	T1store1_type	What kind of food store is store 1?	Categorical: 1=Convenience stop; 2=Drugstore/Pharmacy; 3=Dollar variety store; 4=Farmers Market; 5=Food bank or food pantry; 6=Supermarket; 7=Supercenter; 8=Smaller grocery stores; 9=Specialty store; 10=Warehouse club; 11=Others. **Regroup into**: 1=Supermarket (6, 7, and 10 in above category); 2=Others (1-5,8-9, 11)

			119=Pharmacy; 121=Super store; 122=Supermarket; 123=Club store; etc. **Regroup into:** 1=Supermarket (121- 123 in above category) 2=Other (rest categories in above).			
Store 2						
Travel distance	altstoredist_d	Name and address of household's primary food store. Geocoded, and get travel distance using Good Maps API	Continuous: **Dichotomize** into two categories using urban or rural specific median as cutoff points.	sb_dist_store2_t1	What's the name of the store or market there you shopped the second most for food?—store2 Name and address were recorded during the interview. Geocoded, and get travel distance using ArcGIS	Continuous: **Dichotomize** into two categories using mean as cutoff points after winsorizing the varaible.
Travel time	altstoretime_d	Name and address of household's primary food store. Geocoded, and get travel distance	Continuous: **Dichotomize** into two categories using mean as	NA	NA	NA

		using Good Maps API	cutoff points.			
Shopping frequency	altstorefreq	How many shopping events happen in the alternative store during the survey week?	Continuous: **Dichotomize** according 1 per week	T1store2_times	Over the past year, how often did you usually shop at store 2?	Continuous: **Dichotomize** according 2 per month
Store type	altstoretype	Alternative store type classification based the assortment (depth and breadth) of food products available in each store and the range of nonfood items commonly sold in each store grouping.	Categorical: 102=Combination grocery/other; 103=Convenience store; 105=Direct marketing farmer; 106=Dollar store; 107=Farmers market; 111=Grocery store, large; 112=Grocery store, medium; 113=Grocery store. Small; 114=Grocery store, not further specified; 116=Meat /poultry specialty; 117=Military	T1store2_type	What kind of food store is store 2?	Categorical: 1=Convenience stop; 2=Drugstore/Pharmacy; 3=Dollar variety store; 4=Farmers Market; 5=Food bank or food pantry; 6=Supermarket; 7=Supercenter; 8=Smaller grocery stores; 9=Specialty store; 10=Warehouse club; 11=Others. **Regroup into**: 1=Supermarket (6, 7, and 10 in above category);

			commissary; 118=Non-profit food buying co-op; 119=Pharmacy; 121=Super store; 122=Supermarket; 123=Club store; etc. **Regroup into:** 1=Supermarket (121- 123 in above category) 2=Other (rest categories in above).			2=Others (1-5,8-9, 11)
Store 3	No store 3 information in FoodAPS					
Travel distance	NA	NA	NA	sb_dist_store2_t1	What's the name of the store or market there you shopped the third most for food?—store 3 Name and address were recorded during the interview. Geocoded, and get travel distance using ArcGIS	Continuous: **Dichotomize** into two categories using mean as cutoff points after winsorizing the varaible.
Shopping frequency	NA	NA	NA	T1store3_times	Over the past year, how often	Continuous:

					did you usually shop at store 3?	**Dichotomize** according 1 per month
Store type	NA	NA	NA	T1store3_type	What kind of food store is store 3?	Categorical: 1=Convenience stop; 2=Drugstore/Pharmacy; 3=Dollar variety store; 4=Farmers Market; 5=Food bank or food pantry; 6=Supermarket; 7=Supercenter; 8=Smaller grocery stores; 9=Specialty store; 10=Warehouse club; 11=Others. **Regroup into**: 1=Supermarket (6, 7, and 10 in above category); 2=Others (1-5,8-9, 11)
Community food sources						
Food bank or pantry	foodpantry	Household went to a food bank	Categorical: 0=No;	T1other_food bank	Besides the store 1-3, did you or	Categorical: 0=No;

		or food pantry in past 30 days for groceries	1=Yes.		others in your household get food from food bank or food pantry?	1=Yes.
Church or other social services	NA	NA	NA	T1other_church	Whether obtained food from food box or basket from a church or service organization?	Categorical: 0=No; 1=Yes.
Farmers market	farmersmarket	Household ever gets food from a farm stand or farmer's market in season	Categorical: 0=No; 1=Yes.	T1otherFM2013shop1	During the past market season, did you ever shop at any other farmers' market	Categorical: 0=None; 1=Less than once a month; 2=Once a month; 3=Twice a month; 4=Three times a month; 5=Four or more times a month. **Regroup into**: 0=No (0 in above category; 1=Yes (2-5).
Food desert/Non-healthier retailer tract	NA	NA	NA	Fd_UDSA	Food desert or not	Categorical: 0=No; 1=Yes.
Urbanicity	urban	Urban tract or not	Categorical: 0=No; 1=Yes.	Urban	Urban tract or not	Categorical: 0=No; 1=Yes.

SES domain						
Food assistance program	targetgroup	Participation in the Supplemental Nutrition Assistance Program (SNAP) and total reported household income.	Categorical: 1=NonSNAP & FPL<100%; 2=NonSNAP & 100%=<FPL<185%; 3=NonSNAP & FPL>=185% 4=SNAP. **Regroup into:** 1=SNAP (Category 4 in the above) 2=Non SNAP (1-3)	T1fa_snap	During the last, did you or any members of your household receive benefits form the SNAP program?	Categorical: 0=No; 1=Yes.
Food security	adltfscat	10-item USDA's 30-day Adult Food Security Scale	Categorical: 1= 0 affirmative responses, High FS; 2=1-2, Marginal FS; 3=3-5, Low FS; 4=6-10, Very low FS. **Regroup into:** 1=Food-secure (1-2 categories in above);	T1fs_household	18-item USDA Household Food Security Survey Module	Categorical: 1=0 affirmative responses, High FS; 2=1-2, Marginal FS; 3=3-7, Low FS; 4=8+ Very low FS. **Regroup into:** 1=Food-secure (1-2 categories in above);

			2=Food-insecure (3-4).			2=Food-insecure (3-4).
Education	educ	Highest level of school completed or highest degree received.	Categorical: 11=Less than 1^{st} grade; 12=1^{st}, 2^{nd}, 3^{rd}, or 4^{th} grade; 13=5^{th} or 6^{th} grade; 14=7^{th} or 8^{th} grade; 15=9^{th} grade; 16=10^{th} grade; 17=11^{th} grade; 18=12^{th} grade, no diploma; 19=High school grad, with diploma; 20=High school grad, with GED or equivalent; 21=1 or more years of college, no degree; 22=Associated (2-yr) college degree; 23=Bachelor's degree; 24=Master's or	T1education	What is the highest grad or year of school you competed?	Categorical: 1=Never attended school; 2=Grades 1-8; 3=Grades 9-11 (some high school); 4=Grade 12 or GED (high school graduate); 5=College 1 or more years (some college or technical school); 6=College 4 or more years (college graduate with Bachelor's degree); 7=Graduate degree (Masters, Doctorate). **Regroup into:** 1=High school below (1-3 categories in above); 2=High school

			higher degree. **Regroup into:** 1=High school below (11-19 categories in above); 2=High school and above (20-24).			and above (4-7).
Income	incomehh	Total monthly household income	Continuous: **Dichotomize** into two categories using $20,000 as cutoff points.	T1income	Which category does your household's total income fall into?	Categorical: 1=$0 to $9,999; 2=$10,000 to $19,999; 3=$20,000 to $29,999; 4=$30,000 to $39,999; 5=$40,000 to $49,999; 6=$50,000 or more. **Regroup into**: 1=Below $20,000 (1-2 categories in above); 2=$20,000 and above (4-6)
Nutrition domain						
Nutritional awareness	nutrionsearch	In last 2 months, searched internet for nutrition	Categorical: 0=No; 1=Yes.	NA	NA	NA

		information				
Diet knowledge	myplate	Heard of "MyPlate"	Categorical: 0=No; 1=Yes.	T1know_fv	How many servings of fruits and vegetables should a person eat each day for good health?	Continuous: **Dichotomize** into two categories using 5 as cutoff points.
Psychological factors domain						
Store selection reasons	Primstore prices	Primary store has low price/good value	Categorical: 0=No; 1=Yes.	NA	NA	NA
	primstore close	Primary store is close to home	Categorical: 0=No; 1=Yes.	NA	NA	NA
Perception of food and its environment	NA	NA	NA	T1fe_access	How much a problem would you say that lack of access o adequate food shopping in your neighborhood?	Categorical: 1=A very serious problem; 2=A somewhat serious problem; 3=A minor problem; 4=Not really a problem. **Regroup into:** 1=Problem (1-3 categories in above); 2=Not a problem (4).
Demographic variables						

Age	age	Primary responder's age in year	Continuous: **Dichotomize** into two categories using mean as cutoff points.	T1age	Age and date of birth.	Continuous: **Dichotomize** into two categories using mean as cutoff points.
Gender	sex	Primary responder's sex	Categorical: 1=Male; 2=Female.	T1gender	Specify participant gender	Categorical: 1=Male; 2=Female.
Race/Ethnicity	racecat	Primary responder's race	Categorical: 1=White; 2=Black/ African American; 3=American Indian or Alaskan Native; 4=Asian; 5=Native Hawaiian or Other Pacific Islander; 6=Other race; 7=Multiple Races. **Regroup into:** 1=Black (2 category in above) 2=Non-Black (1, 3-7)	T1race	Which one or more of the following would you say best describes your racial identity?	Categorical: 1=American Indian or Alaskan Native; 2=Asian; 3=Black or African American; 4 =Native Hawaiian or Other Pacific Islander; 5=White; 6=More Than One Race. **Regroup into:** 1=Black (3 category in above) 2=Non-Black (1-3, 4-6).
Marital status	marital	Primary responder's marital status	Categorical: 1=Married;	T1maritalstatus	What is your marital status?	Categorical: 1=Married and

			2=Widowed; 3=Divorced; 4=Separated; 5=Never Married. **Regroup into:** 1=Married (1 category in above); 2=Not Married (2-5).			living together; 2=Married, but separated; 3=Divorced; 4=Widowed; 5=Never married; 6=A member of an unmarried couple living together. **Regroup into:** 1=Married (1-2 categories in above); 2=Not Married (3-6)
Health Status	healthstatus	Primary responder's rating of their general health	Categorical: 1=Excellent; 2=Very good; 3=Good; 4=Fair; 5=Poor. **Regroup into:** 1=Good (1-3 categories in above); 2=Not good (4-5)	T1health_status	In general, would you say your health is excellent, very good, fair, or poor?	Categorical: 1=Excellent; 2=Very good; 3=Good; 4=Fair; 5=Poor. **Regroup into:** 1=Good (1-3 categories in above); 2=Not good (4-5)

Appendix B. Food acquisition and shopping measures by classes of 466 participants from disadvantaged communities in a study of food access, food shopping, and food security in South Carolina (2013/2014)

Characteristics	**Class 1**: Those who use community food resources, are infrequent shoppers, and use someone else's car or public transportation when shopping (35%)	**Class 2**: Those who use community food resources and are more frequent and proximal shoppers (41%)	**Class 3**: Those who do not use community food resources and are distal shoppers (34%)
Store 1 distance (> mean), %	41.42	35.1	70.09
Store 2 distance (> mean), %	47.01	37.86	59.91
Store 3 distance (> mean), %	35.54	35.83	44.31
Store 1 frequency (≥ 1 /week), %	14.09	56.59	46.3
Store 2 frequency (≥ 2 /month), %	13.06	99.78	82.08
Store 3 frequency (≥ 1 /month), %	1.41	58.17	38.8
Store 1 type (supermarket), %	92.43	79.73	98.32
Store 2 type (supermarket), %	87.48	75.63	99.12
Store 3 type (supermarket), %	82.64	76.82	86.24
Store 1 transportation (own), %	74.14	56.38	22.73
Shop at farmers' market, %	35.33	50.11	50.59
Acquire food at food bank/pantry	67.72	69.03	0.61
Acquire food at church/social services, %	66.53	68.19	8.25
Store 1 distance, mean (SD)	2.5 (1.8)	2.2 (1.5)	3.4 (1.8)
Store 2 distance, mean (SD)	3.0 (2.2)	2.5 (1.3)	3.2 (1.4)
Store 3 distance, mean (SD)	3.3 (3.5)	2.8 (1.4)	4.4 (6.1)
Store 1 frequency, mean (SD)	0.7 (0.8)	1.6 (1.3)	1.2 (1.0)
Store 2 frequency, mean (SD)	0.2 (0.1)	0.8 (0.6)	0.7 (0.6)
Store 3 frequency, mean (SD)	0.2 (0.1)	0.4 (0.3)	0.4 (0.4)

Appendix C. Associations between socio-economic, nutrition knowledge, and perceptions of food access and identified food acquisition and shopping patterns of 466 participants from disadvantaged communities in a study of food access, food shopping, and food security in South Carolina (2013/2014)

Class 1 vs. Class 2	**b**	**SE**	**Wald**	***P*** *	**OR****
Intercept	0.20	1.09	0.03	0.86	
SNAP participation	0.21	0.33	0.39	0.53	1.23
Marginal food security	0.20	0.52	0.15	0.70	1.22
Low food security	0.21	0.46	0.21	0.65	1.23
Very low food security	0.03	0.48	0.00	0.99	1.03
High school education	-0.07	0.35	0.04	0.84	0.94
Less than high school education	0.29	0.35	0.66	0.42	1.33
Less than $20,000 household annual income	0.64	0.44	2.09	0.15	1.89
Household size	0.00	0.10	0.00	0.99	1.00
Nutrition knowledge in fruit and vegetable intake amount of less than 5 servings per day	0.16	0.32	0.26	0.61	1.18
Perception of lack of access to adequate food shopping in neighborhood as a problem	0.79	0.29	7.50	**<0.01**	2.21
Class 1 vs. Class 3					
Intercept	-1.76	1.18	2.24	0.13	
SNAP participation	0.82	0.41	4.12	**0.04**	2.28
Marginal food security	1.74	0.56	9.58	**<0.01**	5.68
Low food security	1.66	0.54	9.54	**<0.01**	5.27
Very low food security	2.34	0.55	18.21	**<0.01**	10.41
High school education	0.71	0.42	2.80	0.09	2.04
Less than high school education	2.56	0.84	9.27	**0.03**	12.88
Less than $20,000 household annual income	1.52	0.52	8.55	**<0.01**	4.56
Household size	0.01	0.13	0.00	0.94	1.01

Nutrition knowledge in fruit and vegetable intake amount of less than 5 servings per day	0.23	0.48	0.23	0.63	1.25
Perception of lack of access to adequate food shopping in neighborhood as a problem	-0.17	0.49	0.12	0.73	0.84
Class 3 vs. Class 2					
Intercept	2.22	1.31	2.86	0.09	
SNAP participation	-0.62	0.38	2.70	0.10	0.54
Marginal food security	-1.54	0.58	7.06	**<0.01**	0.22
Low food security	-1.45	0.52	7.84	**<0.01**	0.23
Very low food security	-2.32	0.53	18.93	**<0.01**	0.10
High school education	-0.78	0.41	3.68	0.06	0.46
Less than high school education	-2.27	0.81	7.95	**<0.01**	0.10
Less than $20,000 household annual income	-0.88	0.42	4.50	**0.03**	0.41
Household size	-0.01	0.12	0.01	0.93	0.99
Nutrition knowledge in fruit and vegetable intake amount of less than 5 servings per day	-0.06	0.43	0.02	0.88	0.94
Perception of lack of access to adequate food shopping in neighborhood as a problem	0.96	0.46	4.46	**0.04**	2.62

[*] P-value from Wald test. ** OR stands for Odds Ratios.
Multinomial Logistic regression model adjusted for age, gender, and race/ethnicity.

Appendix D. Socio-demographic characteristics between excluded households and included household in the FoodAPS study

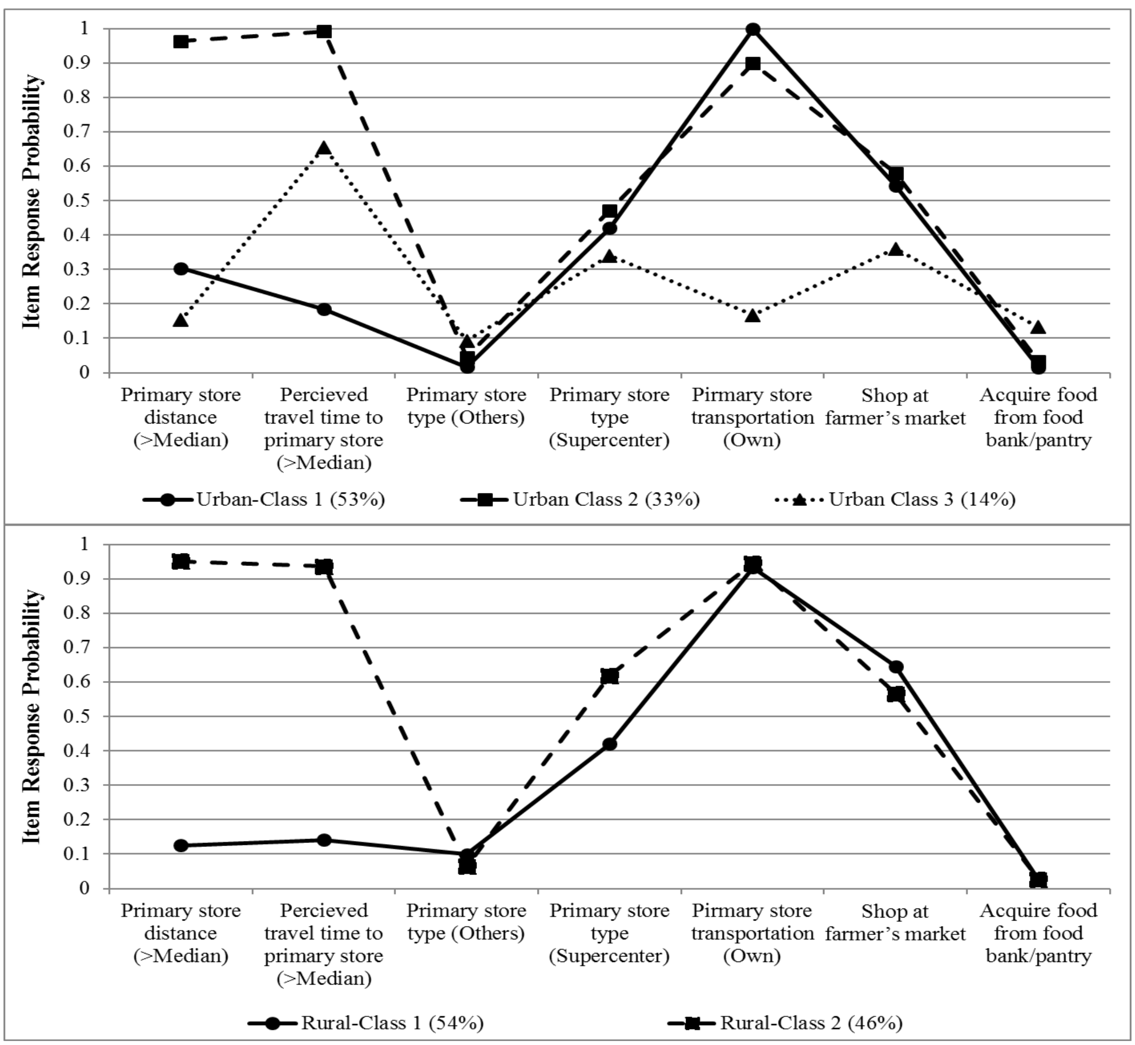
Characteristics	Included n=3,379	Excluded n=1,447	*p*
Age, mean (SD)	49.9 (0.6)	50.3	0.60
Female, %	70.4	61.2	**<0.01**
Race/Ethnicity, %			0.59
White	75.6	77.5	
Black	12.8	12.3	
American Indian or Alaska native	0.5	0.3	
Asian or native Hawaiian or other Pacific islander	4.5	3.5	
Others	6.6	6.3	
SNAP participation, %			0.91
SNAP household	13.4	14.1	
Non-SNAP household, income <100% FPG	4.8	5.0	
Non-SNAP household, income >=100% and <185% FPG	12.5	13.1	
Non-SNAP household, income >=185% FPG	69.3	67.8	
Food security, %			0.92
Very low food security	6.4	6.8	
Low food security	9.6	8.9	
Marginal food security	14.8	14.9	
High food security	69.2	69.4	
Education, %			0.80
Less than high school	9.8	9.4	
High school	24.3	25.7	
Above high school	65.9	65.0	
Annual household income, %			0.57
$0–9,999	13.1	15.4	
$10,000–19,999	13.0	13.1	
$20,000–29,999	10.8	11.6	
$30,000–39,999	8.9	10.0	
$40,000–49,999	8.0	7.0	
$50,000 or more	46.2	43.1	
Being employed, %	55.4	55.4	1.00

Appendix E. Food acquisition and shopping measures by classes by urbanicity of 3,379 participants in the 2012-2013 interview from the Food Acquisition and Purchase Survey (FoodAPS)

Characteristics	Urban			Rural	
	Class 1	Class 2	Class 3	Class 1	Class 2
Primary store distance (>median), %	2.9	97.5	62.4	5.7	94.0
Alternative store distance (>median), %	39.5	67.7	37.2	19.7	77.4
Primary store perceived travel time (>median), %	21.6	66.9	87.7	12.4	87.9
Primary store type (other), %	2.0	2.8	8.9	6.7	7.7
Primary store type (supercenter), %	37.3	42.7	50.6	47.2	59.5
Alternative store (other), %	9.4	6.2	13.6	13.9	10.6
Alternative store (supercenter), %	46.0	43.4	52.4	36.1	54.8
Primary store transportation (own vehicle/bike or walk), %	95.0	99.8	63.3	93.2	96.2
Shop at farmers' market, %	52.8	65.2	34.2	64.2	62.7
Acquire food at food bank/pantry, %	2.3	1.3	12.1	2.3	3.5
Primary store distance in miles, mean (SD)	1.0 (0.04)	4.3 (0.2)	3.6 (0.5)	3.8 (0.2)	15.2 (1.0)
Alternative store distance in miles, mean (SD)	2.6 (0.2)	3.7 (0.3)	1.9 (0.2)	5.6 (0.5)	14.1 (0.8)
Primary store perceived travel time in minutes, mean (SD)	5.9 (0.2)	10.1 (0.4)	14.2 (0.6)	8.6 (0.2)	21.9 (1.2)

Note: the values in the upper part of the table correspond with the classes displayed in Figure 2a and 2b. The additional mean and SD info in in the lower part is supplemental data.

Appendix F. Probability of latent class membership and item-response probabilities of retained unconditional three-class solution for urban and two-class solution for rural of 4,466 participants in the 2012-2013 interview from the Food Acquisition and Purchase Survey (FoodAPS) by urbanicity



Appendix G. Associations between socioeconomic characteristics, nutrition knowledge, and store selection reasons and identified food acquisition and shopping patterns by urbanicity of 3,379 participants in the 2012-2013 interview from the Food Acquisition and Purchase Survey (FoodAPS)

	Urban					Rural				
Class 2 vs. Class 1	**b**	**SE**	**Wald**	***P*** *	**OR****	**b**	**SE**	**Wald**	***P*** *	**OR****
Intercept	-0.08	0.43	0.04	0.85		-1.80	0.90	4.02	**0.04**	
Non SNAP, income FPG<185%	0.07	0.26	0.07	0.79	1.07	0.25	0.42	0.36	0.55	1.29
SNAP participation	-0.62	0.24	6.92	**<0.01**	0.54	-0.20	0.27	0.58	0.45	0.82
Food insecurity	-0.65	0.25	6.57	**<0.01**	0.52	-0.21	0.35	0.35	0.55	0.81
High school education	-0.16	0.22	0.51	0.47	0.85	0.48	0.34	1.97	0.16	1.62
Less than high school education	-1.11	0.62	3.19	0.07	0.33	-0.57	0.38	2.26	0.13	0.57
Between $20,000 and $50,000 annual household income	-0.24	0.22	1.23	0.27	0.78	-0.23	0.35	0.41	0.52	0.80
Less than $20,000 household annual income	-0.05	0.38	0.02	0.89	0.95	-0.09	0.48	0.03	0.85	0.92
Unemployed	-0.13	0.19	0.46	0.50	0.88	0.19	0.16	1.40	0.24	1.21
Household size	0.05	0.06	0.80	0.37	1.05	0.19	0.08	5.91	**0.02**	1.21
No nutrition knowledge*	0.25	0.27	0.86	0.35	1.29	-0.05	0.21	0.06	0.81	0.95
No nutrition awareness*	0.03	0.18	0.02	0.88	1.03	0.06	0.27	0.05	0.83	1.06
Store selection—price	0.40	0.21	3.67	0.06	1.49	0.02	0.10	0.03	0.86	1.02
Store selection—proximity	-0.91	0.23	16.02	**<0.01**	0.40	-0.63	0.11	35.38	**<0.01**	0.53

Class 3 vs. Class 1	**b**	**SE**	**Wald**	***P*** *	**OR****	**b**	**SE**	**Wald**	***P*** *	**OR****

Intercept	-1.86	1.00	3.44	0.06	0.16	Not Applicable
Non SNAP, income FPG<185%	1.16	0.57	4.18	**0.04**	3.20	
SNAP participation	1.27	0.56	5.13	**0.02**	3.56	
Food insecurity	0.78	0.40	3.74	0.05	2.18	
High school education	0.30	0.37	0.66	0.42	1.35	
Less than high school education	1.84	0.44	17.49	**<0.01**	6.29	
Between $20,000 and $50,000 annual household income	-0.34	0.66	0.26	0.61	0.71	
Less than $20,000 household annual income	0.55	0.55	1.00	0.32	1.73	
Unemployed	0.63	0.32	3.87	**0.05**	1.88	
Household size	-0.45	0.13	12.04	**<0.01**	0.63	
No nutrition knowledge*	0.01	0.41	0.00	0.99	1.01	
No nutrition awareness*	0.62	0.39	2.60	0.11	1.86	
Store selection—price	1.33	0.57	5.46	**0.02**	3.77	
Store selection—proximity	-2.15	0.40	29.42	**<0.01**	0.12	
Class 2 vs. Class 3	**b**	**SE**	**Wald**	***P*** *	**OR****	
Intercept	1.34	1.31	1.04	0.31	3.81	Not Applicable
Non SNAP, income FPG<185%	-1.10	0.58	3.54	0.06	0.33	
SNAP participation	-1.89	0.59	10.42	**<0.01**	0.15	
Food insecurity	-1.43	0.48	8.87	**<0.01**	0.24	
High school education	-0.46	0.43	1.16	0.28	0.63	
Less than high school education	-2.95	0.72	16.89	**<0.01**	0.05	
Between $20,000 and $50,000 annual household income	0.09	0.73	0.02	0.90	1.10	
Less than $20,000 household annual income	-0.60	0.60	1.02	0.31	0.55	
Unemployed	-0.76	0.42	3.34	0.07	0.47	
Household size	0.51	0.15	11.54	**<0.01**	1.66	
No nutrition knowledge*	0.25	0.35	0.48	0.49	1.28	
No nutrition awareness*	-0.60	0.44	1.84	0.17	0.55	
Store selection—price	-0.93	0.61	2.34	0.13	0.40	
Store selection—proximity	1.24	0.47	6.84	**<0.01**	3.46	

* P-value from Wald test. ** OR stands for odds ratio.

Multinomial (for urban) and ordinary (for rural) Logistic regression model adjusted for age, gender, and race/ethnicity.