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New insights into grocery store visits among east Los Angeles residents using mobility data

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A R T I C L E I N F O

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A B S T R A C T

In this study, we employed spatially aggregated population mobility data, generated from mobile phone locations in 2021, to investigate patterns of grocery store visits among residents east and northeast of Downtown Los Angeles, in which 60% of the census tracts had previously been designated as “food deserts”. Further, we examined whether the store visits varied with neighborhood sociodemographics and grocery store accessibility. We found that residents averaged 0.4 trips to grocery stores per week, with only 13% of these visits within home census tracts, and 40% within home and neighboring census tracts. The mean distance from home to grocery stores was 2.2 miles. We found that people visited grocery stores more frequently when they lived in neighborhoods with higher percentages of Hispanics/Latinos, renters and foreign-born residents, and a greater number of grocery stores. This research highlights the utility of mobility data in elucidating grocery store use, and factors that may facilitate or be a barrier to store access. The results point to limitations of using geographically constrained metrics of food access like food deserts.

1. Introduction

A healthy diet is protective against most major chronic diseases, including obesity, type-II diabetes, and hypertension, and can also benefit mental health, longevity, and overall wellbeing (Centers for Disease Control and Prevention, 2021). However, in the United States and many other countries, few adults meet healthy dietary recommendations and diet-related disease has become a leading cause of death (Anand et al., 2015; Afshin et al., 2019). Although Americans are increasingly consuming foods away from home, prepared by restaurants and fast-food outlets, food prepared at home tend to be more nutritious, less caloric, and more affordable (Saksena et al., 2018). People’s capacity to prepare and eat healthy foods depends in part on their access to grocery stores and supermarkets; a primary source of affordable healthy food options in the United States (Glanz et al., 2005; Laska et al., 2010, Walker et al., 2010). Frequent grocery shopping is associated with healthier diets and lower obesity rates (Gustat et al., 2015; He et al., 2012; Minaker et al., 2016; Thornton et al., 2012; Widener et al., 2018).

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Visiting a wider variety of grocery stores has also been associated with more healthy and balanced diets (Cervigni et al., 2020; Liu et al., 2014; Shearer et al., 2015; Zenk et al., 2011). However, inequities in access to grocery stores are well-documented: People with low incomes and people of color are more likely to live in areas with limited access to grocery stores, which may contribute to disparities in nutrition and diet-related health outcomes among these populations (Bell et al., 2019; Larson et al., 2009; Maguire et al., 2017).

One limitation of existing research on healthy food access has been a focus on people's access to grocery stores near their home. Often studies examine access within home census tracts, ZIP codes or home-centric buffers, implying the assumption that people primarily shop in areas close to where they live (Caspi et al., 2012; Charreire et al., 2010; Feng et al., 2010; Gamba et al., 2015; Leal and Chaix, 2011). However, research measuring grocery store visits has shown that people do not solely shop at stores that are closest proximity to their home (Lucan, 2015; Matthews and Yang, 2013; Browning et al., 2017; Inagami et al., 2006; Widener et al., 2013). One review suggested that static methods focusing on home neighborhoods overestimate the importance of the residential food environment, though the magnitude of this potential bias has yet to be quantified (Cetateanu and Jones, 2016).

To address this measurement issue, the operationalization of the "activity space" concept, which refers to the spatial trajectories of people's daily movements, becomes increasingly valuable in studying human mobility and contextual exposures (Blondel et al., 2015, Matthews and Yang, 2013; Yi et al., 2019; Yi et al., 2024). Over the last two decades, the activity space research has evolved significantly, employing various data sources and methodologies. This includes the use of transportation survey data (e.g., Lee and Kwan, 2011), self-reported household travel surveys (e.g., Browning et al., 2017; Cheng et al., 2020), qualitative interviews (e.g., Hillier et al., 2011), and combination of qualitative methods and geographical information systems to allow participants to manually draw their activity spaces on a map (e.g., Basta et al., 2010; Chaix et al., 2012). Recent advancements in mobility data collection, including GPS-enabled mobile phones (Chang et al., 2022; Gao et al. 2013, 2020; Horn et al., 2023; Xu et al., 2023), wearable location sensors (Kerr et al., 2011; Widener et al., 2018; Yi et al., 2022), and social media check-ins (Nguyen et al., 2017), have paved the way for novel insights into human behaviors, including grocery shopping patterns. These diverse methodologies in activity space research underscore its adaptations to technological advancements in understanding human mobility and spatial behaviors and call for more quantitative research to complement and enhance our understanding of the insights gained from qualitative studies.

Despite these technological advances, the application of mobility data to research has been constrained to limited spatiotemporal scales, primarily due to the challenges associated with data collection, such as the high cost of GPS devices, and the potential for recall bias in data reporting (Alexandre et al., 2020; Browning et al., 2017; Clary et al., 2017; Perchoux et al., 2019; Smith et al., 2019; Zenk et al., 2011). These obstacles underscore the need for innovative approaches to leveraging mobility data more effectively to uncover the complex dynamics of grocery shopping behaviors and their implications on public health and urban planning. Two recent studies have utilized large-scale anonymized and aggregated mobile phone location data, providing evidence that visits to food retailers are a meaningful proxy for dietary intake (Horn et al., 2023), and significantly predict diet-related diseases (Horn et al., 2023; Xu et al., 2023). However, these analyses were limited to fast-food outlet visits. This study aims to apply this promising approach, using large-scale mobility data to offer insights into grocery store visits for large and diverse populations of mobile phone users over long periods of time, rather than short snapshots of behaviors captured by other methods.

Disparities in poor diets and diet-related diseases are pronounced and pervasive, and a lack of access to healthy food is acknowledged as a key "social determinant of health" (Downs et al., 2020; Glanz et al., 2005; Story et al., 2008; Swinburn et al., 2011). As a result, past research has often explored the sociodemographic disparities in grocery shopping behaviors, identifying barriers to grocery shopping, including racial and ethnic minority status (Shier et al., 2022), age (Angell et al., 2012; Netopil et al., 2014; Wu et al., 2022), disability (Charnes 2022), low income (Darko et al., 2013; Zachary et al., 2013), unreliable transportation (Burns et al., 2011; Thompson et al., 2022; Gustat et al., 2015), financial constraints (Inglis et al., 2009; Burns et al., 2011), and low enrollment in food assistance programs (Rose and Richards, 2004; Ver Ploeg et al., 2015). These studies have primarily relied on interviews and surveys to gather insights, focusing largely on individual experiences and perceptions. While valuable, this approach leaves a gap in our understanding that could be addressed through quantitative research, particular concerning how neighborhood characteristics are associated with grocery shopping patterns. These insights are needed to better understand the role of food access as a key social determinant of health that can give rise to disparities in a range of health outcomes and risk for diseases.

To address these gaps, the goal of our study is to use large-scale mobility data, captured over one year (2021), to investigate visits to grocery stores among residents of a historically under-resourced area of Los Angeles County (LAC)'s east side. By linking this mobility data to information about the neighborhood sociodemographic and retail food environments, we will also explore differences and disparities in grocery store use. Specifically, we will address the following two research questions:

(1) What grocery store visit patterns do we observe using mobility data captured over one year?
(2) Are residents' grocery store visit patterns associated with neighborhood sociodemographic and food accessibility?

2. Methods

2.1. Study area and research design

Our study focused on a cluster of five neighborhoods to the east and northeast of Downtown Los Angeles, California: Boyle Heights, City Terrace, El Sereno, Lincoln Heights, and Ramona Gardens (Fig. 1). It occupies an area of 18.2 miles^2 and accommodates a population of 216,820 residents spread across 55,747 households as of 2021, making it one of the most densely populated areas in LAC (U.S. Census Bureau, 2021). Geographically, the region extends 6.4 miles in length and 4.3 miles in width. The demarcation of our study area was based on the local community's perceptions of their neighborhood boundaries (de la Haye et al., 2023). These areas are predominately inhabited by Hispanic/Latino (83%) and Asian Americans (10%) (U.S. Census Bureau, 2021). Notably, 60% of the census tracts within these neighborhoods are designated as food deserts, defined as census tracts with limited access to grocery stores, highlighting a critical barrier to accessing healthy and affordable food options (U.S. Department of Agriculture Economic Research Service, 2019). The selection of these neighborhoods and the study area as a whole was informed by their significant exposure to environmental justice issues, gentrification pressures, and the encroachment of urban structures, factors that collectively exacerbate health disparities (de la Haye et al., 2023). This backdrop, coupled with the documented challenges faced by the Hispanic/Latino community in securing healthy food access, positions these neighborhoods as critical sites for investigating grocery store visitation patterns (Walker et al. 2010, Larson et al., 2009).

Our research process is summarized is Fig. 2. We followed six steps to complete the overall research, each building upon the last to ensure a robust analysis.

The study protocol was approved by the University of Southern California ethics committee.

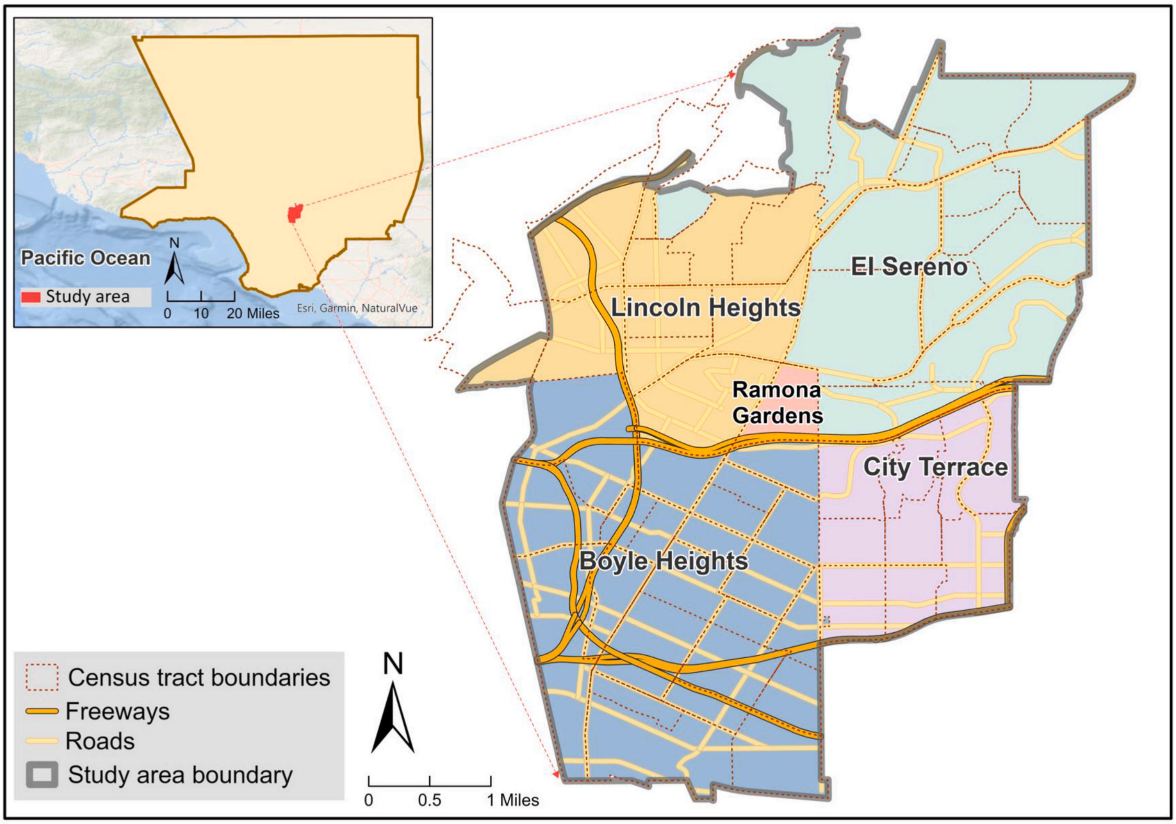

Fig. 1. Map showing the location of the five community-defined neighborhoods and the study area within LAC.

2.2. Data and measures

2.2.1. Residents' grocery store visits based on mobility data

We acquired weekly mobility data from for LAC from SafeGraph. This dataset captures the anonymous visitation details, including the period of observation, the number of mobile phone users tracked, visitor counts, number of visits, visit durations, visit distances, and details about the visited locations (e.g., names, locations, types), as demonstrated in Fig. 3. It is available for academic, noncommercial use by filling out the data access request (note: starting in 2023, access to these data has shifted to the Dewey marketplace). To ensure privacy, SafeGraph pre-assigns users to census block groups, the smallest geographic units of residence identifiable in this data. The determination of a user's home location is based on the analysis of their movements over six weeks, focusing on where the observed users spend the majority of nighttime hours (6 p.m.–7 a.m.). The points of interest, including retail food outlets, were categorized using the North American Industry Classification System (NAICS) codes, which is the standard taxonomy used by the U.S. government to classify business establishments (Widener et al., 2018, Kelton et al., 2008). We described the methodological details of our validation of retail food outlets, our choice of the NAICS codes, the study area, and the evaluation of potential sampling rate bias in the Appendix.

For our analysis, we analyzed mobility data among users whose residential census block groups fell within our study area and the visited grocery stores identified by the NAICS code 445,110 spanning the whole of LAC. Considering the impact of the COVID-19 pandemic and aiming for a stable sampling rate and visitation patterns post-pandemic (Appendix Figs. S1 and S2), we narrowed our focus to data from January 1st to December 14th, 2021. Throughout the 50 weeks in 2021, the average sampling rate was 2.4% and 4799 mobile phone users per week, and these visits had an average duration of 30 minutes.

2.2.2. Patterns of grocery stores visits throughout 2021

We defined four categories of indicators to represent grocery visit patterns using: i) frequency, ii) diversity, iii) distance, and iv) the proportion of visits to stores within users' residential neighborhoods rather than elsewhere.

Regarding the frequency of visits to grocery stores, two normalized statistics were used to enable a more meaningful comparison between different areas: i) the weekly frequency of visits among observed mobile phone users and ii) the weekly frequency among visitors who visited grocery stores at least once during that week. Given the potential for sampling bias – occasionally caused by signal loss – we opted to report the average weekly frequency of visits across the year (50 weeks) to mitigate the impact of temporal data loss. Two diversity indicators were calculated by counting the number of unique stores visited (richness) and by using the Simpsons' diversity index (evenness) to consider the variations in visits to different stores (Su et al., 2019). Street network distances between the residences and visited stores were computed with premium street network datasets from Esri's Business Analyst 2023. Indicators related to visits in residential neighborhoods were calculated based on two sets of commonly used residential neighborhood definitions. The first one was based on administrative units, including (i) home census block groups (CBGs); (ii) home census tracts (CTs); (iii) home and neighboring census tracts considering spatial contiguity to offset the edge effects (Gao et al., 2013; Kim and Kwan, 2021); (iv) the neighborhood defined by local communities (hereinafter "individual neighborhood"); and (v) the entire study area. The determination of neighboring census tracts of a home census tract (i.e., item iii above) was achieved by choosing the adjacent census tracts that shared a boundary or point with the home census tract (Anselin and Rey, 2010). The information of these administrative units is summarized in Table 1. The second approach used home-centric network distance metrics with varying radii, from 0.3 to 5 miles. The measurement approach, mathematical details, and references are provided for all of these indicators in

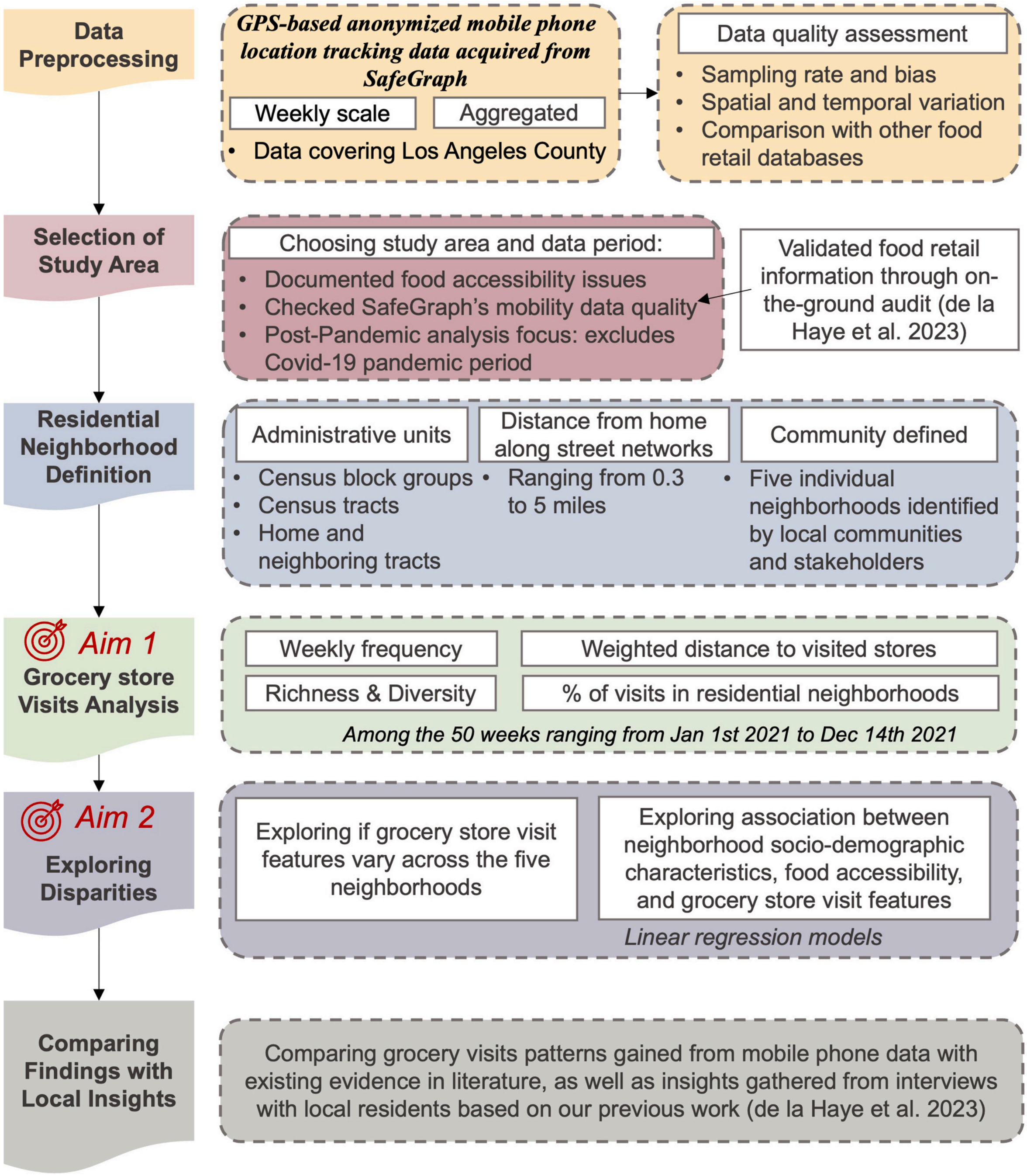

Fig. 2. Overall study design.

Table 2.

2.2.3. *Neighborhood grocery store accessibility*

Spatial accessibility to grocery stores within a given residential neighborhood was calculated as the number of grocery stores within that geographic unit of interest, i.e., within one's home census block group, census tract or home and neighboring census tracts. We extracted the grocery store data from SafeGraph's point-of-interest dataset by identifying stores with NAICS code 445,110 (Widener et al., 2018). In this study, we defined a food desert as a census tract with no grocery stores within it ("home CT food desert") (U.S. Department of Agriculture Economic Research Service 2019)

2.2.4. *Neighborhood sociodemographic variables*

Informed by research on social determinants of health, the concept of obesogenic environments, and socio-ecological models (i.e., Downs et al., 2020; Glanz et al., 2005; Story et al., 2008; Swinburn et al., 2011), we selected sociodemographic variables previously linked to grocery shopping behaviors (Shier et al., 2022, Zachary et al., 2013, Burns et al., 2011, Thompson et al., 2022, Gustat et al., 2015, Angell et al., 2012, Inglis et al., 2009, Charnes 2022) using data from the American Community Survey (ACS) 2017–2021. The ACS is an ongoing survey conducted by the U.S. Census Bureau that provides and updates vital information on the U.S. population's demographic, social, economic, and housing characteristics annually. We included variables from six major categories: i) demographics, ii) disability status, iii) living arrangements, iv) economic factors, v) education, and vi) transportation.

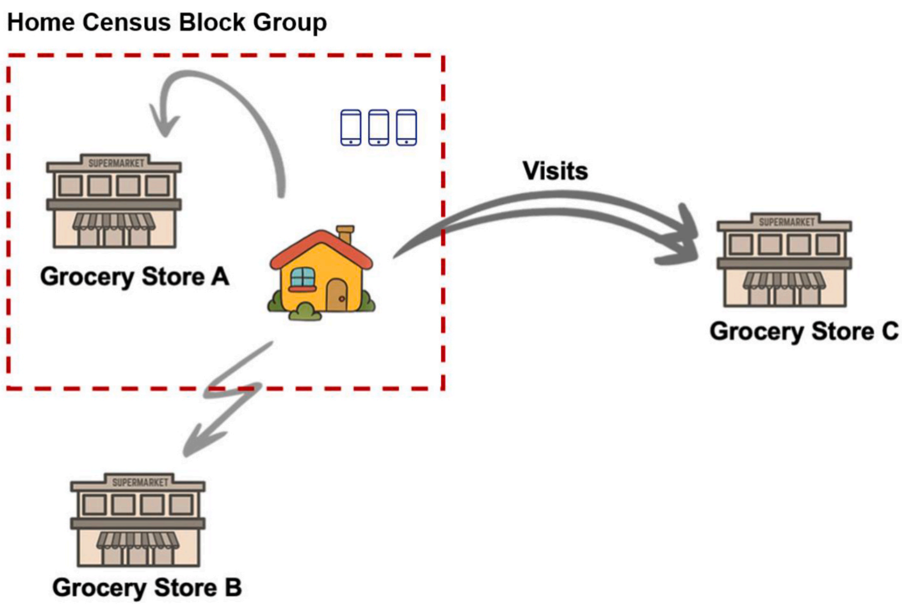

Fig. 3. Conceptual visualization of using mobility data to capture visits to grocery stores from SafeGraph.

Table 1
Administrative units in the study area, based on the American Community Survey 2017–2021 and U.S. Census 2021 data.

Administrative units	Area (miles^2)	Radius (miles)*	No. of units	Average no. of residents per unit [min – max]
Home CBG	0.1	0.2	131	1663 [599–3084]
Home CT	0.3	0.3	58	3757 [1899–5714]
Home and neighboring CTs	2.8	0.9	–	–
Individual neighborhood	3.6	1.1	5	45,392 [4615–89,284]
Entire study area	18.2	2.4	1	217,912

Note: * Radius is calculated by approximating the area in the shape of a circle to estimate its potential largest radius.

Table 3 summarizes our selected variables and provides their descriptions.

2.3. Statistical analysis

To address our first research question – "What grocery store visit patterns do we observe using mobility data captured over one year", we first calculated descriptive statistics, including the mean, maximum, minimum, and standard deviation for the key variables of grocery visit patterns: frequency, diversity, distance, and proportion of visits to stores within users' residential neighborhoods to summarize these patterns over the 50 weeks in 2021. We also produced maps to visually illustrate the geographic variations in these variables across census tracts.

For our second research question – "Are residents' grocery store visit patterns associated with neighborhood sociodemographic and food accessibility", we explored bivariate and multivariate associations. First, Pearson correlation coefficients were computed to identify significant bivariate relationships between neighborhood characteristics that are continuous (i.e., sociodemographic and grocery accessibility) and each of the grocery visit indicators (i.e., frequency, diversity, distance, and proportion of visits within residential neighborhoods). One-way analysis of variance (ANOVA) was used to examine the associations between neighborhood food desert classification (binary) and grocery visit patterns. Neighborhood characteristics with significant correlations ($p < 0.05$) were included in multivariate regression analysis. Variables such as sex ratio, the percentage of the population commuting by car, and the percentage of the population commuting by walking were thus excluded. Variables like the percentage of households with no car, the percentage of families below the 100% FPL, which was only significantly correlated with the weekly frequency of visits among visitors, and the percentage of people living alone, which was only correlated with diversity indicators, were excluded in this step but retained for regression analysis.

Next, as many neighborhood variables were highly correlated, principal component analysis (PCA) with a varimax rotation was applied to distill the neighborhood measures into meaningful, uncorrelated components. This step aims to address multicollinearity among the neighborhood characteristics. A four-factor solution based on the Kaiser criterion (eigenvalues >1.0), which accounted for 78% of the total variance, was selected.

Multiple linear regression models were then utilized to explore associations between the derived neighborhood components and the indicators of grocery store visit patterns. Variables that were excluded from PCA but showed a significant correlation with grocery store visit indicators were considered. All analyses were conducted using SPSS (IBM Corporation, USA).

3. Results

3.1. Grocery store visit patterns among observed mobile phone users in the study area

The weighted neighborhood sociodemographic and grocery accessibility characteristics of the residents in the five community-defined neighborhoods are presented in Table 4.

Using data from SafeGraph, we identified an average of 1474 visits and 1053 visitors to grocery stores among 4799 observed mobile phone users each week, which summed up to 73,729 observed grocery store visits in 2021. These visits were to 574 different grocery stores, with 113 grocery stores located inside these neighborhoods, as shown in Fig. 4. The most frequently visited grocery stores (i.e., the high-traffic hubs in Fig. 4, which were stores with over 1% of total visits, and the visits to these high-traffic hub stores summed to 50% of total visits from observed residents) were located within the study area boundary.

Descriptive characteristics of grocery store visits at the census tract level are presented in Table 5. In terms of frequency, the weekly frequency among observed residents was 0.4 times per week (1.7 times per

Table 2
Mathematical details of indicators to describe grocery store visit patterns.

Indicators	Equation	Explanation	References
Indicators related to frequency			
Weekly frequency among observed mobile phone users ($Frequency_{it}$)	$Frequency_{it} = \frac{V_{it}}{U_{it}}$	V_{it} is the number of visits to grocery stores from the spatial unit i in week t; U_{it} is the number of unique devices whose home addresses are within this spatial unit; i is the spatial unit; t is the week in 2021.	Banks et al. (2020), Horn et al. (2023)
Weekly frequency among observed visitors ($Frequency\_v_{it}$)	$Frequency\_v_{it} = \frac{V_{it}}{VR_{it}}$	V_{it} is the number of visits to grocery stores from the spatial unit i in week t; VR_{it} is the number of observed visitors to grocery stores from the spatial unit i in week t; i is the spatial unit; t is the week in 2021.	Smith et al. (2023)
Proportion of visitors who visited grocery stores at least once during the observation week (FP_{it})	$FP_{it} = \frac{VR_{it}}{U_{it}}$	VR_{it} is the number of observed visitors to grocery stores from the spatial unit i in week t; U_{it} is the number of unique devices whose home addresses are within this spatial unit; i is the spatial unit; t is the week in 2021.	Xu and Saphores (2022)
Indicators related to diversity			
Richness ($Richness_i$)		$Richness_i$ is the number of different grocery stores visited by residents from spatial unit i in 2021.	Su et al. (2019), Buliung et al. (2008), Perchoux et al. (2019), Smith et al. (2023)
Evenness ($Diversity_i$)	$Diversity_i = 1 - \sum_{(Richeness_i)} \left(\frac{n_i}{N_i}\right)^2$	$Evenness_i$ is the Simpson's diversity; N is the total number of visits to grocery stores in 2021; n is the number of visits to a particular grocery store visited in 2021; $Richness_i$ is the number of different grocery stores visited by residents from spatial unit i in 2021.	Su et al. (2019)
Indicators related to distance			
Weighted distance traveled from residences to stores (wD_i)	$wD_i = \sum_{j=1}^{k} \frac{Distance_{ij} * V_{ij}}{V_i}$ $V_i = \sum_{j=1}^{k} V_{ij}$	V_{ij} is the total number of visits from observed visitors in spatial unit i to grocery store j in 2021; $Distance_{ik}$ is the distance along the street network from residents' home locations to grocery store k, which is calculated via Network Analysis in ArcGIS Pro; V_i is the total visits to grocery stores from unit i;	
Indicators related to residential visit			
Proportion of visits to grocery stores within residential neighborhoods ($Residential_i$)	$Residential_i = \frac{\sum_{j=1}^{k} W_{ij} V_{ij}}{V_i}$,	$Spatial\ weights\ matrix: W_{iJ} = \begin{cases} 1, i, J\ sharing\ a\ border\ or\ point \\ 0, i, J\ not\ sharing\ any\ points \end{cases}$ where i is the spatial unit of the observed users, J is the spatial unit of store j. Or $W_{iJ} = \begin{cases} 1, Distance_{ij} \leq R \\ 0, Distance_{ij} > R \end{cases}$ where $Distance_{ij}$ is the network distance between spatial unit I and store j.	Perchoux et al. (2019), Gao et al. (2013)

month), and the weekly frequency among observed visitors was 1.4 times per week. The average number of different stores visited (richness) was 56, with an evenness value of 0.9. In terms of distance, residents traveled an average of 2.2 miles from their homes to the grocery stores (Table 5). Fig. 5 shows the spatial distribution of the frequency of visits to grocery stores among observed mobile phone users and the average distance to visited stores (weighted by the number of visits to different stores) in 2021. Observed residents in Boyle Heights and City Terrance visited grocery stores more frequently, while residents in El Sereno traveled further to visit grocery stores (Fig. 5).

Our analysis also revealed significant variation in the proportion of grocery visits within residential neighborhoods, contingent upon the operational definitions and the sizes of these neighborhoods (Table 5). When residential neighborhoods were defined by a series of administrative boundaries, the proportion of visits in residential neighborhoods varied notably. Specifically, only 8% of visits occurred in stores within the same CBG as the observed residents (CBGs had an average radius of 0.2 miles). The percentage of visits increased to 13% for stores within the same CT, with an average radius of 0.3 miles (Tables 1 and 5). 40% of visits were to stores located in the home or neighboring CTs (with an average radius of 1.1 miles), 54% of visits were to stores within the same community-defined neighborhoods (with an average radius of 1.1 miles), and 75% of visits were to stores within the study area (with an average radius of 2.3 miles) (Tables 1 and 5). Alternatively, when the residential neighborhoods were delineated based on catchment areas defined by network distance from residences, the proportion of visits also varied. Specifically, 8% of grocery store visits were to stores within 0.3 miles of resident's homes. This proportion increased to 18% for stores within 0.5 miles, 30% for those within 1 mile, 60% within 2 miles, and approximately 10% for stores more than 5 miles away (Table 5).

3.2. Disparities in grocery visit patterns across the five neighborhoods

Our analysis explored disparities in the proportion of visits in residential neighborhoods across the five community-defined neighborhoods, as shown in Fig. 6. For example, Ramona Gardens is a neighborhood with a single, 0.3-mile-radius CT, predominantly characterized by its public housing project and inhabited by low-income, Hispanic families, a majority of the renters, and more female than male residents (Table 4). We found that in Ramona Gardens, a significant proportion (31%) of visits to the same home CT was observed (Fig. 6). Conversely, it showed the lowest percentage of visits to grocery stores in neighboring CTs. Contrary to Ramona Gardens, observed residents from Lincoln Heights, which is characterized by a diverse mix of Asians and Hispanics and a higher proportion of the population living alone (Table 4), presented a different pattern. This neighborhood exhibited the lowest percentage of visits to grocery stores within the same home CT (11%), while showing the highest percentage of visits to stores in neighboring CTs (36%).

3.3. Association between neighborhood food desert classification and grocery store visit patterns

The ANOVA analysis provided further insights into the association between the binary neighborhood food desert classification and grocery store visit patterns. We found that the weekly frequency of visits among visitors, the proportion of visits to grocery stores within the home CT, and the proportion of visits to stores within home and neighboring CTs exhibited significant variations based on the areas' classification as a food desert or not, while other grocery visit variables, including the frequency among observed mobile phone users, diversity (richness and evenness), distance, and the proportion of visits in the study area did not show significant differences.

Table 3
Notions and descriptions of the neighborhood sociodemographic variables.

Categories	Variable notions	Descriptions
Demographics	Median age (years)	
	Sex ratio	Ratio of males to females (sex ratio, computed as the number of males per 100 females, based on how respondents identified their sex)
	% black/African American	Percentages of the population that were black/African American
	% Asian	Percentages of the population that were Asian
	% Hispanic/Latino	Percentages of the population that were black/African American
	% Foreign-born	Percentage of the population that were foreign-born Americans
Disability status	% Disability	Percentage of the population with one or more disabilities
Living arrangements	% Renter	Percentage of renter-occupied housing units
	% Living alone	Percentage of the population that were living alone
Economic factors	Median household income (USD)	
	% below the FPL	Percentage of families below the 100% federal poverty level (FPL)
	% with SNAP benefits	Percentage of households enrolled in the Supplemental Nutrition Assistance Program (SNAP), also known as "food stamps"
Education	% ≥25 years with less than 9th grade education	Percentage of population ≥25 years with less than a 9th grade education
	% ≥25 years with a bachelor's degree and above	Percentage of population ≥25 years with a bachelor's degree or higher
Transportation	% Households with no car	Percentage of households with no car
	% Commuting by car	Percentage of workers commuting by car
	% Commuting by transit	the percentage of workers commuting by public transportation
	% Commuting by walking	Percentage of workers commuting by walking.

3.4. Association between neighborhood sociodemographic, grocery accessibility and grocery visit patterns

3.4.1. Principle component analysis

The results of the PCA are shown in Table 6. The four components that were retained explained 78% of the variation. The first component (37% of variance) was primarily defined by neighborhood socioeconomic factors, such as more renters, lower median household income, more households enrolled in SNAP, more transit commuters, and more foreign-born residents. The second component (19% of variance) was primarily defined by neighborhood race/ethnicity and education, such as fewer Black/African Americans, more Hispanics/Latinos, fewer Asians, and a lower percentage of the population with a bachelor's degree or above. The third component (13% of variance) was primarily defined by grocery accessibility in home census tracts and in home and neighboring tracts. The fourth component (9% of variance) was primarily defined by age and disability status.

3.4.2. Regression analysis

Table 7 presents the results of linear regressions that examine the relationship between neighborhood characteristics and each grocery store visit variable. Car ownership and the percentage of families below the 100% FPL were unrelated to any grocery store visit features.

The weekly frequency of grocery store visits among the observed mobile users was significantly associated with all four identified components (Table 7). Specifically, observed residents visited grocery stores more often when they lived in neighborhoods characterized by higher socioeconomic deprivation (Component 1), a predominance of ethnic minorities (Component 2), and younger demographics (Component 4) (Table 6). Additionally, greater grocery store accessibility within these neighborhoods was also linked to increased frequency (Component 3) (Table 7).

In terms of frequency among observed visitors, our analysis suggested that it was positively associated only with Component 1 ($p < 0.01$, Table 7), reflecting the level of neighborhood socioeconomic deprivation (Table 6).

Observed residents were found to visit a more diverse array of grocery stores (richness) in neighborhoods with better grocery accessibility (Component 3, Table 7) and a lower proportion of the residents living alone (Table 7). However, the evenness of visits across different stores was inversely related to Component 2, which is indicative of ethnic and educational composition (Tables 6 and 7).

The distance traveled to grocery stores was significantly and negatively correlated with Components 1 and 2 (Table 7), reflecting the pattern that shorter distances to grocery stores were associated with the neighborhoods having higher proportions of Hispanics/Latinos, foreign-born individuals, renters, low-income households, public transit commuters, and residents aged over 25 years with less than a 9th-grade education (Table 6).

The proportion of grocery store visits within the home CT was significantly related to grocery accessibility in the immediate neighborhood (Component 3, Tables 6 and 7). However, the model's explanatory power suggested a relatively low overall predictive capability ($R^2 = 0.1$).

4. Discussion and conclusions

In this study, we described the dynamic patterns of weekly visits to grocery stores and characterized the spatial and social disparities within these patterns across five predominantly minority communities in Los Angeles. By using anonymous GPS-based mobility data, our research sought to answer critical questions regarding the grocery shopping behaviors of residents of minority communities, the extent to which these visits occurred within their residential neighborhoods, and how these patterns were associated with neighborhood sociodemographic factors and grocery store accessibility. The implications of the findings are discussed below.

4.1. Patterns of grocery store visits

4.1.1. Frequency of grocery store visits

We developed two normalization methods to calculate the frequency of grocery store visits, facilitating a more meaningful comparison with findings from the existing literature. Previous studies have relied on surveys to determine visitation frequencies, targeting either a randomly sampled population segment (e.g. Ma et al., 2017) or primary shoppers (e.g. Gust et al., 2015; Minaker et al., 2016). Our findings showed that observed residents visited grocery stores an average of 0.4 times per week (range: 0.1 to 0.8), which is lower than that reported by Ma et al. (2017), who found that residents visited grocery stores between 0.3 and 1.2 times per week using survey data among residents in food deserts in South Carolina. Moreover, our observation of 1.4 visits per week among grocery store visitors closely matches the findings of Gustat et al. (2015), who conducted qualitative surveys with primary grocery shoppers in Louisiana and reported an average of 1.4 times per week. The agreement of our results with those from different geographic areas and approaches helps validate the reliability of our frequency indicators.

4.1.2. Distance to visited grocery stores and proportion of visits in residential neighborhoods

Our results showed that the weighted average distance traveled by residents to visit grocery stores was 2.2 miles, and 30% of grocery visits occurred within 1 mile of residences, which aligns with the observations

Table 4
Neighborhood characteristics of the five community-defined neighborhoods (weighted by population), using data from American Community Survey 2017–2021.

	Boyle Heights	City Terrace	El Sereno	Lincoln Heights	Ramona Gardens	Study Area
No. of census tracts	23	9	14	11	1	58
Population	89,284	36,320	50,777	35,824	4615	216,820
No. of households	22,442	9305	13,027	9725	1248	55,747
Demographics						
Median age (years)	32.7	32.7	36.0	35.6	30.4	33.9
Sex ratio	95.0	99.8	100.4	97.5	86.3	97.3
% black/African American	1.2	0.5	2.2	2.5	2.2	1.5
% Asian	3.2	2.0	11.5	22.0	2.5	8.0
% Hispanic/Latino	92.7	95.0	77.5	67.0	94.4	85.3
% Foreign-born	63.7	57.6	42.9	49.1	67.0	55.5
Disability status						
% Disability	11.7	8.8	11.6	11.3	9.8	11.1
Living arrangements						
% Renter	73.6	59.6	48.1	67.7	86.9	64.5
% Living alone	15.5	15.9	18.0	24.8	18.0	17.7
Economic factors						
Median household income (USD)	48,593	51,687	66,079	54,187	39,329	53,933
% below the FPL	21.3	15.1	12.9	17.6	21.8	17.7
% with SNAP benefits	20.6	10.0	10.5	14.2	26.0	15.5
Education						
% ≥25 years with less than 9th grade education	31.2	27.7	18.6	23.0	31.4	26.3
% ≥25 years with a bachelor's degree and above	11.4	12.8	22.4	23.2	3.4	16.0
Transportation						
% Households with no car	17.3	10.0	7.7	17.9	11.0	13.8
% Commuting by car	61.0	68.5	68.0	60.3	69.2	64.0
% Commuting by transit	10.2	7.6	5.7	9.5	7.9	8.5
% Commuting by walking	3.3	3.8	2.4	5.3	2.2	3.5
Neighborhood grocery accessibility						
No. of grocery stores in home CT	2.1	3.3	1.7	1.7	2	2.1
No. of grocery stores in home and neighboring CTs	20.1	17.5	9.3	12.4	14	15.7

Note: FPL = Federal Poverty Level, SNAP = Supplemental Nutrition Assistance Program, CT = Census Tract.

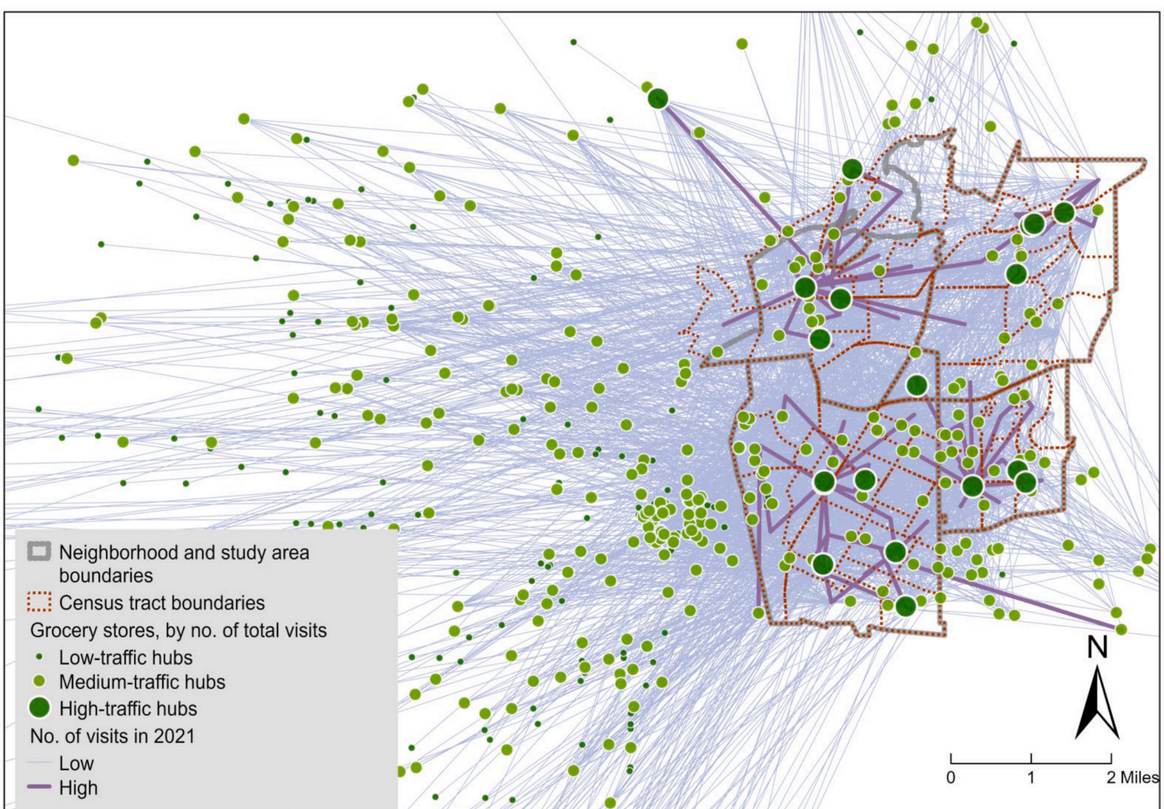

Fig. 4. Spatial distribution of frequently visited and less frequently visited grocery stores in 2021, using mobility data from SafeGraph 2021.

Table 5
Descriptive characteristics of features of grocery store visits, summarized at the census tract level, using data from SafeGraph 2021.

Categories	Indicators	Mean	Min	Max	S.D
Frequency	Weekly frequency among observed mobile phone users (visits per users per week)	0.4	0.1	0.8	0.2
	Weekly frequency among observed visitors (visits per visitor per week)	1.4	1.2	1.7	0.1
	Proportion of visitors who visited grocery stores at least once during the observation week	27%	5%	60%	13%
Diversity	Richness	56	18	116	20
	Evenness	0.9	0.8	1.0	0.0
Distance	Unweighted distance traveled from residences to stores (miles)	3.3	0.1	22.5	2.9
	Weighted distance traveled from residences to stores (miles)	2.2	1.0	3.7	0.7
The proportion of visits to grocery stores in residential neighborhoods (%)	Home census tracts	13	0	51	14
	Home and neighboring tracts	40	5	81	19
	Community-defined neighborhoods	54	10	87	16
	Study area	75	47	92	10
	Within 0.3 miles of residences	8	0	29	8
	Within 0.5 miles of residences	18	0	67	16
	Within 1.0 miles of residences	30	0	81	20
	Within 1.5 miles of residences	48	0	83	21
	Within 2.0 miles of residences	60	1	85	18
	Within 2.5 miles of residences	68	29	89	13
	Within 3.0 miles of residences	71	34	94	13
	Within 3.5 miles of residences	81	51	96	10
	Within 5.0 miles of residences	89	68	99	7
	Within 6.0 miles of residences	92	70	99	6
	Within 8.0 miles of residences	96	80	100	4
	Within 10 miles of residences	98	81	100	3

of Zenk et al. (2014). This study was conducted through surveys in three Detroit communities and reported an average travel distance of 3.1 miles for grocery shopping, with 31% visits within 1 mile from their homes. Similarly, another study by Zenk et al. (2011), which tracked participants' activity patterns using wearable GPS devices in Detroit and Philadelphia, found that individuals traveled between 2.2 and 3.3 miles for food. These results collectively support the notion that people travel beyond residential neighborhoods, but a substantial portion of visits are within a close radius of their homes (e.g., within 2 miles) (Smith et al., 2023; Zenk et al., 2011; Zenk et al., 2014; Hillier et al., 2011; Ver Ploeg et al., 2015).

Contrastingly, our results diverge from these findings when considering a broader expanse of residential neighborhoods. We found that a majority of visits (71%) were within 3 miles from home, and fewer than 10% extended beyond 5 miles, which aligns with the findings by Hillier et al. (2011), but contradicts those of Zenk et al. (2014), who reported that 22% of grocery shopping spanned over 5 miles. Also, our findings differ from those of Li and Kim (2020), who utilized household interviews among participants in Ohio and found that only 9% of visits occurred within 1 mile and 47% of visits were within 3 miles.

4.2. *Association between neighborhood sociodemographic, grocery accessibility, and grocery store visit patterns*

4.2.1. *Disparities in frequency of grocery store visits*

Our analysis of sociodemographic disparities in frequency suggested findings that diverge from the current literature. Specifically, our data indicated that frequency of visits was significantly and positively correlated with indicators of neighborhood socioeconomic deprivation, characterized by higher proportions of renters, families enrolled in SNAP, transit commuters, and lower median household income. This finding differs from the findings of Gustat et al. (2015), who reported that higher-income residents engaged in more frequent grocery shopping. Similarly, our results diverge from those of Smith et al. (2023), who utilized large-scale mobility data from a social media application to explore grocery store visits in major Canadian cities and observed that grocery visit frequency was higher among residents from wealthier areas.

One explanation is that economic constraints could lead residents to purchase smaller quantities each time, which may be more affordable for low-income residents in the short term. Supplementary insights were gathered from our qualitative interviews with residents ($n = 31$) from these areas (de la Haye et al., 2023). For instance, two participants in our study shared: "I go around from one place to another seeing where there are better quality things. Of course, if I get to the store and see that the things are in bad condition, I don't buy them, but I have to go to another place even if it's more expensive" (Participant 21) and "When I don't [find the grocery item] in one place, I go to another place. If I can't find it, I go somewhere else. That's the problem. Sometimes I can't find something, and I have to go to another place to look for it" (Participant 16) (de la Haye et al., 2023). The conversations revealed a strategy among residents of visiting multiple stores to balance the cost and quality of groceries within their limited budgets.

Furthermore, our analysis observed that neighborhoods with more Hispanic/Latino residents exhibit a higher frequency of grocery store visits, and this observation is consistent with the research conducted by Banks et al. (2020), Shier et al. (2022), and Gustat et al. (2015).

Our study challenges the notion that car ownership unequivocally increases the frequency of grocery shopping (Smith et al., 2023; Banks et al., 2020; Shier et al., 2022), as our findings suggested no significant impact of car ownership on frequency. We find indirect support through literature that examined the relationship between car ownership, shopping frequency, and dietary patterns. For example, Gustat et al. (2015) and Fuller et al. (2013) reported that produce consumption was not significantly correlated with car ownership but was positively associated with grocery shopping frequency.

4.2.2. *Disparities in distance and proportion of visits in residential neighborhoods*

Our analysis of the association between sociodemographic and distance to visited grocery stores underscores the complexity of grocery shopping behaviors. Two perspectives emerge in the literature regarding this relationship. The first posits that individuals from under-resourced neighborhoods may have to travel further to find food to meet their needs, a pattern observed by Zenk et al. (2014) and Hillier et al. (2011). The second perspective suggests that wealthier individuals have more resources and means to travel further for food, and this is supported by Smith et al. (2023) and Gustat et al. (2015). Our findings support the latter perspective, showing that grocery store visits closer to home were more common among residents from neighborhoods with socioeconomic deprivation.

Contrary to our expectations, our analysis revealed that local grocery

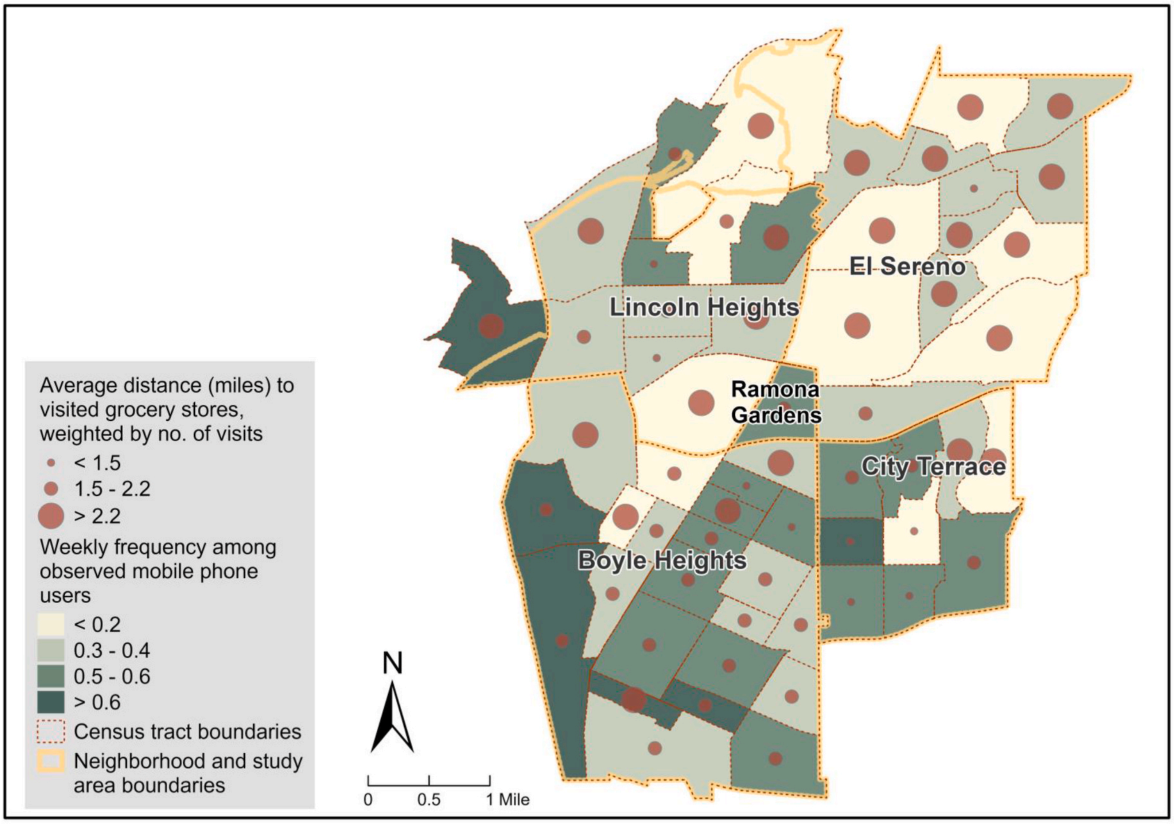

Fig. 5. Spatial variation of weighted distance and weekly frequency to grocery stores among observed mobile phone users across census tracts (n = 58), using mobility data from SafeGraph 2021.

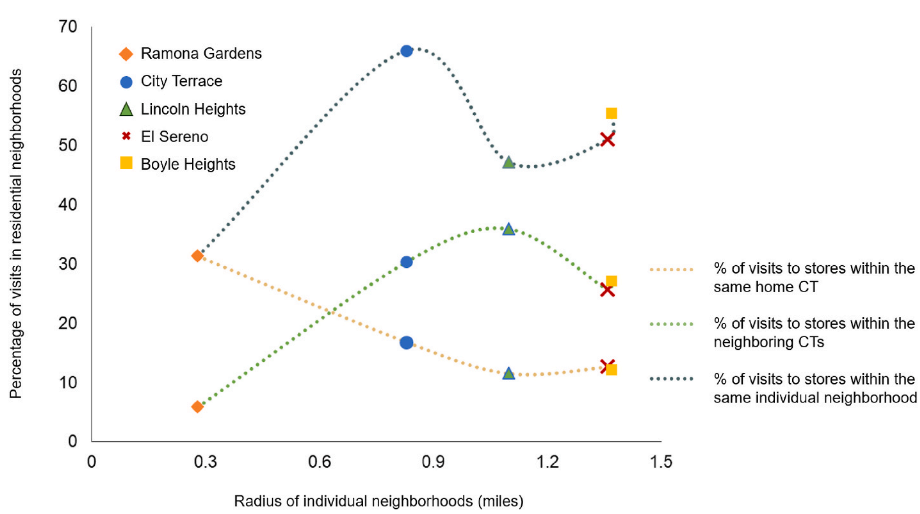

Fig. 6. Relationships between the percentage of visits to grocery stores in residential neighborhoods and different definitions of residential neighborhoods across the five community-defined neighborhoods, using data from SafeGraph 2021.

store accessibility was not significantly correlated with the distance traveled to grocery stores. To delve deeper into this issue, we compared our results to those in a comprehensive on-the-ground audit of food-selling establishments within our study area, as detailed in our previous and forthcoming publications (de la Haye et al., 2023, Lerner et al., submitted). Our audit suggested that among the 113 grocery stores categorized under the NAICS codes for such establishments, only 36 of these stores offered fresh vegetables, fruits, and at least one type of grains, with noticeable variations in price and quality among everyday food products (e.g., milk, egg, bread, banana, apple, chicken breast). Despite the physical proximity to these stores, this scarcity of stores selling quality, affordable food likely contributes to the observed non-significant relationship between grocery accessibility and the distances traveled to grocery stores.

Further insights obtained from the in-person interviews with residents and conversations with local stakeholders reinforce the lack and significance of having accessible, affordable, and healthy food options within local stores, which may explain the insignificant association between grocery accessibility and distance. Many participants voiced a strong desire for an increase in local stores offering affordable, fresh, and

Table 6
Principle component analysis of neighborhood characteristics, using 2017–2021 American Community Survey data (n = 58).

Neighborhood characteristics	Component 1	Component 2	Component 3	Component 4
% of variation explained	37%	19%	13%	9%
Median age (years)	−0.43		0.35	0.68
% black/African American		**−0.78**		
% Hispanic/Latino		**0.87**		
% Foreign-born	0.66	0.55		
% Disability				**0.88**
% Renter	**0.88**			
Median household income	**−0.77**			
% with SNAP benefits	**0.71**			
% ≥25 years with less than 9th-grade education	0.65	0.56		
% ≥25 years with a bachelor's degree and above	−0.35	**−0.83**		
% Commuting by transit	**0.79**			
No. of grocery stores in home CT			**0.90**	
No. of grocery stores in home and neighboring CTs			**0.83**	

Note: Loading factors higher than 0.7 are flagged in bolder font. Values lower than 0.3 are not reported (Perchoux et al., 2019). SNAP = Supplemental Nutrition Assistance Program, CT = Census Tract.

high-quality healthy foods (de la Haye et al., 2023). One participant reflected on the broader socioeconomic challenges impacting healthy food accessibility, stating: "I just wish we had more options here … but what we've been told is that those corporations … will not invest in coming into communities of color and low socioeconomic, because they feel that we will not purchase you know, expensive organic food." The feedback from local communities was instrumental in understanding the nuanced challenges faced by these communities in accessing healthy food options. It also emphasizes the necessity of incorporating local insights to understand the complex patterns observed in the study area to address the limitations and potential biases inherent in cross-sectional research and data (Hawkes et al., 2015; Chaix et al., 2013; Robertson and Feick, 2018; Shannon, 2015).

In summary, this study uncovers new insights into the grocery store visit patterns of predominantly minority populations. By adopting an activity space perspective and drawing on large-scale mobility data, we delved into the nuances of grocery store visits concerning frequency, diversity, distance, and the proportion of visits within residential neighborhoods. Our analysis revealed spatial and social disparities in residents' grocery store visitation patterns. Residents from under-resourced neighborhoods tend to frequent grocery stores more often and choose stores closer to their homes, and distance to visited stores was not significantly associated with car ownership or neighborhood grocery accessibility. Moreover, our results indicate that future research and policy interventions should take into consideration the unique needs and characteristics of under-resourced neighborhoods, examining the reasons behind their distinct grocery shopping patterns and addressing the disparities that arise.

4.3. *Strengths and limitations*

The major strength of this study is the estimation of grocery store visit patterns through repeatedly collecting large-scale anonymous mobility data spanning 50 weeks in 2021, rather than focusing on a snapshot of these patterns. This approach also helps overcome recall bias associated with collecting self-reported survey data and conducting interviews (Livings et al., 2023). Second, the comparisons with the qualitative insights gathered from our comprehensive in-store audits, interviews with local residents, and feedback from local stakeholders substantially contribute to the validity and interpretation of our mobility data. Moreover, the findings of our research have implications for future studies that explore relationships between neighborhood characteristics and grocery shopping behaviors.

This study has some limitations. First, the reliance on GPS data may introduce some level of missingness due to signal loss or be subject to selective daily mobility bias (Chaix et al., 2013). We made efforts to minimize this impact by averaging weekly GPS data over a span of 50 weeks and using number of trips as a weight in developing our indicators, rather than relying on a potentially anomalous single week or day, but there remains the possibility of bias in the data we used for analysis. Second, the mobility data does not capture all potential sources from which residents may obtain groceries, such as food banks and

Table 7
Association between different components of neighborhood characteristics and each of the grocery store visit features (n = 58).

Variables	Weekly frequency among observed mobile phone users		Weekly frequency among observed visitors		Richness	
	β	*p*	β	*p*	β	*p*
Component 1	0.3	0.01*	0.5	0.009**	0.3	0.1
Component 2	0.4	<0.001***	−0.1	0.32	0.1	0.6
Component 3	0.4	<0.001***	–	–	0.2	0.04*
Component 4	−0.3	0.006**	−0.3	0.06	−0.2	0.2
% Households with no car	–	–	−0.0	0.9	–	–
% Below the 100% FPL	–	–	0.0	1.0	0.1	0.2
% Living alone	–	–	–	–	−0.5	0.003**
R^2	0.48	<0.001***	0.35	<0.001***	0.45	<0.001***

Variables	Evenness		Weighted distance		The proportion of visits in home CT	
	β	*p*	β	*p*	β	*p*
Component 1	0.0	1.0	−0.2	0.05*	–	–
Component 2	−0.4	0.009**	−0.5	<0.001***	–	–
Component 3	–	–	–	–	0.3	0.03*
Component 4	0.2	0.1	0.2	0.1	–	–
% Households with no car	–	–	–	–	–	
% Below the 100% FPL	0.0	0.9	–	–	–	
% Living alone	−0.7	<0.001***	–	–	–	
R^2	0.34	0.002**	0.36	<0.001***	0.10	0.03*

Note: Significant results denoted with $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. FPL = Federal Poverty Level, CT = Census Tract.

corner stores (Adam and Jensen, 2016; Bodor et al., 2008; Martin et al., 2012). While we were able to use in-store audit that we previously gathered in our study area to enrich our understanding, we were unable to audit all 574 stores across Los Angeles, due to budget and time constraints. Third, our study focused on five Hispanic neighborhoods in Los Angeles, and the results therefore may not be generalizable to other geographic regions and socioeconomic groups. Despite this narrow focus, our observations provide important insights into the spatial and social disparities in grocery shopping behaviors within this specific community context and our findings and methods can inform future research in urban settings that explores the dynamics of food accessibility, grocery shopping patterns and neighborhood disparities.

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CRediT authorship contribution statement

Mengya Xu: Conceptualization, Data curation, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing. **John P. Wilson:** Conceptualization, Funding acquisition, Methodology, Supervision, Writing – review & editing. **Wändi Bruine de Bruin:** Supervision, Writing – review & editing. **Leo Lerner:** Validation, Writing – review & editing. **Abigail L. Horn:** Writing – review & editing. **Michelle Sarah Livings:** Writing – review & editing. **Kayla de la Haye:** Conceptualization, Formal analysis, Funding acquisition, Investigation, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.healthplace.2024.103220.

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