

Developing a healthy food access index (HFAI): Web-based mapping and future directions for AI integrations

Junfeng Jiao^a, Kijin Seong^{a,*}, Marcus Sammer^b, Ryan Hardesty Lewis^c, Alison Reese^d, Norma Olvera^b, Susie L. Gronseth^b, Elizabeth Anderson-Fletcher^b, Ioannis Kakadiaris^b

^a Urban Information Lab, The University of Texas at Austin, Austin 78712, TX, USA

^b University of Houston, Houston 77204, TX, USA

^c Cornell Tech, New York 10044, NY, USA

^d Tackle Hunger, Bee Cave 78738, TX, USA

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ABSTRACT

Food insecurity remains a pressing issue in urban communities, particularly in underserved areas with limited access to healthy and affordable food. This study introduces a comprehensive approach to assessing and addressing food access challenges in the Greater Houston region by developing a Healthy Food Access Index (HFAI). The HFAI incorporates a wide range of data sources, including economic and sociocultural deprivation indices, retail food environment measures, physical access indicators, and accommodation access data, that offer a multidimensional understanding of food access. Using GIS-based mapping and hot spot analysis, we identify areas of critical need, highlighting significant disparities in food access and health across the region. We also present the web-based platform, "AI-FEED," designed to support community leaders and urban planners by visualizing food access challenges and providing AI-driven suggestions for optimizing food pantry placements, incentivizing healthy options at dollar stores, and improving public transit routes. This platform integrates real-time data, offering dynamic and proactive solutions to enhance food security and improve public health outcomes. Our study introduces the importance of targeted, data-driven interventions in addressing food insecurity and demonstrates the potential of AI and digital platforms in supporting sustainable urban food systems.

1. Introduction

In recent years, the vulnerability of the food security system has been highlighted by events that have exacerbated existing challenges. For example, as communities gradually recovered from the challenges of COVID-19, the issue of food insecurity escalated (Coleman-Jensen, Rabbitt, Gregory, & Singh, 2021; Park et al., 2022), with charitable food organizations across the United States reporting a need to provide up to 50 % more resources to those in need, yet often struggling to meet this heightened demand (Gupta et al., 2024).

In addition to this, disadvantaged communities throughout Harris County in Texas continue to suffer from health issues due to ongoing challenges such as limited access to nutritious foods and a limited awareness about healthy eating practices, which have long been identified as critical factors influencing food security (Bader et al., 2010; Hamm & Bellows, 2003; Pothukuchi, 2004).

Addressing these systemic health disparities requires a

comprehensive approach, and one critical framework that has emerged is community food security (CFS). Community food security (CFS) refers to a condition in which all residents within a community have access to a safe, culturally appropriate, and nutritionally sufficient diet through a sustainable food system that fosters community self-reliance and social justice (Hamm & Bellows, 2003; Pothukuchi, 2004). Achieving CFS is crucial for addressing food insecurity, particularly in underserved communities where access to nutritious foods can be severely limited.

Ensuring geographic access to healthy and affordable foods has become a central focus in U.S. public health initiatives, which stems from the understanding that limited access to nutritious foods is a crucial factor contributing to obesity and other diet-related chronic illnesses (Bodor et al., 2010; Dubowitz et al., 2015; Giang et al., 2008; Larson et al., 2009; Michimi & Wimberly, 2010; Rundle et al., 2009; Ver Ploeg, 2010). One strategy suggested to improve dietary outcomes in underserved areas, often referred to as food deserts, involves the establishment of full-service supermarkets and grocery stores, which are

* Corresponding author at: Urban Information Lab, School of Architecture, The University of Texas at Austin, Austin 78712, TX, United States.

E-mail address: kijin.seong@austin.utexas.edu (K. Seong).

considered reliable sources of healthy and affordable food (Jiao et al., 2012; Rose et al., 2009). Proximity to the nearest food store has traditionally been a standard metric for food access. However, researchers and policymakers increasingly advocate for a more comprehensive approach to food access, considering multiple factors beyond physical distance (Caspi et al., 2012; Ver Ploeg, 2010). Relying solely on proximity overlooks the complex realities of food environments and the numerous barriers individuals face in obtaining nutritious foods. Geographic access encompasses more than just physical distance; it includes the availability of healthful food retailers, transportation options, numerous socioeconomic factors, and federally supported retailers that collectively influence a person's ability to access healthy food (Caspi et al., 2012; Ver Ploeg, 2010; Widener & Shannon, 2014).

Current food access research often relies on overly simplified models that fail to capture the complexity of healthy food accessibility and urban mobility patterns. An example of this simplification was the early iteration of the USDA's Food Access Research Atlas, originally termed the "Food Desert Locator." This tool designated areas as food deserts based solely on family income levels and distance to the nearest grocery store, disregarding evidence that food shopping habits are far more nuanced. As Widener (2018) discussed, many individuals do not necessarily shop at the closest food retailer (Cummins et al., 2014; Inagami et al., 2006), and transportation options can significantly alter accessibility to supermarkets (Widener, 2017; Widener et al., 2015). Recent updates to the USDA's atlas have incorporated additional factors such as vehicle access and populations living in group quarters (USDA ERS, 2024). However, the underlying approach still tends to oversimplify the multifaceted nature of food access by categorizing entire census tracts such as having or lacking access to nutritious food sources. This tract-level aggregation can obscure significant intra-neighborhood disparities and overlook the nuances of food accessibility within smaller geographic areas.

Artificial intelligence (AI) is attracting increasing attention as a tool to address ongoing food insecurity challenges and improve CFS. While traditional methods like Geographic Information Systems (GIS), surveys, interviews, and store audits have helped assess food environments and accessibility issues (Caspi et al., 2012; Walker et al., 2010), they have not been able to capture the complex, dynamic nature of food insecurity. This complexity arises from intricate economic, social, and environmental interactions. Though conventional approaches have offered valuable insights into the spatial distribution of food resources and availability of nutritious options, there is growing recognition that new tools are needed to fully understand and address these multifaceted issues (Caspi et al., 2012).

The advent of AI presents promising solutions to the limitations of traditional methods in predicting and responding to food insecurity. By analyzing large datasets, AI can identify patterns and forecast changes in food access, enabling more proactive measures (Amin et al., 2021). Machine learning algorithms, for example, can optimize the placement of new food resources, like grocery stores or food pantries, by considering population density, socioeconomic status, and transportation networks (Alhindi et al., 2020). AI can also enhance real-time data integration into web-based platforms, allowing for continuous monitoring and rapid response to food access issues - crucial for effective intervention in both urban and rural settings (Gao et al., 2023). For example, on-demand LLM parsing of news or disasters can provide more immediate and flexible data sources rather than relying solely on a government API. By leveraging AI, policymakers and community leaders can develop more targeted and efficient strategies to reduce food insecurity and improve community food security, ultimately fostering healthier and more resilient communities.

Current literature on food insecurity and CFS has primarily focused on identifying and mapping food deserts and swamps using traditional research methods. While these methods provide valuable spatial insights, they often present a static view that misses the dynamics and complex socioeconomic factors influencing food access. Existing studies

tend to neglect critical factors such as transportation, economic barriers, and cultural preferences, which might play significant roles in shaping food security outcomes (Bader et al., 2010; Widener, 2018). Moreover, the health disparities directly tied to food consumption and food insecurity have often been underexplored.

Previous research has examined specific aspects of food security, such as economic deprivation, the retail food environment, or transportation accessibility, but these factors have often been considered in isolation or only to a limited extent, highlighting the need for a more comprehensive approach. This study advances existing research by integrating multiple dimensions into a single, standardized framework, the Healthy Food Access Index (HFAI), allowing for a more scalable and holistic assessment of food security disparities across multiple urban contexts. Unlike conventional food access models that rely primarily on proximity-based measures, the HFAI captures economic and sociocultural deprivation, the balance between healthy and unhealthy food retailers, physical accessibility through multiple travel modes, and the presence of government-assisted food resources. This scalability makes the HFAI adaptable to different cities, offering a broader tool for urban planners and policymakers to assess food access challenges on a larger scale. This multidimensional approach enables a more nuanced understanding of structural barriers to healthy food access, offering actionable insights for urban planners and policymakers. It also brings a new perspective by incorporating health disparities related to food insecurity, a crucial yet often overlooked factor.

Moreover, there is a limited application of advanced technologies such as AI in this domain despite their potential to offer more dynamic and predictive insights. Although some research has explored the use of AI for optimizing food distribution and predicting food access (Alhindi et al., 2020; Amin et al., 2021), these efforts remain fragmented and lack comprehensive integration into broader food security strategies. To address the gap in the literature, this study introduces AI-FEED, a web-based, AI-driven geospatial decision-support tool, designed to enhance food security through four interconnected modules, each addressing the needs of a key stakeholder group: food charities, donors, clients, and community leaders (Sammer et al., 2024). This study introduces the Community Leaders module as part of our larger AI-FEED platform, which currently functions as an interactive web-based mapping platform using ArcGIS Online. AI-FEED is an evolving tool designed to integrate AI-powered functionalities in future iterations, including predictive modeling for food access trends, optimization of food pantry locations, and automated decision-support tools. While the Community Leaders module is operational and available for use, the broader AI-FEED platform is still in development, with these advanced features being actively incorporated into the system. This study specifically focuses on the Community Leaders module, which represents an early phase of the AI-FEED platform's overall functionality.

The proposed study specifically utilizes spatial mapping and data visualization to assist urban planners and policymakers in addressing food insecurity. Although the AI-driven components of AI-FEED are still under development, the platform is structured to incorporate advanced AI capabilities in future iterations, aligning with its broader role in the food charity ecosystem. While the AI-driven optimization tools within AI-FEED are still in active development and not fully implemented yet, this study outlines potential applications for AI in food security planning, including (1) food pantry placement optimization, (2) GeoAI-based suitability analysis for incentivizing healthier food options at dollar stores, and (3) public transit optimization to improve food accessibility. By integrating machine learning techniques and real-time spatial analytics, AI-FEED will present a dynamic, adaptive approach to food access planning. This innovative use of AI has the potential to empower service providers, urban planners, and healthcare professionals with tools to directly combat health disparities related to food insecurity. The present study bridges the gap between traditional GIS-based food environment research and real-time policy decision-making, positioning AI-FEED as an emerging tool for urban resilience

and food security planning at both local and regional levels.

This research seeks to address food insecurity by developing a comprehensive food security index that captures the dynamic factors influencing healthy food access and generating a hotspot map that identifies areas of greatest need for improved food access. Specifically, the Healthy Food Access Index (HFAI) is a composite measure comprising five indices: the Economic Deprivation Index (EDI), which captures economic hardship; the Sociocultural Deprivation Index (SDI), which reflects social and cultural barriers; the Retail Food Environment Index (RFEI), which assesses the balance of healthy and unhealthy food sources; the Physical Access Index (PAI), which measures spatial accessibility; and the Accommodation Access Index (AAI), which evaluates the availability of food assistance programs.

Additionally, this study features the development of an original web-based platform prototype designed to provide community leaders with real-time insights into local food access conditions. The platform aims to serve as a conversation starter for community leaders, focusing on the intersection of food security and health disparities. It helps them assess food security in their communities while encouraging broader discussions on actions to address these issues. Finally, the research suggests AI-driven tools to optimize the placement of food pantries, related services, and transit routes, enhancing food distribution efficiency. It highlights the importance of community-driven solutions to address health disparities, such as improving access to health food stores or supporting food charities for equitable resource distribution.

This study was guided by the following key research questions:

- How can a multidimensional approach to food access improve the identification of food insecurity hotspots?
- What spatial disparities exist in healthy food access across the Greater Houston region, and how do different socio-economic conditions, transportation accessibility, the retail food environment, and financial resources shape these disparities?
- How can web-based mapping tools support community leaders in addressing food access challenges, and what role can AI-driven techniques play in future decision-support applications?

2. Materials and methods

2.1. Study area

This study focused on the Greater Houston region, encompassing Harris County and its surrounding area. As the fourth largest city in the United States, with projections to surpass Chicago by 2035 (NBC Chicago, 2024), Houston presents an ideal setting for investigating nutrition, food security, and supply chain resilience. The region is characterized by significant cultural diversity and pronounced health disparities. Notably, Houston's income gap exceeds the national average, contributing to increased community vulnerability to natural disasters and public health crises (Bergstrand et al., 2015; Flores et al., 2020; Lowe et al., 2019). Houston's Gulf Coast location makes it susceptible to natural hazards, especially hurricanes and subsequent flooding. Recent events, including the unprecedented flooding caused by Hurricane Harvey in August 2017 and the “double disaster” scenario of the COVID-19 pandemic coinciding with severe weather events like Winter Storm Uri in 2021, have underscored the heightened vulnerability of economically disadvantaged Houston communities in terms of access to healthy food. Harris County, at the region's core, has been particularly impacted by these challenges. The unique features of Greater Houston offer a prime opportunity to examine how food networks, community well-being, and resilience are interconnected.

2.2. Data sources, construct, and measures

2.2.1. Data collection

This study utilized datasets collected prior to April 2023. We

obtained indicators for the economic deprivation index (EDI) and sociocultural deprivation index (SDI) from the American Community Survey 2016–2020 5-year estimates, accessed through the Census Data API. To facilitate this data collection, we adapted an established Python script for retrieving Census data (Rosenheim et al., 2021). To determine the locations of healthy and unhealthy food stores and markets for the retail food environment index (RFEI), we utilized Reference USA. We filtered grocery stores and retailers using North American Industry Classification System (NAICS) codes. The specific filtering strategies employed are detailed in Appendix 1. We obtained the locations of Women, Infants, and Children (WIC)-approved grocers and Supplemental Nutrition Assistance Program (SNAP)-authorized retailers through the WIC store locator website (<https://www.wicstorelocator.com/>) and USDA Food and Nutrition Service (<https://www.fns.usda.gov/snap/retailer-locator/>), respectively. The Tackle Hunger Map (<https://map.tacklehunger.org/>) provided food pantry and food bank locations. Local data from the CDC's PLACES project (<http://www.cdc.gov/places/>) was collected to identify health disparities. Finally, the Harris County bus and train route map was collected from the Harris County GIS Open Data Portal (<https://geo-harriscounty.opendata.arcgis.com/>).

2.2.2. Multidimensional food access framework

Our study builds upon Widener's (2018) comprehensive framework for assessing food access. Widener's approach adopted the healthcare accessibility concept proposed by Penchansky and Thomas (1981) to the context of food systems. We further refine and apply this adapted framework to our research. Rather than relying solely on spatial metrics, we consider food access as a function of five key dimensions: Economic Deprivation Index (EDI), Sociocultural Deprivation Index (SDI), Retail Food Environment Index (RFEI), Physical Access Index (PAI), and Accommodation Access Index (AAI). The EDI captures affordability aspects through indicators such as median household income, poverty rates, and participation in government welfare programs. The SDI addresses affordability and acceptability, incorporating education levels, racial demographics, and family structure. The RFEI represents availability by quantifying the ratio of healthful food sources within census tracts. The PAI focuses on accessibility, measuring the spatial configuration of food retailers within various travel distances and modes.

Additionally, we include an AAI that examines the presence of WIC-approved stores and SNAP-authorized retailers, which allow alternative payment options, and food pantries that provide free food assistance. This comprehensive approach allows us to move beyond the oversimplified “food desert” metaphor and provides a more nuanced understanding of the various factors influencing food access in urban environments. Table 1 provides definitions and detailed descriptions of indicators used in this study.

2.3. Methods

The Greater Houston was selected as the study area for this research due to its socio-economic diversity and large health disparities, which make it a strong case study for food access research. As one of the most ethnically and culturally diverse metropolitan areas in the United States, Houston encompasses significant variations in income, education, and race across its neighborhoods (Kinder Institute, 2019). This allows investigators to analyze across a wide range of socio-economic and demographic stakeholders, making the findings applicable to similarly diverse urban areas nationally. The selected study region also exhibits pronounced health disparities, with specific communities experiencing high rates of obesity, diabetes, and other diet-related health issues (Adepoju et al., 2021; HDHHS, 2008). These health issues are often exacerbated by limited access to healthy food, providing a critical context for studying the intersection of food access, health outcomes, and socio-economic deprivation. Additionally, the Greater Houston area encompasses a mix of densely populated urban cores and sprawling

Table 1

Definitions, descriptions, and data sources for indicators used in Healthy Food Access Index (HFAI) development.

Category	Indicator	Description	Data Source
Economic Deprivation Index (EDI)			
Affordability	Median household income (\$1000)	Median household income (\$1000)	2020 ACS 5-year estimates
	Below the poverty line (%)	Percentage of the population that lives below the poverty level (%)	2020 ACS 5-year estimates
	Unemployment rate (%)	Percentage of non-employed for population 16–64 years (%)	2020 ACS 5-year estimates
	Without complete kitchen facilities (%)	Percentage of households lacking complete kitchen facilities in housing units (%)	2020 ACS 5-year estimates
	Households with no car (%)	Percentage of households with no vehicle	2020 ACS 5-year estimates
	Participation in government welfare programs (social benefits)	Percentage of households receiving any social benefits (%)	2020 ACS 5-year estimates
Sociocultural Deprivation Index (SDI)			
Affordability/Acceptability	Without higher education (%)	Percentage of population 25 years or older with 12 years of education or less (%)	2020 ACS 5-year estimates
	Hispanic (%)	Percentage of Hispanic population (%)	2020 ACS 5-year estimates
	Black (%)	Percentage of non-Hispanic Black population (%)	2020 ACS 5-year estimates
	Home renter (%)	Percentage of households living in renter-occupied housing units (%)	2020 ACS 5-year estimates
	Single parent (%)	Percentage of single-parent families with dependents <18 years (%)	2020 ACS 5-year estimates
Retail Food Environment Index (RFEI)			
Availability	(Healthy) Supermarkets and grocery stores	Number of all supermarket and grocery store chains providing healthy food	Reference USA
	(Healthy) Supercenters	Number of warehouse clubs and supercenters providing healthy food	Reference USA
	(Healthy) Specialty food stores	Number of specialty food retailers providing meat, fish, seafood, fruit, vegetable, and other healthy food	Reference USA
	(Unhealthy) Convenient stores	Number of convenience stores providing unhealthy food	Reference USA
	(Unhealthy) Fast-food restaurants	Number of fast-food restaurants providing unhealthy food	Reference USA

Table 1 (continued)

Category	Indicator	Description	Data Source
	(Unhealthy) Dollar stores	Number of dollar stores providing unhealthy food	Reference USA
Physical Access Index (PAI)			
Accessibility	Baseline of <1 mile	Percentage of baseline service area <1 mile in a census tract (%)	Reference USA
	10-min walking distance service area	Percentage area of 10-min walking distance in a census tract (%)	Reference USA
	10-min transit distance service area	Percentage area of 10-min distance from public transit (bus, train) route in a census tract (%)	Reference USA, Harris County GIS Open Data Portal
	10-min driving distance service area	Percentage area of 10-min driving distance in a census tract (%)	Reference USA
Accommodation Access Index (AAI)			
Accommodation	WIC approved stores	Number of WIC-approved grocers in a census tract	WIC Store Locator
	SNAP authorized retailers	Number of SNAP-authorized retailers in a census tract	USDA Food and Nutrition Service
	Food pantries	Number of food pantries/food banks in a census tract	Tackle Hunger Map

suburban and rural zones in which food access challenges can be analyzed across different spatial and socio-economic configurations and offering insights relevant to both high-density and lower-density communities.

2.3.1. Healthy food access index (HFAI) development

2.3.1.1. Economic deprivation index (EDI). The Economic Deprivation Index (EDI) was developed to measure economic hardship and disadvantage at the census tract level, which is crucial for understanding the healthy food access (Charreire et al., 2010; Gamba et al., 2015). The EDI comprises six variables: median household income, percentage of population below the poverty line, unemployment rate, percentage of households without complete kitchen facilities, percentage of households without a car, and participation in government welfare programs. Data for these variables were collected using a Python script via the Census Data API, and then percentile ranks were calculated for each variable. We used the opposite cardinality (1-percentile rank) for median household income, as higher income indicates lower deprivation. Six percentile rank scores were then summed to create a composite EDI score for each census tract. Finally, the composite EDI scores were standardized by calculating z-scores in STATA, allowing for comparison across different areas and integration with other indices in our multi-dimensional food access framework.

2.3.1.2. Sociocultural deprivation index (SDI). The Sociocultural Deprivation Index (SDI) was developed to capture the social and cultural factors influencing healthy food access at the census tract level. This index measures aspects of social disadvantage and cultural barriers that may affect food choices and accessibility beyond economic factors (Larson et al., 2009; Peeters & Blake, 2016). The SDI comprises five variables: percentage of population without higher education,

percentage of Hispanic population, percentage of non-Hispanic Black population, percentage of home renters, and percentage of single-parent families. These variables were selected based on their established relationships with food access and dietary behaviors in previous research (Hilmers et al., 2012; Jin & Lu, 2021; Lillini & Vercelli, 2019; Zenk et al., 2011).

Data for the SDI were collected from the ACS 2016–2020 5-year estimates using the same methods as for the Economic Deprivation Index (EDI). The data processing method mirrored that of the EDI, involving the calculation of percentile ranks for each, which were then summed to create a composite SDI score and z-scored to standardize the index.

2.3.1.3. Retail food environment index (RFEI). The Retail Food Environment Index (RFEI) assesses the availability and balance of healthy and unhealthy food sources at a census tract level (Amin et al., 2021; Cooksey-Stowers et al., 2017; Spence et al., 2009). RFEI provides insight into the abundance of nutritious food options compared to less healthy alternatives in a community. The RFEI considers the number and type of food retailers, categorizing them as either healthful or unhealthful based on their predominant foods (Morland et al., 2006). Our study calculated the RFEI using data collected in April 2023 from Reference USA, a comprehensive business database. We collected information on 2052 healthy food sources, including supermarkets, grocery stores, supercenters, and specialty food stores (e.g., those selling meat, fish, seafood, fruits, vegetables, dairy, and other gourmet foods). Unhealthful food sources (4233 stores) included convenience stores, fast-food restaurants, and dollar stores. We identified them using NAICS Codes and then used ArcGIS Pro to spatially join and count the number of healthy and unhealthy food retailers within each census tract. We then applied weights to different food retailer types based on their potential impacts, with supercenters receiving a higher weight than regular supermarkets. This was based on the ratio of average sales volumes in Harris County, Texas, where supermarkets averaged \$7,378,615 and supercenters averaged \$36,108,555. After removing outliers, we determined a relative weight of 4.894 for supercenters to represent the impact of larger stores on the local food environment. We adopted the modified retail food environmental index (Amin et al., 2021; CDC, 2012) to calculate the score.

$$\text{mRFEI} = 100 \times \frac{\text{Weighted number of healthful retailers in tract}}{\text{Weighted number of healthful retailers in tract} + \text{number of unhealthful retailers in tract}}$$

$$= 100 \times \frac{((1 * \text{Supermarkets}) + (4.894 * \text{Supercenters}) + (1 * \text{Specialty Stores}))}{((\text{Supermarkets}) + (4.894 * \text{Supercenters}) + (\text{Specialty Stores}) + (\text{Convenience Stores}) + (\text{Fast Food Restaurants}) + (\text{Dollar Stores}))} \quad (1)$$

Finally, we standardized the RFEI scores using z-scores to allow for comparison across different areas and integration with other indices. RFEI provides a nuanced understanding of the food retail landscape, considering the overall balance of healthy and unhealthy options available to residents (Zenk et al., 2015).

2.3.1.4. Physical access index (PAI). The Physical Access Index (PAI) was developed to measure the spatial accessibility of healthy food sources within urban environments. This index quantifies the ease with which residents can reach food retailers offering nutritious options (Caspi et al., 2012; Charreire et al., 2010). To create the PAI, we incorporated four key measures of accessibility: (1) a baseline measure

of <1-mile distance, (2) a 10-min walking distance, (3) a 10-min transit distance, and (4) a 10-min driving distance. We used ArcGIS Pro to conduct service area analyses. For the transit measure, we created a 0.25-mile buffer around bus and train routes to represent areas with reasonable access to public transportation. For each census tract, we calculated the percentage of area covered by each of the four service areas, summed these percentages, and then calculated the z-score of these sums across all census tracts to integrate with other indices. PAI represents physical food access that accounts for various transportation modes and travel times, moving beyond simplistic distance-based measures to incorporate the complexities of urban mobility and transportation options.

2.3.1.5. Accommodation access index (AAI). The Accommodation Access Index (AAI) measures the availability of food retailers participating in government assistance programs, specifically focusing on stores approved for WIC and SNAP programs, as well as the presence of food pantries, reflecting access to subsidized or free food resources. AAI captures the financial accessibility of nutritious food options for low-income populations (Amin et al., 2021; Lin et al., 2014; Widener, 2018). The AAI recognizes that physical proximity to food retailers is insufficient if residents cannot afford healthy foods, making government assistance programs crucial in promoting food security and nutrition among vulnerable populations (Carlson & Llobrera, 2022; Lee et al., 2023). We collected data on WIC-approved stores, SNAP-authorized retailers, food pantries, and food banks to create the AAI. We geocoded store addresses to create point data, which were then spatially joined with census tracts in ArcGIS Pro to obtain a count of WIC and SNAP retailers and food pantries/banks within each tract. Likewise, we computed the sum of these variables and calculated z-scores to standardize the index. This approach supports understanding the financial accessibility of healthy food options for low-income residents.

The Healthy Food Access Index (HFAI) was created by combining five z-score indices using a weighted sum approach in STATA. Each component index was assigned an equal weight of 0.2, applying negative weights (−0.2) to EDI and SDI due to their inverse relationship with healthy food access. Equal weighing was selected based on its methodological transparency, empirical precedent, and the multidimensional

nature of food access. Given that food access disparities result from intersecting socio-economic, spatial, and institutional factors, assigning differential weights without robust empirical validation could lead to misrepresentations of food security challenges in different neighborhoods (Ly et al., 2020; Santeramo, 2015). Similar approaches have been used in composite indices in previous studies (Caspi et al., 2012; CDC, 2022; USDA ERS, 2024). The final HFAI formula is:

$$\text{HFAI} = (-0.2)^*(z.\text{EDI}) + (-0.2)^*(z.\text{SDI}) + (0.2)^*(z.\text{RFEI}) + (0.2)^*(z.\text{PAI}) + (0.2)^*(z.\text{AAI}) \quad (2)$$

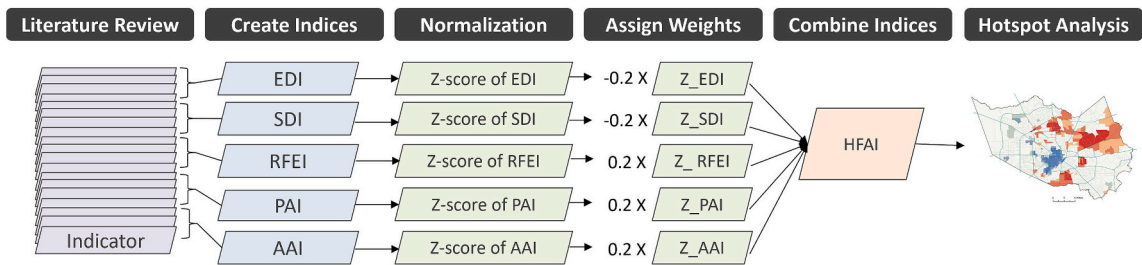


Fig. 1. Methodology framework for developing the Healthy Food Access Index (HFAI).

2.3.2. Hot spot analysis

We employed the Hot Spot Analysis tool using the Getis-Ord Gi* statistic in ArcGIS Pro to identify statistically significant spatial clusters of areas with high and low healthy food access. Z-scores and *p*-values measure statistical significance, with high positive z-scores indicating clustering of high values (hot spots) and low negative z-scores indicating clustering of low values (cold spots) at 90 %, 95 %, and 99 % confidence levels. We used the fixed distance band method for conceptualizing spatial relationships, ensuring each tract had at least one neighbor. Using hot spot analysis, we identified areas with significantly high (hot spots) and low (cold spots) healthy food access, providing valuable insights for targeting interventions and policy decisions to improve food accessibility in the Greater Houston area. A summary of the methodology framework for developing the HFAI is provided in Fig. 1.

2.3.3. Web-based platform development

Web-based GIS platforms can enhance urban policy decision-making by providing accessible, data-driven information (Pettit et al., 2018; Yaakup et al., 2001). Such platforms enable policymakers to make more informed decisions by offering a holistic view of urban challenges. Integrating diverse datasets allows users to visualize and analyze complex relationships among various urban factors, such as food access, health outcomes, and socioeconomic conditions. Recognizing these benefits, we developed a web-based platform using ArcGIS Online for policymakers and community leaders to aid decision-making on local healthy food access.

Called “AI-FEED,” the platform integrates various data layers to provide a comprehensive view of food security issues in Harris County, Texas. The interface includes a base map overlaid with information including healthy food access indicators, correlated health risks (e.g., obesity, diabetes, high cholesterol, coronary heart diseases),

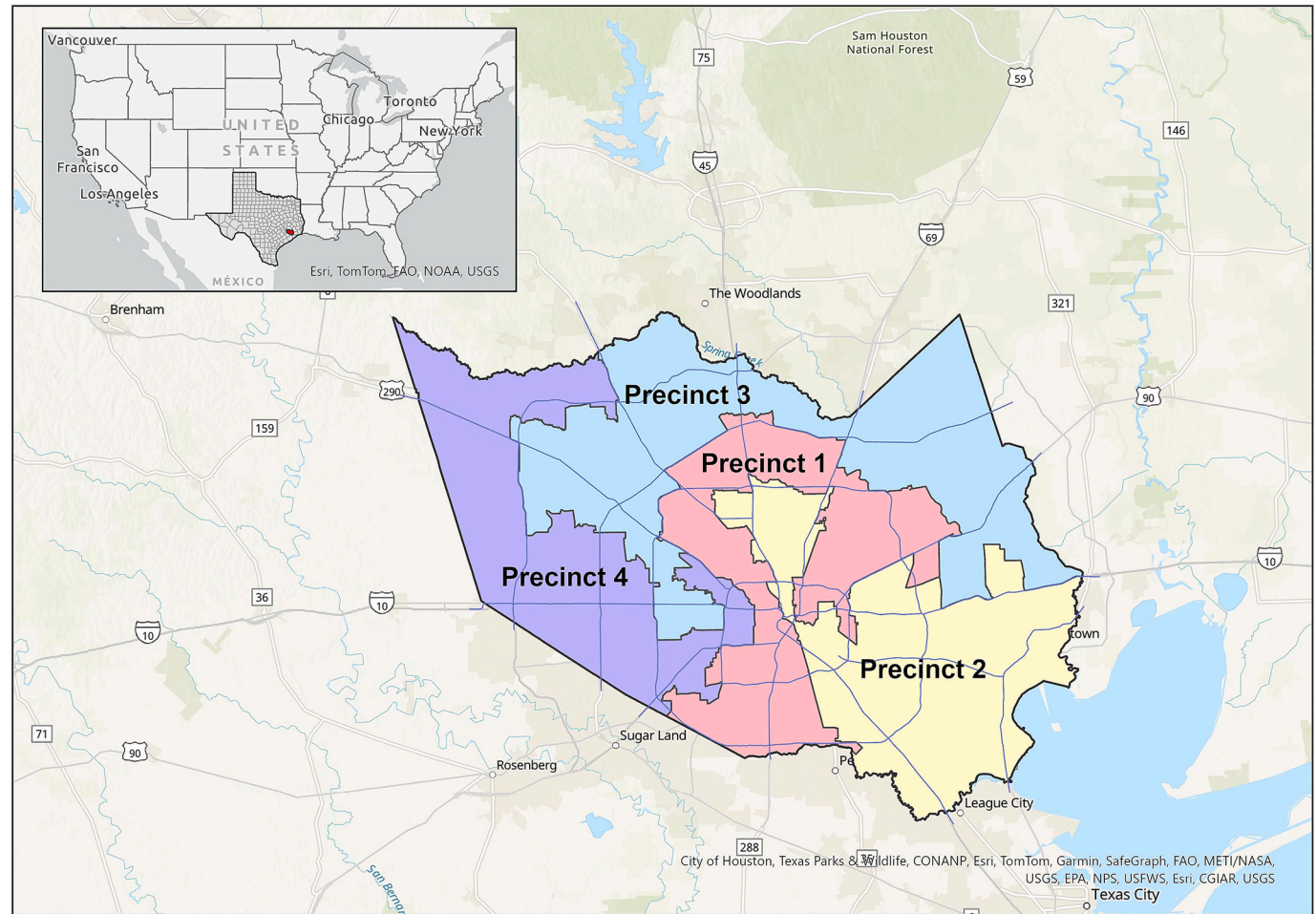


Fig. 2. Precinct Boundaries in Harris County, Texas.

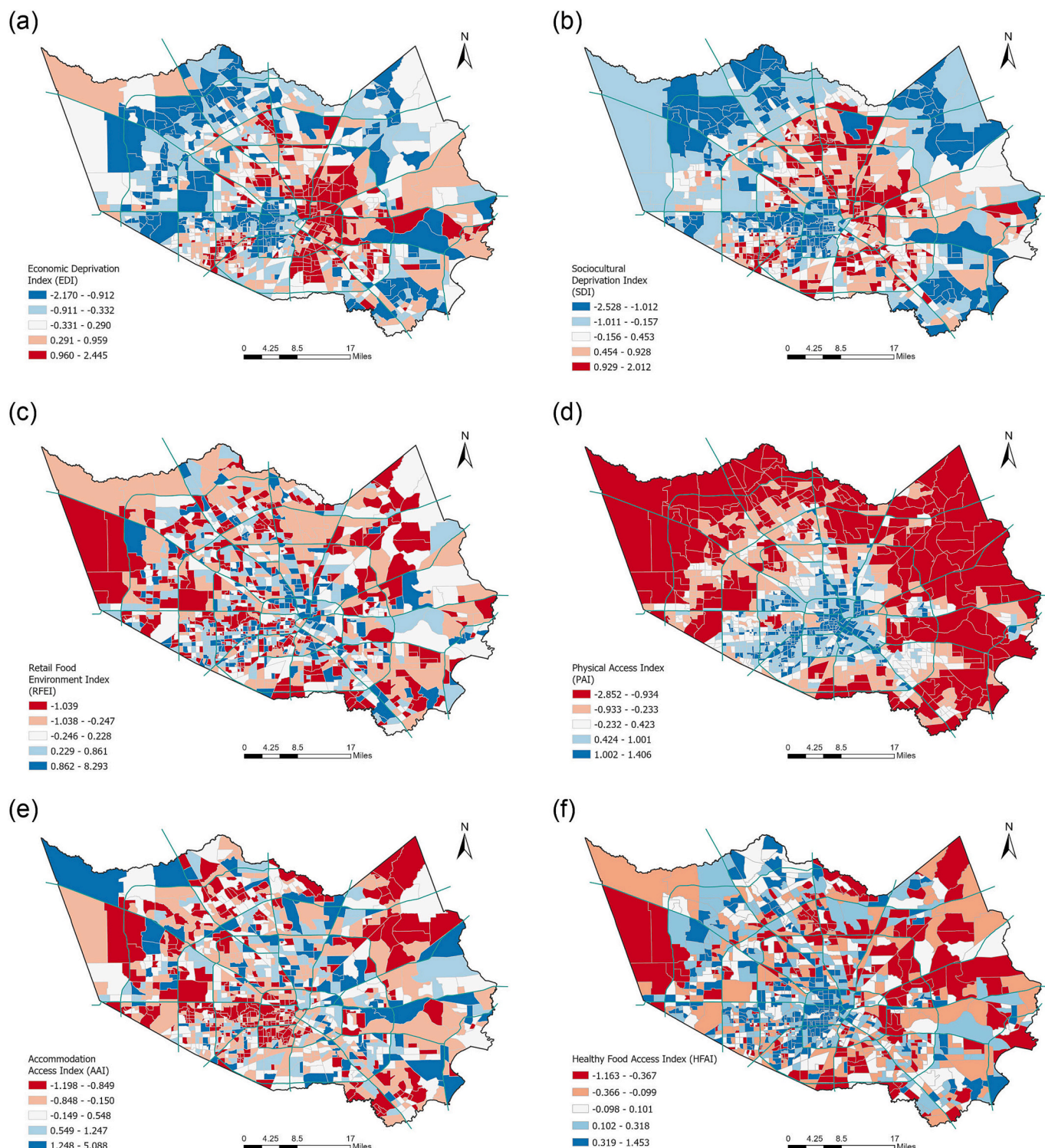


Fig. 3. Spatial distribution of multiple indices in Harris County, Texas: (a) Economic Deprivation Index (EDI), (b) Sociocultural Deprivation Index (SDI), (c) Retail Food Environment Index (RFEI), (d) Physical Access Index (PAI), (e) Accommodation Access Index (AAI), and (f) A composite index of Healthy Food Access Index (HFAI). Analysis was run on August 28, 2024.

socioeconomic deprivation indices, and points of interest like grocery stores, food pantries, dollar stores, and hospitals. To highlight accessibility issues, the platform also incorporates public transportation networks.

To enhance the platform's utility, we are incorporating an AI-driven

placement system that suggests optimal locations for new food-related infrastructure and transportation routes. This feature is backed by data on potential beneficiaries, aligning with studies demonstrating the effectiveness of AI in urban planning and resource allocation (Yigitcanlar et al., 2020).

3. Results

3.1. Healthy food access index (HFAI)

Fig. 2 presents the administrative divisions of Harris County, delineating its precinct boundaries to provide spatial context for the study area.

We generated the spatial distribution of the various indices contributing to the composite HFAI (see Fig. 3). The EDI and the SDI reveal similar patterns, pinpointing areas with more substantial socio-economic deprivation, such as neighborhoods in East Houston, the Third Ward, and parts of North Houston. In contrast, affluent neighborhoods in West Houston, including River Oaks, Memorial, and the Woodlands, exhibit relatively higher socioeconomic status. The RFEI presents a more scattered pattern, but central Houston stands out with a higher concentration of healthy food stores than Harris County's outskirts. This trend is even more pronounced in the Physical Access Index (PAI), which considers factors like public transit routes and proximity to healthy food stores within walking distance. Central Houston, therefore, shows better physical access to healthy food than suburban and rural areas. Regarding AAI, federally assisted programs, such as WIC, SNAP-approved stores, and food pantries, are more widespread in western and north Houston areas. Still, they are relatively scarce in the wealthier neighborhoods of West Houston.

When all these indices are combined, the composite HFAI map clearly shows greater food accessibility in affluent West Houston neighborhoods, particularly in River Oaks and Memorial, depicted by the blue zones on the map. Notably, Southwest Houston neighborhoods like Alief and Gulfton face restricted access to healthy food, as do Southeast Houston areas such as Sunnyside and South Park. In East Houston, the Denver Harbor/Port Houston area is marked by a lower availability of nutritious food. Northeast Houston neighborhoods,

including the Fifth Ward and East Little York/Homestead, are also shown as having limited access alongside parts of Acres Homes in Northwest Houston.

3.2. Hot spot analysis

The hot spot map for limited healthy food access in Harris County, Texas, identifies areas with significant disparities in access to nutritious food (see Fig. 4). Hot spots, indicating restricted healthy food access, are prominently located in the eastern and northeastern parts of the county, including neighborhoods like East Houston, Fifth Ward, and the Denver Harbor/Port Houston area. These hot spots are shown in red, reflecting areas where intervention is most needed.

Although food insecurity is often linked to inner-city neighborhoods, the cold spot areas identified in this study—including Downtown Houston, Montrose, River Oaks, West University Place, Meyerland, and Greater Uptown—exhibit distinct socio-economic characteristics that enhance food accessibility. These areas have a high density of grocery stores and specialty markets, with supermarkets such as Whole Foods, Trader Joe's, H-E-B, and Central Market contributing to higher Retail Food Environment Index (RFEI) scores. Additionally, these neighborhoods are among Houston's wealthiest, where higher incomes and greater transportation access improve food security. Downtown Houston and Greater Uptown also function as economic hubs, attracting a large daytime workforce, which sustains a strong food retail presence. Some food retailers cater primarily to this transient population, and the availability of grocery stores and high-end restaurants increases overall food access. However, food affordability may remain a concern for lower-income residents, particularly those located outside central Houston, who face significant challenges in accessing healthy food options. Future research should examine affordability and food access disparities within both high-income and lower-income areas of the city

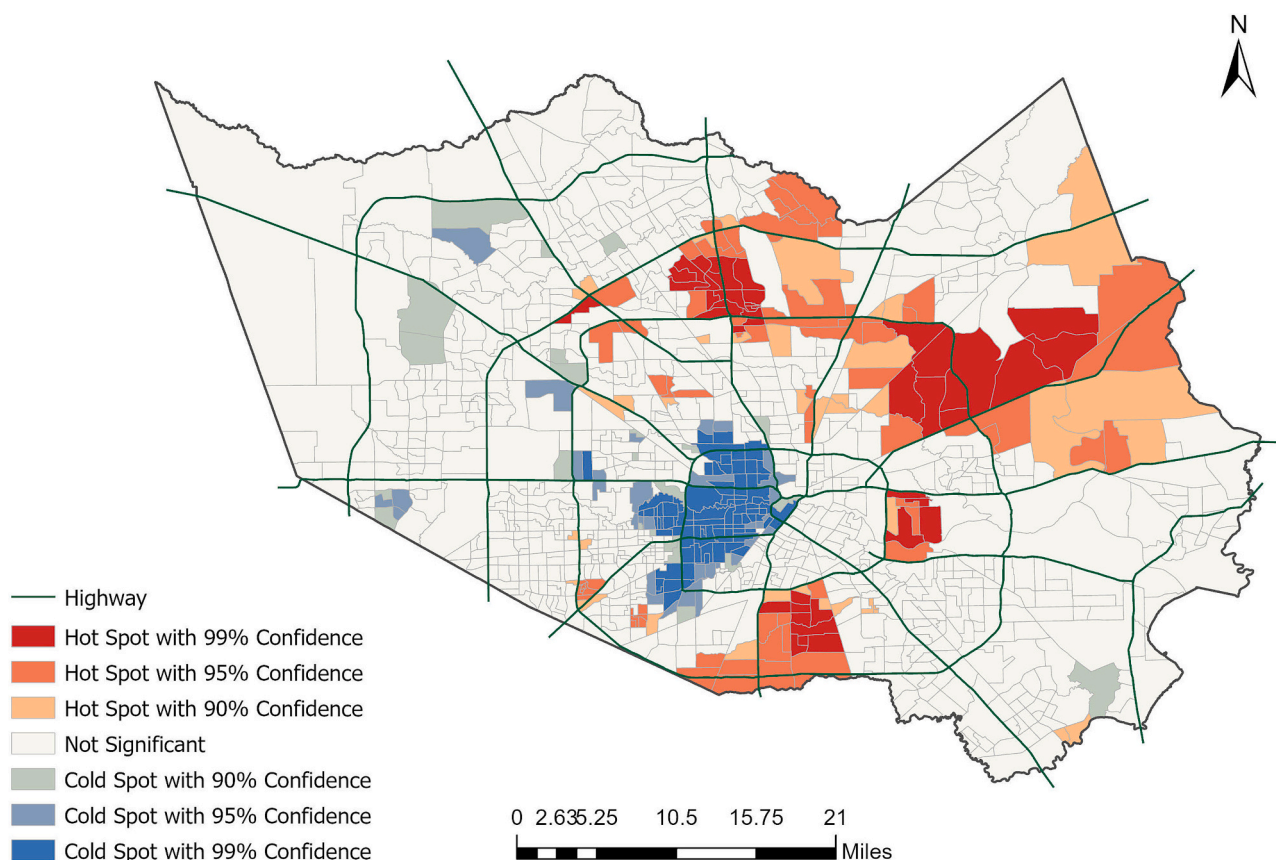


Fig. 4. Hot Spot Analysis of Limited Healthy Food Access in Harris County, Texas.

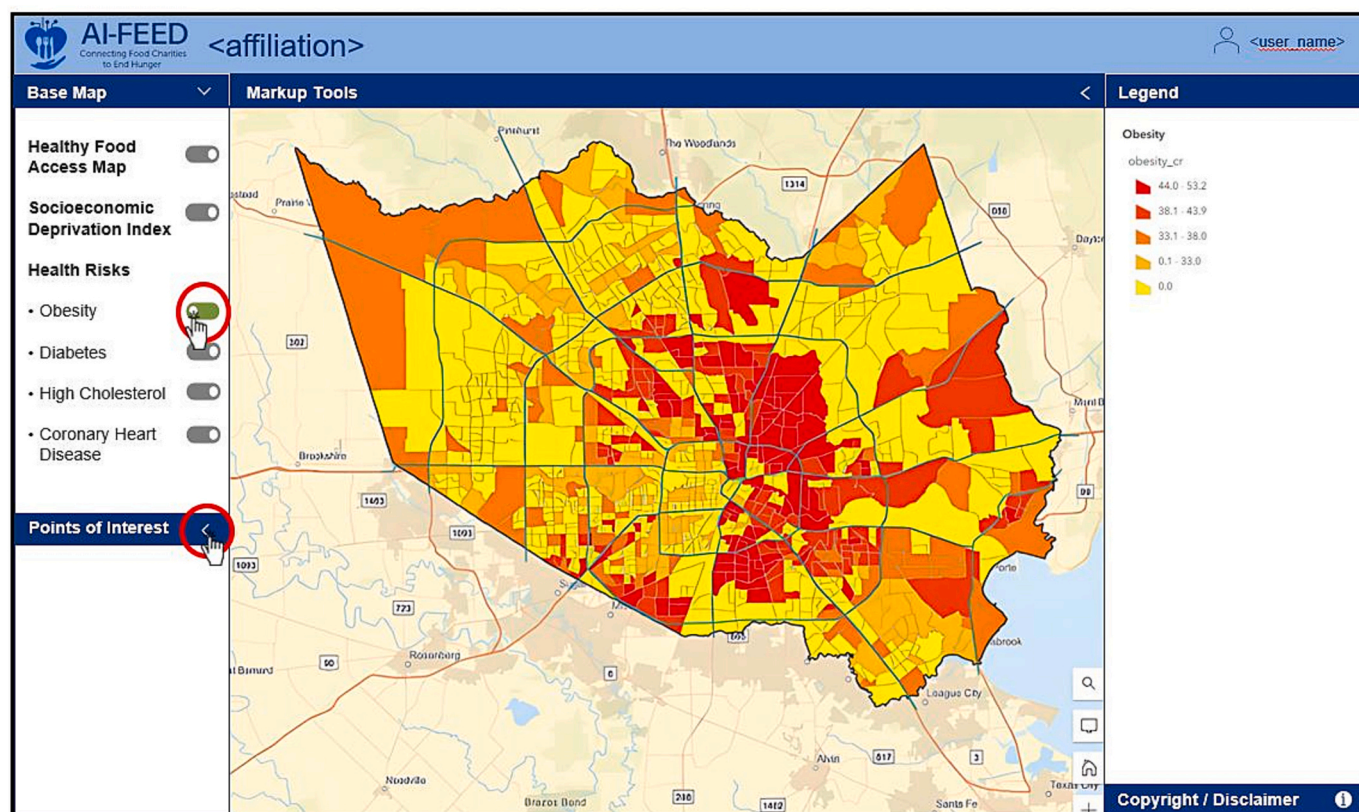


Fig. 5. A low-fidelity mockup of an AI-FEED website demonstrating the prevalence of obesity in Harris County, Texas.

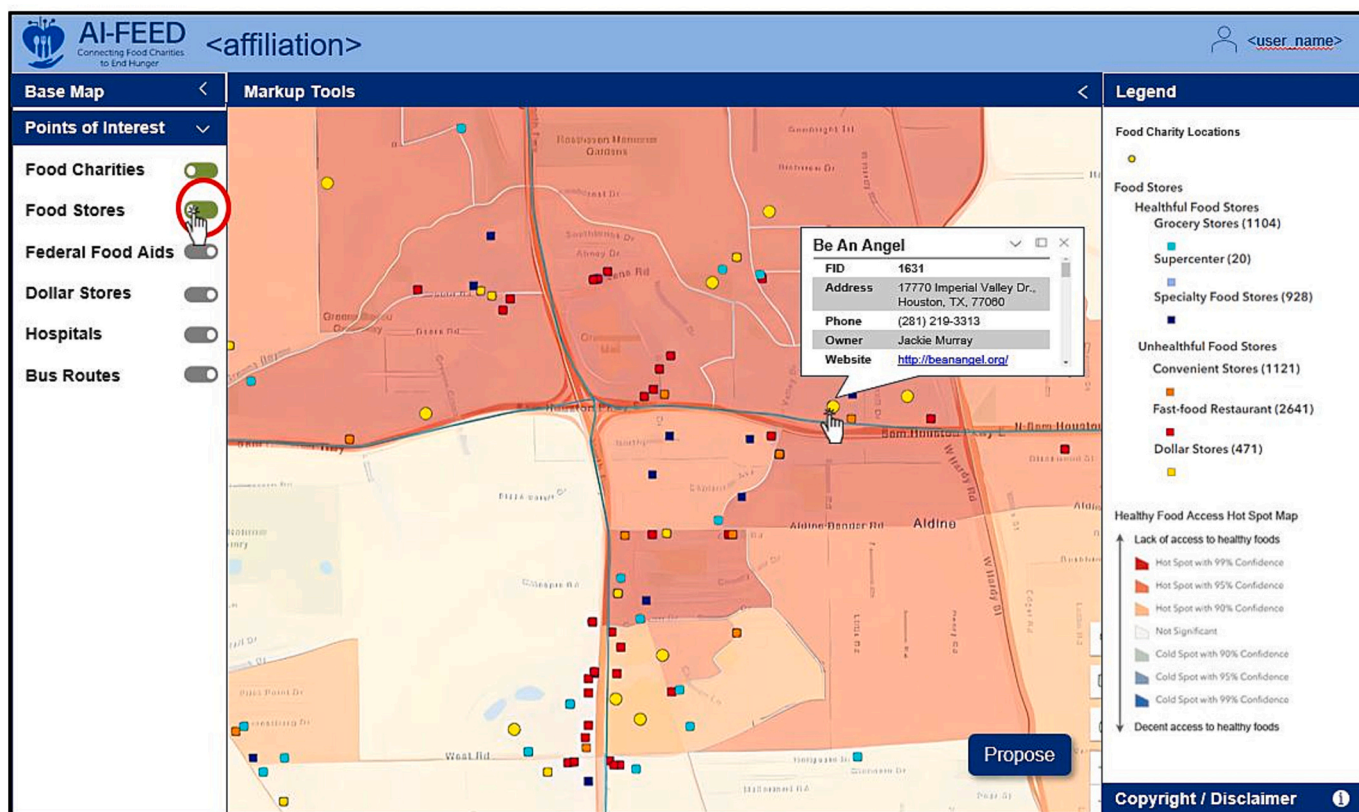


Fig. 6. A low-fidelity mockup of the AI-FEED website demonstrates food charity and food store locations in Harris County, Texas.

for a more nuanced understanding of food security in Houston. The map further reveals the spatial disparities in food availability across the metropolitan area, emphasizing the challenges faced by residents outside the central urban core.

3.3. AI-FEED: The web-based platform for community leaders

The web-based platform, AI-FEED, allows users to overlay different base maps that provide contextual information on healthful food access. The socioeconomic deprivation layer, a combination of SDI and EDI, visualizes spatial disparities in socioeconomic characteristics in neighborhoods, helping identify communities that may be at higher risk of food insecurity. On the webpage, users can also toggle between maps showing the prevalence of health risks such as obesity, diabetes, high cholesterol, and coronary heart disease. For instance, as demonstrated in Fig. 5, the obesity prevalence map uses color gradients to indicate areas with higher or lower obesity rates across the county. These base maps serve as a foundation for understanding the geographic distribution of health factors that may influence food access and nutrition-related health outcomes. Users can easily switch through these layers to explore potential correlations among socioeconomic status, health risks, and food access.

As shown in Fig. 6, the AI-FEED platform overlaps various points of interest on top of the base maps, including food charities, food stores, federal food aid locations, dollar stores, hospitals, and bus routes. When these layers are activated, the map populates with icons representing each type of point of interest. Users can selectively display different combinations of these layers to analyze the spatial relationships among various food sources, health facilities, and transportation routes. When a user clicks on a specific point of interest, such as a food store or food pantry, a pop-up window appears with detailed information about that location, including the store name and type, address, contact information, operating hours, and level of need. This detailed information is intended to help community leaders, as primary users, assess the accessibility and resources available at each location so they can identify gaps in service, plan for resource allocation, and coordinate outreach efforts.

4. Discussion and future work

4.1. Implications for urban planning and policy

This study analyzes food access disparities across Harris County at a census tract level, allowing for a detailed assessment of localized inequities while maintaining a county-wide perspective. Our findings reveal significant variations in food access, with disparities influenced

by socioeconomic conditions, transportation accessibility, the retail food environment, and financial constraints.

Our analysis uncovered a clear east-west divide in healthy food access in Harris County, with eastern areas experiencing notably poorer access than central and western parts. This spatial inequality underscores the need for targeted interventions to address food deserts and improve nutritional outcomes in underserved communities. Especially in Houston, areas with better highway access tend to have more food stores and supermarkets, likely due to improved accessibility for customers and supply chains. The correlation between limited food access hot spots and distance from significant highway networks suggests that transportation infrastructure plays a crucial role in shaping food landscapes.

The concentration of cold spots in central Houston, indicating better food access, points to an urban core advantage, where higher population density contributes to a greater concentration of food retailers and better public transportation options. Conversely, suburban and rural areas, particularly in the north and northwest of the county, face significant challenges in providing equitable food access. This finding highlights the need for innovative solutions to address food insecurity in less densely populated areas, where traditional techniques, such as adding large grocery stores, may not be viable due to lower population density and financial feasibility. Instead, more adaptive approaches like AI-driven resource allocation or mobile food distribution can better meet the unique challenges of these areas. Table 2 suggests potential strategies and approaches for policymakers to effectively target interventions based on the data-driven insights from our analysis.

Several cities have implemented comprehensive food security initiatives that offer valuable models for Harris County and similar urban areas. For example, New York City's FRESH Program (Food Retail Expansion to Support Health) incentivizes grocery store development in underserved neighborhoods by providing zoning and tax benefits to supermarkets that offer fresh produce (City of New York, 2023). Similarly, in London, UK, the Good Food Retail Plan integrates public health, urban planning, and transportation strategies to enhance food access, focusing on local food hubs and financial incentives for retailers promoting healthy food options (London Assembly, 2019). These initiatives illustrate that effective food access strategies require a multifaceted approach, combining zoning policies, financial incentives, improved transportation infrastructure, and community engagement. By adopting similar multidimensional frameworks, urban planners and policymakers can develop more equitable and resilient food environments tailored to their local contexts.

Our web-based platform, AI-FEED, could be a powerful tool for implementing these strategies. By providing a comprehensive visualization of the food environment, socioeconomic indicators, and health risk factors, the platform empowers community leaders and urban planners to make informed decisions. The ability to overlay various data layers supports nuanced understandings of local contexts, allowing these stakeholders to develop tailored solutions for their communities.

In practice, community leaders could use AI-FEED to comprehensively understand their local food environment and how it aligns with community needs. For instance, they could identify areas with high obesity rates that lack nearby healthy food options or locate economically disadvantaged neighborhoods that would benefit from additional food pantry services or improved public transportation to existing food sources.

Methodologically, future research could apply archetype analysis to identify distinct patterns of healthy food access based on unique combinations of indicators in economic deprivation, sociocultural factors, physical accessibility, and retail food environments. This approach, which has been successfully applied in areas such as urban redevelopment (Hampton & O'Hara, 2024) and climate resilience strategies (Oberlack et al., 2019; Sietz et al., 2019; Vidal Merino et al., 2019), offers an opportunity to uncover typologies of food access challenges. By categorizing communities into archetypes, planners and policymakers

Table 2
Strategies and approaches for improving healthy food access.

Strategy	Approach
Incentives for healthy food retailers	● Implement a tiered tax incentive program for new healthy food businesses in underserved areas. ● Create a grant program to help existing small stores expand fresh food offerings.
Improve public transportation	● Extend and optimize bus routes to connect food deserts with major grocery stores. ● Pilot subsidized rideshare program for grocery shopping in areas with limited public transit.
Land use and development guidelines	● Develop voluntary guidelines encouraging a mix of food retail options in new developments. ● Streamline permitting processes for healthy food retailers in identified food insecure zones.
Community-based initiatives	● Expand community garden programs in underserved areas, coupled with nutrition education programs. ● Develop a "Fresh Community Markets" initiative to improve fresh food availability in existing small stores.

could design more targeted interventions that address the specific needs of each group, further enhancing the applicability of the HFAI framework.

Our team's future work involves refining and expanding the capabilities of the AI-FEED platform to provide comprehensive and actionable insights. Efforts are being directed towards integrating real-time data on fresh food availability and prices and the needs of food pantries, offering up-to-date information on food affordability across different neighborhoods. Incorporating predictive modeling capabilities could help forecast future food access challenges based on demographic trends and urban development patterns, allowing for proactive policymaking.

Developing features for community feedback and crowdsourced data would capture valuable local knowledge and experiences related to food access, enriching the platform's insights with ground-level perspectives and helping match food charity needs with donations available in the area. Although the platform remains in the development phase, we are planning to engage community leaders and local government officials to gather feedback on its usability and assess its practical applications. Specifically, we plan to work with urban planners, public health officials, and community-based organizations in Houston to evaluate how the tool can be used to inform food access interventions and optimize resource allocation strategies. These evaluations will help refine the platform's functionality and ensure its relevance for those working to address food insecurity. Future work will focus on piloting AI-FEED with local government departments, including the Houston Health Department and Texas Health and Human Services, to assess its effectiveness in guiding food security policies and programs.

Expanding the analysis to include food quality and cultural appropriateness of available options would provide a more nuanced understanding of food access issues. Creating tools for scenario planning in the AI-FEED platform could assist policymakers in assessing the potential impacts of different interventions before implementation, leading to more effective and efficient policy decisions. Addressing food insecurity requires a justice-oriented approach that integrates urban planning, community engagement, and equitable resource distribution (O'Hara, 2023). By pursuing these enhancements, the AI-FEED platform may continue to evolve as a powerful tool for addressing food access disparities and improving community health outcomes in Harris County and potentially other urban areas facing similar challenges.

4.2. Suggestions for AI-based solutions

Although the current Community Leaders module of AI-FEED is built using ArcGIS Online for geospatial visualization, it is part of a larger AI-powered system designed to support food security initiatives. The mapping component is a foundational tool that will eventually integrate machine learning-based predictive analytics, spatial optimization, and AI-driven decision-support functionalities. Future research will expand

AI-FEED's capabilities by incorporating AI-based geospatial analysis tools, allowing planners to dynamically assess and address food security challenges. We anticipate that the AI-FEED platform can be further enhanced by integrating advanced AI technologies to address food access challenges in Harris County more effectively, leveraging cutting-edge AI techniques such as GeoAI for suitability analysis, simulated incentivization models, and bus route optimization algorithms.

4.2.1. Food pantries

To optimize the placement of new food pantries, the AI-FEED platform could leverage advanced machine learning algorithms such as Random Forest and Support Vector Machines (SVM). These algorithms analyze complex geospatial data by identifying patterns and relationships among demographic, socioeconomic, and existing food resource factors. Random Forest builds decision trees to capture nonlinear dependencies between variables. At the same time, SVM classifies areas by finding the best boundary (or hyperplane) that separates regions with sufficient and insufficient access to nutritious food, ultimately predicting where interventions are most needed. Implementing K-means clustering could help group regions with similar food access needs, ensuring strategic placement of new pantry locations to serve the most vulnerable communities. Furthermore, integrating predictive modeling techniques like ARIMA or LSTM networks, which analyze patterns in time series data to forecast trends over specific periods or events, could allow policymakers to project future food insecurity trends and proactively plan for food pantry locations. This AI-driven approach would offer data-backed suggestions for optimal food pantry allocations, enhancing the efficiency and impact of food security initiatives. Fig. 7 shows a low-fidelity mockup using GeoAI-based suitability analysis to suggest new food pantry locations, effectively illustrating how the platform can visually pinpoint potential areas for development.

4.2.2. Dollar stores

The AI-FEED platform could also use GeoAI-based suitability analysis to identify potential unhealthy food source locations, like dollar stores, that could be incentivized to offer healthier food options. By analyzing patterns in existing dollar store locations, local health indices, and community needs, incorporating incentivized percentages, the system could suggest areas where the introduction of healthier options might have the best impact. Machine learning models, trained in the success of healthy food initiatives in similar settings, predict the potential effectiveness and community benefits of offering healthier choices at specific dollar store locations. This targeted approach would leverage existing retail infrastructure, transforming dollar stores from unhealthy food sources into valuable outlets for nutritious options.

Beyond retail-based solutions, alternative food access strategies such as community gardens, home gardens, farmers markets, and Community-Supported Agriculture (CSA) programs also play a critical

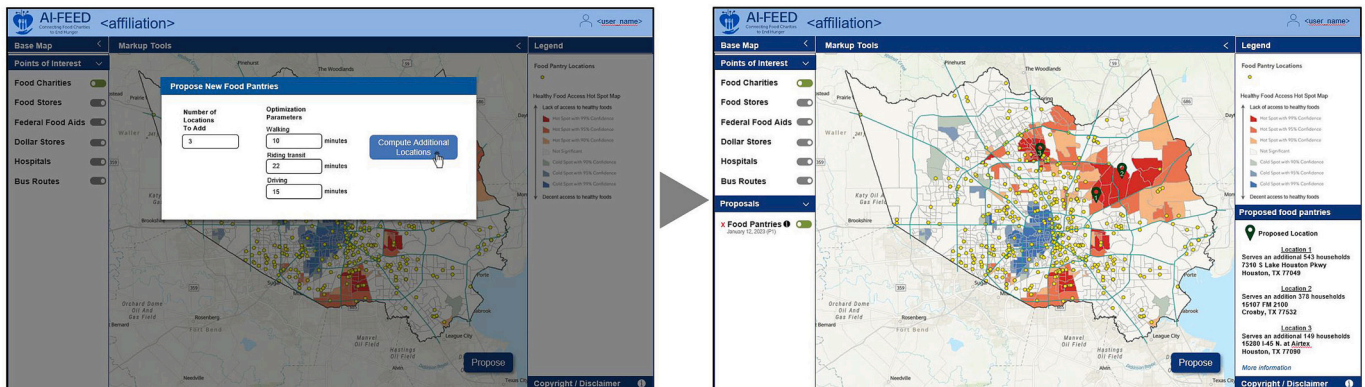


Fig. 7. Low-fidelity mockup for proposing new food pantry locations using GeoAI-based suitability analysis.

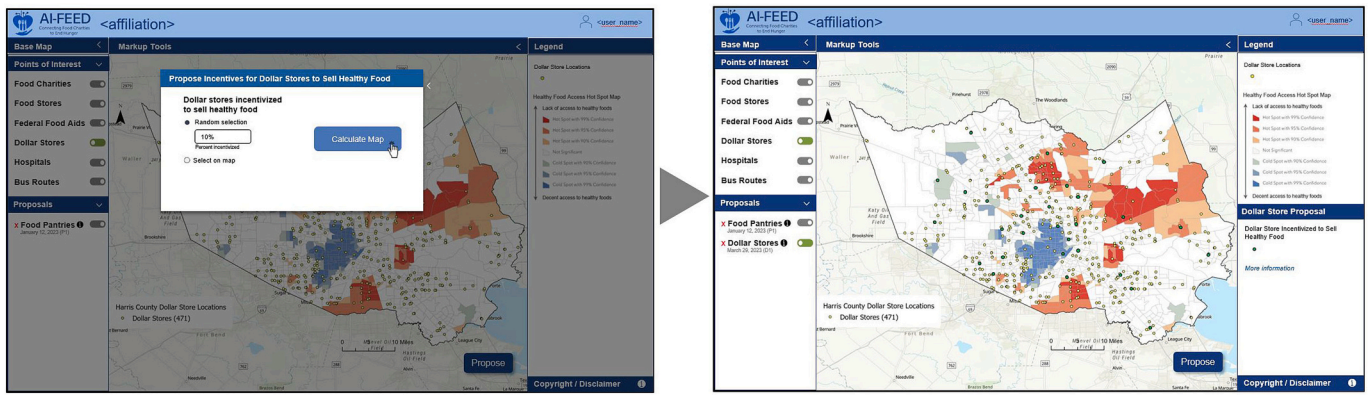


Fig. 8. Low-fidelity mockup for identifying dollar stores to incentivize healthy food sales.

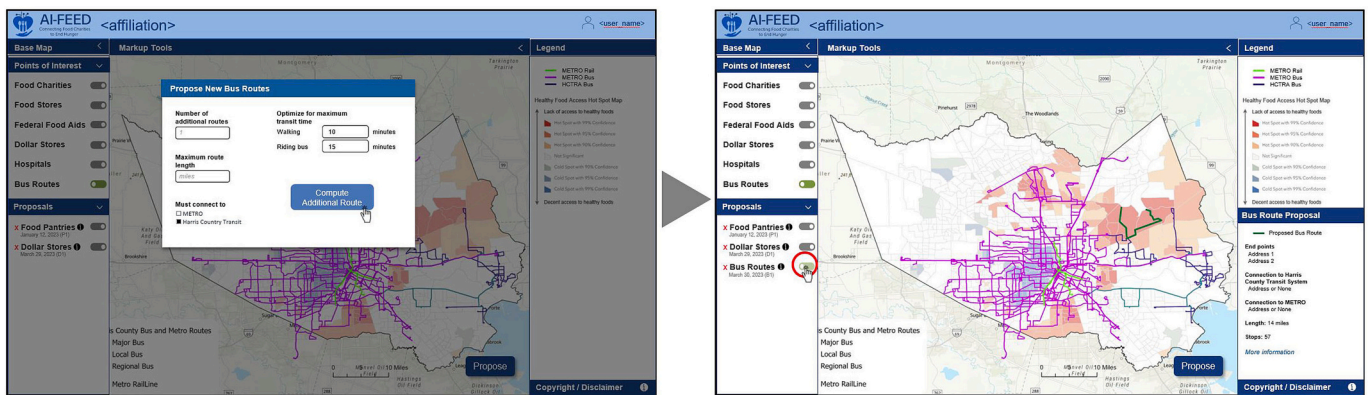


Fig. 9. Low-fidelity mockup for proposing new bus route optimization.

role in food security. These initiatives not only improve access to fresh and nutritious food but also offer additional benefits, including increased physical activity, enhanced social interactions, and strengthened neighborhood resilience. While this study primarily focuses on retail-based food access due to data availability, we recognize the importance of community-based food sources and see future potential for integrating them into AI-FEED. Through partnerships with organizations like Tackle Hunger, which collects crowdsourced data on food bank locations, and other community-driven efforts, AI-FEED could expand to incorporate these alternative food strategies. Machine learning techniques like those applied in the dollar store suitability analysis could be leveraged to identify optimal locations for new community gardens or urban farms, ensuring that these alternative food sources are placed where they are most needed.

Fig. 8 showcases a low-fidelity mockup that identifies dollar stores suitable for promoting healthier food options, suggesting how targeted incentives can turn these local stores into key providers of nutritious food. Future research should explore expanding AI-FEED's capabilities to incorporate non-retail food access strategies, applying AI-driven models to optimize community-based food solutions alongside retail interventions.

4.2.3. Bus routes

The AI-FEED platform could use route optimization algorithms like Dijkstra's or the A* algorithm to suggest new bus routes. Analyzing existing transportation networks, food resource locations, and community demographics, the system could identify transit deserts and recommend new or adjusted bus routes to better serve underserved communities. Fig. 9 presents a mockup page for proposing new bus route optimizations, showing how the website could visually display these changes by setting various additional routes, maximum route length,

travel mode, and maximum transit time. These AI-driven recommendations would aim to reduce travel times to healthy food stores, making nutritious options more accessible. Additionally, the platform could employ predictive modeling to anticipate future transportation needs based on expected demographic changes and urban development trends, ensuring that proposed route modifications remain effective over time.

In all these applications, AI-FEED could provide an interactive interface, helping community leaders adjust parameters and visualize the impact of various scenarios. This user-centric approach and the platform's advanced AI capabilities would facilitate data-driven decision-making responsive to each community's unique needs and contexts.

5. Conclusion

This study presents a comprehensive approach to mapping healthy food access and suggesting AI-driven solutions to support decision-making for communities' food resilience systems. By developing a Healthy Food Access Index (HFAI) that integrates traditional socioeconomic indicators with novel data sources of economic and sociocultural deprivation indices, retail food environment measures, physical access indices, and accommodation access data, we offer a more comprehensive and nuanced understanding of the factors influencing healthy food access. This multidimensional index identifies hotspots where food insecurity is likely most acute, guiding targeted interventions. Additionally, the creation of the AI-FEED platform is designed to equip community leaders and urban planners with a robust tool for visualizing food access challenges by overlaying health risk factors and points of interest. This integration enables the platform to provide real-time data insights, helping stakeholders make informed decisions to enhance food security and address related health issues within their communities. The platform's AI-driven suggestions provide strategic solutions for

optimizing food access by proposing ideal locations for new food pantries, healthier options at dollar stores, and improved bus routes. By analyzing demographic data, economic status, and transportation networks, the platform can predict future changes in food access and recommend proactive interventions, ensuring efficient resource allocation and enhancing public health outcomes.

Our study has limitations that could be addressed in future research. A key limitation of the Sociocultural Deprivation Index (SDI) is that it does not include all racial and ethnic groups as indicators of sociocultural disadvantage and food insecurity risk. While the SDI incorporates Hispanic and non-Hispanic Black populations—groups historically associated with higher rates of food insecurity and diet-related illnesses—the exclusion of other ethnic groups, such as an Asian population, may limit its comprehensiveness. This decision to include Hispanic and Black populations was based on evidence that Asian populations generally experience lower rates of food insecurity and diet-related illnesses despite socio-economic disparities, often due to strong cultural food traditions and access to specialty food markets. Additionally, the spatial distribution of the Asian population in the study area differs from that of Hispanic and Black populations, who face greater systemic barriers to food access (Cooksey Stowers et al., 2020; Hilmers et al., 2012; Zenk et al., 2011). However, future research should explore expanding the SDI to include additional racial and ethnic groups or incorporate factors that better capture variations in food access experiences.

Another limitation of this study is that equal weights were applied to each index when creating the composite HFAI, which may need to accurately reflect the varying importance of different factors influencing healthy food access. Future iterations of this research could employ Principal Component Analysis (PCA), machine learning regression models, or geo-simulation techniques to refine index weighting based on real-world food insecurity patterns for a more dynamic, region-specific assessment of food access disparities. Additionally, while the AI-FEED platform shows promise in Harris County, its scalability and adaptability to other urban and rural contexts need to be tested. Future work should focus on expanding the platform's capabilities, including predictive modeling for scenario planning and integrating feedback mechanisms to capture community input and real-time updates more effectively. We can envision a future 'agentic map' that proactively ingests demographic, economic, and transportation data, recommending interventions based on the evolving landscape. Additionally, this centralized tool could evolve into a more accessible format, such as an app that allows users to easily locate the healthiest food stores or access real-time updates on food availability, further empowering communities with actionable information.

Despite the limitations, the novelty of this paper lies in its development of the HFAI, which incorporates a diverse range of data sources

tailored to local conditions and community needs, thereby enabling it to be a more effective tool for targeted interventions. This multidimensional index captures the complex factors influencing food access, allowing for a more customized approach to addressing food insecurity. Additionally, this study leverages a web-based platform to provide actionable policy recommendations, positioning it as a vital tool for planners and community leaders in food access planning. Integrating AI-driven solutions into the platform further enhances its utility by offering data-driven suggestions that help policymakers address emerging food deserts proactively. This approach transcends static analysis by optimizing the allocation of new grocery stores, food pantries, and bus routes and incentivizing dollar stores, providing a dynamic and adaptable tool for urban planning and resource allocation.

CRediT authorship contribution statement

Junfeng Jiao: Writing – review & editing, Writing – original draft, Supervision, Project administration, Funding acquisition, Conceptualization. **Kijin Seong:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Marcus Sammer:** Writing – review & editing, Visualization, Software, Resources, Data curation. **Ryan Hardesty Lewis:** Writing – review & editing, Software, Data curation. **Alison Reese:** Writing – review & editing, Resources, Methodology, Investigation, Conceptualization. **Norma Olvera:** Writing – review & editing, Validation, Methodology, Investigation, Conceptualization. **Susie L. Gronseth:** Writing – review & editing, Validation, Resources, Project administration, Conceptualization. **Elizabeth Anderson-Fletcher:** Writing – review & editing, Validation, Data curation. **Ioannis Kakadiaris:** Writing – review & editing, Validation, Supervision, Project administration, Funding acquisition, Data curation.

Declaration of competing interest

The authors declare that there are no competing interests.

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Appendix 1. Distribution of healthful and unhealthful food retailers by NAICS category

Category	2022 NAICS Codes	Description	Number of Stores
Healthful Stores	445,110	Supermarkets and Other Grocery Retailers (except Convenience Retailers)	1104
	455,211	Warehouse Clubs and Supercenters	20
	4452	Specialty Food Stores	928
Subtotal of healthful stores			2052
Unhealthful Stores	445,131	Convenience Retailers	1121
	722,513	Limited-Service Restaurants (Fast Food Outlets)	2641
	455,219	Variety Stores (Dollar Stores)	471
Subtotal of unhealthful stores			4233
Total			6285

Data availability

Data will be made available on request.

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