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Dear Reviewers,

We greatly appreciate the opportunity to revise our manuscript for possible publication in the Applied Geography. We again all the constructive and insightful comments and suggestions provided by the reviewers. In response to the feedback received, we have implemented major changes in the revised manuscript. Below, we address each specific comment provided by both reviewers and provide a detailed response to each comment. We hope that the editor and reviewers find our revisions satisfactory. We have highlighted the changes in yellow in the revised manuscript.

Once again, we thank all the Reviewers and the Editors for their support and guidance throughout the manuscript review process.

**Reviewer #1:**

(1) The opening paragraph tried to emphasize the importance of studying food accessibility in relation to food insecurity. However, the discussion on the mechanisms linking food access to food insecurity is only briefly touched upon, leaving the connection underdeveloped. I suggest a more robust opening with supporting reference that clearly articulates why measuring food access is crucial in food insecurity analysis. Key factors such as the availability of nutritious food, affordability, and physical accessibility should be emphasized to strengthen the argument. This will provide a more compelling rationale for the significance of food access in addressing food insecurity.

* We appreciate your comments regarding the need for a stronger connection between food access and food insecurity in the opening paragraph. In response, we have made the following revisions:
  + We expanded the discussion at the end of the opening paragraph to include a more detailed explanation of the dimensions of food and nutrition security—availability, access, acquisition, and utilization (Simelane and Worth, 2020). This framework allows us to highlight the critical role of food access in the broader context of food insecurity.
  + Additionally, we separated the beginning of the second paragraph into its own paragraph to better address the complexity of food access. We now emphasize that food access is influenced by both supply- and demand-side factors, further highlighting the importance of studying food access, particularly observed food acquisition.
* Please find the revisions in the manuscript and included here.

*(Background P1 &P2)*

*Food insecurity* – the lack of stable access to sufficient, safe, and nutritious food for a healthy, active life (Simelane and Worth 2020) – is a major challenge faced by many households in the US. In 2022, the Department of Agriculture reported that 12.8% of U.S. households experienced food insecurity (Rabbitt *et al.* 2023). Meanwhile, prior studies have established strong associations between food insecurity and many critical health conditions, such as obesity, diabetes, and cardiovascular diseases (Bodor *et al.* 2010, Berkowitz *et al.* 2018). However, food insecurity is a multi-dimensional issue. Studies on Food and Nutrition Security (FNS) theory have outlined four key pillars of food security: availability, access, utilization, and stability, where the first three forming a consequential relationship, and stability adding a temporal dimension (Simelane and Worth 2020). In this framework, *food access* is the crucial link between available food and its utilization. Therefore, understanding and analyzing food access is essential for addressing food insecurity effectively (Rabbitt *et al.* 2023).

Food access relies on food *supply*, meaning only available food is considered accessible. Research on food *accessibility* has used various datasets, such as Point of Interest data and satellite imagery, and developed spatial and aspatial measurements (Larsen and Gilliland 2008, Nguyen *et al.* 2020). *Demand*-side factors also play a role, as households or individuals need sufficient financial resources, mobility, and decision-making knowledge to actually *acquire* food (Simelane and Worth 2020). This makes the study of food acquisition informative, as it reflects both supply and demand sides.

(2) The author highlights the limitations of traditional datasets, particularly their small sample sizes, and suggests that large-scale mobile device data could serve as a valuable alternative. This point is valid; however, other datasets also hold potential and should be considered in the discussion. These include Point of Interest data (noticed you mentioned this later on), satellite imagery (e.g., agricultural land use for food production), retail transaction data, and loyalty card data. Although these datasets may be used for different purposes and they may face challenges related to availability. However, they are still worth exploring for their potential contributions to the analysis.

* We appreciate your comments regarding the insufficient discussion on the potential of other datasets. In response, we made the following revisions:
  + We rewrote the section discussing traditional data and created a new paragraph (Paragraph3) in the Background section. This revision includes a more comprehensive discussion on the contributions of various datasets, resulting in a more balanced introduction. We also incorporated the datasets mentioned in your comment that we initially overlooked.

*(Background P3)*Regards food acquisition, researchers have gathered store data (e.g. transaction data or loyalty card information), or engaged individuals through surveys (Todd and Scharadin 2016) and activity-travel diaries (Wray *et al.* 2023). The studies offer detailed insights into acquisition behavior patterns as they studied rich purchase and attitudinal information regarding individuals’ food access practices. However, these studies rely on *primary* data gathered for specific purposes (Rabianski 2003), typically involving small sample sizes, potential sampling bias, and challenges in tracking changes over long periods and large areas. The recent availability of *large-scale mobile device location GPS …*

* + Corresponding changes were made in the literature review section (Section 2.1 Traditional Approaches), where we also added a review of Points of Interest (POI) and satellite data.

*(Literature Review, 2.1)* Studies on *potential* food access primarily focus on the *supply* side. Researchers model food outlet availability using datasets such as Point of Interest (POI) data (Larsen and Gilliland 2008) or satellite imagery (e.g., agricultural land use that informs food production and harvest patterns) (Nguyen, Hoang, *et al.* 2020). These models are then combined with *potential demand*, ...

*(Literature Review, 2.2)* Traditionally, researchers interact *directly* with participants to understand food access patterns using methods like questionnaire surveys, interviews, and focus groups. *Questionnaire surveys*, … collect detailed data on where people shop, how much they spend, and the types of food they purchase (Coleman-Jensen *et al.* 2019). The structured format ensures consistent data collection, enabling comparisons across demographics and socioeconomic groups, and facilitating longitudinal studies on behavioral change (Anekwe and Zeballos 2019). However, these surveys can lack flexibility and often have limited sample sizes in specific groups or areas (Hillier *et al.* 2017). *Interviews and focus groups* offer more flexibility and interactivity, making them effective for exploring participants’ nuanced behaviors and perceptions of food quality, accessibility, and affordability. Moreover, they can reveal the cultural, social, and economic contexts that shape food acquisition behaviors, uncovering motivations and barriers influencing purchasing decisions. However, direct interviews compromise reliability and objectivity. This may occur unintentionally due to unobservable socio-economic factors or knowledge of food and nutrition, which can also provide valuable insights and are considered as advantages of this approach (Tadesse *et al.* 2020). ...

(3) In Section 2, while interviews and focus groups do indeed face challenges such as reliability, objectivity, and recall bias, this is true, it's important to also mention the biases and inaccuracies associated with primary and secondary GPS data, which can often be more significant than those in traditional qualitative methods. Primary GPS data may suffer from sampling bias, over-representing individuals who frequently use smartphones or GPS-enabled devices, and missing data when devices are turned off or not carried. Secondary GPS data can be affected by aggregation bias, inconsistencies due to varying device quality, and loss of detail through anonymization. Additionally, GPS data may have limitations in urban environments (e.g., urban canyon effect) and often lacks context for why specific locations are visited. While you have addressed some of these points in discussion section, it would be beneficial to provide a brief and balanced discussion of the pros and cons of both types of datasets within this section.

* We appreciate your comments on expanding the discussion regarding the biases and inaccuracies associated with GPS data in *Literature Review*. In response, we have made the following revisions:
  + We added a discussion on ecological fallacy and environmental factors influencing GPS data quality in Section 2.3.1.
  + We addressed the comment regarding behavioral biases, which stem from both intrinsic factors (selectively carry/turn-on devices) and external factors (urban/rural foodscape). We discussed the existence of Selective Daily Mobility Bias (SDMB) as a *common challenge* for any tracking studies, not just for secondary GPS data. We moved the discussion on SDMB earlier to Section 2.3.1 and expanded on this topic.
  + We agree that the sampling biases (over-representation of smartphone users, spatial and temporal coverage), aggregation from varying quality devices and the lack of contextual information are important limitations. However, we believe these issues are more pronounced in secondary GPS data. In primary GPS studies, participants are provided with devices, instructed on how to ensure data quality, and asked to input contextual information. So, we added the discussions in Section 2.3.2.
* Please find the revisions in the manuscript and included here.

*(Primary GPS data:)* However, GPS data can be limited by factors like the urban canyon effect or weak signals in rural areas, leading to inaccurate location readings and potential misrepresentation of food access and mobility patterns (Li *et al.* 2023). Also, ecological fallacy—drawing conclusions about individual behavior from aggregate data—is also a concern (Chen *et al.* 2016). Moreover, Selective Daily Mobility Bias (SDMB) is a common issue in behavior research that relies on tracking movement, as individuals’ mobility patterns are not random but shaped by their routines, preferences, and behaviors (Li *et al.* 2023). The awareness of carrying monitoring devices can also lead to increased consciousness of actions and potential behavioral changes over the study period (Zhang *et al.* 2021).

*(Secondary GPS data:)* While secondary GPS data offer considerable potential, they also have drawbacks, such as Ecological fallacy and SDMB. But unlike primary data, the data quality may difference across devices (Li *et al.* 2023). Also, the absence of contextual information about activities also forces reliance on algorithms for inference (Zhao *et al.* 2022); but these algorithms are typically study-specific, limiting broader applicability (Kwan 2016). Most critically, despite larger sample sizes, studies have proven that secondary GPS data also often underrepresent disadvantaged groups, which is problematic when research aims to address social justice issues (Li *et al.* 2023).

(4) For the case study section and beyond, Figures 1 and 2 would benefit from the addition of a north arrow and scale bar, as there is available space to include them.

* We appreciate your comments, and we have incorporated these necessary components into the figures.
* Please note that, in response to another reviewer’s comment, we added an additional figure, so Figures 1 and 2 are now numbered as Figures 2 and 3 in the manuscript.

(5) Considering both demand and supply side accessibility is also an innovation of the current study, particularly in how you address this using secondary GPS data. I would think it is beneficial to briefly highlight this in your introduction as well.

* We appreciate your comments on the consideration of both demand and supply-side accessibility as an innovation of the study. In response,
  + We have added a brief discussion in *Introduction* to emphasize the innovation on the demand and supply perspective of food access, as mentioned in our response to comment (1).
  + Additionally, in light of feedback from the other reviewer, we included a section (Section 2.1) reviewing people’s food access behavior in general and reiterated this point in. In that section, we highlighted this potential of GPS data again. We discussed the traditional supply side analysis including measurements like food desert, with their contributions as well as the shortcomings when talking about demand side. We then briefly discussed the potential of GPS data in the demand side.

Please find the revisions in the manuscript and included here.

Food access, like access to other public services, results from the transition from *potential* access (i.e. food *accessibility*) to actual *realized* access (i.e. food *acquisition*) (Khan 1992, Simelane and Worth 2020, Tadesse *et al.* 2020). This transition is determined by facilitators or barriers from both the *supply* side (i.e. facilities characteristics, like size and distribution) and the *demand* side (i.e. area characteristics, like population and access distance), with moderation from planning and policy efforts.

Studies on *potential* food access primarily focus on the *supply* side. Researchers model food outlet availability using datasets such as Point of Interest (POI) data (Larsen and Gilliland 2008) or satellite imagery (e.g., agricultural land use that informs food production and harvest patterns) (Nguyen *et al.* 2020). These models are then combined with *potential demand*, usually estimated using regional characteristics like population size, income, area, and distance to food outlets (Larsen and Gilliland 2008). This approach has led to the development of many *accessibility* measures including “food deserts” (Berkowitz *et al.* 2018).

In contrast, studies on *revealed* food access directly examine people’s demand by analyzing food *acquisition* behaviors. These analyses provide insights into how individuals perceive and interact with their food environment spatiotemporally (Dubowitz et al. 2015). Such insights, which reveal individual dietary habits and broader public health outcomes, are crucial to the concerns of health researchers and policymakers, helping to shape effective strategies to combat food insecurity (Rodier et al. 2017).

(6) While the paper addresses potential biases in the secondary GPS data, it would benefit from a more in-depth discussion on the representativeness of the sample. For instance, how does the population using GPS-enabled devices compare to the general population in terms of demographics and socioeconomic status?

* We appreciate your comments regarding the representativeness of the GPS data. To address your comment:
  + We included a brief discussion on the relationship between sampling rates and SES characteristics in Section 3.4.1 *Sampling Rate*. We also note that the anonymity of GPS data hindered in-depth analysis.

We can notice fluctuations within the study area from the histogram and the map. This aligns with findings from prior studies, suggesting the potential geographic bias in GPS data (Li et al. 2023). If we compare the sampling rate map with socio-demographic maps (Figure 2), we can observe that the areas with larger spatial variability also demonstrate socio-demographic disadvantages, such as fewer vehicle ownership and lower income levels. These socio-demographic disparities position them at the center of the discussion on the issue of food insecurity. Consequently, the variation in sampling rates within these communities may carry implications for the findings. While further analysis comparing the demographics and socioeconomic status of GPS device users to the general population would enhance our understanding of data representativeness and result generalizability, we currently lack the necessary information for such comparisons.

* + We included a discussion on representative bias in GPS data in the Discussion section, stressing its implications.

The bias in representativeness leads to a major limitation: mobile location data are inadequate for comparing mobility patterns across population groups due to potential representativeness issues; moreover, the absence of individual-level sociodemographic information complicates efforts to address this. Existing studies have shown that while the GPS data are well-sampled across demographic categories (Squire 2019), some population groups are underrepresented in the data. For example, by using mobile device location data collected by SafeGraph (Coston *et al.* 2021) showed that older and non-white individuals are under-sampled. (Li *et al.* 2023) found that the Hispanic and low-income populations were underrepresented across the states in the U.S., while the advantaged groups, e.g., the high-income and highly educated people were overrepresented. Additionally, GPS data collection can exhibit temporal biases, as the frequency and regularity of data collection may vary depending on the time of day, week, or season (Li *et al.* 2023). (In our study, the use of only two months of data may have introduced such biases.)

(7) The paper compares GPS-based metrics with those derived from traditional surveys, a further statistical validation could be helpful, say, conducting hypothesis testing to evaluate whether the differences observed between GPS data and survey data are statistically significant would strengthen the argument about the advantages and limitations of GPS data - if not applicable at this moment, it might be worth discussing this point in the discussion section.

* We appreciate your comments regarding the comparison of GPS-based metrics with those derived from traditional surveys. However, in our study, we do not have survey data relevant to our research objectives in the City of Jacksonville. So, in Section 3.4.2, we compared our results with the nationwide USDA survey and a statewide study in Florida.
* To address your comment, we expanded the discussion in the original manuscript (where we emphasize the need for a mixed-methods approach) by incorporating the concerns you mentioned.

(3) *Value of Mixed-Methods Research:* Our results underscore the importance of mixed-method research. While both big and small data—and their associated methods—have limitations, they can complement and enhance each other (Kwan 2016). As noted in the literature review, studies using primary GPS data combined with surveys have challenged previously held behavioral assumptions by uncovering new insights. Applying a mixed-method approach to secondary GPS studies could similarly provide a more holistic understanding of food access behaviors and improve the interpretation of key metrics and is beneficial for future planning and policy making. For instance, conducting surveys alongside GPS data collection for the same population would allow for integrating the granular, sensor-generated insights from GPS with the nuanced, human-generated insights from surveys. Such integration would facilitate statistical validation of the metrics extracted from both sources, addressing potential intrinsic or inference-induced inaccuracies in secondary GPS data and enhancing the generalizability of the findings.

(8) The study period spans from September 1st, 2022 to October 15th, 2022, covering a duration of 45 days. While I appreciate the detailed temporal analysis, the results may also be influenced by seasonal variation, which could result in different patterns in other part of a year. It would be valuable to address this potential limitation in the discussion.

* We appreciate your comments regarding the temporal generalizability bias in our study. We have included a discussion of this limitation in the *Discussion* section.
* (2) *Bias in Representativeness:* The bias in representativeness … Additionally, GPS data collection can exhibit temporal biases, as the frequency and regularity of data collection may vary depending on the time of day, week, or season (Li *et al.* 2023). In our study, we use two months of data, which may not be generalizable for other time periods.

This study has several limitations, particularly concerning the temporal and spatial generalizability of the findings. Temporally, research on food sales has shown seasonality in food demand (Hu *et al.* 2021, Balagtas *et al.* 2023), which may influence mobility patterns. Therefore, generalizing our findings from the 45-day study period could introduce bias and limit the representativeness of the results. Spatially…

(9) While the study focuses on Jacksonville, Florida, it would be beneficial to discuss the generalizability of the findings to other regions. This could include a discussion of how different urban environments or food landscapes might impact the applicability of the results.

* We appreciate your comments regarding the spatial generalizability bias in our study. We have included a discussion of this limitation in the *Discussion* section.

This study has several limitations, particularly concerning the temporal and spatial generalizability of the findings. Temporally, ... Spatially, the case of Jacksonville may not be transferable to other contexts. A 2012 study noted disparities in food access among Health Zones, with Urban Core residents facing a greater health burden (Healthy Jacksonville Children Obesity Prevention Coalition 2012). Additionally, Jacksonville’s poverty rate (14.8%) exceeds both the national (12.5%) and state averages (12.9%) (U.S. Census Bureau 2022). These socio-economic factors should be considered when generalizing the results to other contexts or similarly sized cities.

(10) Moreover, studying food accessibility has broader implications beyond food insecurity and health encompassing critical areas such as social equity and justice, economic impact, and sustainability and environmental concerns. These aspects are equally important and should be included in the discussion to provide a comprehensive understanding of the significance of food accessibility.

* We appreciate your comments on this issue. And we included a discussion in the *Discussion* section.

Furthermore, improving food access has broader implications beyond food security. It addresses social equity, as marginalized communities face disproportionate barriers to accessing healthy food. It can also strengthen local economies by supporting community-based food businesses, promoting local sourcing, and reducing food transport—ultimately enhancing environmental sustainability. Policymakers should consider these wider social equity, economic, and environmental impacts when developing interventions for more equitable, sustainable, and economically beneficial outcomes.

**Reviewer #2:**

First, the literature review section is severely underdeveloped. The current review primarily focuses on summarizing who used what datasets in selected studies, organizing the discussion by data types rather than providing a comprehensive overview of food acquisition behaviors as reported in existing literature. This omission is particularly concerning, as it fails to establish a strong foundation for understanding the nuances of food acquisition behavior. A more thorough and expansive review is needed, covering not only the specific datasets used in previous studies but also the behavioral insights they revealed. Additionally, the authors should incorporate more recent studies that have employed mobile phone data in food access research and broader human mobility studies. Expanding the literature review will better justify the research gap and contextualize the study within the existing body of work.

* We appreciate your feedback regarding the literature review being underdeveloped. We agree that focusing on food access behaviors rather than solely on datasets is essential for strengthening the study. To address your comments, we have rewritten the literature review as follows:
  + **New section: *Section 2.1 Food Access and Food Acquisition***: We added a comprehensive discussion on food access behavior, beginning with a framework of food security and the vital role of food access as a link between availability and utilization. We then discussed the transition from *accessible* food to revealed food *acquisition* behaviors, highlighting how both supply and demand factors shape these behaviors. The section concludes with a summary of typical food acquisition behaviors reported in the literature (e.g., origin, frequency, items shopped), which we referenced in later sections (2.2 and 2.3).
  + **Restructured Methodology-Related Sections (2.2 and 2.3):** We restructured the content in these sections to focus on methodologies and the behavioral insights they provide, rather than just the datasets. We discussed the types of behavioral information each method can gather and their respective advantages, incorporating insights from selected studies.
  + We also made modifications in *Introduction* to reflect the changes.
* Please find the revised literature review section in the manuscript.

Second, more detailed information is required on the collection and characteristics of the mobile phone GPS data used in the study. How is the accuracy of the data measured? What about the representativeness of the sample? It is crucial to determine whether the samples are truly representative of the population being studied. Without this information, it is difficult to assess the validity and reliability of the findings.

* We appreciate your comments in sufficient discussion on the collection and characteristics of the GPS data. We made the following modifications:
  + **Accuracy of the Data:** The dataset has been pre-processed for quality control, with accuracy assessed by the data provider and indicated by a forensic identifier field. For our study, we filtered to retain only the High Frequency records. We have added a detailed description of this process, noting that using unprocessed data may impact the accuracy and generalizability of the identified mobility patterns. In Section 3.2.1 (Mobile Device GPS Data), we have rewritten the corresponding paragraph. Please find the revision below and in the manuscript.

The dataset is pre-processed for quality control, with accuracy indicated by a forensic identifier field, which measures GPS *positioning* errors caused by factors like spoofed locations, IP address-derived signals, and abnormal signal density (Xu *et al.* 2022, Gravy Analytics 2023). For this study, we included only records classified as *High Accuracy* by *Gravy*, where GPS positioning errors do not exceed 35 meters. While lower accuracy data may be useful for broader neighborhood analyses or overall trend identification, it is not suitable for pinpointing specific customer visits to particular locations (Gravy Analytics 2023). This *pre-analysis* filtering minimizes positioning errors, ensuring more reliable results. (However, inherent limitations in this GPS-based approach still affect results accuracy and generalizability, as discussed later.)

* + **Responsiveness of the Data:**
    - We included a brief discussion on the relationship between sampling rates and SES characteristics in Section 3.4.1 *Sampling Rate*. We also note that the anonymity of GPS data hindered in-depth analysis.

Upon closer inspection of the histogram and the map, we can notice fluctuations within the study area. This aligns with findings from prior studies, suggesting the potential geographic bias in GPS data (Li et al. 2023). If we compare the sampling rate map with socio-demographic maps (Figure 2), we can observe the areas with larger spatial variability also demonstrate socio-demographic disadvantages, such as fewer vehicle ownership and lower income levels. These socio-demographic disparities position them at the center of the discussion on the issue of food insecurity. Consequently, the variation in sampling rates within these communities may carry implications for the findings. While further analysis comparing the demographics and socioeconomic status of GPS device users to the general population would enhance our understanding of data representativeness and result generalizability, we currently lack the necessary information for such comparisons.

* + - We included a discussion on representative bias in GPS data in the Discussion section, stressing its implications.

The bias in representativeness leads to a major limitation: mobile location data are inadequate for comparing mobility patterns across population groups due to potential representativeness issues; moreover, the absence of individual-level sociodemographic information complicates efforts to address this. Existing studies have shown that while the GPS data are well-sampled across demographic categories (Squire 2019), some population groups are underrepresented in the data. For example, by using mobile device location data collected by SafeGraph (Coston *et al.* 2021) showed that older and non-white individuals are under-sampled. (Li *et al.* 2023) found that the Hispanic and low-income populations were underrepresented across the states in the U.S., while the advantaged groups, e.g., the high-income and highly educated people were overrepresented. Additionally, GPS data collection can exhibit temporal biases, as the frequency and regularity of data collection may vary depending on the time of day, week, or season (Li *et al.* 2023). (In our study, the use of only two months of data may have introduced such biases.)

Third, the research design raises several concerns. The inclusion of gas stations, CVS, and similar businesses in the analysis is puzzling. What percentage of trips to these locations actually involve food purchases? If this is not well-evidenced, the inclusion of such points of interest (POIs) could introduce significant bias into the analysis. It is worth noting that the authors mention excluding some POIs and conducting a sensitivity test, which suggests they were aware of this issue. However, if this concern was recognized, it would have been more effective to carefully select relevant food retailers from the outset and focus exclusively on those. This would have strengthened the study's validity by ensuring that only relevant data were analyzed.

* We appreciate your comments on this issue.
* First, we want to note that all gas station stores, CVS, and similar POIs included in our analysis do sell food. According to the data provider, the University of Florida GeoPlan Center, their team conducted significant data wrangling (acquiring, cleaning, and organizing) efforts, including fieldwork, phone calls, and, to distinguish between places that do and do not sell food (<https://www.geoplan.ufl.edu/portfolio/foodshed/>). They ensured that the POIs in the “food retail” categories used in this study are indeed places that sell food.
* Second, we recognize that not all trips to these POIs necessarily involve food acquisition, and due to the limitations of using secondary GPS data without transaction or survey information, we cannot definitively identify food-related trips. This introduces a trade-off: either overestimate food acquisition trips by including these locations or underestimate them by excluding such POIs.
  + We first chose to overestimate, as the number of grocery trips captured by GPS data tends to be lower than expected (Jin *et al.* 2023).
  + However, we addressed this concern through sensitivity analysis by excluding these POIs and only keep the more relevant ones. To do this, we used store information (photos, menus, etc.) from Google Maps.
  + As detailed in Section 4.1, this exclusion resulted in notable findings, such as an increased number of individual grocery store visits, suggesting that people who primarily visit stores dedicated to food may already have relatively better access to them.
* Third, it is worth noting that there has been ongoing discussion about including healthy food options at dollar stores or gas station stores (Chenarides *et al.* 2021), which are traditionally viewed as unhealthy food access locations. This intervention aims to increase food and nutrition security. In this context, the inclusion-then-exclusion of these POIs discussion in our study could be seen as contributing to this trend rather than detracting from the analysis. Our findings suggest that people are visiting these potential food access locations, so adding healthy food options to them could be beneficial for food security.
* Thanks to the reviewer’s comment,
  + We added a footnote in the data introduction section.

We obtained a comprehensive database from the University of Florida GeoPlan Center … which includes grocery stores, supermarkets, drug stores, corner stores, gas station stores1 and restaurants.

( The drug stores, corner stores, and gas station stores in the dataset have been verified to sell food, as indicated on the data webpage: https://www.geoplan.ufl.edu/portfolio/foodshed/)

* + We also revised the paragraphs in *Section 3.2.2 Food Outlets* where we eplain our rationale for distinguishing between primary food-selling and non-primary food-selling categories, as well as the decision to include the latter in our analysis. We rephrased “we developed two classifications” to “we developed *a two-step* classification approach” to clarify our methodology.

Unlike traditional datasets, secondary GPS data lack trip purpose or purchasing information. However, from a supply-side perspective, different food outlets offer varying types, prices, quantities, and varieties, which significantly impact the health outcomes of individuals and communities (Ma *et al.* 2017). Also, from a demand-side perspective, individuals visit different food retailers for various purposes, not limited to food access. For instance, some may frequent big box stores for non-food items while visiting gas station stores for food. The USDA’s FoodAPS indicates that SNAP households allocate 13% of their food spending to convenience stores, dollar stores, and pharmacies (Todd and Scharadin 2016).

To address these complexities, we drew from existing survey practices and literature (Todd and Scharadin 2016, Xu *et al.* 2023) to develop a two-step classification approach:

1. *Food quality and physical size*, four types:

* *Large Groceries or Supermarkets* that mainly sell food (e.g. Publix, Winn-Dixie)
* *Big Box Stores* that carry a full range of food products in addition to other products (e.g. Walmart Supercenter, Target)
* *Small Retailers* that sell healthy grocery items like milk, eggs (e.g. CVS, Dollar General)
* *Stores Selling Only Processed or Low-Quality Food* (e.g. Circle K, 7-Eleven)

1. *Purpose of visitation*: We distinguish between

* *Stores Primarily Selling Food*, where individuals predominantly visit for food-related purposes (e.g., groceries, food marts).
* *Locations Visited for Various Purposes*, such as big box stores, gas stations, and *pharmacies*.

We will first consider all POIs and categorized them into these four types, then narrow our analysis to those that primarily sell food, aiming to explore the implications of the data’s secondary nature. *Figure 2* shows the distribution of the stores under the two classifications and *Table 1* summarizes the numbers.

Fourth, I am not convinced that using Euclidean distance as a metric is appropriate for a well-developed, high-density urban area. In such a context, where the road network is extensive and complex, Euclidean distance may not accurately reflect actual travel patterns or accessibility. A more nuanced metric that accounts for the urban environment's specific characteristics would provide more meaningful insights.

* We appreciate your comments regarding the use of Euclidean distance as the distance measure.
* In the original manuscript, we opted for Euclidean distance since it has been widely used in literature to study food accessibility. However, we acknowledge your valuable point that network distance may better reflect actual travel patterns and accessibility in well-developed, high-density urban areas.
* In this study, we considered two aspects related to distance measurements: identifying food-related visits based on distance range and calculating the home-to-store distance. We decided to update only the latter with network distance due to the following reasons.
* The figures below show a dummy home-food outlet point pair in our study area. We first identify a visit to the store by considering activity stays within a certain radius of a food access-related POI (e.g., 200 meters, as shown in the left-hand figure). Then, we calculate the pairwise home-to-store distance (see the right-hand figure).

A map of a network connection

Description automatically generated

(Base road network: Open Street Map)

The left figure shows that the circular buffer around the POI aligns closely with the areas defined by points within the same network distance value. However, the right figure reveals that the two home-to-store distances can differ significantly. The two figures below also confirms this difference.

A graph of a number of numbers

Description automatically generatedA graph of a number of people

Description automatically generated with medium confidence

* Based on this discussion, we have decided to retain Euclidean distance for identifying food-related visits and home-based visit (which means those metrics and the temporal patterns remain unchanged), but we recalculated the home-to-store distances.
* While the new distance metrics are larger, the general findings remain similar to earlier results. Although, there are some small differences, they do not alter our discussions. For instance, the distribution curves of home-to-visited-store distances to processed outlets (2nd figure in Figure 5) are less smooth than before, and the cross-group differences are smaller.
* Please refer to the updated manuscript for these changes.

Fifth, the study's conclusions are based on comparisons with metrics from a single study, for each food acquisition metric, that focused on a different location. This approach raises questions about the validity of the research design. Comparing results to a single study does not provide a robust foundation for drawing generalizable conclusions. The authors should improve their research design by either incorporating a broader range of comparative studies or conducting parallel analyses using traditional methods. This would allow for a more comprehensive assessment of the data and strengthen the study's conclusions.

* We appreciate your comments on our research design and acknowledge the limitations involved.
* Unfortunately, we do not have access to comparative data for our study area (Jacksonville, FL) beyond the secondary GPS dataset used in this study. To address this, we sought out studies conducted in the same region. Ultimately, we included the data from a Florida study (Hodges and Stevens 2013) as well as the US-wide FoodAPS dataset, given its widespread use and recognition in food access studies.
* We agree that future research would benefit from incorporating a broader range of comparative studies or conducting parallel analyses with traditional methods. For example, parallel analyses could include survey-based studies to compare findings on food access behaviors more directly. In response to this comment, we have added a discussion in the manuscript on the robustness and generalizability of our findings and emphasized the value of adopting a mixed-method approach for future research.

(3) *Value of Mixed-Methods Research:* Our results underscore the importance of mixed-method research. While both big and small data—and their associated methods—have limitations, they can complement and enhance each other (Kwan 2016). As noted in the literature review, studies using primary GPS data combined with surveys have challenged previously held behavioral assumptions by uncovering new insights. Applying a mixed-method approach to secondary GPS studies could similarly provide a more holistic understanding of food access behaviors and improve the interpretation of key metrics and is beneficial for future planning and policy making. For instance, conducting surveys alongside GPS data collection for the same population would allow for integrating the granular, sensor-generated insights from GPS with the nuanced, human-generated insights from surveys. Such integration would facilitate statistical validation of the metrics extracted from both sources, addressing potential intrinsic or inference-induced inaccuracies in secondary GPS data and enhancing the generalizability of the findings.

Lastly, the paper falls short in providing a comprehensive and engaging discussion on the broader implications of the study. Specifically, it does not adequately explore how food access scholars and policymakers can leverage the findings to inform their work. The discussion should delve into the potential policy implications, offering insights on how the results could influence food access strategies, urban planning, or public health interventions. Presently, the discussion is minimal and does not fully address the significance of the research, leaving the reader without a clear understanding of its practical applications or contributions to the field.

* We appreciate your comments on this matter. In the original manuscript, we included some discussion on policy implications, but we recognize that it was somewhat scattered and lacked organization. We have now reorganized the discussion to present policy implications more clearly.
* Please find the revised discussion section in the manuscript.