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ANALYSING AUTONOMOUS DELIVERY ACCEPTANCE IN FOOD DESERTS BASED ON SHOPPING TRAVEL PATTERNS

Final Report

by

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EXCUTIVE SUMMARY

Food desert communities in the US have a widely recognized gap between the demand for healthy foods and the minimum order size that makes it worthwhile for food purveyors to deliver to such neighborhoods, thereby creating delivery deficiencies. A diverse set of mobility constraints and activity-travel patterns exist for disadvantaged segments in these communities, especially the elderly, unemployed, and socially excluded. Appreciating this complexity, an effective solution would be to improve the food access of such communities by providing faster, inexpensive, and flexible online deliveries of healthy foods. However, little is currently known about the shopping travel pattern in food desert communities and the associated mobility inequalities. This paper fulfills this critical research gap and quantifies the differences in shopping travel behavior observed among consumers residing in food deserts and food oases using data collected from Portland and Nashville Metropolitan areas. The paper subsequently captures the perceived acceptance of autonomous delivery robots (ADRs) among these consumers to overcome their mobility inequalities. The results indicate that food desert residents aged between 18 to 25 years, African Americans and earning more than $75,000 are more likely to engage in internet shopping than food oasis residents. Despite the perceived potential of ADRs to reduce the mobility inequalities in food deserts, acceptances levels for this emerging technology are found to be significantly less among food desert residents, especially among older generational cohorts and less qualified. This study will provide key takeaways to e-commerce companies to expand their delivery service through ADRs in underserved areas.

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1.0 INTRODUCTION

Socially distressed communities with a high degree of inaccessibility to healthy, fresh, and affordable foods like fruits and vegetables are termed as food deserts (Walker et al., 2010). The residents in food deserts are more likely to purchase unhealthy pre-processed food from convenience stores and fast-food restaurants, including higher sodium and energy densities, because of their inability to include healthy foods in their diet (Larsen and Gilliland, 2009). Existing literature exploring the eating habits of these communities underline the direct relationship between the food environment and health-related comorbidities like hypertension, heart disease, diabetes, obesity, and many more (Budzynska et al., 2013; Caballero, 2007; Chen et al., 2016; Pollard et al., 2015). Inaccessibility problems in food desert communities are also a critical reason for the underutilization of supplemental nutrition assistance program (SNAP) benefits (USDA, 2021); only 21% of households in these communities are presently utilizing SNAP benefits to purchase healthy food (Joassart-Marcelli et al., 2017). The geographic locations of these food deserts are not exclusive to urban or rural areas, but are more indicative of low-income, minority communities with high unemployment rates (Gordon et al., 2011; MacNell et al., 2017; Walker et al., 2011). Low-income households - especially those with single parents – face the extra burden of time poverty in addition to access barriers. Hence, access to healthy, fresh food in these communities is a multi-dimensional problem. Its role in improving mobility inequalities in food deserts differs conditional on many micro-level factors such as job locations, time use, household characteristics, and activity-travel behavior. For instance, low-income residents engaged in multiple jobs to complete their household needs face the surplus pressure of time poverty while fulfilling their food access needs. Providing increased access to food stores or mobility services to the supermarkets located in distant locations are often infeasible for such households (Hodgins and Fraser, 2018). Likewise, distinct constrictions and activity patterns exist for other underprivileged segments, such as the physically disabled, socially excluded , elderly, and unemployed (Choi and Suzuki, 2013).

Despite the awareness of the mobility inequalities existing in these food deserts, little is currently quantified on the differences in shopping travel patterns observed in these communities and the potential solutions to overcome the deficiencies. The shopping travel patterns of food desert residents are inherently multi-faceted; the combination of poor accessibility with lack of private car ownership, activity-space constraints, time budget constraints, expenditure budget constraints, public transport service coverage, and low levels of community interaction contributes significantly to the food desert problem. These issues have been exacerbated considerably in the aftermath of the COVID-19 pandemic, primarily due to the fall-out faced by small businesses, which has predominantly affected low-income neighborhoods.

Existing research shows that online grocery delivery services have a crucial role in increasing the accessibility of healthy food in low-income households (Bower et al., 2014; Dillahunt et al., 2019). The past research also indicates that targeting low-access households either through shared rides to the nearest supermarket (Widener et al., 2013) or providing mobile produce distribution (Widener et al., 2012) are effective strategies to increase their access to healthy foods (Robinson et al., 2016; Widener et al., 2013). However, the higher costs associated with last-mile delivery distribution are critical challenges deterring the success of such initiatives. In this direction, recent research indicates the potential of third-party delivery services in decreasing delivery costs (Choi et al., 2021).

Coupled with small sidewalk autonomous delivery robots (ADRs), third-party delivery services can further reduce these costs (Chen et al., 2021; Jennings and Figliozzi, 2019). Hence ADRs have tremendous potential to decrease such costs while improving access to healthy and fresh foods. To the best of our knowledge, existing efforts in capturing the food desert and oasis residents' shopping activity engagement and their acceptance of ADRs in delivery are missing in scholarly literature. Hence, this study attempts to fill the existing literature by posing the following fundamental question: "How are the shopping activity-travel pattern and acceptance for emerging autonomous delivery robots different in food desert communities as compared with the food oasis communities?". While posing and answering this fundamental question, this paper contributes on three fronts by *(i)* jointly exploring the distinction between online and in-person shopping engagement of food desert and food oasis residents in three intertwined purposes, i.e., general shopping, grocery shopping, and restaurants *(ii)* investigating and quantifying the correlations between six different shopping decisions spread across offline and online purchase channels for both food desert and food oasis residents and *(iii)* jointly modeling the food desert and oasis residents' intention to use ADRs for their internet orders and all other orders, if given an option to be served by ADRs. The study findings are expected to provide actionable insights on improving the food access inequities and last-mile delivery inefficiencies in underserved areas like food deserts.

The remainder of this paper is organized as Sections 2 provides a comprehensive overview of the background and existing studies on food deserts, online delivery, and application of ADRs in last-mile delivery. Section 3 describes the methodological framework, and Section 4 explains the data with the collection procedure and some summary statistics. Section 5 discusses the results, and Section 6 provides the key policy implications identified from the results. Finally, Section 7 concludes the study.

2.0 LITERATURE REVIEW

2.1 FOOD DESERTS: CHARACTERISTICS AND SOCIAL IMPACTS

The nomenclature "food desert" dates way back to the late 1990s when (Cummins and Macintyre, 1999) defined it as areas consisting of residential communities, census tracts, or areas with limited access to nutritious, healthy, and affordable food options. These areas tend to coincide with minority or low-income neighborhoods (Wright et al., 2016). Such low-income households, inaccessible from healthy food (Haider et al., 2020; Hendrickson et al., 2006; LeDoux and Vojnovic, 2014; Pothukuchi, 2005; Smoyer-Tomic et al., 2006), pay more for groceries (Bridle-Fitzpatrick, 2015; Hendrickson et al., 2006; Smith et al., 2010), spend more time traveling, and develop poor food habits (Bridle-Fitzpatrick, 2015; Hendrickson et al., 2006; LeDoux and Vojnovic, 2014; Ploeg et al., 2012; Sharkey et al., 2010; Walker et al., 2010). The lack of access to healthy foods hence forces the food desert community residents to travel to supermarkets or grocery stores outside the neighborhood, despite the financial and physical constraints to mobility.

Due to the presence of a plethora of fast-food restaurants and small convenience stores and a dearth of grocery access, food desert residents find it challenging to make healthy choices (Bridle-Fitzpatrick, 2015; Hendrickson et al., 2006; Hilmers et al., 2012; Metcalf and Widener, 2011) as the majority stores provide unhealthy foods (Bridle-Fitzpatrick, 2015; Ploeg et al., 2012; Raja et al., 2008). Instead of fruits and veggies, these stores are stocked with processed foods, alcohol, and sodas (Bustillos et al., 2009; Cannuscio et al., 2013; Pinard et al., 2016). Such residents are at a more significant disadvantage from a health and nutrition point of view and, hence, are exposed to economic, physical, and social changes. The formation and impacts of food environments in these communities on public health are well-documented in the literature (Beaulac et al., 2009; McGill, 2012; McKinnon et al., 2009; Walker et al., 2010). For instance, poor access to affordable and nutritious food is the principal cause of obesity and other chronic diseases like cardiovascular and type 2 diabetes (Haider et al., 2020). Hence, systemic gaps exist for food desert residents in terms of "what people food options people have, what options they want and what option they get (through local convenience stores)" (Walker et al., 2010). The census tracts identified as food deserts (USDA, 2015) are extracted and presented in Fig. 1 to quantify and report the extent of the problem in the U.S.

The existing literature has explored numerous solutions to improve access to healthy food in food deserts. Studies have recommended farmer's markets (Brinkley et al., 2017; Gustafson et al., 2013; Larsen and Gilliland, 2009; Widener et al., 2013) and food co-ops (Armstrong, 2000; Corrigan, 2011) to encourage food desert residents to grow their food individually or in community gardens. Several studies also explored increasing the number of food stores (Franco et al., 2009; Sparks et al., 2011). However, such an effort only increased food access and did not affect poor food habits or result in positive dietary outcomes (Adam and Jensen, 2016; Allcott et al., 2017; Cummins et al., 2014; Ghosh-Dastidar et al., 2017; Karpyn et al., 2019). Appreciating this complexity, an effective solution to improve the food access of socially distressed community segments would be to provide inexpensive and flexible online deliveries of nutritious and fresh foods to each individual as per their constraints on time and activity space. Understanding the tremendous potential of this solution to address the

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nutritional deficiencies of food deserts, the U.S. Department of Agriculture has already launched pilot programs in several states that allow SNAP recipients to purchase fresh food online. The delivery of foods to SNAP recipients not only increases their access to a wide variety of food retailers but also acts to increase the quality of their dietary content (Jilcott Pitts et al., 2020). However, given that more than 70% of non-urban food deserts are reportedly "undeliverable" using existing services (Brandt et al., 2019), *effectively* delivering fresh foods to these currently underserved locations—at a scale and cost that are sustainable—is a daunting research challenge.

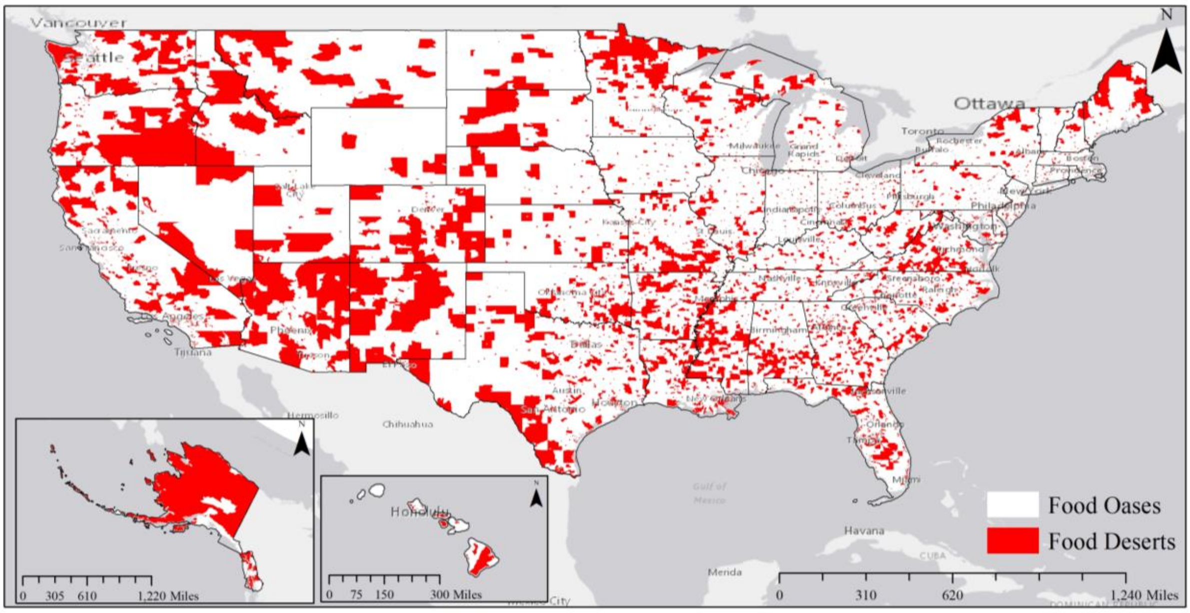


Figure 1: Tracts identified as Food deserts in the United States

Recent research indicates the potential of third-party delivery services in decreasing delivery costs (Choi et al., 2021). Widener et al. (2013) utilized an agent-based model to assess food accessibility among low-income households through different scenarios. The authors concluded that targeting low-access households through mobile produce distribution is the most effective intervention to increase their access to healthy foods (Widener et al., 2012). Robinson et al. (2016) report similar findings for two mobile markets in Syracuse, New York. When coupled with small sidewalk autonomous delivery robots (ADRs), such services can further reduce these costs (Chen et al., 2021; Jennings and Figliozzi, 2019). Hence ADRs have tremendous potential to decrease such costs while improving access to healthy and fresh foods. In the next subsection, we provide a brief overview of existing literature exploring the deployment questions related to ADRs.

2.2 AUTONOMOUS DELIVERY ROBOTS: IMPROVING ACCESS TO HEALTHY AND FRESH FOODS

In the US, many companies have already launched their plans of using delivery robots for food and grocery delivery, such as, Starship (Starship, 2018, 2017), Marble (Sawers, 2017), Dispatch (Kokalitcheva, 2016), Udelv (Mogg, 2018), FedEx (FedEx, 2019), Ford (Vincent, 2019), Nuro (BBC, 2020) and Waymo (Korosec, 2020). Starship technologies, for instance, have achieved food delivery times less than 15 minutes (Starship, 2018). The company claims that the robots haven't encountered a single accident in thousands of miles traveled while serving millions of people (Harris, 2017). COVID-19 pandemic accelerated the adoption of such robots in product delivery (Lienert and Lee, 2020). Such robots can be appropriate to deliver products at low cost in scenarios where the conventional truck-based delivery tours are not appealing due to scattered demand points or inconvenient delivery times. Past literature also corroborates their potential as the last mile delivery comprises up to 30% of the total delivery cost (Ranieri et al., 2018). In addition, such robots will provide additional benefits like fast delivery times, energy conservation, increased safety, and a higher level of accuracy (Figliozzi and Jennings, 2020).

Recent studies have demonstrated the potential of ADRs in product delivery (Abrar et al., 2020; Prause and Boevsky, 2018; Sindi and Woodman, 2021), especially during the COVID-19 pandemic (Abrar et al., 2020; Chamola et al., 2020; Chen et al., 2021; Kapser et al., 2021; Pani et al., 2020). Prause and Boevsky (2018) show the potential of delivery robots in last-mile delivery in rural areas. Boysen et al. (2018) investigated truck-based ADRs' potential in last-mile delivery based on a scheduling problem to minimize the weight times for the trucks during the delivery. The robots carried the package to only one customer from the truck and then returned to the nearest warehouse, not to the truck. The findings showed a significant increase in delivery efficiency, and ADRs can significantly reduce the truck fleet.

Jennings and Figliozzi (2019) provide a review of regulations for sidewalk ADRs. The authors then compared their product delivery operation with conventional vans under different scenarios. The authors conclude that ADRs can significantly reduce costs, delivery times, and vehicle miles traveled (if they are operated on sidewalks). In another study, authors (Figliozzi and Jennings, 2020; Figliozzi, 2020) compared sidewalk ADRs with on-road ADRs and concluded that the latter would also reduce emissions and energy consumption, and parking utilization. Abrar et al. (2020) also proposed a cost-effective contactless last-mile ADR, based on GPS information and password encryption, to deliver food products. Mourad et al. (2020) proposed integrating pick and drop delivery robots with existing passenger transport while utilizing an optimization framework. Results show that such a service can provide 18% cost savings. Simoni et al. (2020) also explored the potential of sidewalk ADRs in last-mile delivery based on an optimization framework (heuristic). The authors concluded that cost and travel savings depend on the capacity and customers' profile and benefit the limited customers living in dense areas. Yu et al. (2020) provided a truck-based autonomous delivery model using an optimization framework solved using heuristics and concluded that low-speed ADRs can significantly reduce the costs and workforce. Chen et al. (2021) also studied the adoption of ADRs in last-mile delivery using a metaheuristic-based vehicle routing problem to minimize the route length. Most of the existing literature have explored the operation of ADRs through an optimization framework or scenario-based simulations. However, limited literature is available on the perceived utility of ADRs in one of its core benefit segments in low-income communities, and how it is linked to their shopping activity-travel pattern.

Research Gaps and Contribution

The past literature shows that inaccessibility to healthy foods in food deserts is a multi-dimensional problem with significant impacts on dietary habits, health-related comorbidities, time poverty, employment, household characteristics, and the actualization of SNAP-based benefits. Such impacts underline the research need to explore the shopping activity-travel engagement of food desert communities, with the principal focus on their online versus offline travel pattern and the potential solutions to overcome the deficiencies through emerging vehicle technologies such as ADRs. This study aims to fulfill this research need and explore the impacts of recent advancements in e-commerce and autonomous vehicle technology in providing affordable healthy foods to such communities. To the best of our knowledge, in particular, no past study has investigated this fundamental research question and associated premise: "*what does delivery automation mean for the food deserts, and how does it fulfill their shopping activity travel pattern?*" To answer this question, first, we attempt to capture the difference in shopping behavior of food desert and oasis residents, segregated using USDA's geographical tool (USDA, 2015). We then uncover the acceptance of ADRs in delivering online orders in food deserts while accounting for the preference heterogeneity of these residents. Hence our research contributes to the existing literature in three different outlooks. *First,* we model the differences between the food desert and oasis residents' weekly engagement frequency in online and in-person participation forms of three intertwined shopping or eating-related activity purposes. Such analysis is first-of-its-kind and vital to capture food desert residents' behavior towards the internet orders to tackle their current inaccessibility to healthy food. The findings will provide critical insights to E-commerce and delivery companies to extend their service to underserved areas like food deserts through emerging vehicle technology such as ADRs. *Second,* we explore the correlation among all three categories of both online and in-person shopping for both food desert and food oasis residents. The findings of such exploration will assist companies in identifying the impact of in-person shopping activity on internet orders and vice versa, especially in the context of significant changes in shopping patterns due to the COVID-19 pandemic. *Third,* we capture the differences between food desert and food oasis residents' intention to use ADRs for their future shopping needs. The findings will help to identify the residents' who are willing and unwilling to receive orders from ADRs. The food desert residents' shopping activity behaviors, identified from their online versus offline shopping decisions, will assist in pinpointing the key determinants to boost the adoption rate of ADR-based healthy food delivery services among such residents.

3.0 DATA

This study uses survey data collected from two U.S Metropolitan Statistical Areas (MSA) – Nashville MSA in Tennessee and Portland MSA in Oregon. The middle Tennessee region that Nashville MSA belongs to is disreputably known as the 'hunger capital of the U.S' and is a particularly intense example of food deserts in the mid-south with a history of redlining and socially excluded minority neighborhoods. The Northwest region in the US that Portland belongs to also has several food desert communities, although lesser than Nashville. Both these MSAs provide a unique setting as it enables us to investigate the geographical variation in shopping travel behavior based on the location of food deserts. The rest of the section elaborates on the survey design and data processing used in this study.

3.1 SURVEY DESIGN

3.1.1 Questionnaire and Response Collection Procedures

The survey instrument used in this study with four parts was approved by the Institutional Review Board (IRB) of the University of Memphis. The survey questionnaire is provided in Appendix A. In the first part, an informed consent statement was provided to the respondents, explaining the reasons for collecting their location information and the overall purpose of the survey. In the second part, the questionnaire focused on sociodemographic characteristics (e.g., age, income, gender, employment), vehicle ownership, and availability of driving license. In the third part, the shopping frequencies of the respondent were collected in both online and offline shopping channels. The next part informed the respondents about ADRs' operational characteristics and performance attributes using an information sheet (more details in survey questionnaire included in Appendix A). Subsequently, the respondents were asked about their willingness to pay (WTP) for ADR delivery and intention to use ADR-based delivery. The survey was only open to Nashville and Portland MSA residents aged at least eighteen years. Quota sampling was applied using age, gender, race/ethnicity, and geographic region strata to ensure that the sample reflected the socio-demographic characteristics of both MSAs.

The survey was hosted in Qualtrics platform and was administered by Centiment – a market research company. The respondents who matched the eligibility criteria were identified from the Centiment's respondent panel and were sent survey invitations by email and phone texts. Upon providing the informed consent and completing the 9-minute survey, the respondents received compensation provided through Centiment. The data collection took place between June and July 2020. A total of 1931 respondents consented to participate in the survey, out of which 372 did not meet the eligibility criteria (19.26%), 194 did not complete the survey (10.05%), 156 respondents were excluded from the response pool due to in-survey quality violations based on attention-check question and response time checks (8.08%). The final sample consisted of 1309 responses, out of which 558 and 751 respondents were from Nashville and Portland, respectively. When compared to population demographics in terms of age, gender and ethnicity, survey respondents slightly overrepresented population aged less than 40 years, females and minority ethnicities. The detailed comparison is portrayed in Fig. B.1 in Appendix B.

Data Processing: Mapping Respondents into Food Deserts and Food Oases

The respondents' residence in a food desert was determined using the mapping tool provided by the USDA's Food Access Research Atlas (USDA, 2015). USDA atlas is the most comprehensive tool available currently to designate census tracts as food deserts based on the availability of shopping destinations (Chi et al., 2013; Colón-Ramos et al., 2018; Coveney and O'Dwyer, 2009; Schwartz et al., 2019). The tool utilizes a national database of food stores based on the SNAP and TDLinx database (annual directory of operational food stores), the population from US Census 2010, and income and vehicle availability from American Community Survey 2010-14. The tool excludes convenience stores, warehouse clubs, military commissionaires, drug stores, and dollar stores. Such stores either do not include healthy options or require annual memberships, both unfavorable for food desert residents. The tool provides census tracts identified as having inadequate access to food opportunities. The tool employs distinct criteria for rural and urban areas regarding the buffer radius from the food stores (0.5 and 1 mile for urban and 10 miles for rural areas).

Being consistent with the previous literature, we utilized the buffer radius of 0.5 miles from the food stores for food oases (Apparicio et al., 2007; Walker et al., 2012) as such radius is well in limits for an adult to carry bags from the food store to the home (Apparicio et al., 2007). A nationwide food desert map, obtained from a buffer radius of 0.5 miles for Food oasis and 10 miles for rural areas from USDA's mapping tool, is shown in Fig. 1. For this study, we define the areas with access and no access to food stores as "Food oasis" and "Food deserts", respectively. The definition of food oasis as anonym to food desert is consistent with the existing literature (Bilková et al., 2017; Short et al., 2007; Walker et al., 2012, 2011). We applied this classification to the collected survey sample based on the five-digit zip code of respondents' house location. Using survey data to categorize food desert residents is not uncommon (Gray et al., 2018; Wilcox et al., 2020). The survey respondents living in food deserts and food oases in Portland and Nashville MSAs are presented in Fig. 2.

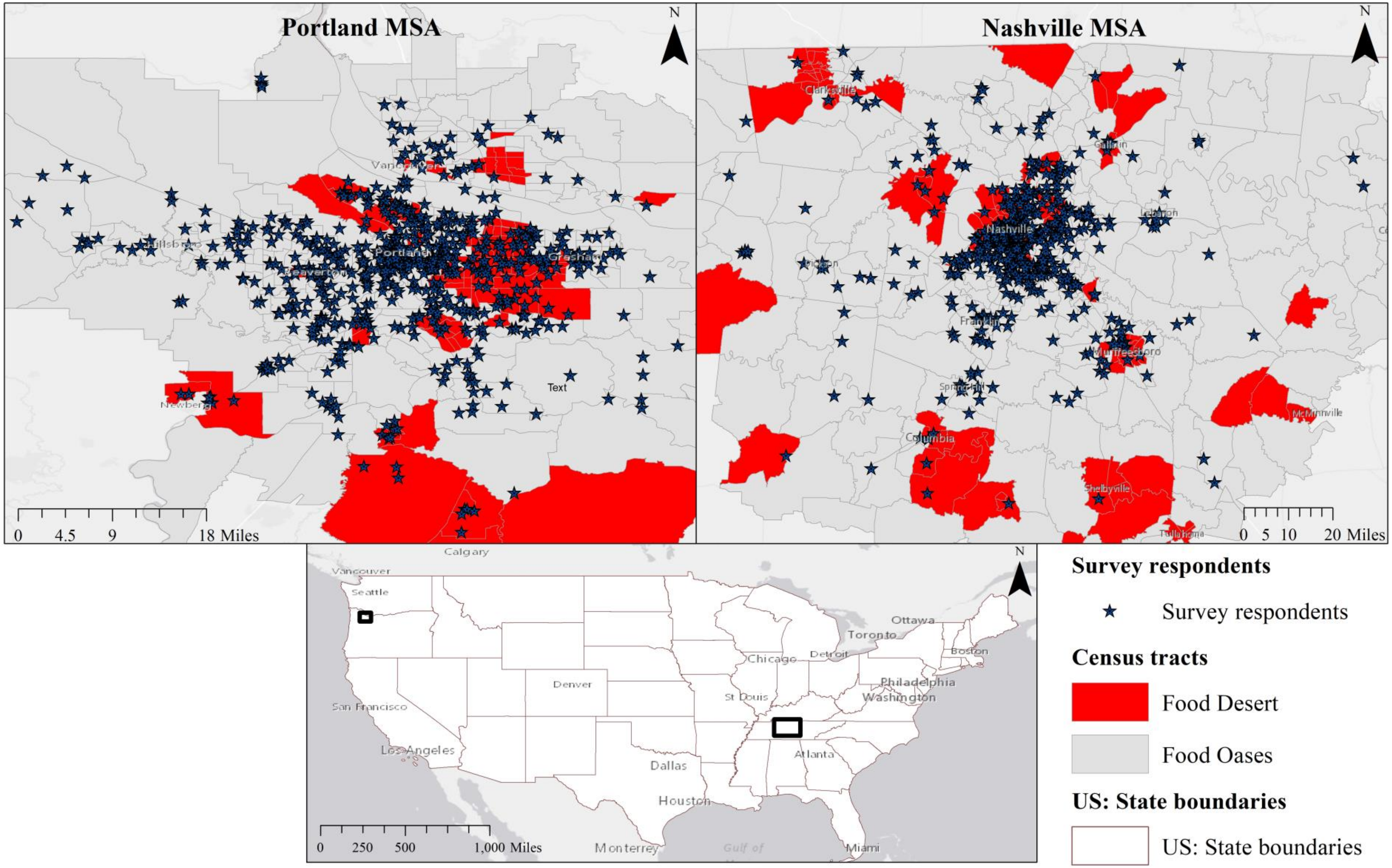


Figure 2: Survey respondents living in food deserts and food oasis tracts in Portland and Nashville metropolitan statistical area.

3.2 PRELIMINARY ANALYSIS

This section discusses the differences between the food oasis and food desert samples based on the respondent's attributes. Table 1 and Table 2 delineate the descriptive statistics of categorical and continuous attributes for the full dataset for food oases and food deserts, respectively. As per Table 1, in both food oasis and food desert samples, most respondents are female, aged between 25 to 40 years, working full time, completed high school, own a driving license, own a smartphone, and own two or more cars in the household. The proportion of Gen Y respondents, low-income individuals, and African Americans, appears to be more in food deserts than food oases. This is in line with previous food desert studies that highlight the higher prevalence of lower-income individuals from African American ethnicity in food deserts (Beaulac et al., 2009; Mark et al., 2012; Morland et al., 2002; Morton et al., 2005; Wright et al., 2016). The food oases include a comparatively high proportion of individuals with an annual income of more than $75,000, two more cars, and aged more than 55 years (baby boomers). A higher prevalence of Nashville MSA respondents in food deserts is expected since the region is known to have several neighborhoods with food access problems (Hineman, 2020). A closer look at these results shows that food desert residents are more excited about newly launched gadgets when compared to food oasis respondents. Respondents in both samples are similar in terms of their familiarity with ADRs and willingness to adopt ADRs for their future orders.

In addition to the survey attributes, we also added built environment attributes from the survey while utilizing the five-digit ZIPCODE of survey respondents and US census tract-level data. As per Table 2, food deserts include fewer households with access to the internet and a lower per capita crime rate when compared to food oases. Food deserts include a high violent crime rate (per capita), residential density in 1000 mi^2, road density per mi^2, number of road intersections per mi^2, and number of courier services per mi^2 compared to food oases. The average density of food stores in food deserts is higher than in food oases. It is because the food stores (obtained from ESRI (2019)), much like the previous studies investigating food shopping behavior (Vaughan et al., 2017), also include convenience stores, ethnic stores, and even gas station stores where food products are stocked. Furthermore, food deserts include a higher-than-average density of convenience stores than food oases (Hilmers et al., 2012). Based on the weekly frequency of internet orders, food desert residents were less frequent than their urban counterparts. However, food desert residents are more frequent in making in-person shopping or eating trips to the nearest food stores or restaurants when compared to food oases residents. The distribution of weekly occurrences of online and in-person shopping for a total of six activity types for both food desert and food oasis residents is also included in Appendix A (Table B.1). These activity types are endogenous variables for the multivariate count data model described in the methodology section. Overall, it can be seen that the residents make more in-person trips to all three activity types compared to internet orders for grocery and prepared meals. There is no considerable difference between general-purpose packages related to internet orders among food desert and food oasis residents, highlighting the presence of e-commerce companies like Amazon in both areas. Marginal differences exist among food desert and food oasis residents in all six shopping activities.

Table 1: Descriptive statistics categorical variables in the full dataset, and the subsets

Variable		Percentage		
		Total Sample (N =1,309)	Food oasis (N=967)	Food deserts (N=342)
Gender	Male	41%	41%	40%
	Female	59%	59%	60%
Age	Gen Z (18 to 25 years)	18%	19%	15%
	Gen Y (25 to 40 years)	36%	33%	44%
	Gen X (41 to 55 years)	24%	23%	24%
	Baby boomers (> 55 years)	22%	24%	17%
Ethnicity	White	77%	78%	76%
	African American	7%	6%	10%
	Others	16%	16%	14%
Employment status	Full-time	50%	50%	53%
	Part-time	14%	13%	15%
	Seeking work	10%	11%	10%
	Retired	12%	13%	10%
	Student	6%	7%	4%
	Unable to work	7%	6%	8%
Educational attainment	High school or below	44%	44%	44%
	Bachelor's degree or equivalent	34%	35%	32%
	Master's degree or higher	22%	21%	24%
Annual Income	less than $25,000	26%	25%	29%
	$25,000 to $50,000	26%	24%	30%
	$50,000 to $75,000	21%	22%	20%
	More than $75,000	27%	29%	21%
Driving license	Yes	89%	89%	90%
	No	11%	11%	10%
Cars in the household	Zero	6%	6%	7%
	One	40%	39%	44%
	Two or more	54%	55%	49%
Smartphone ownership	Yes	96%	96%	97%
	No	4%	4%	3%
Excited about newly launched Gadgets or accessories	Frequently (always or most of the time)	46%	44%	51%
	Infrequent (sometimes or half of the time)	44%	44%	41%
	Never	11%	11%	8%
Familiarity with ADRs	Not familiar	40%	39%	43%
	Somewhat familiar	57%	58%	54%
	Very familiar	3%	2%	3%
Willingness to pay for ADR deliveries	$0	40%	40%	38%
	$1 or less	23%	23%	23%
	$1 to $4	26%	26%	27%
	$5 or more	11%	11%	11%
Case city	Nashville	43%	40%	51%
	Portland	57%	60%	49%

Table 2: Descriptive statistics continuous attributes in full dataset, food oasis and food deserts samples

Variable	Descriptive Statistics											
	Full Sample (N =1,309)				Food Oasis (N=967)				Food Desert (N=342)			
	Min	μ	σ	Max	Min	μ	σ	Max	Min	μ	σ	Max
Built Environment related variables (Census)												
Percentage of households with access to internet	0	82.83	11.20	100	46	85	9.82	100	0	78	13.10	98
Property crime rate per capita	136	396	429	2518	136	400	434	2518	136	386	413	1645
Violent crime rate per capita	0	147	158	406	14.66	128	145	406	0	202	179	406
Population Density in 1000 per sq. mile	0	3.45	3.37	26.83	0	3.27	3.59	26.83	0	3.95	2.56	12.03
Residential Density in 1000 per sq. mile	0	1.53	1.67	17.22	0	1.45	1.81	17.22	0	1.77	1.14	5.19
Road density per square mile	0.03	0.29	0.20	1.13	0.03	0.27	0.20	1.13	0.03	0.34	0.19	1.01
Number of food stores per square mile	0	9.88	14.34	85	0	8.54	13.88	85	0	13.69	14.95	70
Number of Restaurants per square mile	0	72	102	806	0	65	104	806	0	92	96	504
Number of bike facilities per square mile	0	1.18	5.18	78	0	1.10	5.47	78	0	1.41	4.25	29
Residential ratio	0	0.63	0.31	1	0	0.65	0.30	1	0	0.60	0.33	1
Industrial ratio	0	0.06	0.15	1	0	0.06	0.15	1	0	0.06	0.13	0.87
Business Ratio	0	0.08	0.14	0.98	0	0.08	0.13	0.69	0	0.11	0.16	0.98
Percentage of unemployed population	0	0.03	0.02	0.12	0	0.03	0.02	0.12	0	0.03	0.01	0.08
Percentage of uninsured population	0	0.08	0.06	0.34	0	0.07	0.05	0.32	0	0.11	0.07	0.34
Number of intersections per square mile	0.40	152	278	3206	0.40	148	306	3206	0.63	162	175	1086
Number of courier services per square mile	0	1.71	5.66	61	0	1.00	3.05	47	0	3.71	9.55	61
Respondents' weekly frequency (in days) to receive at least one internet order per day												
General Purpose Packages (e.g., Amazon, Walmart, eBay, Target)	0	1.70	1.54	7	0	1.71	1.54	7	0	1.68	1.52	7
Grocery deliveries (Instacart, Kroger, Walmart, Whole Foods)	0	0.87	1.42	7	0	0.88	1.42	7	0	0.83	1.40	7
Prepared Meals (e.g., UberEats, GrubHub, Postmates, Doordash, goPuff)	0	0.96	1.48	7	0	0.92	1.44	7	0	1.08	1.59	7
Respondents' weekly frequency (in days) to make at least one in-person shopping or eating trips per day												
General Shopping (Excluding Groceries)	0	1.69	1.57	7	0	1.68	1.57	7	0	1.71	1.57	7
Grocery Shopping	0	2.06	1.48	7	0	2.06	1.48	7	0	2.06	1.47	7
Restaurants	0	1.43	1.53	7	0	1.40	1.50	7	0	1.52	1.61	7
Respondents' intention to use Autonomous Delivery Robots (Likert scale: 1- Strongly disagree to 5- Strongly agree)												
ITU_1: I plan to use delivery robots for my internet orders in the future	1	2.92	1.13	5	1	2.87	1.13	5	1	3.05	1.12	5
ITU_2: I will prefer delivery robots whenever the option is available	1	2.74	1.13	5	1	2.70	1.12	5	1	2.84	1.13	5

Interestingly, food oasis residents appear to be more likely to make in-person trips for dining in restaurants. Food desert residents, in contrast, appear to be more likely to order prepared meals. Food oasis residents are more likely to order groceries online than food desert residents. This can be attributed to the minimum order size and high delivery costs associated with grocery deliveries. For instance, major grocery delivery companies like Instacart, Amazon Fresh, Walmart and Shipt serving in both MSAs require a minimum order amount of $35 and a membership (worth at least $9.99/month) for free delivery. For orders below $35, the companies charge from $5.99 to $10 per order (Haider et al., 2020; Kirkham, 2020). There is no such requirement of minimum order size for food delivery. However, delivery charges tend to remain constant or decrease for an order amount of $10 or more. On average, delivery costs for prepared foods vary from $1.59 to $3.09 (Munster and Stokman, 2021). Lesser delivery costs, no requirement of memberships, and minimum order size compared to grocery deliveries justifies a higher frequency of ordering prepared meals in food deserts. Furthermore, the number of in-person shopping trips in food oases are equal to or less than food deserts which might be due to trips chaining behavior among food oases residents (combining shopping trips with work trips), which is in line with existing literature (Chowdhury and Scott, 2020; Le et al., 2021; Suel and Polak, 2018).

The distribution of perceptions of a food desert and oasis residents' intention to use ADRs for their internet orders and all orders where the ADR option is available are presented in Fig. 3. Among both the samples, most residents are neutral about their intention to use ADRs for their orders. Interestingly, despite making more in-person shopping trips, food desert residents are more likely to use ADRs for internet and other orders than food oasis residents. It can be attributed to unavailability of delivery services in food deserts or residents' unfamiliarity with the ADR-based delivery costs.

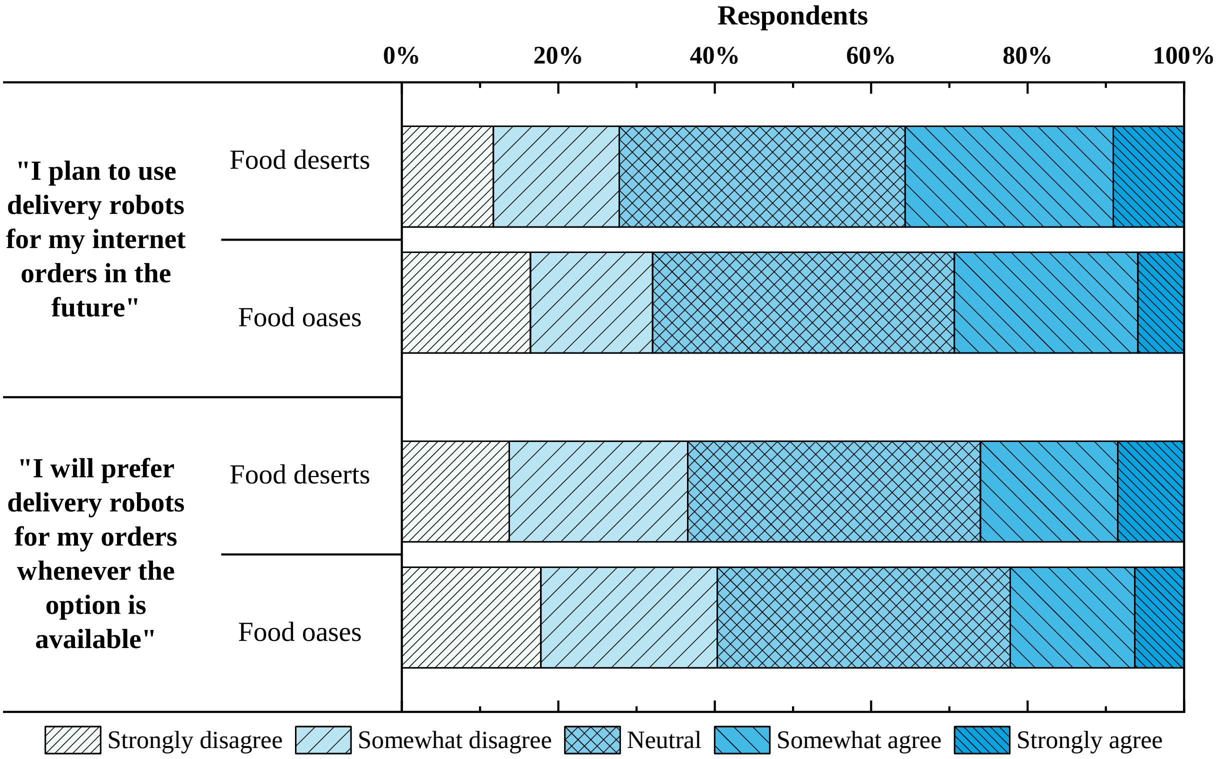


Figure 3: Distribution of perceptions of food desert and oasis residents towards ADRs.

4.0 METHODOLOGY

The methodological approach used in this study is to compare the shopping activity engagement of both food desert and food oases residents and subsequently analyze the acceptance levels for ADR deliveries, as depicted in Fig. 4. The modeling approach and model formulations are explained below. First, we used a multivariate count data model to capture individuals' shopping activity engagement for food oasis and food desert residents. Then, we use a bivariate ordered probit model to capture the food desert and food oasis residents' intention to adopt ADRs for internet orders and other orders if ADRs are available as a delivery option.

4.1 MULTIVARIATE POISSON-LOGNORMAL MODEL

One of this paper's objectives is to capture the shopping activity engagement of food desert and food oasis residents based on the frequency of internet orders and in-person shopping trips that form a multivariate count distribution for a total of six subtypes. Existing literature suggests that it is challenging to model the multivariate distribution of count data compared to multivariate continuous distribution (Aitchison and Ho, 1989; Inouye et al., 2017). However, recent research on multivariate Poisson-lognormal (MPLN) models addresses this challenge (Chiquet et al., 2021). MPLN model first maps some f -dimensional observational vectors y_n to f-dimensional Gaussian latent variable vectors y_n^* as given below in Eq. (1).

$$y_n | y_n^* \sim (\exp\{y_n^*\}) \tag{1}$$

Where n is the set of the number of individuals in the sample $(1,2,3,4, \ldots\ldots, N)$ and f being the observed dependent variables capturing the frequency of internet orders and in-person shopping trips. To capture the effect of a linear combination of e explanatory variables x_n, including intercept vector, on the count matrix, the Gaussian latent vector y_i^* is then mapped to the covariate matrix x_n as in Eq. (2).

$$y_i^* \sim (\beta x_i^T, \sigma) \tag{2}$$

Where β is a matrix of regression coefficients $(e \times f)$ and σ is the covariance matrix. After stacking all individuals together, i.e., $n = (1,2,3,4, \ldots\ldots, N)$, the data input matrices for the model will be count matrix Y $(n \times f)$ and covariates X $(N \times e)$. The model parameters $(\beta \; and \; \sigma)$ can then be estimated using variation inference, specifically the variational expectation-maximization algorithm (VEM). The log-likelihood function is first approximated through a variational strategy. Then a gradient-ascent-based approach is utilized for the optimization of the likelihood function. For more details, readers are referred to (Chiquet et al., 2021). We utilize the R-package "PLNmodels" to formulate and estimate the model (Chiquet et al., 2018).

4.2 BIVARIATE ORDERED PROBIT MODEL

This research's final objective is to simultaneously capture residents' intention to use ADRs for their future internet orders and all other orders wherever the option of ADR is available. To achieve we utilize a bivariate ordered probit model (Butler and Chatterjee, 1997; Sajaia, 2008; Yamamoto and Shankar, 2004), an extension to a univariate ordered probit model with correlated error terms. We model two ordered probit models for residents' intention to adopt ADRs for the internet and all other orders, with their error terms correlated. We assume a bivariate normal distribution for error terms. The probability of different outcomes (5-level

Likert scale in our case) can be estimated from U_{nk}^*, threshold parameter and error correlation, as shown in Eq. (3):

$$\begin{cases} U_{n1}^* = \theta_1 x_{n1} + \varepsilon_{n1} \\ U_{n2}^* = \theta_2 x_{n2} + \varepsilon_{n2} \end{cases} \quad (3)$$

Where, U_{nk}^* =Utility for response z, intention to use ADRs for purpose k (1=internet orders, 2=all orders), resident n (1,2,3, ..., N),

$z = 1 \; if \; U_{nk}^* < \tau_{k1}; 2 \; if \; \tau_{k1} \leq U_{nk}^* < \tau_{k2}; \dots\dots; \; 5 \; if \; U_{nk}^* \geq \tau_{k4}$,

τ = threshold parameter, x_{nk} = Explanatory variable matrix for purpose k and respondent n, θ_k = unknown coefficient matrix for purpose k, and ε_{nk} = error term for respondent n and purpose k.

The unknown coefficient matrix can then be estimated after formulating a log-likelihood function based on the bivariate normal distribution and maximizing the function using the maximum likelihood method. We used the package "bioprobit" in Stata (Sajaia, 2008) to code and estimated the model.

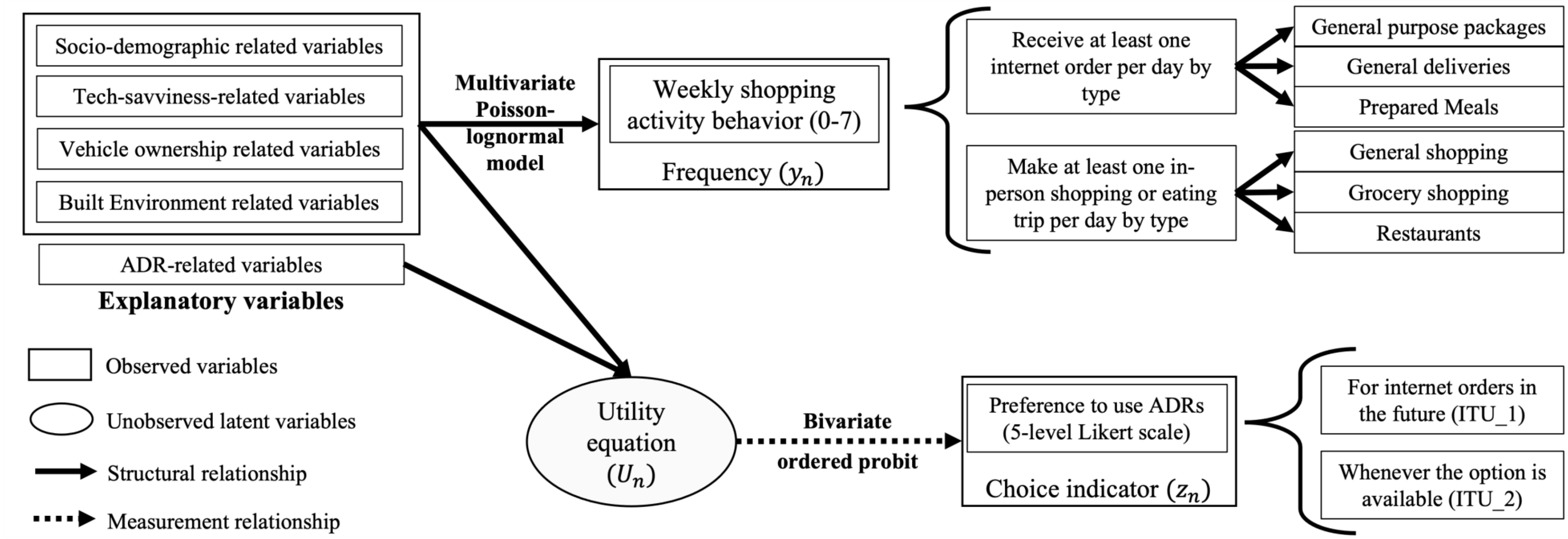


Figure 4: Methodological approach

5.0 RESULTS AND DISCUSSION

This section analyzes the food desert and food oasis residents' propensity to engage in internet ordering and in-person shopping travel and their intention to receive orders from ADRs.

5.1 COMPARING SHOPPING RELATED ACTIVITY ENGAGEMENT

The MPLN model results to capture the shopping activity engagement of food desert and food oasis residents are presented in Table 4 for both internet orders and in-person shopping trips. The model fits the data well in terms of Pseudo R^2 values of 0.545 and 0.495, respectively. We removed all insignificant variables from the model (p>0.10). We removed all insignificant variables from the model (p>0.10). The insignificant variables include educational attainment, driving license, case city, and built environment-related variables (population density, road intersections, bike facilities, courier services, residential ratio, industrial ratio, business ratio, and unemployed population. The insignificant impact of education and driving license ownership on shopping behavior aligns with existing literature (Kim and Wang, 2021). The insignificance of the case city can be attributed to the similar demographics between Nashville and Portland MSAs. Insignificant built environment-related variables can be attributed to the availability of such data at census tract level rather than for each respondent. The model results are discussed in the upcoming paragraphs and compared to the existing literature (whenever applicable).

For the interpretation purposes, the positive (negative) sign of the coefficients can be inferred as the increasing (decreasing) effect of the respective explanatory variable on the residents' frequency of making six different shopping activities. The magnitude of the coefficient can be inferred as the intensity of the covariate effect on particular shopping activity. Among the significant results, compared to Portland residents, Nashville food oasis residents are more likely to make in-person shopping trips for general shopping and restaurants consistent with Portland's comparatively higher cost of living (BestPlaces, 2021). Among internet orders (general delivery and prepared meals), compared to males, in food oases, females are more likely to place internet orders. This is in line with the previous research (Pradhana and Sastiono, 2019) and further supported by the in-person shopping model results of food oasis, where males are more likely to make in-person shopping trips. *Interestingly, for food deserts, all significant results correspond that males are more likely to make in-person shopping trips and receive grocery and prepared food deliveries, which is consistent with Kim and Wang (2021), where authors report that males are more likely to make both in-store walking trips and receive grocery deliveries.* Food desert residents with a driving license are found to be less likely to make in-person grocery shopping trips because either they do not have a vehicle as license availability does not necessarily relate directly with vehicle ownership, or due to the lack of food stores in the vicinity.

Table 3: Multivariate Poisson-lognormal model results: weekly shopping activity

Variable	Coefficient^{Significance}											
	Internet orders						In-person shopping or eating trips					
	General packages		Grocery Deliveries		Prepared meals		General shopping		Grocery		Restaurants	
	FO	FD	FO	FD	FO	FD	FO	FD	FO	FD	FO	FD
Intercept	--	1.16*	-1.858***	--	--	--	--	--	1.218***	--	--	2.131***
Case city (base: Portland)												
Nashville	--	--	--	--	--	--	0.133*	--	--	--	0.346***	--
Gender (base: Female)												
Male	-0.138*	--	-0.148$^{\#}$	0.26$^{\#}$	-0.195*	0.209$^{\#}$	0.134*	0.254**	--	0.149$^{\#}$	0.111$^{\#}$	0.218*
Driving license (base: No)												
Yes	--	--	--	--	--	--	--	--	--	-0.362*	--	--
Smartphone ownership (base: No)												
Yes	--	--	--	--	-0.752***	-0.764$^{\#}$	--	--	-0.302**	--	-0.357*	--
Age. (base: Gen Z (18 to 25 years)												
Gen Y (25 to 40 years)	--	0.308$^{\#}$	0.311**	--	--	-0.653***	-0.07*	--	-0.141$^{\#}$	--	-0.144$^{\#}$	-0.533***
Gen X (41 to 55 years)	-0.254**	--	-0.308*	--	-0.907***	-1.139***	-0.21**	-0.371*	--	--	-0.292**	-0.653***
Baby boomers (more than 55 years)	-0.5***	--	-0.709***	-0.555$^{\#}$	-1.303***	-1.487***	-0.283*	-0.411*	-0.243**	--	-0.767***	-0.806***
Ethnicity (base: White)												
African American	--	--	--	0.485**	--	--	0.219***	--	--	0.246*	-0.195$^{\#}$	0.313*
Others	--	--	--	0.558***	--	0.436**	--	--	-0.265*	0.233*	-0.534***	--
Employment status (base: Full-time)												
Part-time	-0.171$^{\#}$	--	--	--	-0.251*	--	--	--	--	--	--	-0.309*
Seeking work	--	--	--	--	-0.229*	--	--	--	--	--	-0.612***	--
Retired	--	--	--	--	--	--	-0.177*	--	-0.187$^{\#}$	--	--	--
Student	--	--	--	--	-0.732***	--	--	--	-0.304**	--	-0.475***	-0.542$^{\#}$
Unable to work	--	0.29$^{\#}$	--	--	-0.452**	0.766***	-0.154*	--	--	--	--	--
Annual Income (base: More than $75,000)												
less than $25,000	-0.565***	-0.514***	--	-0.516**	--	-0.992***	0.165**	-0.318*	--	-0.331**	--	-0.596***
$25,000 to $50,000	-0.302***	-0.462***	-0.184$^{\#}$	-0.549**	--	--	--	--	--	--	--	-0.283*
$50,000 to $75,000	-0.182**	-0.426***	--	--	--	-0.28$^{\#}$	0.089**	--	--	--	--	-0.305*
Cars in the household (base: two or more)												
Zero	0.332***	-0.457*	0.938***	--	1.009***	--	--	0.359*	0.305***	--	--	--
One	-0.104$^{\#}$	--	0.132$^{\#}$	--	0.179*	--	-0.027***	0.16$^{\#}$	--	--	--	--
Excited about newly launched tech gadgets (base: Never)												
Frequently	0.387***	0.388***	0.814***	0.801***	0.569***	0.794***	0.456$^{\#}$	0.248**	0.156$^{\#}$	0.211*	0.274**	0.378***
Infrequent	0.193$^{\#}$	--	--	--	--	--	--	--	--	--	--	--

Table 4 continued

Variable	Coefficient^{Significance}											
	Internet orders						**In-person shopping or eating trips**					
	General packages		**Grocery Deliveries**		**Prepared meals**		**General shopping**		**Grocery**		**Restaurants**	
	FO	**FD**	**FO**	**FD**	**FO**	**FD**	**FO**	**FD**	**FO**	**FD**	**FO**	**FD**
Percentage of households with internet access	--	--	1.006*	-1.831***	--	--	--	-0.758*	--	--	--	-1.044*
Property crime rate per capita	--	--	-0.533*	--	-0.69**	--	--	--	--	0.778**	--	--
Violent crime rate per capita	0.261**	--	0.302*	--	0.483***	0.379$^{\#}$	--	--	0.199*	0.24$^{\#}$	0.196$^{\#}$	--
Population Density in 1000 per sq. mile	--	--	--	--	--	--	--	--	1.564$^{\#}$	--	--	--
Residential density in 1000 per sq. mile	--	--	--	--	--	-2.838*	--	--	-2.079$^{\#}$	--	--	2.061$^{\#}$
Road density per square mile	--	1.389$^{\#}$	1.593**	--	1.253*	2.696**	-0.199*	--	--	--	1.238**	-1.889*
Number of restaurants per square mile	--	--	-0.822$^{\#}$	--	--	--	--	--	-0.606$^{\#}$	--	--	--
Number of bike facilities per square mile	--	--	--	4.44***	--	--	--	--	--	--	--	--
Residential ratio	--	--	-0.563**	--	--	--	--	--	--	--	--	--
Industrial ratio	-0.537*	--	--	--	--	-1.169$^{\#}$	--	--	--	--	--	--
Business Ratio	--	--	-0.655*	--	--	1.613***	--	--	--	--	--	--
Percentage of unemployed population	0.472*	--	1.166***	--	0.627$^{\#}$	-0.846$^{\#}$	--	--	--	--	--	--
Percentage of uninsured population	-0.404*	--	-0.825***	--	-0.549*	--	-0.107*	--	--	--	--	--
Number of intersections per square mile	--	--	--	--	--	--	--	--	1.163*	--	-1.943$^{\#}$	--
Number of courier companies per square mile	--	--	--	--	-2.087$^{\#}$	--	--	--	--	--	--	--

Goodness of fit measures – FO;Food oasis: Log-likelihood = -15,083.56; BIC = -15,876.21; Pseudo-R^2 = 0.545
FD;Food desert: Log-likelihood = -5,347.73; BIC = -5,880.81; Pseudo-R^2 = 0.495
Significance levels: -- not significant, $^{\#}$0.10, *0.05, **0.01, ***0.001

As expected, for in-person shopping trips, food oasis residents owning a smartphone are less likely to make in-person grocery shopping because residents might use their smartphones for placing online grocery delivery orders as such residents have access to food stores. For food oasis residents, smartphone ownership was linked negatively for both in-person restaurant dining trips and ordering prepared meals. It might be so due to the availability of traditional dial-in services for ordering food in such areas and the increased level of social presence associated with phone ordering (Leung and Wen, 2020).

For all six shopping-related activities, both in food deserts and food oases, baby boomers and Gen X residents are less likely to engage as compared to Gen Z residents. This is consistent with the tech-savviness associated with internet ordering and increased travel activities from in-person shopping trips. However, Gen Y residents living in food deserts and oases are more likely to order general-purpose packages and groceries online, respectively. As compared to Whites, African Americans and individuals with other ethnicities living in food deserts were more likely to order grocery deliveries online, which can be justified by racial inequity for access to food stores well-argued in previous literature (Beaulac et al., 2009; Lee et al., 2011; Raja et al., 2008; Zenk et al., 2005). We found similar results in in-person grocery shopping trips for such individuals highlighting their intention to use internet order when available and make in-person shopping trips to the nearest food store as they do not have any other option. The coefficient associated with online grocery delivery is higher than in-person grocery shopping, reflecting their increased inclination towards receiving online groceries. Such residents, when living in food oases, are more likely to make in-person grocery shopping trips that can be justified with the availability of home delivery services.

Interestingly, African Americans living in food deserts are more likely to make in-person restaurant trips than food oases which can be attributed to the presence of fast-food restaurants (unhealthy food) in the food deserts (Bridle-Fitzpatrick, 2015; Hendrickson et al., 2006; Hilmers et al., 2012; Metcalf and Widener, 2011). We found expected results for employment status, as we found a negative relationship for students, part-time workers, and work-seeking individuals in food oases compared to full-time workers. As compared to full-time workers, individuals working part-time in food oases are less likely to make general-purpose internet orders due to the possibility of spending the extra time making trips to the nearest store. Such residents living in food deserts appear to be less likely to dine in, which can be due to their preference for preparing their meals due to the flexibility in the schedule. Interestingly, retired individuals living in food oases are less likely to make in-person grocery and general shopping trips due to the possibility of limited travel activity due to age (senility). As expected, individuals not working and living in food deserts are more likely to order general packages and food online if they have such an option available. This can be due to their effort to save on travel-related expenditure or any physical disability acting as a barrier to their employment opportunities. This result is further supported by their lower likelihood of making in-person general shopping trips in food deserts.

The income effects revealed in the model are logical because low-income individuals are less likely to engage in online ordering and in-person shopping trips when compared to high-income counterparts (Jaller and Pahwa, 2020). This result holds good for all shopping-related activities in both food deserts and food oases except for general shopping trips in food oases. Individuals with income below $25,000 living in food oases are more likely to make general shopping trips because of supermarkets' availability within walking distances, making it favorable for the carless and transit-dependent population to travel for shopping. Carless individuals living in food oases are more likely to order online (all three order types) when compared to individuals with two or more cars. The result is consistent with the no requirement of cars for internet shopping in food oases, especially in food oases. When living in food deserts, such individuals are less likely to place online orders for general packages and are more likely to make an in-person shopping trip to the nearest physical store, which can be attributed to the availability of convenience stores in food deserts (Bridle-Fitzpatrick, 2015; Ploeg et al., 2012; Raja et al., 2008). We found expected results for the tech-savvy lifestyle for all six activities in both food desert and food oases (positive). Interestingly for internet orders, the effect of tech-savviness was higher in food deserts which highlights their inclination towards internet ordering if given an option.

Food oasis residents living in areas with high property crime rates appear to be less likely to order food and groceries online, perhaps due to the fear of package theft. This result is further substantiated by the increased likelihood of their food desert counterparts who are more likely to engage in grocery shopping trips. In the areas with violent crimes, we found a positive relationship for internet orders for all three types in food deserts. However, such residents were more likely to make in-person grocery shopping trips which can be attributed to increased security around the supercentres or grocery stores. Food desert residents living in areas with high residential density are more likely to prefer dine-in over-ordering food online, which might be due to the availability of many restaurants near their residence (due to a higher number of residences or apartment complexes). For internet grocery ordering, road density was related positively for food oasis residents, which is consistent with previous literature concluding the negative relationship between road density and driving to grocery stores (Jiao et al., 2011). For food desert residents, road density was related positively to online food ordering and negatively with dining in, which can be attributed to the availability of doorstep delivery services from fast-food restaurants (Bridle-Fitzpatrick, 2015; Hendrickson et al., 2006; Hilmers et al., 2012; Metcalf and Widener, 2011). Interestingly we found a negative relationship of the number of restaurants per square mile with food oasis residents' likelihood of engaging in both grocery shopping trips and online grocery orders. The number of bike facilities per square mile was related positively for food desert residents engaging in online grocery orders. Similarly, an increased percentage of the unemployed population is found to be related positively with the affinity to engage in internet ordering in food oases. Such areas might save on travel-related costs and order more affordable consumables from the internet (through attractive offers).

In addition to the impact of exogenous variables on six shopping activity types, we also explored the error correlations among these six activity types and delineated the results in Table 5. We found positive error correlations between all six activity types, which is in line with the previous study by Dias et al. (2020), where authors explore the shopping activity engagement behavior in urban areas. The findings are also synonymous with previous research on the positive association between online shopping and physical store shopping (Zhai et al., 2019, 2016; Zhen et al., 2016). These positive correlations highlight the interrelation among all the six activity engagements and offer key takeaways for increasing internet-based shopping activity on their in-person shopping counterparts. These correlations might be due to omnichannel consumers and other unobserved factors like tech-savviness, which motivates existing in-person shoppers to also place online orders for their shopping needs. The correlations observed in food oases were higher than the food deserts, which can be associated with the increased opportunities for food oasis residents to combine their eating out trips with shopping trips or availability of in-person or online shopping for the same activity. Internet orders for prepared meals and groceries have the highest positive correlation among all food desert and oasis pairs. This result can be attributed to the increased access of supercentres like Walmart or Costco to food oases residents. Such supercentres offer both grocery shopping and dining under the same roof.

Table 4: Error correlations between all six shopping activities

Variable		Error Correlations											
		Internet orders						In-person shopping or eating trips					
		General purpose		Grocery		Prepared meals		General shopping		Grocery		Restaurants	
		FO*	FD*	FO	FD	FO	FD	FO	FD	FO	FD	FO	FD
Internet orders	General purpose packages	--	--										
	Grocery Deliveries	0.367	0.306	--	--								
	Prepared meals	0.349	0.300	0.413	0.383	--	--						
In-person shopping trips	General shopping	0.322	0.241	0.364	0.290	0.345	0.291	--	--				
	Grocery Shopping	0.264	0.189	0.303	0.240	0.286	0.227	0.315	0.209	--	--		
	Restaurants	0.288	0.206	0.327	0.252	0.322	0.278	0.347	0.251	0.277	0.186	--	--

*FO: Food Oasis; FD: Food Desert

5.2 COMPARING THE RELATIVE ACCEPTANCE OF ADRS IN FOOD DESERTS AND FOOD OASES

The bivariate ordered probit model results capturing food desert and food oasis residents' intention to use ADRs for the internet orders and other orders are presented in Table 6. The insignificant variables include built environment-related variables (households with internet access, nearby restaurants, industrial ratio, nearby courier services, and unemployed population. It can be attributed to the availability of such data at census tract level rather than for each respondent. For interpretation purposes, the coefficient's positive (negative) sign can be interpreted as the increased (decreased) intention to use ADRs. In contrast, the *magnitude* of the coefficient can be inferred as the intensity of the effect. The error correlation between dependent variables highlights that the residents intending to adopt ADRs for their internet orders are more likely to use ADRs for all other orders whenever the ADR option is available (or vice versa). This result holds good for food desert and food oasis residents, where food oasis residents experience more significant influence.

From the case study perspective, individuals living in Nashville's food deserts are less likely to adopt ADRs for their future internet orders, which is logical since Portland is more urbanized than Nashville based on population based classification (USDOT, 2021). Males living in food oasis are more likely to accept deliveries from ADRs when compared to females, which can be attributed to the increased likelihood of males receiving online deliveries (Kim and Wang, 2021). Individuals living in a food oasis and owning a driving license are less likely to receive all orders from ADRs because of their affinity to order food from drive-thru or dining-in. As expected, smartphone ownership is linked positively with the intention to use ADRs for internet orders in food oasis.

Compared to Gen Z, baby boomers living in food deserts are less likely to adopt ADRs for all orders, including internet orders. This aligns with previous research on technology adoption in the elderly population (Liu et al., 2019; Menon et al., 2020; Robertson et al., 2017). Compared to White Americans, African Americans living in food oasis are less likely to adopt ADRs for all orders. They might prefer to walk or drive to the nearest food store. This result was counter-intuitive for individuals with an ethnicity other than Whites and African Americans. The food desert residents who are unable to work are less likely to use ADRs. This can be due to their unemployment status and subscription costs associated with ADR deliveries. Another reason for such finding might be their preference to utilize the extra time available due to their unemployment status in making in-person trips to the nearest shopping center. We found expected results for individuals seeking work and working full time in a food oasis. Such individuals are less likely to adopt ADRs to receive internet orders when compared to full-time workers, perhaps due to the money-saving behavior and available free time to make physical visits to the stores. When compared to highly educated individuals, food desert individuals completing high school or below are less likely to adopt ADRs, which less receptive attitude towards autonomous vehicles (Bansal et al., 2016; Liljamo et al., 2018).

Regarding ADR adoption, we received logical results for income across both food desert and oasis residents. Less income meant less likelihood to adopt ADRs consistent with high costs anticipated in the initial stages of ADR operation. When compared with individuals with two or more cars, food desert individuals with no cars are less likely to adopt ADRs. Such a result can be due to the high initial costs perceived for ADRs. We did not find any significant results in the case of food deserts for tech-savvy behaviour, although previous literature autonomous vehicle (AV) adoption highlights such a connection. In contrast, as expected, tech-savvy food oasis residents intend to use ADRs to receive the deliveries.

Table 5: Bivariate ordered probit: Intention to use ADRs for internet and other orders.

Variable	Coefficient^{Significance}			
	Planning to use ADRs for internet orders		Prefer to use ADRs for all orders if available	
	Food oases	Food deserts	Food oases	Food deserts
Case city (base: Portland)				
Nashville	--	-0.442^{**}	--	--
Gender (base: Female)				
Male	0.245^{***}	$0.22^{\#}$	0.195^{**}	--
Driving license (base: No)				
Yes	--	$-0.342^{\#}$	-0.259^{**}	--
Smartphone ownership (base: No)				
Yes	0.469^{***}	--	--	--
Age. (base: Gen Z (18 to 25 years)				
Gen Y (25 to 40 years)	0.075	--	--	--
Gen X (41 to 55 years)	--	--	--	--
Baby boomers (more than 55 years)	--	-0.585^{***}	--	-0.465^{**}
Ethnicity (base: White)				
African American	--	--	$-0.199^{\#}$	--
Others	0.246^{*}	--	0.386^{***}	--
Employment status (base: Full-time)				
Part-time	--	--	-0.174^{*}	--
Seeking work	$-0.197^{\#}$	--	-0.286^{*}	--
Retired	--	--	--	--
Student	--	--	--	--
Unable to work	--	-0.657^{**}	--	-0.682^{**}
Educational attainment (base: Master's degree or higher)				
High school or below	--	-0.287^{*}	--	--
Bachelor's degree or equivalent	--	--	--	--
Annual Income (base: More than $75,000)				
less than $25,000	-0.19^{*}	--	-0.225^{**}	$-0.209^{\#}$
$25,000 to $50,000	--	--	--	--
$50,000 to $75,000	--	--	-0.224^{***}	--
Cars in the household (base: two or more)				
Zero	--	-0.586^{**}	--	--
One	--	--	--	--

Table 6 continued

Variable	Coefficient^{Significance}			
	Planning to use ADRs for internet orders		**Prefer to use ADRs for all orders if available**	
	Food oases	**Food deserts**	**Food oases**	**Food deserts**
Excited about newly launched tech gadgets (base: Never)				
Frequently	0.581***	--	0.661***	--
Infrequent	0.321**	--	0.287*	-0.258*
Familiarity with ADRs (base: Very familiar)				
Not familiar	-0.199***	-0.709*	--	-0.735*
Somewhat familiar		--	--	-0.67$^{\#}$
Willingness to pay towards receiving an order from ADRs (base: $5 or more)				
$0	-0.967***	-1.675***	-0.957***	-1.374***
$1 or less	-0.399***	-0.598**	-0.359***	-0.521***
$1 to $4	--	-0.403*	--	--
Property crime rate per capita	-0.215	-0.91**	--	--
Violent crime rate per capita	0.209**	--	--	--
Population Density in 1000 per sq. mile	0.989***	--	--	5.059**
Residential density in 1000 per sq. mile	--	-3.85*	-2.173$^{\#}$	-3.584$^{\#}$
Road density per square mile	--	-1.799$^{\#}$	--	-2.002*
Number of bike facilities per square mile	--	--	--	2.121*
Residential ratio	--	--	--	-0.354$^{\#}$
Business Ratio	-0.479*	--	--	-0.531
Percentage of uninsured population	--	--	--	-1.183***
Number of intersections per square mile	--	--	1.361*	-4.557***
Thresholds				
Threshold 1 (Strongly disagree/Somewhat disagree)	-0.517**	-4.24***	-1.33***	-3.755***
Threshold 2 (Somewhat disagree/ Neither agree nor disagree)	0.159	-3.329***	-0.444**	-2.69***
Threshold 3 (Neither agree nor disagree /Somewhat agree)	1.346***	-2.184***	0.677***	-1.557***
Threshold 4 (Somewhat agree/Strongly agree)	2.522***	-0.982*	1.512***	-0.674$^{\#}$
Error Correlation				
Prefer to use ADRs for all orders if available	0.781***	0.713***	--	--

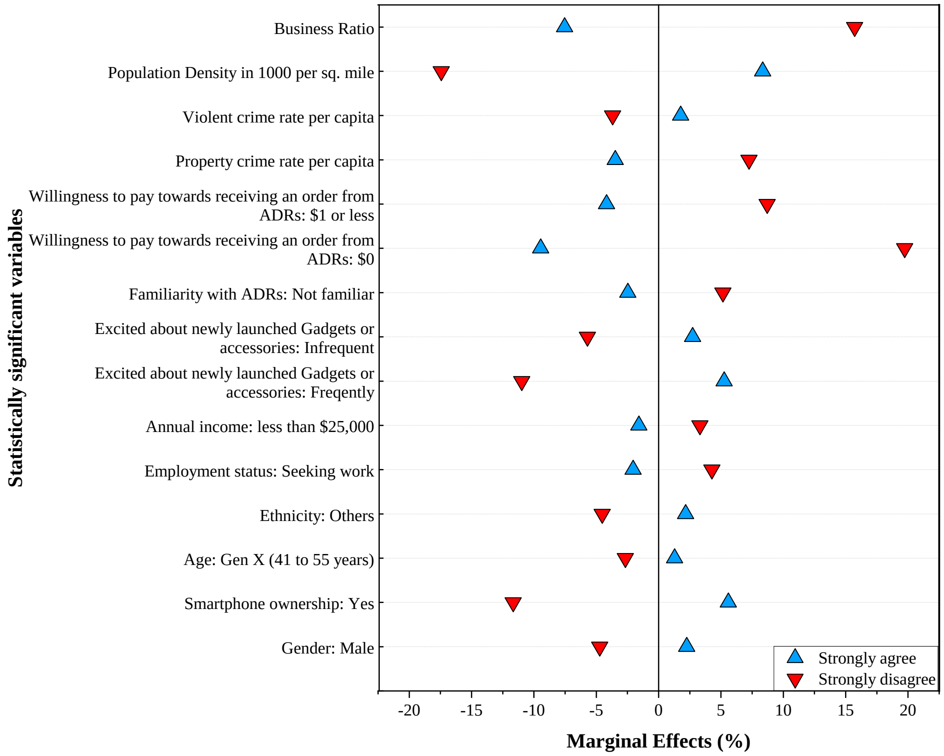
Goodness of fit measures Food oasis: Log-likelihood = -2,196; LR test of independent equations: $Chi^2 = 636$ | Food desert: Log-likelihood = -779; LR test of independent equations: $Chi^2 = 168$

Likert scale levels: 1- Strongly disagree, 2- Somewhat disagree, 3: Neither agree nor disagree, 4- Somewhat agree,5- Strongly agree

Similarly, the familiarity with ADRs contributes to an increased likelihood of their adoption both for food desert and food oasis residents. This finding aligns with the existing literature exploring the impact of familiarity with autonomous technology on the acceptance of AVs (Dubey et al., 2022; Golbabaei et al., 2020; König and Neumayr, 2017; Kyriakidis et al., 2015; Mishra et al., 2021; Samani et al., 2022; Samani and Mishra, 2022; Sharma and Mishra, 2022a, 2022b, 2020; Simpson et al., 2022; Sweet and Laidlaw, 2020; Talebian and Mishra, 2022, 2018; Thapa et al., 2021). This effect is higher in food desert residents when compared to food oasis residents in terms of their intention to receive internet orders from ADRs. We found similar results for the willingness to pay towards receiving an order from ADRs. Individuals not willing to pay anything to receive their orders from ADRs are less likely to adopt. This effect was again higher among food desert residents. Potentially due to the fear of package theft, food desert residents are less likely to adopt deliveries from ADRs.

Among the built environment indicators, higher population density is positively related to receiving internet orders from ADRs in the case of food oases; this relationship is significant for all orders from ADRs in the case of food deserts, highlighting the market potential of ADR deliveries in highly populated areas. Increased road density is related negatively to the use of ADRs in food deserts. This can be due to the fewer residences available in the area making it less serviceable. Interestingly, bike facility density positively relates to using ADRs for all food desert orders as ADRs can potentially utilize bike tracks as their delivery paths. Food oasis residents living in census tracts with high violent crime rates are more likely to receive internet orders from ADRs, consistent with their attempt to make less trips to physical stores due to safety reasons. We also explored the error correlation between both dependent variables. We received highly significant positive results for both food oasis and food desert residents. Such finding highlights that the individuals who intend to use ADRs for their internet orders are more likely to use ADRs for all their orders if given an option.

We also scrutinize results based on the model's marginal effects and present the results in Fig. 5 and Fig. 6**.** For brevity and applicability, we only present results for the highest and lowest level of the Likert scale (Strongly Agree and Strongly Disagree). The Marginal effects can be inferred as the effect of one unit change of a particular exogenous variable on the likelihood of residents' intention to use ADRs for receiving their orders. The positive (negative) sign emulates the increasing (decreasing) effect. In contrast, when multiplied by 100, magnitude gives the percentage change in the likelihood of a particular outcome of the dependent variable. The results in Fig. 5 and Fig. 6 are already multiplied by 100. For instance, as per Fig. 5, an increase in population density increases the likelihood of food desert residents' intention to use ADRs for their internet order by about 28% (strongly agree). An increase in residential density, on the other hand, decreases this likelihood by 49%. Similarly, the likelihood of food desert residents' intention to use ADRs for all their future orders increases by 62% with a unit change in population density.



(a)

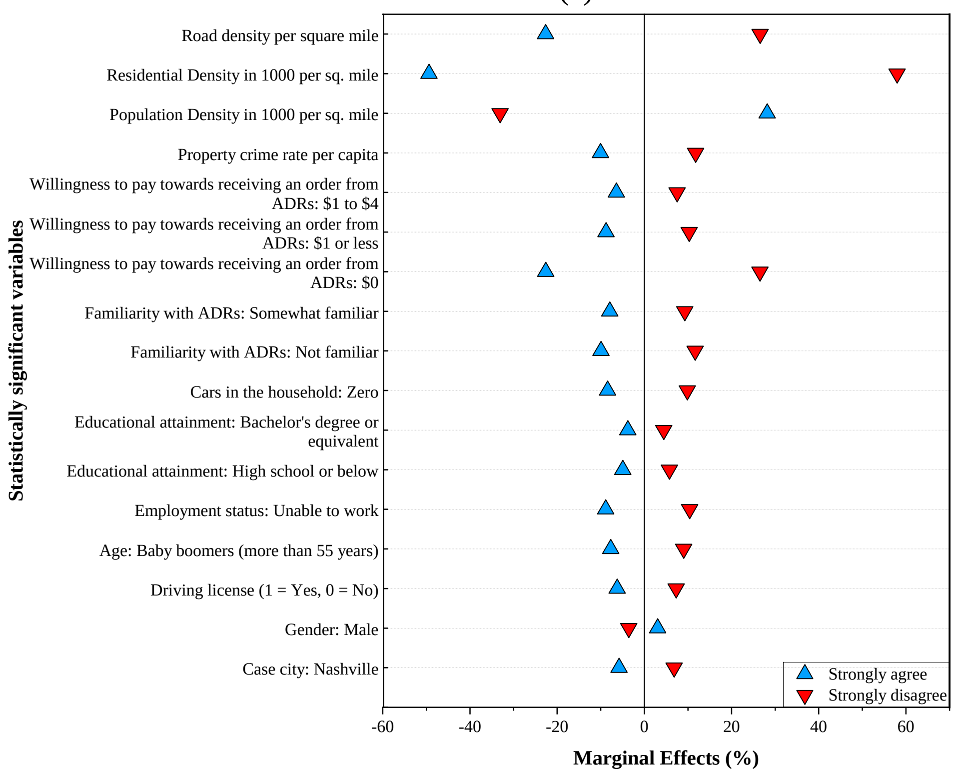
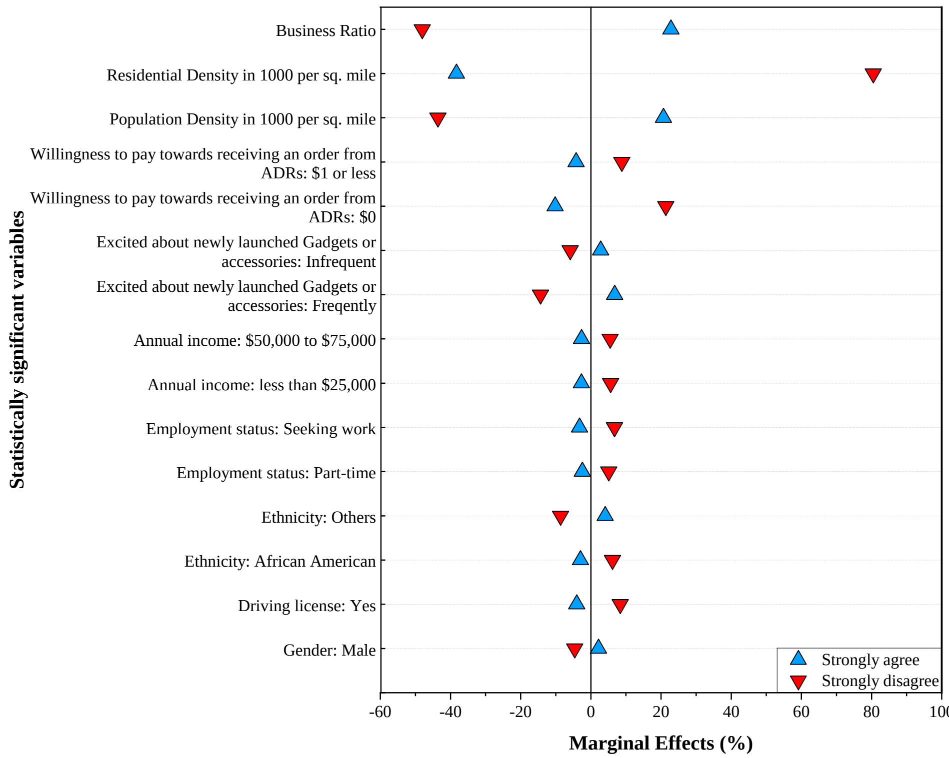


Figure 5: Bivariate ordered probit: Marginal effects for intention to use ADRs for internet orders (a) Food oases (b) Food deserts

(b)



(a)

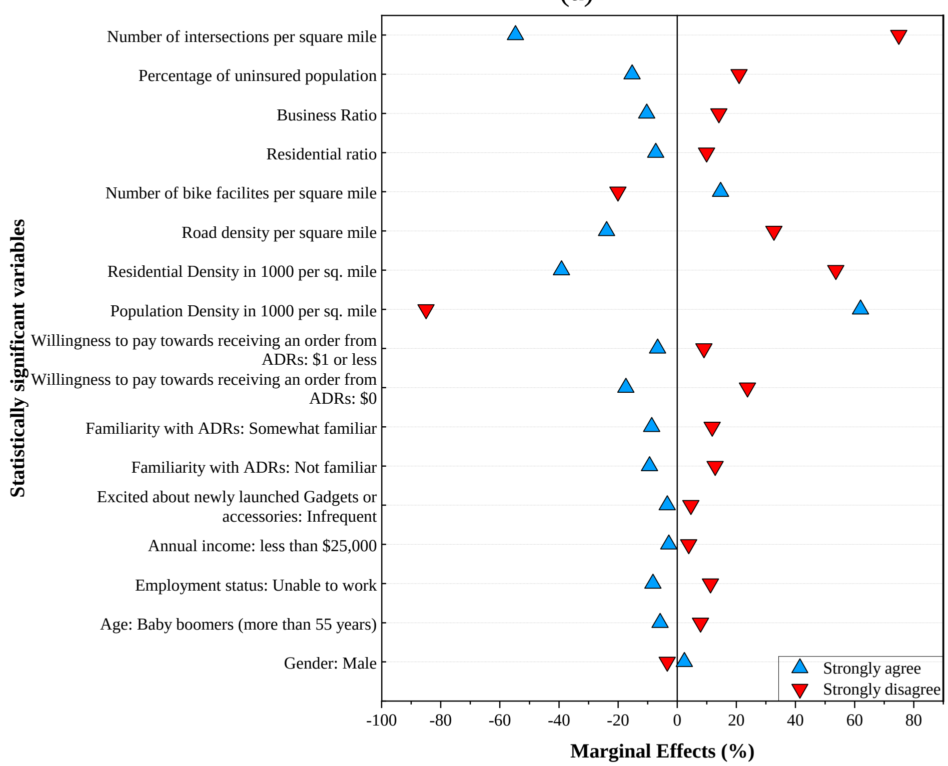


Figure 6: Bivariate ordered probit: Marginal effects for intention to use ADRs for all orders if available (a) Food oases (b) Food deserts

(b)

6.0 RESEARCH AND POLICY IMPLICATIONS

E-commerce has reduced the need for in-person shopping trips to the nearest supercentres but at the expense of minimum order size requirements and increased logistics effort (vehicle and personnel deployment for door-to-door delivery). However, the population living in food deserts does not have the same level of access to supercentres or internet orders. Such populations live far away from the supercentres and either spend more time traveling to these supercentres or develop poor food habits after purchasing their food from the convenience stores, stocked with unhealthy food options, located in their neighborhood. Internet ordering is also challenging for these neighborhoods due to the constraints of minimum order size requirements or the unavailability of delivery services. Hence, ADRs have the tremendous potential to increase the availability of healthy foods in these neighborhoods at no or reasonable order sizes. In this study, we explored the existing shopping activity engagement of residents in food deserts and compared them with their counterparts in food oases communities. We then analyzed their intention to use ADRs for their internet-based orders. Based on the results, key implications of this study for research and practice are explained below in three distinct fronts.

First, the shopping activity engagement model results presented in this study indicate that minority ethnicities, tech-savvy, unemployed, and residents living near the high density of bike facilities are more likely to engage in online shopping. Such residents are a significant proportion of food desert areas. Hence, it can be inferred that internet ordering will succeed in such areas. However, the intention to use ADR indicates that residents are less likely to adopt ADRs even if ADRs are offered at no delivery cost. This effect was higher in food desert residents. We found significantly higher resistance towards ADR technology among the elderly individuals in food deserts. However, such a result can be attributed to distrust in autonomous technology due to its incipient stage. This result can also be attributed to the present business model of subscription-based companies like Amazon, where customers pay a monthly premium over per order fee. Proper information campaigns to educate such populations about the anticipated benefits of ADRs could help to tackle this challenge.

Second, the past literature well posits that food desert residents spend more time traveling to the nearest supercentres for shopping and, in turn end up developing poor food habits (Bridle-Fitzpatrick, 2015; Hendrickson et al., 2006; LeDoux and Vojnovic, 2014; Ploeg et al., 2012; Sharkey et al., 2010; Walker et al., 2010). However, through ADRs, such people can save the time spent traveling to the shopping in stores located in far-off places and improve their quality of life through healthy food. ADR-based food delivery can also help them in improving their food habits resulting in travel expense savings and increased work productivity. From the results, men living in food deserts are more likely to engage in internet ordering than women. They are also found to be more inclined to use ADRs for their internet orders. One of the main barriers in the success of door-based delivery of healthy and fresh food for this population segment is the minimum order size requirement and high costs associated with the vehicle and human personnel deployment (Haider et al., 2020). ADRs have the potential of relaxing both of these constraints. ADRs are also unique in their ability to deliver "small but regular orders" and thereby attract more users to use online delivery of healthy and fresh vegetables and fruits. From our model results, familiarity with ADRs is positively related to their anticipated adoption. This effect was even higher among food desert residents highlighting the potential of successful operation of ADRs in food deserts.

Third, the recent research indicates that e-grocery ordering through traditional delivery-based services can save about 10 to 30 % emission levels in the last mile (Siragusa and Tumino, 2021) and progressive reduction in vehicle kilometers traveled (Dalla Chiara et al., 2020; Stinson et al., 2019). ADRs have transformative potential to further reduce emissions and energy consumption compared to conventional delivery vehicles (Figliozzi, 2020). Our results indicate that tech-savvy food desert residents and minority ethnicities are also more likely to make e-groceries orders in the food deserts. It is worth mentioning that such residents are also likely to make physical in-person grocery trips. However, the magnitude of the coefficient is less than that of internet orders. Hence, providing internet ordering services to such individuals will further decrease the emission and road traffic. In the long-term, these trends suggest that such individuals may opt for giving up driving to the nearest supercentre by relying on ADRs. Interestingly, the number of bike facilities was also positively associated with food desert residents' affinity to make e-grocery orders and their intention to receive all their orders from ADRs, highlighting the positive relationship of green lifestyle (non-motorized travel) with e-grocery ordering and adoption of ADRs. Hence the environmentally concerned residents living in the food deserts will be among the early adopters of ADRs during its initial deployment.

7.0 CONCLUSIONS

This study is motivated due to the discernible lack of research quantifying the shopping travel decisions in marginalized communities such as food deserts and analyzing the potential of delivery automation to overcome the underlying mobility inequalities. A large systematic gap exists between the demand and supply of healthy food in food deserts. None of the previous studies captured how the acceptance of emerging delivery technologies such as ADRs varies in these communities and what it means for the residents with accessibility constraints. To address this research gap, this paper utilizes the survey results of two metropolitan statistical areas (Nashville and Portland) and USDAs' food desert accessibility map to identify residents living in food deserts and food oases. We then applied a multivariate count data model to quantify the differences in the shopping activity engagement of food desert and food oasis residents. The results indicate that online grocery delivery preferences are higher than in-person grocery shopping in food deserts, reflecting their increased inclination towards receiving online groceries. In the case of prepared meals, models indicate that food desert residents, especially African Americans, are more likely to make in-person restaurant trips than their counterparts in food oases communities. This may be linked to the abundance of fast-food restaurants in food deserts, much in line with the previous literature establishing the linkage between the food environment in communities and the dietary choices of its residents.

In the second part of the paper, we utilized a bivariate probit model to capture ADRs' perceived acceptance among food desert residents to overcome mobility inequalities. Consistent with existing autonomous technology acceptance results, baby boomers living in food deserts are less likely to adopt ADRs for all orders, including internet orders. Food desert residents familiar with ADRs are more likely to adopt ADRs for their future orders. Individuals with high income and education levels are more likely to be adopters of ADRs. Overall, the study findings will assist e-commerce companies, supercentres, and policymakers plan an efficient ADR-based delivery system for the underserved population in food desert communities. The study includes data limitations in terms of the timing gaps between the survey dataset (2020), data sources utilized for identifying food deserts (2015), and adding built environment characteristics to the food deserts (2010) because of the unavailability of food desert/census database for public use for the year 2020. Future studies can overcome this limitation by eliminating the timing gap among all three datasets. Future studies are also recommended to conduct discrete choice experiments involving food desert residents for exploring their preferences towards ADR-based delivery services' pricing and anticipated features. Over time, research investigations in this direction are expected to offer actionable guidance for overcoming the mobility inequalities in food desert communities using ADRs.

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9.0 APPENDIX A. SURVEY QUESTIONNAIRE

Consent for Research Participation

Title	A Survey to Understand Consumer Perceptions on Autonomous Delivery Robots

You are being asked to participate in a research study. The box below highlights key information for you to consider when deciding if you want to participate. More detailed information is provided below the box. Please ask the researcher(s) any questions about the study before you make your decision. If you volunteer, you will be one of about **1350** people to do so.

Key Information for You to Consider

Voluntary Consent: You are being asked to volunteer for a research study. It is up to you whether you choose to participate or not. There will be no penalty or loss of benefit to which you are otherwise entitled if you choose not to participate or discontinue participation.

Purpose: The purpose of this research is to gain insights about the influential factors driving the consumers' perceptions and intention to use autonomous delivery robots (ADRs).

Duration: It is expected that your participation will last 9 minutes

Procedures and Activities: You will be asked to provide information on your socio-demographic characteristics, the five-digit ZIP code, nearest road intersection, shopping patterns, preferences and willingness to pay for ADRs.

Risk: The potential risks or discomforts of your participation are minimal. There is a confidentiality loss since location Information on ZIP codes and nearest road intersection will be collected. However, no personal identification is at risk since the information is recorded at zonal level that contains several individuals.

Benefits: Some of the benefits that may be expected include key insights for providing better facilities and regulatory policies for ADRs.

Alternatives: Participation is voluntary, and the only alternative is not to participate.

Who is conducting this research?

Dr. Agnivesh Pani of the University of Memphis, Department of Civil Engineering is in charge of the study. His faculty advisor is Dr. Sabyasachee Mishra. There may be other research team members assisting during the study.

What happens if I agree to participate in this Research?

If you agree you will be asked to provide your socio-demographic characteristics, the five-digit ZIP code, the road intersection nearest to your home, shopping patterns, preferences and willingness to pay for autonomous delivery robots (ADRs). You may stop participating at any time or decide not to respond to any specific question by closing the survey. There will not be any follow-up research activities and you will not be contacted again regarding this survey.

What happens to the information collected for this research?

Information collected for this research will be used to provide a framework for required facilities and policies associated with large-scale introduction of ADRs. The results may be published or presented as the outcome of this research. However, information collected on ZIP codes or the nearest road intersection from your home and any other identifying information will remain confidential and only be analyzed at most in a zonal-level. The zones are defined by state and/or local transportation officials for tabulating traffic-related data and they are bigger than census blocks. The survey data will be stored in password-protected databases to ensure confidentiality. In all cases, the information provided will not be released in any way or form violates participants' privacy. Information collected as part of the research, even if identifiers are removed, will not be used or distributed for future research studies.

How will my privacy and data confidentiality be protected?

We promise to protect your privacy and security of your personal information as best we can. Although you need to know about some limits to this promise. Measures we will take include:

- Anonymize all the received responses from survey platform "Qualtrics".
- Only members of the immediate research team will review the data, and they will review only aggregate-level statistics.

Individuals and organization that monitor this research may be permitted access to inspect the research records. This monitoring may include access to your private information and the location of the nearest intersection to your home. These individual and organization include

- Institutional Review Board

What if I want to stop participating in this research?

It is up to you to decide whether you want to volunteer for this study. It is also ok to decide to end your participation at any time. There is no penalty or loss of benefits to which you are otherwise entitled if you decided to withdraw your participation. Your decision about participating will not affect your relationship with the researcher(s) or the University of Memphis. To stop participating, close the survey window from your internet browser.

Will it cost me money to take part in this research?

There are no costs associated with participation in this research study.

Will I receive any compensation or reward for participating in this research?

You will not be compensated for taking part in this research.

Who can answer my question about this research?

Before you decide to volunteer for this study, please ask any questions that might come to mind. Later, if you have questions, suggestions, concerns, or complaints about the study, you can contact the investigator, Dr. Agnivesh Pani at 901-485-6431 or plypptta@memphis.edu and his faculty advisor Dr. Sabyasachee Mishra at 901-678-5043 or smishra3@memphis.edu. If you have any questions about your rights as a volunteer in this research, contact the Institutional Review Board staff at the University of Memphis at 901-678-2705 or email irb@memphis.edu. We will give you a signed copy of this consent to take with you.

STATEMENT OF CONSENT

I have had the opportunity to consider the information in this document. I have asked any questions needed for me to decide about my participation. I understand that I can ask additional questions through the study. By signing below, I volunteer to participate in this research. I understand that I am not waiving any legal rights. I have been given a copy of this consent document. I understand that if my ability to consent for myself changes, my legal representative or I may be asked to consent again prior to my continued participation

CONS Do you **consent** your participation?

○ Yes, I consent (1)

○ No, I do not (2)

Skip To: End of Survey If CONS = 2

CITY Do you **live** in the following cities?

○ Nashville, TN (1)

○ Portland, OR (2)

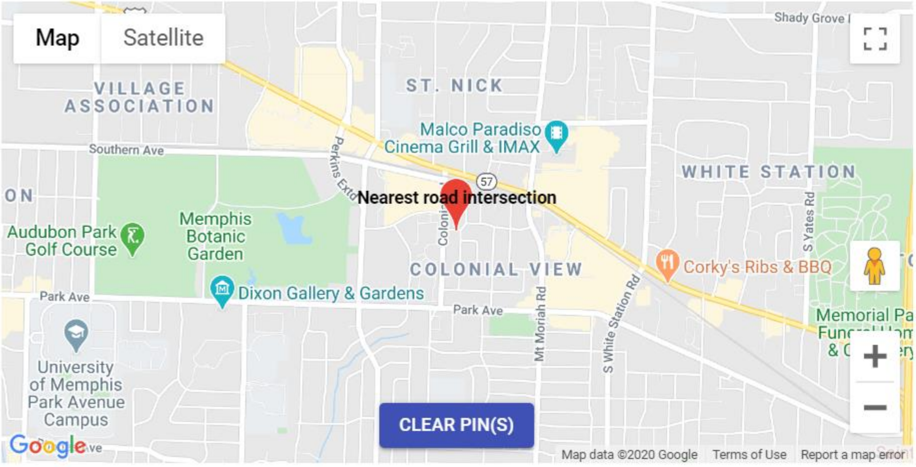
○ None of the above (3)

Skip To: End of Survey If CITY = 4

ZIP Please enter the 5-digit **ZIP CODE** of your home location in **${CITY/ChoiceGroup/SelectedChoices}**

LOC Please select the **nearest road intersection** from your **home** in the **map given below.** Alternatively, you can enter the name of road intersection in text box given below:

Nearest road intersection (1)



AGE Please indicate your **age (drop down list)**

Less than 18
18
19
………
………
78
79
80
80 or more

GENDER Please indicate your **gender**.

- ◯ Male (1)
- ◯ Female (2)
- ◯ Non-binary / Third gender (3)

<u>RACE</u> Please indicate your **race/ethnicity**?

- White (1)
- African American (2)
- Asian (3)
- Hispanic / Mexican (4)
- Native American or Alaska Native (5)
- Multi-race (6)
- Other (7)
- Prefer not to disclose (8)

<u>INC</u> What was your approximate **annual income** (before taxes) in 2019?

- Below $10000 (1)
- $11,000 to $15,000 (2)
- $16,000 to $25,000 (3)
- $26,000 to $35,000 (4)
- $36,000 to $50,000 (5)
- $51,000 to $65,000 (6)
- $66,000 to $75,000 (7)
- $76,000 to $100,000 (8)
- $101,000 to $125,000 (9)
- More than $125,000 (10)

EDU What is your **highest education**?

- Less than high school degree (1)
- High school degree or equivalent (2)
- Bachelor's degree or equivalent (3)
- Master's degree or more (4)
- Professional Degree (e.g., MD, JD) (5)
- Others (6)

EMPSTAT What is your **employment status**?

- Full-time employment (1)
- Part-time employment (2)
- Seeking work (3)
- Retired (4)
- Student (5)
- Unable to work (6)

CARS How many **cars** does your household own?

- Zero (1)
- One (2)
- Two (4)
- More than two (3)

DRIVLIC Do you have a **driver's license**?

- Yes (1)
- No (2)

SMARTPH Do you have a **Smartphone**?

◯ Yes (1)

◯ No (2)

TECHSAVVY Do you get **excited** about buying **newly-launched Gadgets or accessories** (e.g., smartphone, watches, tablets, or bikes) ?

◯ Always (1)

◯ Most of the time (2)

◯ About half the time (3)

◯ Sometimes (4)

◯ Never (5)

INTORD How many days in a week do you receive **at least one internet order per day** in the following categories?

	Number of days in a week with at least one internet order 0 1 2 3 4 5 6 7
General Purpose Packages (e.g., Amazon, Walmart, eBay, Target, Costco, Macy's) ()	
Grocery deliveries (Instacart, Kroger, Walmart, Whole Foods Amazon, among others) ()	
Prepared Meals (e.g., UberEats, GrubHub, Postmates, Doordash, goPuff) ()	

PHYORD How many days in a week do you make at least one of the following **in-person shopping or eating trips**?

	Number of Days in a week with at least one shopping or eating trip 0 1 2 3 4 5 6 7
General Shopping (Excluding Groceries) ()	
Grocery Shopping ()	
Restaurants ()	

INFO **Information Sheet about Autonomous Delivery Robots (ADRs)**

Autonomous delivery robots (ADRs) are defined as **self-driving ground vehicles**, which can deliver parcels or other goods like groceries and prepared meals to the doorstep. ADRs look like little robots (picture 1) or like mobile parcel locker (picture 2) and they drive at a speed of approximately 5–10 km/h sidewalks. Once the ADR arrives at the delivery destination, consumer can authorize and receive their order by **scanning QR codes**.

Picture 1

Picture 2

FAMILIAR Which of the following statements best **describe your familiarity** with autonomous delivery robots (ADRs)

- ◯ I had never heard of ADRs before taking this survey (1)
- ◯ I have heard of ADRs, but don't know much about them (2)
- ◯ I am somewhat familiar with ADRs (3)
- ◯ I am very familiar with ADRs (4)
- ◯ I have actually received an order using an ADR (5)

ADD_COST If delivery robot option requires **an additional cost per order** (without monthly fee), how much at most would you be willing to pay per order?

- ◯ No, I will not pay extra (1)
- ◯ Less than $1 (8)
- ◯ $1 (2)
- ◯ $2 (3)
- ◯ $3 (4)
- ◯ $4 (5)
- ◯ $5 (6)
- ◯ More than $5 (7)

ITU Please state to what extent you agree or disagree with the following statements on the **intention to use** delivery robots:

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
I **plan to use** delivery robots for my internet orders in the future (1)	○	○	○	○	○
I **will prefer** delivery robots for my orders whenever the option is available (2)	○	○	○	○	○

APPENDIX B.

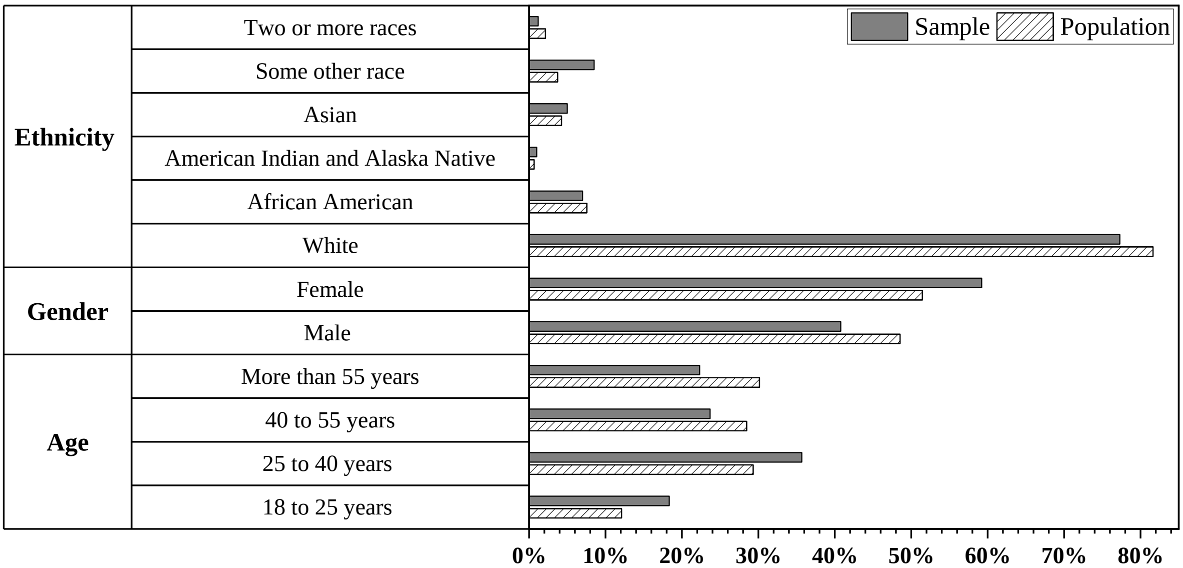


Figure 7: Comparison of survey sample with target population.

Table 6: Distribution for food oasis and desert residents' weekly occurrences of internet orders and in-person trips by type

Days in week	Internet orders												In-person shopping or eating trips											
	General-purpose packages				Grocery Deliveries				Prepared meals				General shopping				Grocery Shopping				Restaurants			
	FO		FD		FO		FD		FO		FD		FO		FD		FO		FD		FO		FD	
	n	%	n	%	n	%	n	%	N	%	n	%	n	%	n	%	n	%	n	%	n	%	n	%
0	184	19%	67	20%	540	56%	201	59%	544	56%	186	54%	195	20%	73	21%	69	7%	23	7%	303	31%	115	34%
1	372	38%	125	37%	247	26%	80	23%	211	22%	58	17%	375	39%	117	34%	360	37%	128	37%	323	33%	83	24%
2	176	18%	81	24%	73	8%	27	8%	84	9%	46	13%	175	18%	71	21%	247	26%	90	26%	167	17%	70	20%
3	118	12%	29	8%	44	5%	12	4%	65	7%	24	7%	110	11%	38	11%	160	17%	49	14%	83	9%	37	11%
4	55	6%	19	6%	19	2%	6	2%	29	3%	11	3%	45	5%	21	6%	61	6%	31	9%	45	5%	12	4%
5	31	3%	10	3%	20	2%	11	3%	13	1%	6	2%	32	3%	9	3%	30	3%	7	2%	22	2%	15	4%
6	14	1%	4	1%	16	2%	1	0%	10	1%	5	1%	13	1%	8	2%	20	2%	7	2%	9	1%	6	2%
7	17	2%	7	2%	8	1%	4	1%	11	1%	6	2%	22	2%	5	1%	20	2%	7	2%	15	2%	4	1%

*FO: Food Oasis; FD: Food Desert