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Improving community resilience to disrupted food access: Empirical spatio-temporal analysis of volunteer-based crowdsourced food delivery

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A R T I C L E I N F O

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A B S T R A C T

Unplanned disaster events can greatly disrupt access to essential resources, with calamitous outcomes for already vulnerable households. This is particularly challenging when concurrent extreme events affect both the ability of households to travel and the functioning of traditional transportation networks that supply resources. This paper examines the use of volunteer-based crowdsourced food delivery as a community resilience tactic to improve food accessibility during overlapping disruptions with lasting effects, such as the COVID-19 pandemic and climate disasters. The study uses large-scale spatio-temporal data ($n = 28,512$) on crowdsourced food deliveries in Houston, TX, spanning from 2020 through 2022, merged with data on community demographics and significant disruptive events occurring in the two-year timespan. Three research lenses are applied to understand the effectiveness of crowdsourced food delivery programs for food access recovery: 1) geographic analysis illustrates hot spots of demand and impacts of disasters on requests for food assistance within the study area; 2) linear spatio-temporal modeling identifies a distinction between shelter-in-place emergencies and evacuation emergencies regarding demand for food assistance; 3) structural equation modeling identifies socially vulnerable identity clusters that impact requests for food assistance. The findings from the study suggest that volunteer-based crowdsourced food delivery adds to the resilience of food insecure communities, supporting its effectiveness in serving its intended populations. The paper contributes to the literature by illustrating how resilience is a function of time and space, and that similarly, there is value in a dynamic representation of community vulnerability. The results point to a new approach to resource recovery following disaster events by shifting the burden of transportation from resource-seekers and traditional transportation systems to home delivery by a crowdsourced volunteer network.

1. Introduction

The COVID-19 pandemic has exposed long-standing barriers to reliable access to fundamental resources, especially for groups that have been made to be socially vulnerable. During the pandemic lockdown, owing to physical distancing restrictions, disruptions in logistics and agricultural systems, and increased need, federally administered disaster relief could not reach many community members, necessitating innovation in the delivery of support and resources such as food (Jo et al., 2021). The pandemic has created tremendous challenges for communities to reliably access essential resources, and simultaneously, it has generated an opportunity to re-evaluate and adopt additional approaches for coping with future emergencies and crises and thereby increase community resilience. The term *community resilience* refers to the capacities of societal groups to recover and adapt over time following a disaster (Wisner and Kelman, n.d.). This definition stresses that to strengthen community resilience, we need to understand two interdependent aspects: the functionality of the physical infrastructure (Curt and Tacnet, 2018) and the coping capacity of a given community (Cutter et al., 2014; Wisner and Kelman, n.d). What is more, concurrent extreme events, such as the COVID-19 pandemic and simultaneous climate disasters, are placing further stress on the ability of communities to sustain resilience as both demand for and supply of transportation resources are disrupted. That is, concurrent extreme events affect both the ability and willingness of households to travel and the functioning of traditional transportation and logistics networks to supply resources.

This paper examines the use of volunteer-based crowdsourced food delivery as a resilience tactic to improve food accessibility during

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concurrent disruptions. Specifically, we explore community resilience in coping with disrupted food access in Houston, Texas during a two-year period following the start of the pandemic. Resilience in this study is explored from the perspective of *adaptiveness*, where crowdsourced food delivery is a means to innovate the system to function under disrupted conditions. The use of a crowdsourcing platform facilitates food delivery in periods of (multiple) disruptions by adding *reliability* and *resourcefulness* in the operations. Further, we argue that community resilience of food access needs to be understood with respect to *vulnerability (*Faturechi and Miller-Hooks, 2015*)*. That is, while continued food access is the key performance metric in our analysis, it is important to note that many groups and communities did not have sufficient access to begin with (Logan et al., 2021), because food insecurity is tied to long-standing socio-economic disadvantages and racial discrimination (Bailey et al., 2017) that need to be understood as part of the analysis. As such, to understand the ability of a volunteer-based crowdsourced delivery platform to improve food accessibility and bolster community resilience, we need to understand the existing context of food access and vulnerability of impacted communities.

In this paper we examine the information and communications technology-based platform *CrowdSource Rescue*, which coordinates professional and voluntary first responders in disaster relief efforts (Barrera Gutierrez, 2019; Humphrey, 2019). By leveraging the power of the crowd to conduct rescue operations and plan resource distribution, this platform increases access to resources through the coordination of on-demand crowdshipping to deliver goods (Pourrahmani and Jaller, 2021). The crowdshipping model replaces resource-seeking mobility with the delivery of goods by volunteers to supplement the mobility needs of individuals who face travel burdens. In response to the COVID-19 pandemic and concurrent climate disasters, this type of non-profit platform can adapt and respond to disaster relief efforts to help target food insecurity.

1.1. Research questions

Volunteer-based food delivery promises an expedient and low-cost (yet temporary) response to food insecurity in populations who are burdened by food-related costs and travel, as it relies on pre-existing mobility resources available to the volunteers rather than costly expansions of transportation infrastructure. This study examines data from *CrowdSource Rescue* to evaluate the effectiveness of volunteer-based food delivery as a community resilience tool following a disaster.

We aim to answers the following research questions:

1. Locational Characteristics of Urban Food Access Resilience: What community-level social-demographic factor(s) is(are) associated with requests for crowdsourced food delivery? Is the system helping populations who are the most vulnerable to food insecurity?
2. Time-Based Characteristics of Urban Food Access Resilience: How does demand change over time, especially in response to multiple stressors? Specifically, how does poverty, the pandemic, and concurrent climate disasters affect food demand and delivery?
3. Characteristics of Food Vulnerability: What are the main segments of community vulnerability to account for in understanding food assistance needs during and following concurring disasters? Specifically, is there value in a more dynamic representation of vulnerability throughout a recovery process rather than a static vulnerability profile index?

The remainder of this paper is structured as follows. Section 2 presents a literature review that defines resilience concepts, explores food insecurity in the context of the COVID-19 pandemic, and contextualizes this study within the transportation resilience literature. Section 3 provides a description of the dataset studied and outlines the analytical methods used in this research. Section 4 presents the analysis results, and, finally, Section 5 discusses the study's main conclusions, as well as limitations and potential for future work.

2. Literature review

Before the specific volunteer-based food delivery platform of *CrowdSource Rescue* can be evaluated, it is necessary to define the theoretical basis of this study with respect to existing analytical frameworks. Fig. 1 illustrates the framing of our community resilience investigation building on the foundational concept of the resilience triangle representation (Bruneau et al., 2003). As illustrated in row 1 of Fig. 1, the resilience outcome (i.e., recovery and/or transformation) that we are observing depends upon three categories of determinants: the local baseline context (e.g., food security, socioeconomic stresses, and transportation infrastructure), disturbances (acute, chronic, and overlapping), and coping capacity (dependent on the degree of exposure and baseline vulnerability of the community). Row 2 shows the system performance and the key resilience actions in each of the temporal stages from pre to post-disaster (Bruneau et al., 2003). Row 3 highlights how each of these indicators informs community resilience, which in turn, is dependent on two interdependent systems: infrastructure resilience (e.g., resourcefulness and reliability) and community vulnerability. Holistically, as shown in Row 4, this framework allows us to examine three important resilience questions: (1) locational characteristics of resilience (i.e., food access), (2) time-based characteristics of resilience (i.e., overlapping disruptions), and (3) characteristics of vulnerability (i.e., sociodemographics of food insecure communities). The bottom row of the figure shows the focus of our empirical investigation (i.e., the interaction between human mobility and food logistics) through the short-term adaptation (and possibly long-term transformation) of crowdsourced food delivery, along with our three specific research questions.

In the following, we present literature related to the definition of resilience and its intersection with food logistics and vulnerability, an evaluation of food (in)security, and we conclude by contextualizing this work within the field of transportation resilience literature.

2.1. Resilience

First defined in the context of ecological systems (Holling, 1973), *resilience* in terms of urban environments can be thought of as "the ability to anticipate, prepare for, and adapt to changing conditions and withstand, respond to, and recover rapidly from disruptions" (*FHWA Order 5520 - Transportation System Preparedness and Resilience to Climate Change and Extreme Weather Events | Federal Highway Administration*, 2014). Bruneau et al. developed a resilience framework that remains a fixture in the field; in the so-called 4R structure, resilience is measured by four properties, namely Robustness, Redundancy, Resourcefulness, and Rapidity (Bruneau et al., 2003). Taking a broader perspective, infrastructure resilience is primarily conceptualized as "strengths or weaknesses measured by risk, vulnerability, reliability, robustness, and survivability (i.e., resistance) and adaptability measures" (Faturechi and Miller-Hooks, 2015). In the same study, Bruneau et al. introduced the first *resilience triangle*, a graphical representation of infrastructure's quality before, during, and following a disaster event as a function of time (Bruneau et al., 2003).

This study examines resilience within the context of interdependent physical infrastructure and social systems. Thereby, our analysis focuses on the following two resilience concepts: (1) *reliability* (the "probability that a system remains operative at a satisfactory level post-disaster") of the transportation network, and (2) *resourcefulness* ("related to the availability of materials, supplies, and teams to restore functionality") within urban food systems (Faturechi and Miller-Hooks, 2015; Leobons et al., 2019). Inspired by transportation resilience studies examining the relationship between resilience, vulnerability, and reliability, such as that performed by Gu et al. (Gu et al., 2020), in Fig. 2, we present a variation on the traditional resilience triangle. In this diagram, we show

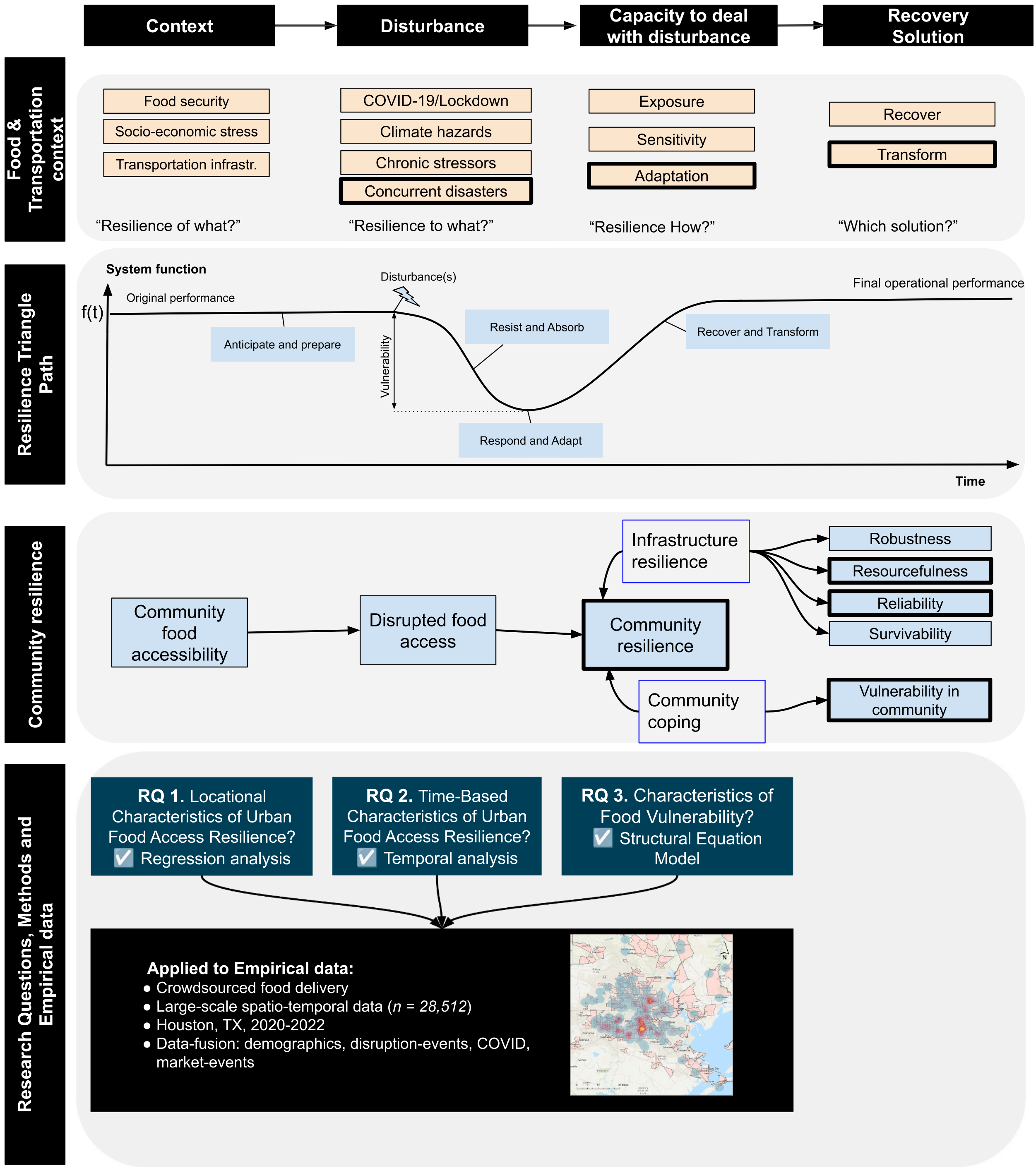

Fig. 1. Framework for evaluating the contribution of crowdsourced food delivery to community resilience founded on the resilience triangle concept.

that through an increase in reliability and resourcefulness, crowdsourced food delivery can accelerate the recovery rate of urban food systems for vulnerable populations following a (concurrent) disaster event.

Community resilience takes the study of resilience one step further by focusing on the ability of people and communities to cope with disasters (Wisner and Kelman, n.d.). Unlike more traditional disaster planning for infrastructure systems, community resilience focuses on the ability of communities or regions to adapt to changing conditions caused by disruptions. This expands on the aforementioned concept of *resourcefulness*, implying a focus on maintaining a flexible mobility system (Faturechi and Miller-Hooks, 2015) and organizational flexibility where additional resources can be mobilized in times of need (Berger, 2017), as observed in crowdsourced mobility (Borowski et al., 2023). Likewise, social systems can also contribute to the *reliability* of service provisions. While in an ideal 'resilient system', all people would have and maintain equal access to food and transportation despite disruptions (MacKinnon, n.d.), this is not yet a reality. Therefore, volunteer-based food delivery after disasters offers a flexible framework to expedite recovery of food access.

During the timeframe of this study, the COVID-19 pandemic and concurrent climate disasters highlighted the (lack of) resilience of many urban systems, but especially the food supply chain. The failure of the urban food supply chain was felt most severely by the most vulnerable

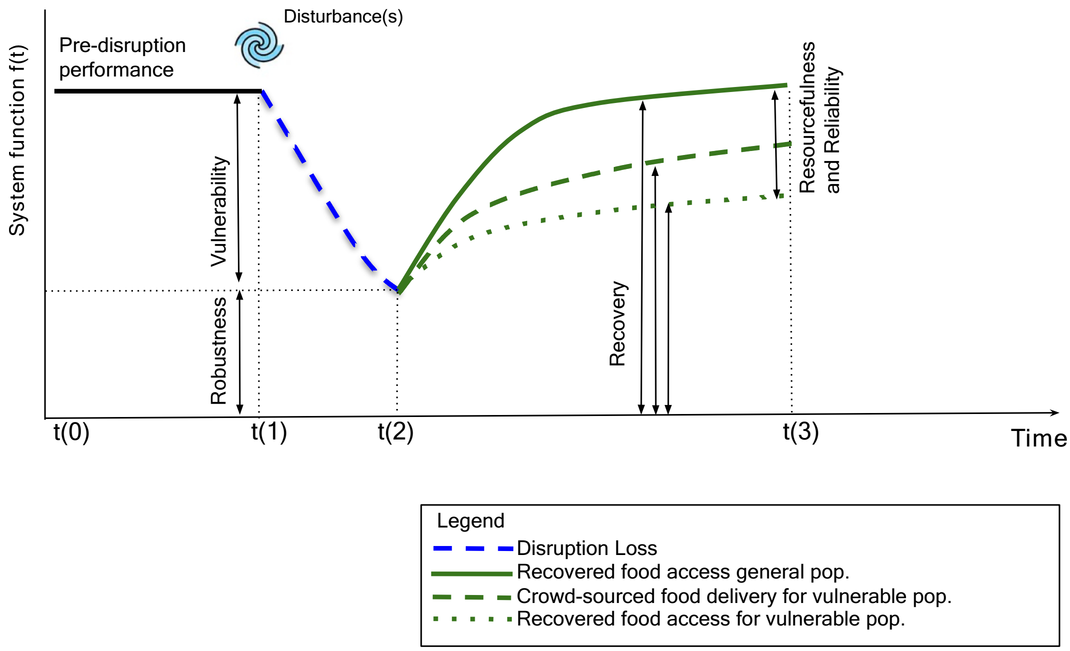

Fig. 2. Representation of crowdsourced food delivery in the resilience triangle framing: effects of resourcefulness and reliability on recovery path.

populations in our society. Therefore, we subsequently discuss the linkages between resilience and food logistics and between resilience and vulnerability.

2.1.1. Resilience and food logistics

The COVID-19 pandemic highlighted the lack of resilience in urban food logistics, especially in terms of the reliability and resourcefulness of the food supply chain. The pandemic affected grocery store supply both due to over-purchasing (Fang et al., 2021; Kinsey et al., 2020) and supply chain defects (Aday and Aday, 2020; Kakaei et al., 2022). The two causes of reduced grocery supply also share a recursive relationship: bulk purchasing was due in part to uncertainties of the food supply chain (Thompson et al., 2022), which caused strain on the system, resulting in uncertain food supply in many stores (Kakaei et al., 2022). The supply chain was further stressed due to changes in international trade agreements following border closures, fear of COVID-19 infection in food management workplaces, and updated worker protections (Aday and Aday, 2020).

An impact of the pandemic outside of grocery stores was the spike in food-delivery service utilization due to restrictions on restaurant dining (Brewer and Sebby, 2021; Chen McCain et al., 2021; Jain, 2024; Meena and Kumar, 2022; Puram et al., 2021; Savitz, 2024; Yang et al., 2020). Apps such as UberEats, DoorDash, GrubHub, and PostMates saw a 70 % spike in usage between March 2019 and March 2020 (Savitz, 2024). Grocery delivery services, too, exploded in use (Budziński and Daziano, 2023; Hossain et al., 2022; Morgan, 2024; Tyrväinen and Karjaluoto, 2022). During the pandemic, 79 % of U.S. shoppers reported ordering groceries online (Morgan, 2024), though some portion of the population is excluded from grocery delivery, especially vulnerable populations who cannot afford the delivery fees or have barriers to online shopping (Castner and Henke, 2011; Fang et al., 2021; Kinsey et al., 2020) and thus have a higher rate of return to in-store shopping (Hossain et al., 2022). However, the staying power of these crowdshipped food-delivery applications that employ drivers for grocery and meal delivery services has augmented the study of crowdshipping within the logistics literature (Fan et al., 2022; Liu et al., 2020; Paloheimo et al., 2016; Perboli and Rosano, 2019; Rey et al., 2018; Yıldız, 2021). While humanitarian logistics literature considers specific routing problems for food assistance programs (Bartholdi et al., 1983; Campbell et al., 2008; Davis et al., 2014; de la Torre et al., 2012; Ichoua, n.d; Solak et al., 2014; Tzeng et al., 2007), there is a gap in the research in considering crowdshipped food delivery services utilizing spontaneous volunteers. Traditional models represent top-down, structured volunteer networks rather than the on-demand availability of volunteers in a food-delivery applications framework. This study will fill that research gap by evaluating how spontaneous volunteer systems contribute to the resilience of food access for vulnerable communities by comparing the serviced population against populations known to be food insecure.

2.1.2. Resilience and vulnerability

In this study, *vulnerability* refers to *social vulnerability* or the unequal access to resources by individuals that inhibits full societal participation and is thereby further perpetuated (Davino et al., 2021). This unequal access is typically facilitated by age, gender, race, or socio-economic-based marginalization (Mah et al., 2023).

Over the past several decades, there has been a push in the literature for researchers to implement a hybrid approach to studying social vulnerability and infrastructure resilience (Miller et al., 2010; Uekusa and Matthewman, 2017). These calls recognize the fact that creating resilient built environments hinges on understanding the impact of disasters on the most at-risk populations (Uekusa and Matthewman, 2017). There exists varying indices and frameworks designed to study social vulnerability, but the most widely cited is the *Social Vulnerability Index* developed by the U.S. Centers for Disease Control and Prevention's Agency for Toxic Substances and Disease Registry (*CDC/ATSDR SVI*) (Mah et al., 2023). The CDC/ATSDR SVI database compiles 16 census variables at the census tract level and then quantifies the vulnerability of a tract into a single static index (the SVI) used to allocate disaster aid within the United States (U.S.) (CDC/ATSDR Social Vulnerability Index (SVI), 2024). This study uses variables compiled within the SVI database to assist in understanding adoption of volunteer-based food delivery over time. Ultimately, this analysis highlights the effectiveness of crowdsourced delivery systems to increase resilience of food access not just in general, but specifically for vulnerable populations following a (concurrent or overlapping) disaster.

2.2. Food insecurity

The failings of the food supply chain during the pandemic, especially for vulnerable populations, perpetuated the cycle of *food insecurity*. Food insecurity is a public health crisis and a matter of social injustice in American society, defined as "a lack of consistent access to enough food for an active, healthy life" (Dubowitz et al., 2021). Historically, low-income households are more likely to live in food deserts (i.e., neighborhoods with limited access to grocery stores) and must travel greater distances to acquire food (Cannuscio et al., 2013; Fang et al., 2021).The rapidly changing lifestyle conditions of the COVID-19 pandemic exacerbated pre-existing disparities and inequities in food access in many ways (Dubowitz et al., 2021). Limited public transportation options during the lockdown made accessing food more difficult for transit reliant households, which intensified the effects of existing food deserts (Clark et al., 2020; Fang et al., 2021; Kinsey et al., 2020). Some food benefit programs initially prohibited recipients from applying benefits to food purchased online, further reducing equitable access to food resources during lockdowns for low-income households (Fang et al., 2021). Furthermore, while many households resorted to stockpiling food, most low-income households could not afford to buy in bulk, and in many cases their shopping was restricted to stores that accepted monthly food benefits and specifically approved food items (Castner and Henke, 2011; Fang et al., 2021; Kinsey et al., 2020). In search of approved items, or simply affordable items, low-income households often visited multiple stores, food banks, food pantries, and soup kitchens, but increased prices, diminished resources, and reduced supply made this shopping around more challenging (Cannuscio et al., 2013; Clark et al., 2020).

Even prior to the COVID-19 pandemic, the burden of food insecurity was disproportionately high among Black and Hispanic households (Coleman-Jensen and Nord, 2013; Fitzpatrick et al., 2021; Leddy et al., 2020; Morales et al., 2021), low-income households (Coleman-Jensen and Nord, 2013; Leddy et al., 2020), households with children under 6 years of age, female-headed households, adults living alone, and households with adults with disabilities (Coleman-Jensen and Nord, 2013). These trends continued during the pandemic wherein food insecurity was more likely among individuals who were Black and/or Hispanic, low-income, or living with children (Fitzpatrick et al., 2021; Lauren et al., 2021). Pandemic findings mirror the inequitable risk factors that have been observed to predict food insecurity during similar disaster-like events and climate-induced hazards, such as flooding, hurricanes, and severe winter weather in the U.S. (Clay and Ross, 2020; Clay et al., 2018; Fitzpatrick et al., 2021; Haynes-Maslow et al., 2020). During climate disaster events, food insecurity is exacerbated, while simultaneously access to food pantries can be more limited than usual. Household mobility to access food was fraught during the pandemic, especially for households dependent on public transit who were forced into close quarters with others at a time when social distancing was mandated (*COVID-19 Best Practice Information: Public Transportation Distancing*, 2020). To help eliminate mobility barriers to food access, many food banks and food pantries deployed food delivery programs during the pandemic (Feeding America, 2024). In our study, we understand requests for crowdsourced food delivery as a proxy measure of food insecurity in the wake of disaster events. Because all requests recorded in the dataset were met, we use these filled requests over time as an indicator of resilience to food insecurity following disaster events.

2.3. Approaches to transportation resilience

Resilience in transportation systems is often thought of in terms of a system's ability to resist and recover from disruptions (Gu et al., 2020; Serdar et al., 2022). There is a three-fold approach to studying transportation resilience in the literature related to this study: resilience of (1) supply chains, (2) physical infrastructure and network capacity (transport supply), and (3) traveler behavior (transport demand).

(1) *Resilience of the supply chain* is thought of in terms of "operational flexibility" of corporations (Shen and Sun, 2021) or from the perspective of consumer satisfaction (Meena and Kumar, 2022; Tiganis et al., 2023). The effect of the COVID-19 pandemic on the urban food network is discussed in detail in section 2.1.1 above. This study will take existing research on supply chain resilience one step further by evaluating crowdsourced food delivery as a means of expanding the reliability of the urban food supply chain in the recovery period.
(2) *Resilience of physical transportation infrastructure and network capacity (transport supply)* research evaluates built asset conditions before and after disruption events and the resulting resilience of the network capacity in the wake of infrastructure perturbations (Henry and Emmanuel Ramirez-Marquez, 2012; O'Kelly, 2015; Omer et al., 2011; Xu and Chopra, 2023). This is the most classic example of transportation resilience research; the resilience triangle was first developed to measure the resilience of physical infrastructure following earthquake events (Bruneau et al., 2003). Other recent studies focus on the resilience of public transportation capacity, especially following social disruption events such as terrorist attacks (Cox et al., 2011; Xu and Chopra, 2023) or political demonstrations (Chan et al., 2022). Complementing research on public transportation capacity resilience, Borowski et al. evaluate how on-demand app-based ridesourcing offers a substitute for rail-based trips during disruptions (Borowski et al., 2023), revealing socio-spatial variations in system robustness. This research adds to the study of infrastructure and transportation capacity resilience by highlighting the role of crowdsourced delivery. Without operational roadways, volunteers would be unable to deliver food within the system, and vice versa, thus the use of informal resources can add resilience after disruptions (Borowski and Stathopoulos, 2020a).
(3) *Resilience of traveler behavior (transport demand)* research focuses on the choices of passengers following a service perturbation event, such as the choice to transfer from rail to app-based ridesourcing described above (Borowski et al., 2023). Mode choice (Borowski and Stathopoulos, 2020b; Chan et al., 2022), as well as evacuation choice (Borowski et al., 2021) of travelers, is centered in this line of research. Our work falls within the realm of transport demand, but rather than the demand for travel by households in our dataset, we focus on induced demand by proxy trips made by food delivery volunteers.

2.4. Contribution to transportation resilience literature

This study provides a cross-sectional analysis of food logistics resilience and transport demand by evaluating a transportation-based food resilience program. This work complements the existing literature by assessing food access for vulnerable populations. Though many studies seek to understand inequities in transportation access (King et al., 2022; Lee et al., 2019; Raza et al., 2023), measures of resilience in transportation studies often have the objective of evaluating system performance for the population on average (Gu et al., 2020; Serdar et al., 2022). The dataset used in this study offers the opportunity to understand resilience not for the average household, but for those who are already at a disadvantage before a disaster hits. As such, this study offers unique insight into the behaviors of the most vulnerable, who may be excluded from traditional network analysis (due to this averaging effect) and food logistics literature (due to not being existing customers). By characterizing the locational and time-based characteristics of urban food security resilience and providing an analysis of food vulnerability characteristics, we expand upon the traditional resilience triangle structure to account for spontaneous volunteerism. Our analysis results center the resilience of vulnerable populations, who are commonly excluded from explicit consideration in post-disaster resilience studies. As illustrated in the resilience triangle representation in Fig. 2, the value of the crowdsourced food delivery program is in its ability to bolster the rate of recovery in vulnerable populations.

3. Methods

3.1. Study area

Houston, Texas, the location of *CrowdSource Rescue*, is home to over 2.3 million people, 19.5 % of whom are living in poverty (*U.S. Census Bureau QuickFacts: Houston City, Texas*, 2024). While Houston has been regarded as the most diverse city in the U.S. (*Houston Named the Most Diverse City in the US by New Report. ABC13 Houston*, 2024), it ranks 273rd out of 274 U.S. cities for overall racial and economic inclusion (*Measuring Inclusion in America's Cities*, 2024). This can be seen geographically in the distribution of racial groups across the city, as shown in Fig. 3 and also economically; research shows that low-income communities in Houston are more likely to have more residents of color (Olin, 2020). This racial divide also shows up in the transportation landscape. Houston is a primarily car-centric city and underperforms nationally both in terms of the coverage provided by public transit and accessibility of jobs for carless households (Tomer, 2011). The impacts of this underperformance are racially skewed, as 78 % of Houston transit users are non-white (2017 Regional Fixed Route Transit Rider Survey. 6, 2017).

Geographically, Houston is an ideal location for a case study examining the effects of disasters on food access. Due to its position along the Gulf Coast, Houston provides numerous examples of large-scale disasters of flooding and hurricanes. Concurrent with the pandemic, five climate events warranted either a 'Major Disaster Declaration' or 'Emergency Declaration' from the Federal Emergency Management Agency (FEMA): one hurricane, one tropical storm, one storm marked as both a tropical storm and a hurricane-level disaster, and two winter storms (FEMA Declared Disasters, 2024). These events present a unique opportunity to study the effects of concurrent disasters of different natures.

3.2. Data description

Data used in this study were provided by the non-profit organization *CrowdSource Rescue*. *CrowdSource Rescue* was started as a disaster response service to help Houstonians after hurricanes and other major climate disasters and expanded its mission to food assistance at the beginning of the COVID-19 pandemic due to growing food insecurity. To this end, the organization partnered with existing food-based organizations. Local food banks, food pantries, and grocery stores provided food donations, and *CrowdSource Rescue* coordinated delivery logistics. *CrowdSource Rescue* is unique in its volunteer-based delivery system; its food deliveries are completely reliant on volunteers. While other organizations, such as My Pantry Express in Northern Illinois (My Pantry Express, 2024) and Baltimore City Grocery Delivery (*Find Food in Baltimore City | 211 Maryland*, 2021), offer request-based grocery delivery to food-insecure households, these programs are administered by employees of the organization as opposed to spontaneous volunteers. The program also differs from the well-known organization Meals on Wheels, a non-profit organization focused on bringing cooked meals to older adults. While Meals on Wheels relies on a shift-work based volunteer model (Bartholdi et al., 1983), *CrowdSource Rescue* more resembles crowdshipping food delivery apps (such as UberEats, GrubHub, etc.) in that its volunteers are spontaneous and not subject to a set

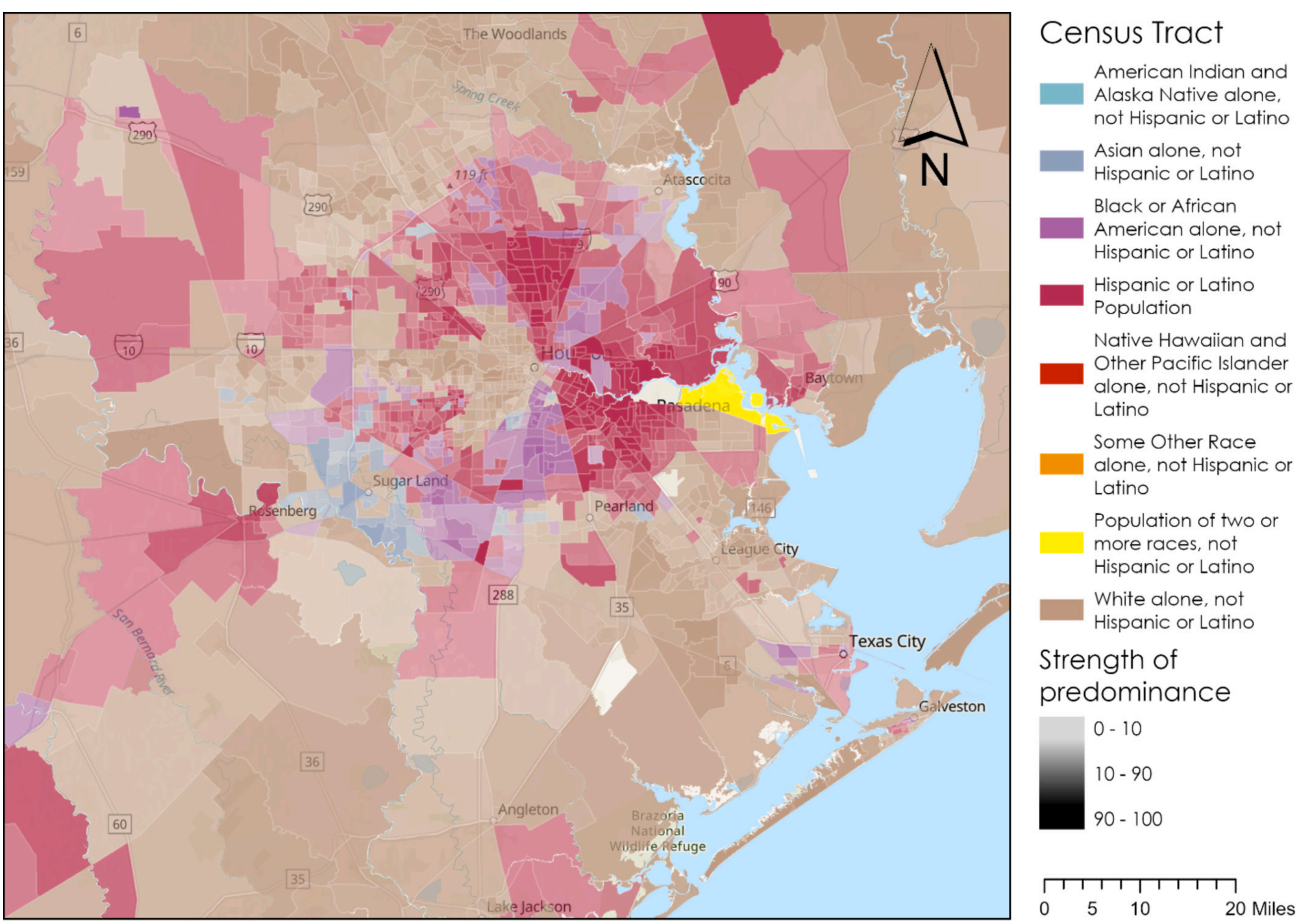

Fig. 3. Spatial distribution of race and ethnicity across Houston, per the 2020 U.S. Census (Census, 2020); created Using ArcGIS Pro (ArcGIS Pro, 2019).

timeframe.

Drivers for *CrowdSource Rescue* register via an online form and must complete a federally required child nutrition rights training. Once registered, volunteers download the 'Zello' app, where they can connect with dispatchers, receive support, and accept food delivery requests as they are able. Once a volunteer accepts a request, they are dispatched to the most centrally located food bank or partner agency to pick up the food shipment (CrowdSource Rescue: COVID-19 Driver Training, 2024). The food to be delivered is provided in part by a U.S. Temporary Emergency Food Assistance Program Grant, monetary donations by individuals, and food donations from Houston Food Bank partners, Harris County, Hope City Missions, and H-E-B Grocery Stores (CrowdSource Rescue, 2024b). While the volunteer experience mirrors that of a food delivery app driver, the *CrowdSource Rescue* platform differs from the app-delivery experience on the user end. To not exclude individuals or households without internet access, requests for food assistance can be made either on the *CrowdSource Rescue* website or by calling in a request. There is no eligibility benchmark for food assistance through *CrowdSource Rescue* or for the number of repeat requests made; the request intake form explicitly states, "We are not the food police. All are welcome to apply." (CrowdSource Rescue Intake form Instructions, 2020).

Data used in this study included 28,512 de-identified help requests from March 17, 2020, through February 2, 2022. Each observation in the database includes request latitude and longitude, date of request completion, household characteristics (i.e., number of older adults, number of adults, number of children, and housing type), monthly income, and participation in a social program [i.e., Medicaid, Supplemental Nutrition Assistance Program (SNAP), Supplemental Security Income (SSI), Temporary Assistance for Needy Families (TANF), and the National School Lunch Program (NSLP)]. Table 1 provides a descriptive overview of the variables investigated in this study, and Fig. 4 shows the location of each help request in the dataset. Fig. 5 depicts the timeline of requests and of other disasters concurrent with the data timeframe.

To preserve the anonymity of those seeking assistance, *CrowdSource Rescue* collected only the demographic information from individuals required by a U.S. Temporary Emergency Food Assistance Program Grant (CrowdSource Rescue, 2024a), and the coordinates of request locations were rounded to the hundredth. To gain understanding of drivers of food delivery requests, *data fusion* was used to amalgamate a number of complementary data sources for more comprehensive modeling (Cariou et al., n.d.). External data used in modeling to bolster the base dataset are described in Table 2. Only variables significant to modeling efforts are displayed in Table 2.

While supply-side data was not available for this study, the base data included the day and time in which a request was matched to a volunteer. Overall, 99.56 % of requests were matched within the day to a volunteer able to provide support. 0.35 % of requests were matched within a month, and only 0.11 % of requests took over one month to match. While little can be made of this trend without domain knowledge of the request-matching algorithm used, it does indicate an adequate supply-side availability to match demand and suggest a potential volunteer surplus.

Table 1
Descriptive statistics for investigated variables in the *Crowdsource Rescue* dataset.

	n [binary]	*Min*	*Max*	*Mean*	*Std. Dev*
Household Variables					
Household size	–	0	92	6.60	0.02
Number of older adults	–	0	90	0.95	1.40
Number of adults	–	0	32	1.58	1.35
Number of children	–	0	58	0.77	1.41
Monthly household income (U.S. dollars)	–	$0	$10,342	$1157	$808
Housing type: Single family home	14,325	–	–	–	–
Housing type: Shelter	623	–	–	–	–
Housing type: Apartment	13,071	–	–	–	–
Social Program Variables					
Medicaid [binary]	5004	–	–	–	–
National School Lunch Program: NSLP [binary]	616	–	–	–	–
Supplemental Nutrition Assistance Program: SNAP [binary]	4247	–	–	–	–
Supplementary Security Income: SSI [binary]	8027	–	–	–	–
Temporary Assistance for Needy Families: TANF [binary]	38	–	–	–	–
N. Social Program Recipients (sum of reported binary variables per census tract)	–	0	416	92.18	101.18

3.3. *Analytical methodology*

To uncover trends in the requests for assistance via crowdsourced disaster relief, three evaluation frameworks are used, each of which builds on the findings of the last. Research Question 1 is addressed using *geographic analysis* to identify request trends in time and space; Research Questions 1 and 2 are further answered using *linear modeling* to understand the characteristics of these trends; and *structural equation modeling* is then used to account for the correlation among demand-determinant variables and food need by the creation of latent identity groups for use in modeling to address Research Question 3.

3.3.1. *Geographic analysis*

Before data sharing, residence locations in the base dataset were anonymized to protect privacy by rounding the latitude and longitude to the hundredths. These de-identified data points were dynamically mapped to identify salient time-space trends in the geographic analysis.

3.3.2. *Regression modeling*

Due to the anonymization of residence locations, data points are only traceable to Census Tract, and trends of adoption among individuals by spatial adjacency is not possible. In lieu of spatial regression modeling, Ordinary Least Squares linear regression modeling was used to determine factors related to the time-space trends identified using geographic analysis. Specifically, a *time-based* model was constructed to measure the number of requests for food delivery made per day (y_{time}; $n = 659$), and a *locational characteristic* model was constructed to understand locational characteristics of requests per census tract (y_{space}; $n = 815$). The dependent variable of each model, y_f, corresponds to the number of food requests made for each framework. f refers to the modeling framework and includes the two frameworks: space and time. The *time-based model* considered the time-based characteristics listed in Table 2 as independent variables, while the *locational characteristic* model considered the locational characteristics listed in Table 2 as well as request characteristics from Table 1 as independent variables.

3.3.3. *Structural equation modeling*

Following the linear modeling, structural equation models (SEM) were estimated to identify the characteristics of request behavior during *lockdown* ($y_{lockdown}$; $n = 3491$) [used here to refer to any time before June 3, 2020, when Texas businesses were allowed to reopen at 50 % capacity (Limón, 2024)] and *re-opened time* ($y_{re\text{-}open}$; $n = 9143$). This distinction was informed by the strong lockdown effects shown in Fig. 5. The SEM framework was selected to represent more complex relationships of vulnerability determinants across time and space than what is suggested in traditional static vulnerability indices. SEMs are well suited to incorporate latent variables into a regression model (Greene and Hensher, 2009; Muthén, 2002). The use of latent variables in the analysis allows for the clustering of census indicators reflecting the existence

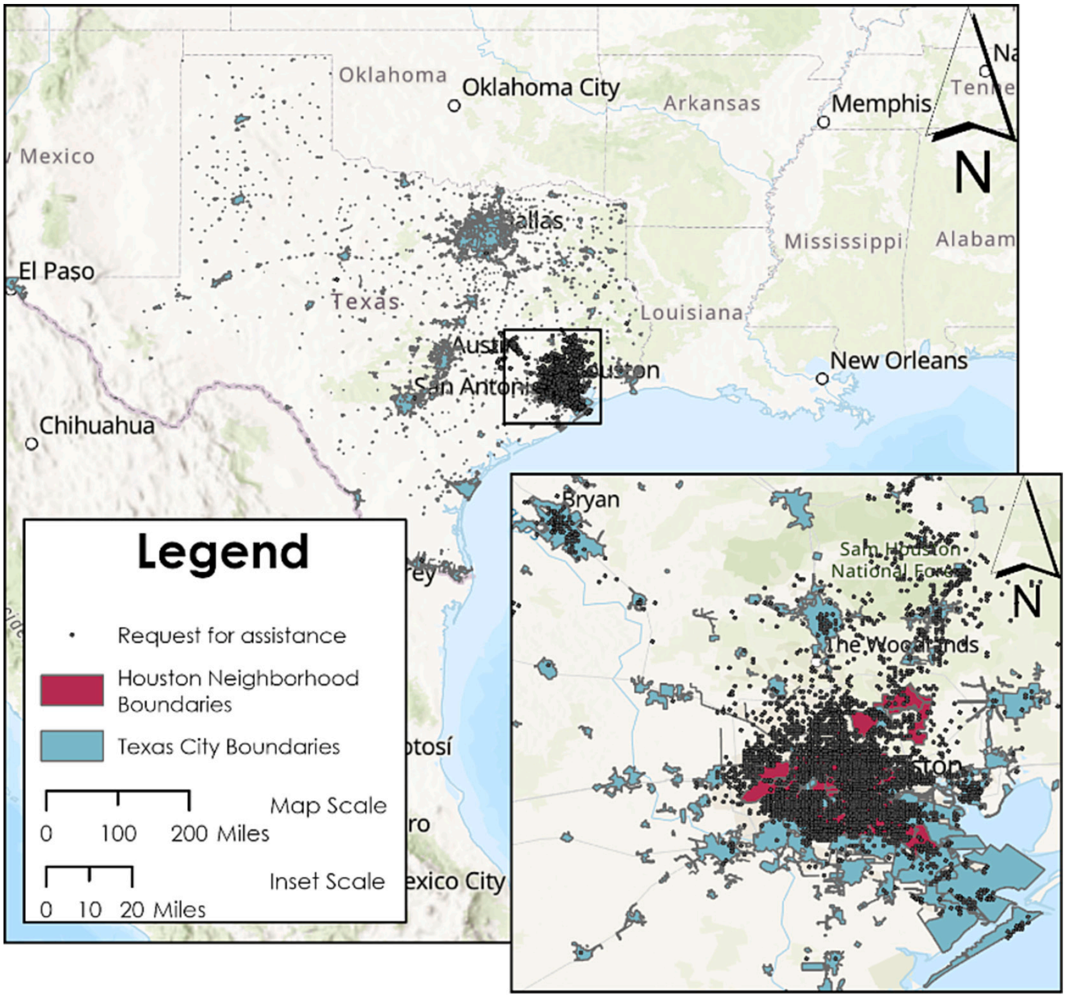

Fig. 4. Service Request Locations (Black), City Boundaries (Blue), and Houston Neighborhood Boundaries (Red). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

of different types of vulnerability and to study how those types of vulnerability interact with the dynamics of the recorded disruptions. Specifically, the approach enables us to capture vulnerability determined by intersectional identity groups and to carefully link vulnerability to time-based factors, such as the COVID-19 positivity rate or the daily unemployment rate measured by the ˆGSPC. The SEM formulation is presented in Eq. 1.

$$y_i^* = \nu + \lambda\eta_i + Kx_i + \epsilon_i \tag{1}$$

For both lockdown and re-opened time, ν is an n-dimensional vector of measurement intercepts; η is an m-dimensional vector of latent variables, and λ is an n x m matrix of slope coefficients related to each latent variable; x is a q-dimensional vector of covariates, and K is an n x q matrix of slope coefficients related to each covariate; ϵ refers to an n-dimensional vector of errors (Muthén, 2002). The two models ($i \in${lockdown, re-open}) weave both locational and time-based characteristics into a regression model explaining n: the number of requests made in each census tract on each day included in the data. The path diagrams for the two phases, depicting the relationships between all variables, are illustrated in Fig. 6 (lockdown period) and Fig. 7 (re-opened period). Latent variable SEM estimation results are reported in Tables 5 (shared determinants) and Table 6 (distinct determinants of food delivery requests). The full SEM model results structural component and covariances can be found in Appendix A. For ease of interpretation, the factors that increase the number of food requests are displayed on the left, while factors that have a negative relationship with requests are depicted on the right. We further examine each latent variable structure for the two time-periods to gain insight on the shifting patterns of vulnerability during and after the lockdown. The full latent variable formulations are presented and discussed in the *Results* section.

4. Results

4.1. Geographic analysis

Geographic analysis in ArcGIS Pro (ArcGIS Pro, 2019) was used to create an animation of request data over time from the dataset, as well as all other maps included in this paper. Weeklong snapshots of key events, including all five climate disasters within the data (i.e., Hurricane Hanna, concurrent Tropical Storms Marco and Laura, and concurrent Winter Storms Uri and Viola), the week of peak unemployment during the pandemic, and the week of the COVID-19 Omicron variant peak in Houston are shown in Fig. 8. In addition to key events, a one-week, non-climate disaster snapshot of the first week of October is provided for both 2020 and 2021. It is important to note that the heat map intensity scale depicted for each map is relative to the number of requests made within the specified date range only (i.e., a week may show more concentrated need but have a lower total number of requests in one area at a certain time). Interpreting Fig. 8, we observe that the need for *CrowdSource Resource* food delivery is concentrated within low-income census tracts. Importantly, patterns of food need are different during climate disasters versus health or economic disasters; in climate disaster

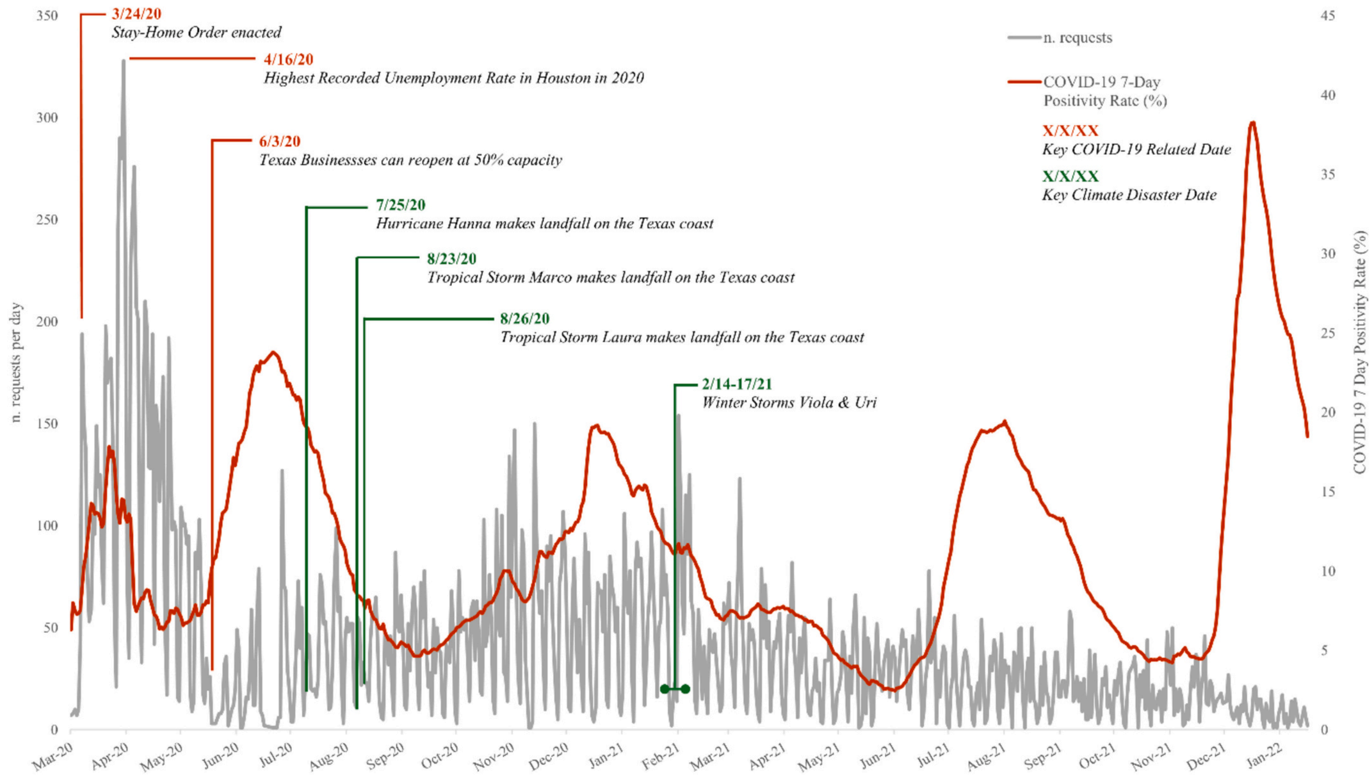

Fig. 5. Timeline of food delivery requests (grey) and COVID-19 7-Day positivity rate (red) with key events highlighted. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

events, centers of need expand beyond the main hot spots observed in all time frames, while during economic and health disasters (i.e., peak unemployment and peak Omicron variant spread), food need intensifies but stays concentrated in the same hot spots seen in the '*Non-Climate Disaster*' plots. Due to the anonymization of specific residence locations, spatial regression modeling is not possible for any significant analysis using this dataset. Thus, a regression model using location-based characteristics at the Census Tract level (the most granular level at which locational data can be traced) and structural equation modeling incorporating locational characteristics are used to explain the spatial disparities depicted in Fig. 8.

4.2. Regression modeling

Parameter estimates for the locational characteristics model are listed in Table 3. The adjusted rho-squared of the model is 0.61, which shows the relative strength of the model. Notably, a tract being predominantly low income or having low access to healthy food was not a significant determinant of requests in the final model. If race is excluded from the model, the 'low income' binary variable becomes significant, but notably, low access to healthy food remains nonsignificant. The insignificance of these two variables shown in Table 3 illustrates that including Black and Hispanic population proportions in the model completely accounts for the significant effect of a tract being low income. This is an unsurprising, yet socially distressing, result as the most economically depressed areas of Houston house the most people of color (Olin, 2020), and it indicates high covariance of race and income variables.

Parameter estimates for the time-based characteristics model are listed in Table 4. The adjusted rho-squared of the model is 0.46, which suggests the model paints a reasonable picture of requests for food assistance throughout the COVID-19 pandemic using associated time-based characteristics. Though not exceedingly robust, variable significance is more important in this case than model significance, as this linear model is used to understand preliminary variable relationships that will be built upon to develop a more robust structural equation model. In addition to this linear model, Fig. 5 depicts a timeline of service requests throughout the provided timeframe, illustrating a qualitative effect of exogenous events included in the model on the number of daily requests. Temporal characteristics found to be insignificant to the number of requests included the amount of precipitation in a day, a binary variable of whether precipitation occurred on a given day, whether a date was a holiday, and the Consumer Price Index of food.

4.3. Structural equation modeling

SEM was employed to account for the covariance between race and income seen in the locational linear model presented in Table 3. We carried out extensive data exploration using principal component analysis (PCA) on standardized variables to identify latent clusters in the data acting as determinants of food need. The results of the PCA indicated suitability of data owing to high variable correlation. Seventeen clusters displayed eigenvalues of over 1, while the Scree plot revealed a break after four factors. Following extensive segmentation testing, the SEM was deployed to model two major phases of the data separately: i.e. the COVID-19 lockdown in Fig. 5 (all requests prior to June 3, 2020) versus re-opened time in Fig. 6 (all requests following June 3, 2020) due to the strong effect of lockdown seen in the time-based linear model (i.e., the variable *Lockdown*) and the steep drop in request number after June 3, shown graphically in Fig. 5. Exploratory factor analysis and an exploration of fit improvement indices were used to refine the SEM modeling to include a total of five latent variables for re-opened time and five latent variable identity clusters for COVID-19 lockdown time.

SEM model specifications are enumerated in the *Methods* section of this paper and the latent variable formulations are presented in Table 5 (presenting common variables for the two time-phases) and Table 6 (time-specific, unique variables). Corresponding visual representations

Table 2
Data fusion variable sources and resolution specification.

–	Data	Data Source	Matching Data Field
[all]	Census Tract	U.S. Census Geocoder API (Census Geocoder, 2024)	Latitude/ Longitude
Locational Characteristics	% Crowded Quarters % Disabled % Limited English Speaking % Living in Group Quarters % Living in Poverty in Census Tract % Mobile Homes % Multiunit Residences % No High School Diploma % No Vehicle % Single Parent Households % Unemployed in Census Tract % Uninsured % Black, Hispanic, white Population in Census Tract	CDC/ADSTR SVI (CDC/ATSDR Social Vulnerability Index (SVI), 2024)	Census Tract
	Low Access to Healthy Food (binary)[1] Tract Below Federal Poverty Line (binary)	U.S. Department of Agriculture Food Access Research Atlas (Food Access Research Atlas, 2024)	Census Tract
	% Non-US Citizens	U.S. Census (US Census, 2024)	Census Tract
	Number of Requests in the 1 % Annual Chance Floodplain Number of Requests in the 0.2 % Annual Chance Floodplain	Texas Water Development Tract Floodplain Quilt (Texas Water Development Board, 2024)	Latitude/ Longitude
Time-Based Characteristics	Daily Weather (High, Low, Average °F)	Weather Underground (*Houston, TX Weather History March 2020–February 2022*, 2024)	Request Date
	S&P 500 (ˆGSPC) Daily Performance[2]	R 'tidyquant' Package (Dancho and Vaughan, 2023)	Request Date
	% Unemployment Rate	Bureau of Labor Statistics (*Houston-Sugar Land-Baytown, TX Economy at a Glance*, 2024)	Request Date
	7-Day COVID Positivity Rate in Harris County	U.S. CDC COVID Data Tracker (COVID Data Tracker, 2024)	Request Date
	Tropical Storm Dates	FEMA Declared Disasters (FEMA Declared Disasters, 2024)	Request Date
	Key COVID-19 Policy Dates, Texas	Texas Tribune (Limón, 2024)	Request Date

[1] The U.S. Department of Agriculture (USDA) defines low access to healthy food as "being far from a supermarket, supercenter, or large grocery store." The most common metric to determine low access defines a "low access" census tract as one in which at least 33 % of residents are 0.5 miles or more from the nearest food source in urban areas or 10 miles in rural areas.
[2] The New York Stock Exchange is not open on weekends or holidays. In these instances, the ˆGSPC performance was set equal to the most recent, previous closing price.

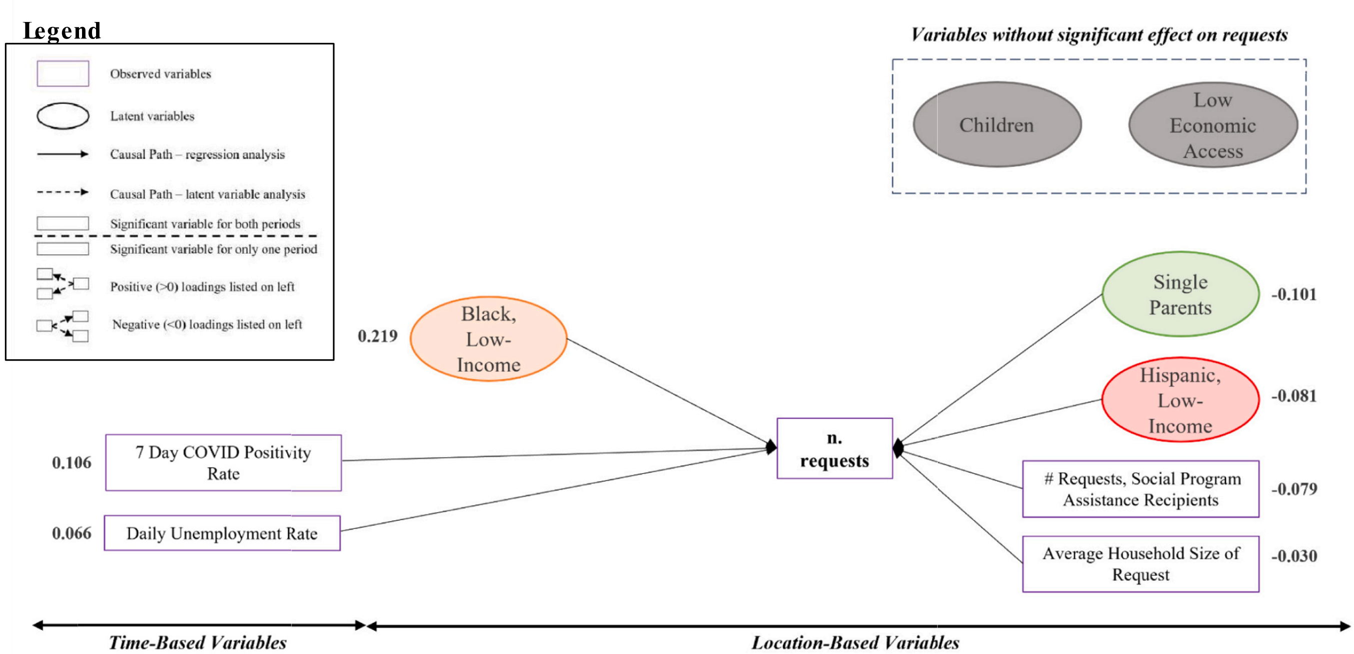

Fig. 6. Structural equation model path diagram for food delivery requests in COVID-19 lockdown period.
Note: for easier interpretation the factors that boost food request numbers are listed to the left, and the opposite to the right. 'Children' and 'Low Economic Access' are included to reflect later significance in *Re*-opened Period model.

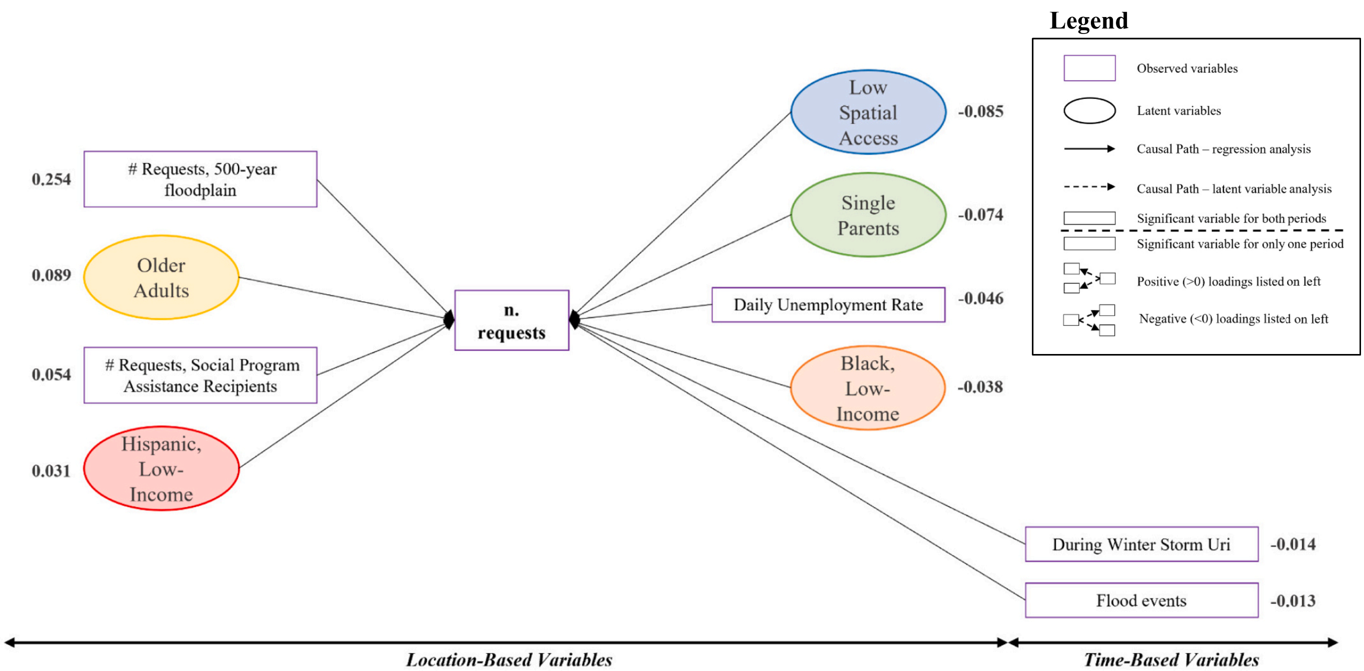

Fig. 7. Path diagram for re-opened period structural equation model.
Note: for easier interpretation the factors that boost food request numbers are listed to the left, and the opposite to the right.

of these latent variables are displayed in Appendix B.

Here we discuss the five latent variable groupings that determine food need vulnerability for *re-opened* time:

1. *Hispanic, Low Income*: Key indicators of this locational identity group include a high rate of Hispanic residents and a low rate of other races, as well as a low monthly income. During the re-opened time, this group showed a positive relationship with daily requests, reflecting the findings of the locational linear model (the *Hispanic Population* variable) and the patterns of need within the local Houston context (Olin, 2020). (See Table 5).
2. *Black, Low Income:* As compared to the *Hispanic, Low Income* identity group, this latent identity group shows a high rate of Black residents and a negative correlation with Hispanic residents, but also shows a low monthly income. However, in re-opened time, this group shows a negative relationship with food delivery daily requests. (See Table 5).
3. *Older Adults:* A latent identity grouping of older adults shows a positive contribution to increased requests for assistance throughout the re-opened time (see Table 6). Census tract characteristics in this grouping include higher rates of older adults, disabled residents, and unemployed residents.
4. *Single Parents*: The single parent identity group is identified as including census tracts with higher rates of children and single parents. This group shows a negative relationship with daily assistance requests. (See Table 5).
5. *Low Spatial Access:* This group is so named due to the low accessibility of fresh and healthy food available within these census tracts (see Table 6). However, despite the limited local access to food, this group also has a negative relationship with SNAP recipients and with zero-vehicle households, indicating ownership of mobility tools and economic means to purchase food despite the distance required to travel to access the food. Overall, the group shows a negative relationship with daily assistance requests.

Interestingly, clear identity groupings are more difficult to ascertain during the *lockdown period* potentially owing to a more unilateral need for assistance during the lockdown (Fitzpatrick et al., 2021; Schanzenbach and Pitts, 2020; Wolfson and Leung, 2020); however, three latent food need identity variables are identified as having a significant effect on the number of requests for food assistance during lockdown (listed below), while two identified latent identity variables are not significant, despite becoming significant in the post-lockdown phase. Notably, the *older adult* identity group is no longer significant for re-opened time, likely indicating not so much a lack of need but rather a slower dissemination of information among older individuals due to smaller social networks (Bruine de Bruin et al., 2020).

The three groups with significant effects on the number of requests during the *lockdown* period are consistent with the re-opened phase model, though with varying effects of independent variables. They are:

1. *Hispanic, Low Income*: During the initial lockdown, this group showed a negative relationship with daily requests, an opposite effect as during the re-opened time.
2. *Black, Low Income:* During the initial lockdown, this group showed a positive relationship with daily requests, an opposite effect than during re-opened time.
3. *Single Parents:* The single parent identity group shows a negative relationship with daily assistance requests for both lockdown and re-opened time.

The remaining two identified latent identity variables do not have a significant effect on assistance requests during lockdown, yet they are included for completeness:

1. *Low Economic Access:* This group does not have a significant relationship with spatial proximity to food, similar to the '*Low Spatial Access*' latent variable, it but does show a positive relationship with the proportion of SNAP recipients in the census tract and with zero-vehicle households (see Table 6). These indicators suggest limited food accessibility and low purchasing power, regardless of the spatial availability of food. However, this group is not making a significant number of requests for food assistance.

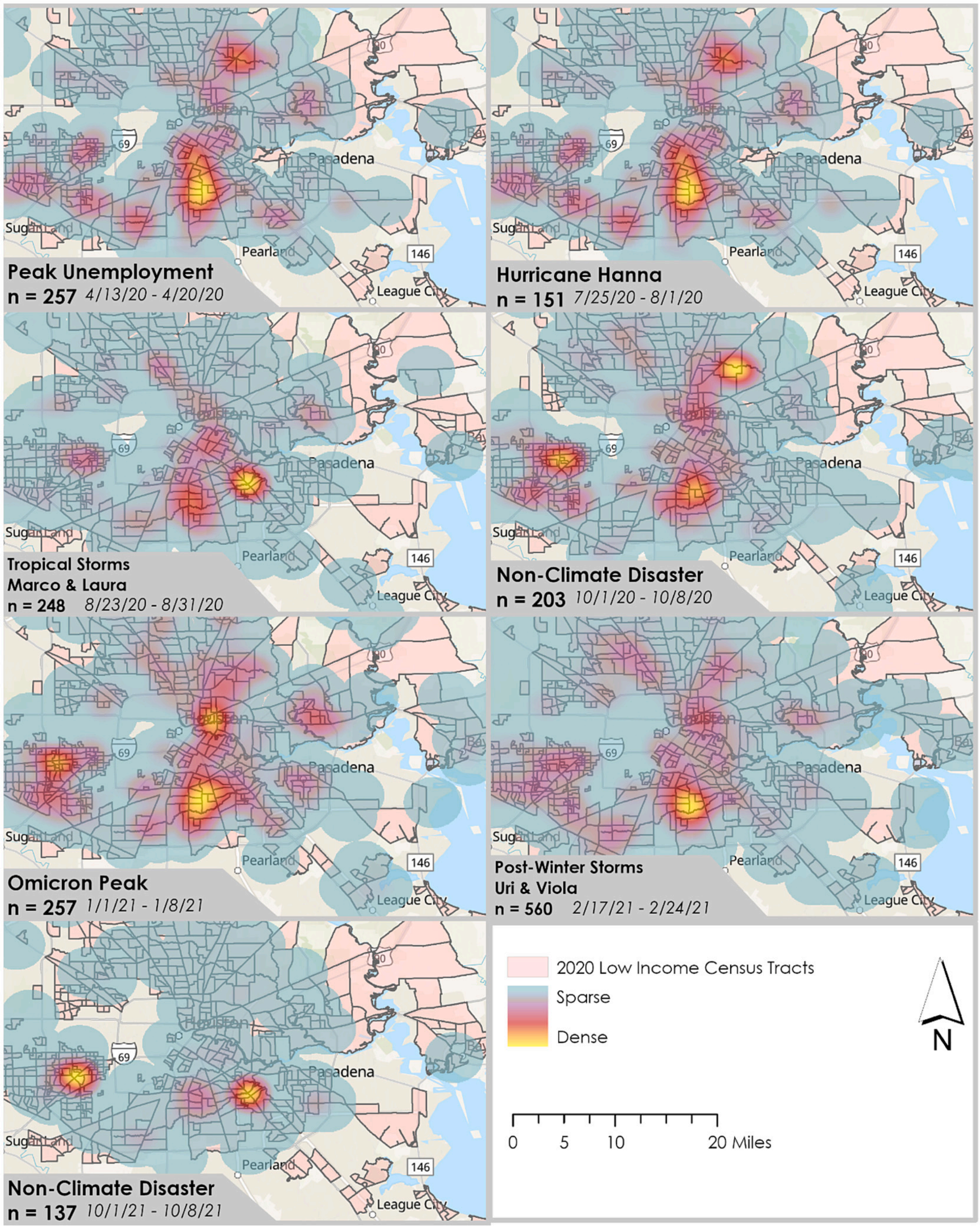

Fig. 8. Heat maps at key time periods showing requests for food assistance.

2. *Children*: This group (not included in the re-opened time model where “older adults” is instead identified) seems to be a ‘catch-all’ for vulnerable census tracts without a significant number of food requests but with high rates of children, larger household sizes, and more single-parent households (see Table 6).

The absence of an effect of the *Low Economic Access* and *Children* latent variables comprised of socially vulnerable identities may indicate a potential latent demand for food delivery services under a disaster prompting a lockdown. These are both significant latent variable groupings within the data but do not show a significant effect on the number of assistance requests. It is important to note that a lack of requests does not equate to an absence of need but may indicate that barriers need to be overcome.

All variables included in the models are significant, and both models are found to be acceptable by common significance thresholds for SEM evaluation (CFI > 0.90 and RMSEA <0.10) (Worthington and Whittaker, 2006). However, it is important to highlight that all modeling is done at the census tract level due to the lack of individual information provided about requesters. The existing data is rich and provides unique real-world insights into spatial and temporal dynamics of crowdsourced food delivery functioning. Yet, we note that the results are expected to improve if modeling is performed on individual-level data rather than aggregate census data, which may obscure vulnerabilities and heterogeneity in need among actual requesters.

Notably, the significant indicators that make up each latent variable vary between the lockdown and re-opened periods. For example, *percent unemployed* and *percent single parent households* are significant positive indicators of the ‘Black, Low Income’ latent variable during the re-opened period but not the lockdown period. This example illustrates

Table 3
Results of linear modeling of locational characteristics ($y = n.$ *requests per census tract*).

	Estimate, βi	*Std. Error*	*t-value*	*Pr(>|t|)*	
(Intercept)	−1.720	4.248	−0.405	0.686	
Below Federal Poverty Line [binary]	3.246	3.794	0.856	0.392	
Low Access to Healthy Food [binary]	−3.038	3.751	−0.810	0.418	
% Black Population in Tract	76.652	8.093	9.472	< 2E-16	***
% Hispanic Population in Tract	28.845	7.378	3.91	0.0001	***
N. request, 0.2 % annual chance floodplain	1.04383	0.060	17.438	< 2E-16	***
N. request, 1 % annual chance floodplain	0.9606	0.040	24.524	< 2E-16	***

Residual standard error: 40.15 on 815 degrees of freedom.
Multiple R-squared: 0.6126, Adjusted R-squared: 0.6098.
F-statistic: 214.8 on 6 and 815 DF, p-value: < 2.2e-16.
*– Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1.*

Table 4
Results of linear modeling of time-based characteristics ($y = n.$ *requests per day*).

	Estimate, βi	*Std. Error*	*t-value*	*Pr(>|t|)*	
(Intercept)	−95.810	28.604	−3.350	8.55E-04	***
^GSPC (S&P 500 Performance - Scale 2000s)	0.024	0.007	3.550	4.12E-04	***
% Unemployed in Houston Area by Month	7.729	1.009	7.661	6.58E-14	***
Vaccine Available [binary]	−19.623	5.856	−3.351	8.51E-04	***
Stimulus Payment Month? [binary]	16.248	3.676	4.420	1.15E-05	***
Lockdown [binary]	84.411	7.097	11.894	< 2E-16	***
During Uri [binary]	−11.212	15.138	−0.741	0.459	
Week After Uri [binary]	76.000	15.166	5.011	6.95E-07	***
Hurricane/Tropical Storm [binary]	−15.503	9.203	−1.685	0.093	.
7-Day % COVID Positivity Rate in Harris County	−1.010	0.203	−4.979	8.17E-07	***

Residual standard error: 33.07 on 659 degrees of freedom.
Multiple R-squared: 0.4723, Adjusted R-squared: 0.4635.
F-statistic: 53.61 on 11 and 659 DF, p-value: < 2.2e-16.
*— Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1.*

Table 5
Latent variable specifications, variables common to both periods.

Latent Variables:	COVID-19 LOCKDOWN			RE-OPENED TIME		
	Estimate	*Std. Err*	*P(>|z|)*	*Estimate*	*Std. Err*	*P(>|z|)*
Hispanic, Low Income						
% No High School Diploma	0.96	0.011	0.000	1.021	0.007	0.000
% Limited English Speaking	0.931	0.013	0.000	0.851	0.007	0.000
% Uninsured	0.881	0.013	0.001	0.853	0.007	0.000
% Hispanic	0.845	0.01	0.000	0.734	0.007	0.000
% Non-US Citizens	0.663	0.015	0.018			
% Crowded Quarters	0.649	0.015	0.000	0.62	0.008	0.000
Tract Monthly Income	−0.615	0.017	0.028	−0.641	0.011	0.000
% Black	−0.259	0.004	0.000	−0.219	0.003	0.000
% ≥ Age 65	−0.215	0.013	0.000	−0.165	0.01	0.000
% Unemployed	−0.161	0.012	0.000			
Black, Low Income						
% Black	0.825	0.008	0.000	0.789	0.005	0.000
500-year Flood Plane	0.25	0.021	0.000	0.327	0.014	0.000
% Uninsured	0.236	0.01	0.000	0.164	0.007	0.000
% Unemployed				0.284	0.018	0.000
% Single Parent				0.265	0.008	0.000
% Hispanic	−0.255	0.008	0.000	−0.523	0.005	0.000
% ≤ Age 17	−0.302	0.02	0.000			
Tract Monthly Income	−0.358	0.022	0.000	−0.55	0.011	0.000
% Mobile Homes	−0.656	0.03	0.000	−0.23	0.008	0.000
% White	−0.978	0.008	0.000	−0.921	0.005	0.000
Single Parents						
% ≤ Age 17	1.123	0.029	0.000	0.972	0.012	0.000
% Single Parent	0.767	0.028	0.000	0.669	0.009	0.000
% Mobile Homes	0.352	0.025	0.000	0.223	0.01	0.000
% Non-US Citizens	0.215	0.014	0.000			
% Crowded Quarters	0.192	0.014	0.000			
% SNAP Recipients	0.169	0.013	0.000			
500-year Flood Plane	−0.226	0.021	0.000	−0.214	0.013	0.000
% Disabled	−0.587	0.016	0.000	−0.393	0.012	0.000
% ≥ Age 65	−0.658	0.022	0.000	−0.344	0.014	0.000
% Living in Group Quarters				−0.433	0.026	0.000

the value of our dynamic vulnerability index, which provides a time-sensitive and nuanced profile of vulnerability that reflects an evolving context following overlapping disasters. Vulnerability is not a fixed trait of an individual or group; it reflects the present and historic contexts within which individuals and groups are embedded. Resilience is understood to be a function of time, hence vulnerability (which informs resilience) should be, as well. Our modeling methodology supports this advancement in the field.

4.4. Comparing SEM results against a static index of social vulnerability

The use of real data also contributes to the nuanced profiles of social vulnerability identified. Due to the lengthy data collection period, it is possible to create dynamic groupings of shifting cohorts of vulnerable identities and understand profiles of need across time. The dynamic nature of these groupings also allows a unique look at intersectional identities across time; that is, we can examine the interconnectedness of vulnerable identities and identify changes in relation to concurrent disaster and significant events. This contrasts with more traditional metrics of need, such as the CDC/ADSTR SVI. The SVI consists of a single index created from deterministically combined vulnerability themes (socioeconomic status, household composition, disability, minority status and language, and housing type and transportation), comprised of non-overlapping social factors measured by the census (CDC/ATSDR Social Vulnerability Index (SVI), 2024). Though durable and useful for a more large-scale understanding of vulnerability, this static index does not provide the same nuance of intersectional identities within a changing horizon of vulnerability.

We designed an analytical process to formally compare the CDC/ADSTR SVI approach to the proposed SEM model revealing vulnerability identity groupings. Specifically, this allows us to assess formally how the more complex latent vulnerability grouping performs in comparison to the CDC/ADSTR SVI. Table 7 presents this analysis, reporting the final model along with eight different simplifications. Relevant fit indices of all model permutations are reported in Table 7: (1) the 2018 CDC/ADSTR SVI theme groupings, (2) a 'latent variable only' model that excludes independent observed variables from the SEM, (3) a model that removes all latent variable cross-loadings by restricting observed

Table 6
Latent variable specifications, variables unique to lockdown vs *re*-opened period.

COVID-19 LOCKDOWN				RE-OPENED PERIOD			
Latent Variables:	*Estimate*	*Std.Err*	*P(>|z|)*	Latent Variables:	*Estimate*	*Std.Err*	*P(>|z|)*
Low Economic Access				Older Adults			
% No Vehicle	1.101	0.033	0.000	% SNAP Recipients	1.506	0.026	0.000
% Living in Multiunit Buildings	1.012	0.036	0.000	% No Vehicle	1.057	0.019	0.000
% SNAP Recipients	0.968	0.021	0.000	% Disabled	1.021	0.018	0.000
% Unemployed	0.696	0.031	0.000	% Unemployed	0.714	0.050	0.000
% Disabled	0.489	0.015	0.000	% ≥ Age 65	0.566	0.010	0.000
% Single Parent	0.380	0.024	0.000	% Black	0.200	0.004	0.000
Tract Monthly Income	−0.331	0.017	0.000	% Uninsured	−0.318	0.007	0.000
Children				% Limited English Speaking	−0.378	0.008	0.000
% ≤ Age 17	0.947	0.038	0.000	Low Spatial Access			
% Mobile Homes	0.650	0.031	0.000	Low Access to Food	0.387	0.014	0.000
% No High School Diploma	0.380	0.008	0.000	% No High School Diploma	0.156	0.007	0.000
% Single Parent	0.316	0.036	0.000	% Unemployed	−0.332	0.035	0.000
% Black	0.134	0.006	0.000	% Crowded Quarters	−0.392	0.012	0.000
Household Size	0.065	0.017	0.000	% Disabled	−0.474	0.023	0.000
% Living in Group Quarters	−0.125	0.022	0.000	% Living in Multiunit Buildings	−0.580	0.011	0.000
% No Vehicle	−0.427	0.031	0.000	% No Vehicle	−0.953	0.023	0.000
% Living in Multiunit Buildings	−1.123	0.033	0.000	% SNAP Recipients	−1.315	0.030	0.000

Table 7
Comparison of robust fit indices between final model and eight SEM modifications (dependent variable = number of food delivery requests).

COVID-19 LOCKDOWN				
Modification:	Model	CFI	TLI	RMSEA
Standard threshold cut-offs		0.9	0.8	0.08–0.1
Final Model	*COVID-19 Lockdown Period SEM (Fig. 6)*	0.9	0.873	0.089
1.	*CDC/ADSTR SVI Themes*	0.461	0.269	0.241
2.	*Latent Variable Only*	0.691	0.626	0.14
3.	*No cross-loading (except income)*	0.565	0.504	0.162
4.	*Remove Hispanic Low Income latent variable*	0.681	0.626	0.156
5.	*Remove Black Low Income latent variable*	0.78	0.731	0.122
6.	*Remove Single Parents latent variable*	0.779	0.735	0.128
7.	*Remove Access latent variable*	0.716	0.656	0.146
8.	*Remove Children latent variable*	0.818	0.781	0.117
RE-OPENED PERIOD				
Modification:	Model	CFI	TLI	RMSEA
Standard threshold cut-offs		0.9	0.8	0.08–0.1
Final Model	*Re-opened Period SEM (Fig. 7)*	0.912	0.886	0.08
1.	*CDC/ADSTR SVI Themes*	0.439	0.292	0.242
2.	*Latent Variable Only*	0.731	0.674	0.179
3.	*No cross-loading (except income)*	0.65	0.587	0.196
4.	*Remove Hispanic Low Income latent variable*	0.768	0.714	0.128
5.	*Remove Black Low Income latent variable*	0.681	0.609	0.134
6.	*Remove Senior latent variable*	0.814	0.771	0.103
7.	*Remove Single Parents latent variable*	0.824	0.782	0.111
8.	*Remove Access latent variable*	0.83	0.787	0.114

variables (except income) to the latent variable in which they show the strongest effect, and then (4 – 8) by individually excluding each latent variable from analysis. This comparison demonstrates that every simplification of the models presented in this paper leads to a strong loss of statistical significance based on CFI, TLI, and RMSEA. However, it is possible that some periods have more concise vulnerability groupings.

5. Discussion and conclusion

This study reveals the effectiveness of crowdsourced food delivery as a flexible, community resilience tactic that leverages existing crowdsourced mobility availability rather than structurally adding transportation capacity to address food access disruptions. It does so by analyzing the time-space trends of demand for food assistance through data from the non-profit organization *CrowdSource Rescue* to uncover patterns of food insecurity, thereby validating that the platform reached populations known to be food insecure during disaster times when food insecurity is known to spike. It also shows evidence that a volunteer-based food-delivery program such as *CrowdSource Rescue* offers the potential to reach populations whom traditional emergency assistance systems fail to serve.

5.1. Locational characteristics of urban food access resilience: Context and socio-spatial profile of food requests

The SEM regression magnitudes contextualize the idea of who is requesting food assistance: primarily low-income individuals who are recipients of governmental assistance. Studies have shown that individuals already receiving governmental assistance are more likely to seek the aid of food banks (Gorb, 2022; Starkey et al., 1998), which is consistent with our significant finding that areas with higher rates of governmental aid (the *N. Social Program Recipients* variable) were more likely to make food assistance requests during re-opened time. Individual characteristics, as well as intangible, latent characteristics of individuals, like culture and trust, are also expected to play a role in assistance requests, as discussed subsequently in *Section 5.5* of this paper: *Limitations and Future Work*.

When assessing the locational-based linear model (Table 3), the results are striking. For every 1 % increase in the Hispanic population, a census tract sees 0.288 more daily requests, and for every 1 % increase in the Black population, a census tract sees 0.767 more requests. At scale, this indicates 28.8 more requests in a 100 % Hispanic area than elsewhere and 76.7 more requests in a 100 % Black area, as compared to the median value of 13.0 requests per census tract. Prior research shows that low-income communities in Houston are more likely to have more residents of color (Olin, 2020), which is also observed in our modeling process where the inclusion of race in the model causes insignificance of the low-income variable. Our observations about the racial disparity in food needs is also consistent with USDA findings that, compared to the national average of 10.2 % of households experiencing food insecurity, 19.8 % of Black households and 16.2 % of Hispanic households face food insecurity.

Furthermore, while poverty is an insignificant indicator of the number of food delivery requests in our model, it should be noted that 26.5 % of households below the poverty line experience food insecurity (United States Department of Agriculture, 2024). 33.3 % of impoverished households in Houston are Hispanic and 16.8 % are Black

(DataUSA, 2023). These findings are also consistent with the outreach demographics of the Houston Food Bank, a partner organization of *CrowdSource Rescue*: 26 % of those served by the Houston Food Bank are Black and 44 % are Hispanic (Houston Food Bank, 2024). We help address the issue of correlation and paint a more complete picture of vulnerability and food need in the SEM model where we identify separate clustering of *Hispanic, Low Income,* and *Black, Low Income* latent variables. That is, poverty coexists with racial and ethnic minority statuses, but we also underscore some distinct patterns that exist in Hispanic versus Black communities.

Lastly, the location in underserved and hazardous areas play a role for requests. Food insecurity is known to be exacerbated after flooding events. Specifically, many people in Harris County food deserts are cut off from accessing grocery stores or food banks following flood events (Casellas Connors et al., 2023). This is reflected in our modeling by the positive relationship between the number of households in a floodplain and food requests in a census tract. Another aspect of this relationship is explained by the housing availability within floodplains: 35 % of affordable housing units in Houston are located within a floodplain (Park, 2024).

5.2. Time-based characteristics of urban food access resilience: Interplay of economic stressors and climate hazards

The timing of requests also corresponds with known trends in seeking food assistance, though some results may seem initially counterintuitive. Unemployment rates, COVID-19 spread, and COVID-19 lockdown levels all have contributed to large demand spikes at food banks across the country, as also found in our time-based linear model (Table 4) (Kulish, 2020; Ludden, 2023). Disasters are known to be one of the top causes of worldwide hunger (Odubela et al., 2019; WFP, 2024), which is reflected in the significant spike in requests in the week after Winter Storm Uri hit the area. There was a smaller – 90.8 % – uptick in requests due to flooding in the week following Hurricane Hanna and Tropical Storms Marco or Laura. The lesser rise in the wake of these flooding events is likely due to the center of the destruction of these storms on the coastline (FEMA Declared Disasters, 2024), where *CrowdSource Rescue* requests are sparse (see Fig. 1), and due to the evacuation-based nature of flooding events. If residents must evacuate after a disaster, their needs would not originate from their home census tract. This disparity in evacuation-based versus shelter-in-place type storms is also seen in the SEM model: flooding events (an evacuation-based emergency) show a negative relationship with daily requests, whereas COVID-19 positivity rates (a shelter-in-place emergency) show a positive relationship with daily requests. The week following Winter Storm Uri did not exhibit a significant effect on request numbers in the SEM, but this is likely because the winter storm caused an increase in requests in already vulnerable areas with elevated numbers of requests (see Fig. 5) underscoring that the lack of a significant effect needs to be understood in the context of existing need. The interrelationship between these climate disaster events and the ongoing COVID-19 pandemic are controlled for in the model by including time-based variables to specify disaster period. However, the results remain inconclusive illustrating that additional data is needed to further disentangle the way longstanding food insecurity from the pandemic may have affected food insecurity during concurrent climate disasters.

A less intuitive temporal trend is that of the ˆGSPC performance and how it relates to requests: intuitively, one would assume that as the economy improves, purchasing power would increase and food assistance requests would decrease. However, the COVID-19 era economy was marked by economic uncertainty, supply chain disruptions, and shifting demand for goods and services. This led to a spike in inflation concurrent with the economic upturn of the post-quarantine wave of businesses reopening (Economics, 2023). Thus, the trend between increased requests with increased closing prices of the ˆGSPC is most likely due to the interrelationship between stock prices and inflation at this time.

5.3. Characteristics of food vulnerability: Validity of model findings

Validity refers to the degree to which a model measures what it claims to measure. Both the linear and structural equation modeling performed in this study reveal trends in line with what is already known about food insecurity and food bank demand peaks, namely:

1. Individuals who already receive assistance are proactive about requesting assistance (Gorb, 2022; Starkey et al., 1998).
2. Areas with higher rates of Black and Hispanic residents see higher rates of food insecurity (United States Department of Agriculture, 2024) and make more requests for assistance (Houston Food Bank, 2024).
3. Climate disasters cause a spike in demand for assistance (Odubela et al., 2019; WFP, 2024), and residence in a floodplain corresponds to higher numbers of requests (Casellas Connors et al., 2023).

The resonance of the findings of this investigation with existing research into food insecurity and patterns seen at food banks points to the efficacy of the crowdsourced assistance model. The groups who are known to be at risk of food insecurity are also overwhelmingly the groups making requests and receiving support from *CrowdSource Rescue*. This finding has implications for future community resilience research exploring how to best address resource disruptions. Mobility of households and traditional government support can be complemented by spontaneous volunteer models to reach vulnerable target audiences. The only exception to the validation of need profiles is shown in tracts with high numbers of children. However, this may be due to the elimination of all requirements for free lunch at public schools throughout the pandemic (Herndon, 2024).

Further, our dynamic grouping of vulnerable populations through structural equation modeling presents a better method of understanding vulnerability than a static index. While static indices, such as the CDC/ADSTR SVI, deterministically group vulnerable populations through non-overlapping census metrics, vulnerable households often have intersectional identities characterized by several facets included in a static index. By dynamically processing need profiles, we can uncover more nuanced groupings of vulnerable identities that represent a significant improvement on the understanding of vulnerability from a static index (see Section 4.4 for an in-depth comparison of the SEM results to the CDC/ADSTR SVI).

5.4. Practical implications

There are several ways to use these findings in practice. There are listed as follows.

- Public agencies such as FEMA can promote community resilience by partnering with crowdsourcing based organizations to better cope with emergency-based shortages to essential resources. This can increase the resilience of urban food access after complex disaster events where either the transportation network is disrupted, or people's mobility is impaired, by keeping the system operational (reliability). Such investments in partnerships can help address long-term gaps in food access so that emergency systems have the resources needed to respond to a crisis without additional strain on the system (resourcefulness). This mirrors the importance of contingency planning in the aftermath of disruptions (Faturechi and Miller-Hooks, 2015).
- For operational and logistics purposes, the three model investigations reveal the main differentiators that ought to be accounted for in trying to predict and prepare for resource delivery. These factors are summarized in Fig. 9. The geographic analysis shows that operations need to account for differences in long-

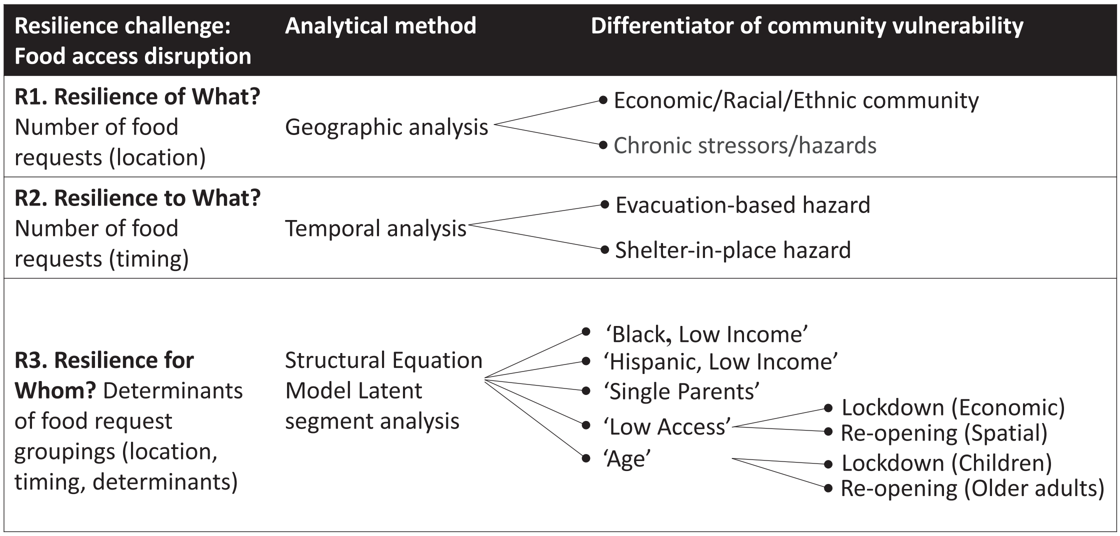

Fig. 9. Highlights of differentiators for food requests.

standing flood-risk and existing poverty characterizing different communities. Further, the analysis shows that there are important dynamics to consider, with evidence that hazards that require sheltering-in-place have differential effects on needs than hazards that require evacuation. This suggests a need to consider the type of hazard, as well as overlapping emergencies when planning for emergency logistics.

- The sensitivity testing of the SEM model suggests that simplifying the analysis of vulnerable population segments comes at a high cost. Therefore, agencies and operators should consider implementing the type of dynamic vulnerability analysis proposed in this paper. An especially valuable insight is that the vulnerability profiles are quite distinct comparing lockdown to re-opened times, suggesting that profiling different needs is justified.

5.5. *Limitations and future work*

There are four primary limitations to this study presenting opportunities for future work:

1. The data were limited to one geographic region of the U.S., and the sample was not representative, so the findings are not generalizable, and individual-level sociodemographic characteristics (e.g., gender, race/ethnicity, etc.) were not available in the dataset. While this was partially addressed by using data fusion, proxy variables were only able to be matched to the census tract level, which could result in the under-representation of those requesting assistance. Ideally, future work should also incorporate data on repeat requests, as well as personal latent variables, such as trust) obtained through communication with community members, including focus groups in key geographic areas.
2. Since the realization of an innovation's benefits requires a critical mass of users, both the supply and demand sides need to be understood. Prior research indicates a shortage of volunteers during the pandemic lockdown (Leddy et al., 2020), due in part to volunteers typically being older adults or retired (Castro et al., 2021). The data used in this study represent the demand side of crowdsourced food delivery, but many questions remain unanswered about the supply side of the system. For example, how does willingness to volunteer change over time following a sudden onset crisis, and what motivating incentives may assist in recruiting additional volunteers?
3. This study presents an analysis of effectiveness of volunteer-based food delivery based on a comparison of populations served by *CrowdSource Rescue* as compared to known profiles of need. A fitting next step would be to study routing algorithms to optimize delivery, similar to studies done for other humanitarian logistics platforms (Davis et al., 2014; Bartholdi et al., 1983). A network modeling approach could also approximate delivery location with finer granularity and therefore use distance to the nearest food pantry or grocery store as a variable in the analysis, rather than the more general binary 'access to healthy food' variable analyzed in this study due to data anonymization.
4. This study uses data from only one non-profit, which only allows highlighting profiles of vulnerable populations who effectively make requests. Though the identified latent variables highlight key food-insecure populations, this study may not allow for a comprehensive understanding of food insecurity due to the limited scope of data. Some socially vulnerable populations are likely to receive food assistance by other means and would therefore be excluded from the identified need profiles in this study. However, the socially vulnerable populations identified by the two structural equation models are important to the understanding of which populations will utilize the novel platform of *crowdsourced food assistance*. Recreating the *CrowdSource Rescue* model in other cities would provide more rich data to better understand universal effectiveness of crowdsourced food assistance as a resilience tactic.

CRediT authorship contribution statement

Gretchen Bella: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Elisa Borowski:** Writing – review & editing, Writing – original draft, Investigation, Data curation, Conceptualization. **Amanda Stathopoulos:** Writing – review & editing, Writing – original draft, Supervision, Resources, Methodology, Formal analysis, Conceptualization.

Data availability

The authors do not have permission to share data.

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Appendix A. SEM results

Table A-1
COVID-19 lockdown structural component model results.

COVID-19 LOCKDOWN			
Fit Statistics:			
Number of observations			3491
Robust Comparative Fit Index (CFI)			0.900
Robust Tucker-Lewis Index (TLI)			0.873
Robust RMSEA			0.089
Regressions:	*Estimate*	*Std.Err*	*$P(>\lvert z\rvert)$*
N. requests ~			
Black, Low Income	0.219	0.026	0.000
% COVID Positivity	0.106	0.021	0.000
Unemployment Rate	0.066	0.016	0.000
Household Size	−0.030	0.016	0.054
N. Social Program Recipients	−0.079	0.017	0.000
Hispanic, Low Income	−0.081	0.024	0.001
Single Parents	−0.101	0.025	0.000
Covariances:	*Estimate*	*Std.Err*	*$P(>\lvert z\rvert)$*
% Non-US Citizens ~~			
% Limited English Speaking	0.108	0.007	0.000
% ≤ Age 17 ~ ~			
% Living in Group Quarters	−0.293	0.037	0.000
Tract Monthly Income ~~			
% Living in Group Quarters	−0.208	0.023	0.000
% No Vehicle ~~			
% Living in Group Quarters	0.191	0.018	0.000
Hispanic, Low Income ~~			
Black, Low Income	−0.206	0.017	0.000
Single Parents	0.413	0.018	0.000
Low Economic Access	−0.081	0.017	0.000
Children	−0.165	0.020	0.000
Black, Low Income ~~			
Single Parents	−0.143	0.023	0.000
Low Economic Access	0.722	0.011	0.000
Children	0.606	0.015	0.000
Single Parents ~~			
Low Economic Access	−0.287	0.023	0.000
Children	−0.565	0.023	0.000
Low Economic Access ~~			
Children	0.750	0.012	0.000

Table A-2
Re-opened time structural component model results.

Fit Statistics:				Covariances:	*Estimate*	*Std. Err*	*$P(>\lvert z\rvert)$*
Number of observations			9143	% ≥ Age 65 ~ ~			
Robust Comparative Fit Index (CFI)			0.912	% Living in Group Quarters	−0.240	0.012	0.000
Robust Tucker-Lewis Index (TLI)			0.885	Tract Monthly Income ~~			
Robust RMSEA			0.084	% Living in Group Quarters	−0.213	0.011	0.000
				% Limited English Speaking ~~			
Regressions:	*Estimate*	*Std. Err*	*$P(>\lvert z\rvert)$*	% ≥ Age 65	0.105	0.003	0.000
N. requests ~				% No Vehicle ~~			
500-Year Flood Plane	0.254	0.041	0.000	% Living in Group Quarters	0.156	0.008	0.000
Older Adults	0.089	0.024	0.000	% Crowded Quarters ~~			
N. Social Program Recipients	0.054	0.016	0.001	% ≤ Age 17	0.113	0.003	0.000
Hispanic, Low Income	0.031	0.008	0.000	% Disabled ~~			
During Flood Event	−0.013	0.006	0.018	% Living in Group Quarters	−0.215	0.015	0.000

(*continued on next page*)

Table A-2 (*continued*)

Fit Statistics:				Covariances:	*Estimate*	*Std. Err*	*P(>|z|)*
During Freeze Event	−0.014	0.003	0.000	% Black ~~			
Black, Low Income	−0.038	0.017	0.028	% White	−0.098	0.005	0.000
Unemployment Rate	−0.046	0.011	0.000	% Disabled ~~			
Single Parents	−0.074	0.012	0.000	% ≤ Age 17	−0.009	0.013	0.497
Low Spatial Access	−0.085	0.023	0.000	% No Vehicle ~~			
				% Living in Multiunit Buildings	0.206	0.009	0.000
				% Hispanic ~~			
				Tract Monthly Income	−0.108	0.004	0.000
				% Uninsured ~~			
				% Unemployed	0.074	0.004	0.000
				% No High School Diploma ~~			
				% Mobile Homes	0.082	0.004	0.000
				Hispanic, Low Income ~~			
				Black, Low Income	−0.093	0.012	0.000
				Older Adults	−0.065	0.016	0.000
				Single Parents	0.502	0.008	0.000
				Low Spatial Access	−0.276	0.016	0.000
				Black, Low Income ~~			
				Older Adults	0.523	0.010	0.000
				Single Parents	0.011	0.010	0.293
				Low Spatial Access	0.061	0.012	0.000
				Older Adults ~~			
				Single Parents	0.079	0.012	0.000
				Low Spatial Access	0.757	0.009	0.000
				Single Parents ~~			
				Low Spatial Access	−0.149	0.011	0.000

Appendix B. Visual presentation of latent variable path diagrams

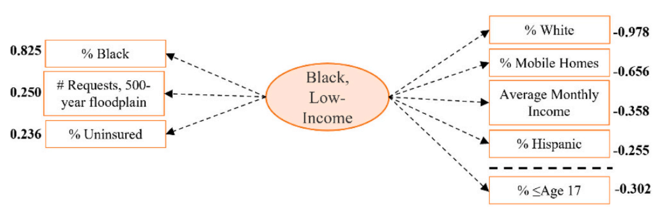

Fig. 1a. COVID-19 lockdown black, low income latent variable path diagram.

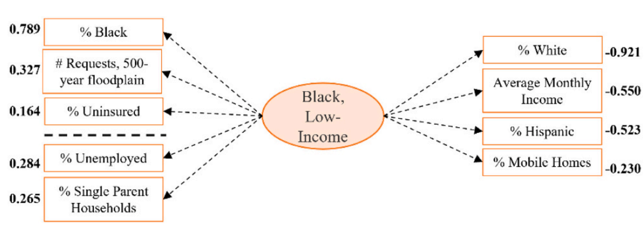

Fig. 1b. Re-opened period black, low income latent variable path diagram.

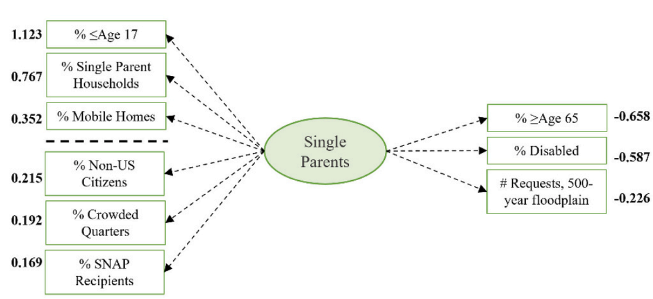

Fig. 2a. COVID-19 lockdown single parents latent variable path diagram.

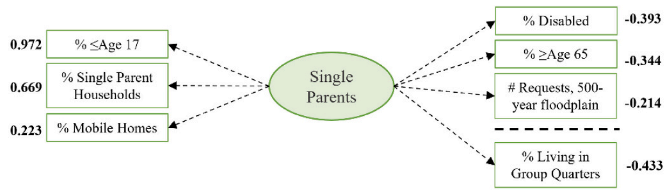

Fig. 2b. Re-opened period single parents latent variable path diagram.

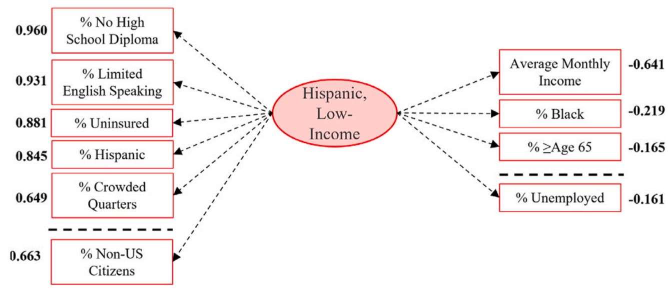

Fig. 3a. COVID-19 lockdown hispanic, low income latent variable path diagram.

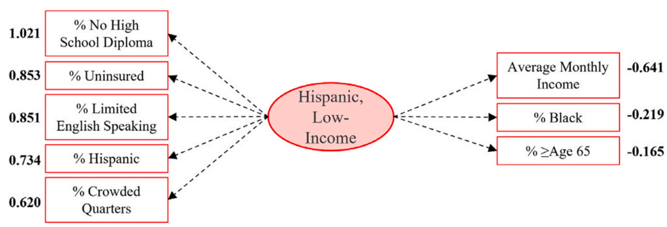

Fig. 3b. Re-opened period hispanic, low income latent variable path diagram.

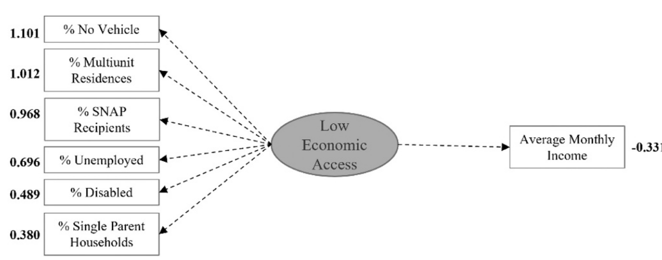

Fig. 4a. COVID-19 lockdown low economic access latent variable path diagram.

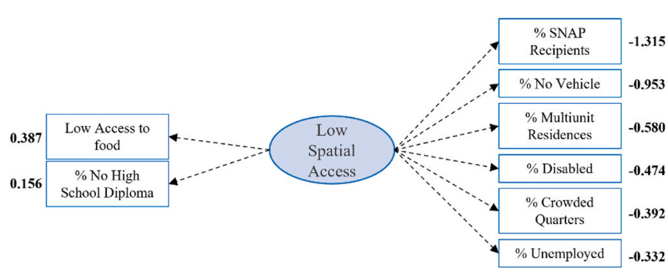

Fig. 4b. Re-opened period low spatial access latent variable path diagram.

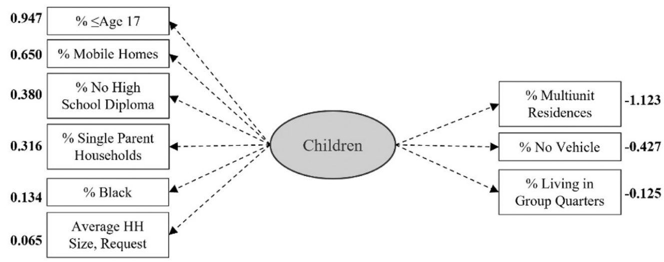

Fig. 5a. COVID-19 lockdown children latent variable path diagram.

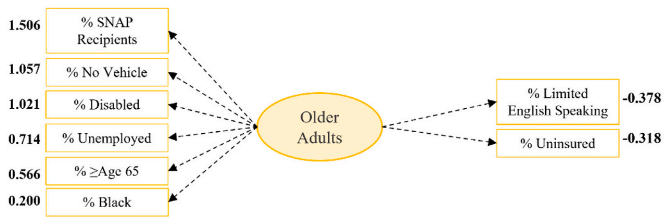

Fig. 5b. Re-opened period older adults latent variable path diagram.

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