

Access to Food in a Severe Prolonged Disruption:  
The Case of Grocery and Meal Shopping During the COVID-19 Pandemic

by  
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## ABSTRACT

The COVID-19 pandemic has revealed the fault lines in society. Whether it be remote work, remote learning, online shopping, grocery and meal deliveries, or medical care, disparities and inequities among socio-economic and demographic groups leave some segments of society more vulnerable and less adaptable. This thesis aims to identify vulnerable and less adaptable groups in the context of access to food. Using a comprehensive behavioral survey data set collected during the height of the pandemic in 2020, this thesis aims to provide insights on the groups that may have experienced food access vulnerability during the disruption when businesses and establishments were restricted, the risk of contagion was high, and accessing online platforms required technology-savviness and the ability to afford delivery charges. This thesis presents estimation results for a simultaneous equations model of six endogenous choice variables defined by a combination of two food types (groceries and meals) and three access modalities (in-person, online with in-person pickup, and online with delivery). The model estimation results show that attitudes and perceptions play a significant role in shaping pandemic-era access modalities. The model revealed that even after controlling for a host of attitudinal indicators, minorities, those having low household incomes, those living in low-density or rural locations, females, and those with lower educational attainment are particularly vulnerable to being left behind and experiencing challenges in accessing food during a severe and prolonged disruption. Social programs should aim to provide these vulnerable groups with tools and financial resources to leverage online activity engagement and access modalities. Policy recommendations to increase food access for the most vulnerable in future disruption scenarios are explored.

## DEDICATION

To my parents, for their unconditional encouragement of all my academic aspirations and for their constant friendship and emotional support, which have been invaluable to my accomplishments.

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## TABLE OF CONTENTS

	Page
LIST OF TABLES .....	vi
LIST OF FIGURES.....	vii
CHAPTER	
1. INTRODUCTION.....	1
1.1 Objectives .....	4
1.2 Organization.....	5
2. LITERATURE REVIEW OF FOOD ACCESS .....	6
2.1 Food Access Vulnerabilities and Aid Programs During the Pandemic.....	6
2.2 The Pandemic Impact on Online Food Shopping .....	9
2.3 Socio-Demographic Characteristics of Those Shopping Online for Food ....	10
2.4 Role of Attitudes in Shaping Online and In-person Shopping Modalities ....	12
2.5 Contribution of the Study to the Field.....	13
3. COVID FUTURE SURVEY ANALYSIS DATA SET.....	15
3.1 Overview of Survey and Sample Characteristics.....	15
3.2 Endogenous Variables and Attitudinal Indicators .....	18
3.3 Descriptive Analysis of Endogenous Variables.....	32
4. METHOD OF STUDYING ENDOGENOUS VARIABLE INTERACTIONS ..	43
4.1 Model Structure .....	43
4.2 Model Estimation Methodology.....	45
5. MODEL ESTIMATION RESULTS .....	50
5.1 Latent Constructs Model Component.....	50

CHAPTER	Page
5.2 Multivariate Model of Behavioral Outcomes .....	56
6. POLICIES FOR ADDRESSING FOOD ACCESS DISPARITIES .....	63
6.1 Aid Interventions for Overcoming Health Risks Due to Social Isolation .....	64
6.2 Aid Interventions to Address Food Insecurity Due to the Digital Divide .....	66
6.3 Aid Interventions by Subgroup .....	68
7. SUMMARY AND CONCLUSIONS .....	71
REFERENCES .....	77

## LIST OF TABLES

Table	Page
1. Sample Characteristics.....	17
2. Determinants of Latent Variables and Loadings on Indicator .....	52
3. Estimation Results of Grocery and Meal Model Components .....	58
4. Vulnerable Population Estimation Coefficient Signs and Policy Implications....	62



## LIST OF FIGURES

Figure	Page
1. In-Store Grocery and Meal Frequencies Pre- vs. Peak-Pandemic .....	20
2. Grocery and Meal Pickup Frequencies Pre- vs. Peak-Pandemic .....	21
3. Grocery and Meal Delivery Frequencies Pre- vs. Peak-Pandemic .....	22
4. Modality Frequencies Pre- vs. Peak-Pandemic by Children in Household .....	23
5. Modality Frequencies Pre- vs. Peak-Pandemic by Household Income .....	25
6. Modality Frequencies Pre- vs. Peak-Pandemic by Household Vehicles .....	29
7. Modality Frequencies Pre- vs. Peak-Pandemic by Gender.....	31
8. Response Distributions for Attitudinal Indicators of Latent Constructs .....	33
9. Coronavirus Concern by Weekly Shopping Modality Frequency .....	34
10. Age Group by Concern for Having a Severe Reaction to the Coronavirus .....	35
11. Age Group by Weekly Frequency of Shopping for Meal Delivery .....	36
12. Online Business Meeting Perceptions by Weekly Modality Frequency.....	37
13. Educational Attainment by Perceptions of Online Learning Alternatives.....	38
14. Educational Attainment by Weekly Frequency of Grocery Delivery .....	39
15. Affinity for Seeing People by Weekly Shopping Modality Frequency .....	40
16. Household Income by Affinity for Seeing and Being Around People.....	41
17. Household Income by Weekly Frequency of In-store Grocery Shopping.....	38
18. Modeling Framework .....	44
19. Latent Construct Factor Scores by In-store Engagement Frequency.....	54
20. Latent Construct Factor Scores by Pickup Engagement Frequency .....	55
21. Latent Construct Factor Scores by Delivery Engagement Frequency .....	56

# CHAPTER 1

## INTRODUCTION

Access to good food is critically important to leading a healthy life. Even in a wealthy and well-developed nation such as the United States, 38 million people struggle with hunger (USDA, 2022), and 13.8 million households, which comprise 10.5 percent of all US households, were considered food insecure at some time during 2020 (USDA, 2022). The proportion of under-nourished people globally stands at about 10 percent (i.e., 828 million people) (WHO, 2022). These statistics suggest that, despite enormous progress in advancing food security, access to good food remains challenging for many. Access to good food generally involves ensuring that a variety of healthy, wholesome food options are available within close proximity to the household and that the food options are affordable. In the United States, nearly 20 million people live in a food desert, which the US Department of Agriculture defines as a place where at least one-third of the population lives greater than one mile away from a supermarket for urban areas, or greater than 10 miles away for rural areas (2021). In other words, the ability to access good food by traversing distances is critical to good health, thus implying that transportation plays a major role in enabling food security.

During a severe disruptive event, food security may come under threat (Mouloudj et al., 2020; Savary et al., 2020). This was seen during the height of the COVID-19 pandemic. Due to public health concerns, many jurisdictions ordered businesses to close, restaurants to cease operations, and grocery stores to limit hours and occupancy levels (Niles et al., 2020). Many individuals, especially those with immunocompromised systems and other underlying health conditions, feared going to stores or restaurants for fear of

becoming infected (Ahmed et al., 2021). Even individuals without such health conditions avoided going to food establishments to avoid risks (Jacobsen & Jacobsen, 2020). However, in response to the COVID-19 disruption, many grocery stores and restaurants quickly ramped up their virtual options. Grocery stores enabled systems allowing people to order groceries online and then travel to the store to pick them up (in a reasonably touchless transaction system) or have them delivered to the home. Similarly, restaurants also pivoted rapidly, implementing systems that made it easy to order freshly prepared meals over the phone or online. The consumer could travel to the restaurant to pickup the meal or use a delivery service to deliver the food to the doorstep. All of these virtual options (online grocery with pickup/delivery; online restaurant with pickup/delivery) provided many with the ability to access food during the height of the pandemic while minimizing exposure and risk of contagion. This represents a high degree of adaptability, with systems rapidly adjusting to circumstances to retain access to goods and services.

The extent to which different socio-economic and demographic groups utilized such services and options is worthy of exploration. Many pickup and delivery services charge an additional fee, possibly rendering such services unaffordable for low-income households (Rummo et al., 2020). Some households may be on the wrong side of the digital divide or not have the technology-savviness to use virtual platforms for ordering groceries and fresh meals (Ali et al., 2021). Individuals in these households may feel compelled to go in-person (to avoid paying a fee), even though they may be concerned about their safety amid a pandemic. Individuals who are unable or unwilling to travel (due to health risks) and unable to take advantage of virtual platforms (due to affordability or technology constraints) may end up experiencing food insecurity (Ahmed et al., 2021; Ali et al., 2021).

This thesis aims to explore and identify the market segments most at risk of food insecurity in the wake of a severe, prolonged disruption such as the COVID-19 pandemic. Subgroups capable of accessing food through virtual means may be considered *adaptable*, i.e., they can adapt to circumstances and not be compromised with respect to food and meals. On the other hand, subgroups of the population unable to travel and afford or use virtual platforms are left behind and *vulnerable*. These groups do not exhibit adaptability and need assistance through public services to ensure they do not lose access to healthy food and meals. Through a comprehensive modeling effort, this thesis aims to identify the subgroups that are adaptable and those that are vulnerable. Not only does the study seek to characterize the subgroups in terms of socio-economic and demographic attributes, but it also seeks to characterize them in terms of their attitudes, perceptions, and risk averseness or tolerance. The thesis utilizes a rich data set collected through a survey administered across the United States. The data set, collected as part of the COVID Future Survey study, includes all respondent records for the first wave (Wave 1A and Wave 1B records) of the panel survey conducted at the height of the pandemic in 2020. The extensive survey is able to obtain a detailed picture of physical and virtual activity engagement during the pandemic.

The thesis considers two commodities: groceries and freshly prepared meals. There are three access modalities for each commodity type: in-person, online order + in-person pickup, and online order + home delivery. Thus, there are six possible options for accessing food and meals. In the survey data set, respondents have recorded the number of days they participated in each of these six modalities in the past seven days. The six frequency variables constitute the thesis's endogenous (dependent) variables; they are all modeled

jointly in a simultaneous equation modeling framework, thus enabling the consideration of all six dimensions as a lifestyle choice bundle, where decisions to participate in each of the modalities are made contemporaneously. As the frequency variables may be treated as ordered choices, the multivariate ordered probit modeling methodology is adopted in this thesis. The joint modeling framework explicitly accounts for error correlations across the six endogenous variables, thus capturing the potential presence and effects of correlated unobserved factors that simultaneously impact multiple endogenous variables. The Generalized Heterogeneous Data Model (GHDM) modeling methodology (Bhat, 2015) was adopted for model estimation.

## **1.1 Objectives**

In light of the COVID-19 pandemic, food establishments encountered constraints in their ability to provide service to customers, such as reduced operating hours, limited capacity, discontinuation of in-store purchases or dine-in, and, in some instances, complete closure. Additionally, in-store shopping put those accessing food at increased risk of catching the coronavirus. Finally, purchasing food via online modalities required both technology-savviness to complete the task and household incomes sufficient to cover online fees. Considering these challenges faced by the food service industry, the significant health-related risks of shopping in-store, and the skills and resources necessary to purchase food online, the objectives of this thesis are as follows:

- Examine the interaction and substitution relationships of in-person versus online food modality engagement frequency during disruption, comparing grocery and meal activity

- Differentiate between the use of online pickup and delivery services
- Examine the impact of attitudes on food modality engagement frequency
- Characterize subgroups, based on socio-demographic and economic attributes, who may have encountered decreased access to food or heightened health risks based on modality engagement frequencies (noting the caveat that engagement frequency has limitations in speaking to food access)

The findings of this thesis, centered around these objectives, will inform policy implications for food access in future severe and prolonged disruptions.

## **1.2 Organization**

The remainder of the thesis is organized as follows. The second chapter explores the current literature in this field and discusses how this thesis will build on existing knowledge. The third chapter provides an overview of the data set used in the study. The fourth chapter presents an overview of the GHDM modeling methodology and framework. The fifth chapter presents detailed model estimation results. The fifth chapter discusses policy implications based on model estimation results. The sixth and final chapter summarizes and overviews the conclusions of this thesis.

## **CHAPTER 2**

### **LITERATURE REVIEW OF FOOD ACCESS**

This literature review aims to examine the impact of the COVID-19 pandemic on food access, with a particular focus on online grocery and meal shopping. The review explores food insecurity and subsequent aid provided during the pandemic, highlights the socio-demographic and economic characteristics of those who are more likely to shop for food online, and examines the attitudes that influence shopper's behavior. Additionally, the chapter offers a comprehensive overview of the intricate interplay between the pandemic, online food shopping, and individual-level factors that influenced food access during the pandemic. Moreover, this review identifies the areas that necessitate further research to enhance the community's understanding of the topic.

#### **2.1 Food Access Vulnerabilities and Aid Programs During the Pandemic**

The COVID-19 pandemic triggered or exacerbated food access vulnerability in the United States for many households (Lauren et al., 2021; O'Hara & Toussaint, 2021). Food access vulnerabilities have serious implications for individuals' health and wellbeing and have the potential to amplify existing inequalities experienced by marginalized population groups (Lauren et al., 2021). A number of programs were implemented in the United States during the pandemic to minimize increasing food insecurity. The Families First Coronavirus Response Act (FFCRA), passed in March 2020, increased funding for the Supplemental Nutrition Program for Women, Infants, and Children (WIC) and provided assistance for children no longer obtaining meals in school (Library of Congress, 2020). The Coronavirus Aid, Relief, and Economic Security (CARES) Act, passed in March 2020, provided

additional funding and flexibility for food purchases for schools as well as supplemental funds for the Supplemental Nutrition Assistance Program (SNAP) (Library of Congress, 2020). The American Rescue Plan passed in March of 2021 increased SNAP's benefits by 15 percent (USDA, 2021). One study examining the effectiveness of the American Rescue Plan's aid found that it resulted in a total of 850,000 cases of food insufficiency, defined as instances of not having enough to eat in the past week, from occurring (Bryant & Follett, 2022). The CARES Act, the Consolidated Appropriations Act, and the American Rescue Plan also included stimulus checks which were provided to those under the maximum income limit in varying amounts depending on the round of stimulus (U.S. Department of the Treasury, 2021). Additionally, the American Rescue Plan increased Child Tax Credit reliefs for families with qualifying children by \$1,000 (White House, 2021). These checks and credits provided financial relief during the pandemic.

However, despite these efforts, millions of Americans still struggled to safely access sufficient and nutritious food during the pandemic (USDA, 2022). A study conducted in mid-March 2020 in the United States examining the impacts of the pandemic on low-income individuals, found that 64 percent of low-income adults were not food secure (Wolfson & Leung, 2020). Other studies had similar findings of increased food insecurity following the pandemic outbreak, with one study finding a 32 percent increase in household food insecurity (Niles et al., 2020).

There are many reasons for this increase in food insecurity, including but not limited to decreased household income resulting from pandemic-induced unemployment, limited store and restaurant hours and capacity, increased restaurant closures, decreased access to meals at school for children, and food hoarding and shortages (Heuer et al., 2020).



Households that were food insecure before the pandemic faced exacerbated food acquisition challenges during the pandemic, as many previous approaches to maximizing the food bought with limited funds were made more difficult or impossible (Kinsey et al., 2020). For instance, appropriating food from social circles, food pantries, and soup kitchens was complicated by social distancing policies and food assistance program closures. Social distancing orders made sharing club store membership cards or shopping in groups for bulk savings at stores like Costco more difficult. A strategy of visiting multiple stores to purchase food for the lowest possible prices of each item put shoppers at increased risk of exposure to the virus. Finally, stocking up on food to limit the total number of grocery trips required was impossible for low-income households with limited funds. In addition to these challenges in accessing food, purchasing food in person was especially dangerous at the peak of the pandemic for those who have increased health vulnerability or live with someone who does, notably for older adults and the immunocompromised (Hansson et al., 2022; Singu et al., 2020).

The research examined in this section illustrates how the COVID-19 pandemic exacerbated food access vulnerabilities in the United States, leading to increased food insecurity for many households, particularly those already facing economic challenges. Programs were implemented to alleviate the situation, but they were not enough to prevent millions of Americans from struggling to access sufficient and nutritious food during the pandemic. The pandemic increased unemployment, limited store and restaurant hours and capacity, and increased food hoarding and shortages leading to increased food insecurity. Furthermore, households that were food insecure before the pandemic faced exacerbated food acquisition challenges during the pandemic due to social distancing policies and food

assistance program closures. This overview of food insecurity and relief initiatives during the pandemic provides a foundational framework for understanding the advantages in terms of health, security, and access benefits that online food shopping provided during the pandemic and the susceptibility to food insecurity faced by those who were unable to utilize these online modalities.

## **2.2 The Pandemic Impact on Online Food Shopping**

Many stores and restaurants began offering or improving their existing online grocery and meal pickup and delivery options, as customers aimed to reduce their frequency of in-store trips to purchase groceries or meals during the pandemic. Both grocery and meal shopping saw a sharp spike in spending and engagement during the peak of the pandemic (Aryani et al., 2022; Chenarides et al., 2020; Jensen et al., 2021). A study from June 2020 in the United States found that 55 percent of respondents shopped for groceries online at least once during the pandemic peak, and 20 percent of those shoppers were doing so for the first time (Jensen et al., 2021). The Food Marketing Institute (2020) found that the percentage of online grocery shopping nearly doubled following the pandemic outbreak. Similarly, Google searches for online meal delivery platforms like Doordash and Grubhub were found to increase sharply in March 2020, nearly doubling for some platforms (Belarmino et al., 2021). Chenarides et al. (2020) found a 255 percent increase in households engaging in grocery pickup and a 158 percent increase in households engaging in grocery delivery shopping during the peak of the pandemic.

Increased online food shopping is attributable to a multitude of causes, such as the need to shop more frequently or travel to multiple stores due to food shortages (Aryani et

al., 2021; Jensen et al., 2021); not being healthy enough to shop in-person (Chenarides et al., 2020), concerns about catching the COVID-19 virus when shopping in-store (Chenarides et al., 2020; Jensen et al., 2021); as well as convenience related reasons such as saved time, a simplified shopping experience, and eliminated need to travel (Aryani et al., 2021; Jilcott Pitts et al., 2020).

### **2.3 Socio-Demographic Characteristics of Those Shopping Online for Food**

The literature illustrated above that online food shopping significantly increased during the pandemic and offered a multitude of advantages to its users. However, equitable access to these modalities remains a challenge for certain segments of the population. Some of the barriers that limit portions of society from using online food access platforms include online shopping fees (Jilcott Pitts et al., 2020), an inability to purchase food online without an e-wallet or bank card (Aryani et al., 2021), fewer deals online compared to in-person shopping experiences (Jilcott Pitts et al., 2020), and lack of understanding or resources that prohibit the use of online services (Aryani et al., 2021).

A large body of literature also explores who uses online food platforms and who does not, and findings vary based on many sociodemographic and economic characteristics as well as by modality (grocery versus meal and pickup versus delivery). It should be noted that many studies do not differentiate between pickup and delivery modes, but rather combine the two modes when examining online shopping behavior. There is a consensus that as age increases, the likelihood of shopping for either groceries or meals online decreases (Figliozi et al., 2021; Jensen et al., 2021; Kim & Wang, 2021; Wang et al., 2021; Zatz et al., 2021). There also is concurrence that individuals or households with

higher incomes engage in online food shopping more frequently than lower income households (Dias et al., 2020; Kim & Wang, 2021; Naseri & Elliot, 2011; Wang and Schrimgeour, 2011). Those with higher incomes were also found to eat meals at restaurants more frequently (Dias et al., 2020; Lund et al., 2017).

The findings on the frequency of using online grocery access modalities by gender vary. Some studies find men more likely to shop for groceries online (Kim and Wang et al., 2021; Naseri & Elliot, 2011; Wang et al., 2021), while other studies find women more likely to engage in these online grocery modalities (Droogenbroeck & Hove, 2020; Wang et al., 2020; Zatz et al., 2021). Men were found to be more likely to engage in online meal purchases compared to women (Kim & Wang, 2021; Wang et al., 2020). Findings regarding children in the household are consistent. Studies show that households with children present are more likely to shop for food online (Dias et al., 2020; Harris et al., 2017; Jensen et al., 2021; Younes et al., 2022; Zatz et al., 2021). Full-time employment has been found to increase the likelihood of online grocery shopping (Jensen et al., 2021). Increased workers in the household have been associated with increased in-store meal engagement whereas households with no workers were more likely to order meals for delivery (Dias et al., 2020). Higher educational attainment was associated with greater online food purchases (Naseri & Elliott, 2011; Wang & Schrimgeour, 2021; Younes et al., 2022).

According to these studies, the characteristics of people, such as their age and income, play a significant role in their online food shopping behavior. Moreover, these studies have made a distinction between buying food in a physical store versus online, but

very few have examined the differences between pickup and delivery options, especially during the COVID-19 pandemic.

#### **2.4 Role of Attitudes in Shaping Online and In-person Shopping Modalities**

The research examining how attitudes, perceptions, and perspectives of individuals impact online food shopping engagement is more limited than the research on the impacts of socio-demographic and economic characteristics. Most studies exploring the impact of attitudes on online shopping behavior focus on concerns about the COVID-19 pandemic. These findings show increased rates of online food access platform use in households that are concerned about the pandemic and its health and safety impacts (Figliozi et al., 2021; Jensen et al., 2021; Nguyen et al., 2021; Yenerall et al., 2022). Similarly, households with health and safety concerns were less likely to shop in a store for food (Grashuis et al., 2020), whereas households who believed society was overreacting to the pandemic were less likely to decrease in-person shopping (Younes et al., 2022).

Several studies explored how attitudes about substituting online activities for in person activities have impacted online shopping behavior. Virtual activity participation significantly increased during the pandemic as people substituted in-person interactions for alternative modalities such as virtual socialization, online school, online shopping, virtual medical visits, and telecommuting (Chakraborty et al., 2020). The research studying the correlation between virtual activity participation and online shopping is limited, but a few studies do suggest positive correlations between these attitudes and behaviors. Two studies found that increased technology savviness is associated with increased online shopping (Akhter, 2015; Syahrivar et al., 2020). Similarly, Ali et al. (2021) found that those who

were less comfortable and more insecure about online activity engagement were less likely to adopt online food delivery. Women, those with lower incomes, and those with lower educational attainment were more likely to be insecure or uncomfortable with online shopping. A final study found that those who use social networking platforms more frequently were more likely to adopt and use online shopping platforms (Zhang et al., 2017). These findings illustrate how those who are most comfortable and willing to use online platforms are more likely to engage in online food purchasing activities and how those less comfortable with technology are likely to have reduced access to these online services.

To the best of the authors' knowledge, no studies have yet to analyze the connection between the inclination to socialize and online shopping adoption. However, some research has been conducted on the relationship between social interaction propensity and social distancing behavior. One study found that individuals with higher extroversion scores were less likely to follow social distancing protocols (Carvalho et al., 2020). Another study found that one common reason for breaking social distancing mandates included feeling stressed or alone during isolation (Coroiu et al., 2020). While these studies do not speak directly to online food shopping behavior, they do imply that those who most enjoy in-person social interactions are more likely to break social distancing mandates to engage in such interactions (e.g., conversations at a grocery store or restaurant).

## **2.5 Contribution of the Study to the Field**

In summary, the literature review exposed important knowledge gaps in addressing food insecurity during disruptions and examining the characteristics and attitudes of those using

online food modalities. There are clear limitations to the reach of policies implemented to ameliorate food insecurity during the pandemic. Online shopping has been explored by socio-demographic and economic characteristics, but further research differentiating between online pickup and delivery modalities, especially during disruptions, is needed. Finally, research exploring how attitudes impact online food shopping behavior is limited, and studies accounting for social propensity impacts on online shopping behavior could not be identified.

This thesis aims to examine relationships between in-person and online grocery and meal shopping, differentiate between the use of pickup and delivery services, examine the impact of attitudes on engagement in these services, and characterize subgroups with potentially limited food access during disruption. Additionally, this thesis overcomes limitations in existing research in the following ways. First, six food shopping modalities are explored, including separate categories for pickup and delivery for both groceries and meals. Second, three latent constructs are included in the modeling effort, informed by three attitudinal statements each, meaning that attitudes regarding COVID-19 risk perceptions, acceptance of online modality alternatives, and social propensity are all accounted for in the modeling effort. The thesis utilizes a nationally representative data set, the COVID Future survey, which was collected at the peak of the pandemic, offering a unique perspective into disruption behavior. Finally, the model structure is estimated in one step in a robust and holistic econometric Generalized Heterogenous Data Model (Bhat, 2015) framework, which is a comprehensive data modeling approach that accounts for heterogeneity, interrelated factors, and complex relationships in the data.

## **CHAPTER 3**

### **COVID FUTURE SURVEY ANALYSIS DATA SET**

This chapter presents a description of the data set used in the study and the survey that served as the data source. In addition, the section offers a detailed description of the sample, both in terms of socio-economic and demographic characteristics, as well as the endogenous variables of interest in this thesis. Finally, a preliminary examination of the data is conducted to validate the necessity of a full modeling effort.

#### **3.1. Overview of Survey and Sample Characteristics**

The data set for this research is derived from the COVID Future Panel Survey (Chauhan et al., 2021). The survey was administered to a stratified random sample across the United States. The sampling strategy for the survey involved deploying multiple methods to recruit survey respondents and yield a large sample size. Multiple recruitment methods were used to enhance the sample size, including e-mail invitations sent to an extensive address database purchased from a commercial vendor, social media channels, an online Qualtrics survey panel, a study website, and news stories in transportation-oriented and university websites. The survey collected detailed information about socio-economic and demographic attributes, mobility choices and activity-travel patterns, attitudes and perceptions towards mobility options and activity engagement modalities (physical or virtual), lifestyle and mobility preferences, and adaptation to the COVID-19 pandemic circumstances. The survey also elicited information about the degree to which individuals considered the COVID-19 virus a threat to themselves, their family and friends, and society



at large. The three waves of the survey were administered in April – October 2020, November 2020 – May 2021, and October – November 2021.

This study utilizes the subset of data from the first wave of the COVID Future Panel Survey. Wave 1 data, obtained from April – October 2020, was used because this data was collected at the peak of the pandemic when there were significant health concerns, fear of the spread of the virus, and public and private entities that attempted to stem the spread through the implementation of limited business and restaurant operations. These restrictions may have differentially impacted various market segments. This study aims to identify the socio-economic and demographic groups that may have been more adversely affected by the pandemic regarding food access. A total of 9,912 responses were obtained in the first wave of the panel survey. After filtering the data to remove records with substantial missing data, the final analysis sample includes 8,392 responses.

Table 1 presents an overview of the sample's socio-economic and demographic characteristics. The large sample covers the entire nation and exhibits considerable variation for variables in the data set. It is found that 62.3 percent of the sample is female. The age distribution shows a reasonably even spread across the age groups, with about 15-20 percent of records in each group. About 43.2 percent of individuals are employed, while another 44.3 percent are neither workers nor students. About 30 percent of respondents have a bachelor's degree, while another 21.6 percent have a graduate degree. About 80 percent of respondents are White, and nearly 10 percent are Black.

**TABLE 1 Sample Characteristics**

<i>Individual characteristics (N=8,392)</i>		<i>Household characteristics (N=8,392)</i>	
<b>Variable</b>	<b>%</b>	<b>Variable</b>	<b>%</b>
<b>Gender</b>		<b>Household annual income</b>	
Female	62.3	Less than \$25,000	16.4
Male	37.2	\$25,000 to \$49,999	21.5
Other	0.5	\$50,000 to \$99,999	31.7
<b>Age category</b>		\$100,000 to \$149,999	16.8
18-30 years	17.5	\$150,000 to \$199,999	6.7
31-40 years	16.9	\$200,000 or more	6.9
41-50 years	14.0	<b>Household size</b>	
51-60 years	17.6	One	18.7
61-70 years	20.2	Two	38.0
71+ years	13.8	Three or more	43.3
<b>Employment status</b>		<b>Housing unit type</b>	
Student (part-time or full-time)	4.2	Stand-alone home	65.5
Worker (part-time or full-time)	43.2	Condo/apartment	19.7
Both worker and student	8.4	Other	14.7
Neither worker nor student	44.3	<b>Home ownership</b>	
<b>Education attainment</b>		Own	65.1
High school or less	17.4	Rent	30.0
Some college or technical school	31.2	Other	4.9
Bachelor's degree(s)	29.8	<b>Vehicle ownership</b>	
Graduate degree(s)	21.6	Zero	6.7
<b>Race</b>		One	37.7
Asian	4.6	Two	38.3
Black or African American	9.7	Three or more	17.4
Native American	1.3	<b>Presence of household children</b>	
White or Caucasian	79.9	Yes	26.7
Other	4.5	No	73.3
<b>Main Outcome Variables (Number of Days in Past Week)</b>			
<b>Grocery in-store</b>		<b>Meal in-store</b>	
Zero	19.8	Zero	71
One	46.7	One	17.9
Two or three	29.4	Two or three	9.4
Four or more	4.1	Four or more	1.7
<b>Grocery pickup</b>		<b>Meal pickup</b>	
Zero	81.4	Zero	49.1
One	12.2	One	31.7
Two or three	5.4	Two or three	17.0
Four or more	1.0	Four or more	2.3
<b>Grocery delivery</b>		<b>Meal delivery</b>	
Zero	80.3	Zero	67.4
One	12.0	One	19.4
Two or three	6.1	Two or three	11.0
Four or more	1.6	Four or more	2.2

In terms of household characteristics, the sample is skewed towards the lower income groups, with 16.4 percent in the less than \$25,000 bracket and another 21.5 percent in the \$25,000 - \$49,999 bracket. Nearly 7 percent reside in households with an income greater than or equal to \$200,000. About 43 percent of individuals reside in households with three or more members, nearly two-thirds live in a stand-alone home, and 65 percent own the home they reside in. Almost 7 percent of the respondents are in households with no vehicles, 38 percent are in households with two vehicles, and 17.4 percent are in households with three or more vehicles. Nearly three-quarters of the sample resides in households with no children. Overall, the sample characteristics reflect the variability needed for a modeling study of this nature.

### **3.2. Endogenous Variables and Attitudinal Indicators**

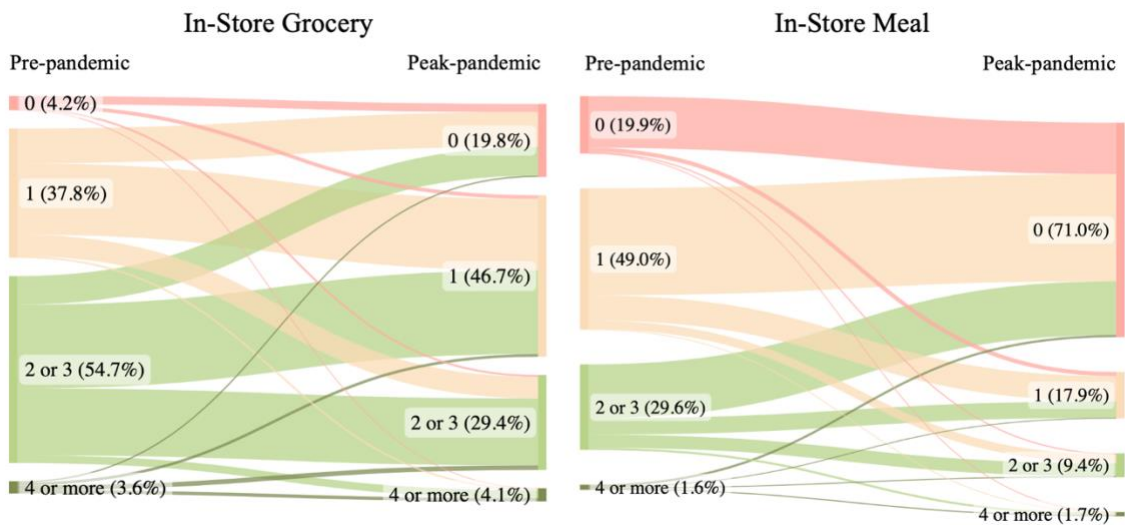
Access to food is reflected through a focus on shopping for groceries and meals. The COVID Future Survey data set includes rich information about shopping modalities and frequencies, thus enabling a focus on these two commodities. Three different modalities are possible for each commodity (groceries or meals). Commodities may be purchased in-store; this may involve shopping in the grocery store in person or dining in a restaurant in person. Alternatively, food may be accessed through virtual means. Online platforms may be used to order groceries or meals, and the consumer may travel in person to the establishment to pickup the items. The consumer would not need to spend any extended duration in the establishment and may even benefit from curbside pickup, enabling touchless transactions. Finally, the consumer may purchase food via online platforms and have the goods delivered to the home using any number of delivery services. Thus, six

possible outcome variables are defined by two food commodity types and three modalities for each.

The distributions for these six endogenous choice variables are seen in the bottom half of Table 1. The survey asked respondents to report the number of days in the past seven days that the individual participated in each of the six activity modalities considered in this thesis. Thus, responses represent the number of *days* (not the number of *times*) an activity was undertaken in the past 7 days. The sanky diagrams in Figures 1, 2, and 3, compare pre-pandemic (retrospective observations) to peak-pandemic (April to October 2020) meal and grocery shopping by the modes of in-store, pickup, and delivery, respectively. The pre-pandemic frequencies were measured differently in the COVID Future survey than peak-pandemic frequencies, and therefore some assumptions have been made in doing this analysis. It is assumed that a response of “never” or “a few times a year” is equivalent to “0 days in the past 7 days”. Similarly, a response of “a few days a month” has been equated to “1 day in the past 7 days”, a response of “a few days a week” has been equated to “2-3 days in the past 7 days”, and a response of “every day” has been equated to “4 or more days in the past 7 days”. It should additionally be noted that many children no longer attended school in-person and that increased percentages of individuals were home during the peak-pandemic period, which may have increased the amount of household food being purchased, increasing engagement frequencies during the peak-pandemic period.

As seen in Figure 1, in the pre-pandemic period more than 95 percent of respondents reported shopping in a grocery store at least one day in the past week. The percentage drops substantially when compared to peak-pandemic data, with only about 80

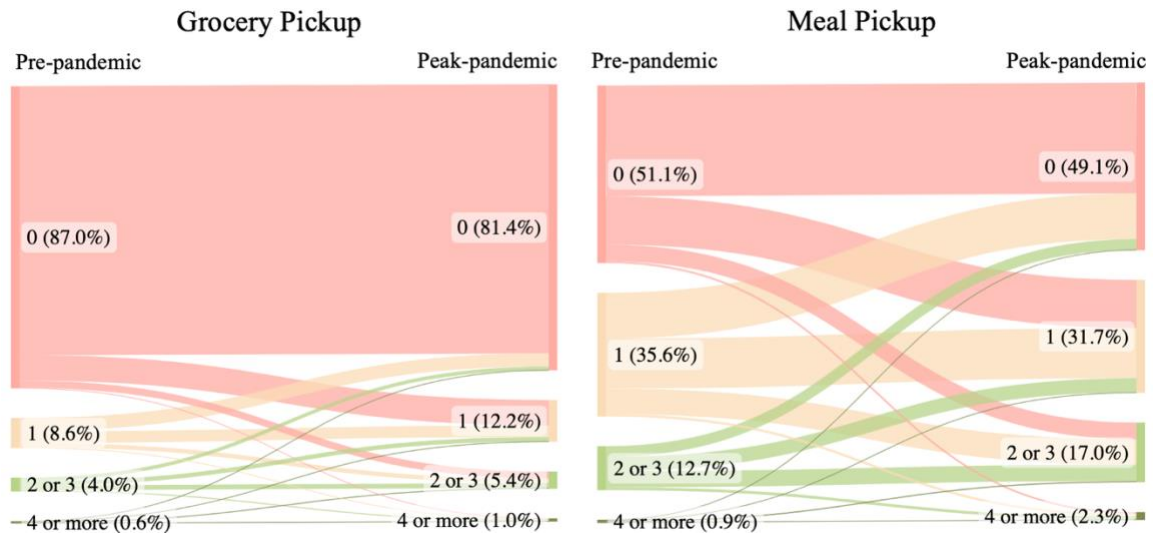
percent of respondents stating they had shopped in-store for groceries in the past week peak-pandemic. Despite a decrease in engagement, it appears many continued shopping for groceries in-store, possibly because grocery stores were largely open during the pandemic, and these locations served as places to connect with people (Palmer et al., 2021). Many dined in at restaurants frequently before the pandemic, with less than 20 percent of respondents reporting zero days of engagement in the past week. In comparison, during the peak-pandemic period, more than 70 percent of respondents reported not dining in for a meal in the past week. This may be partly due to restaurants being closed or not entertaining in-person dining at the height of the pandemic.



**FIGURE 1 In-Store Grocery and Meal Frequencies Pre- vs. Peak-Pandemic (N=8,392)**

Figure 2 illustrates a comparison of online *pickup* of groceries and meals during pre-pandemic and peak-pandemic times. Figure 3 shows a similar comparison for online *delivery* of groceries and meals both pre-pandemic and peak-pandemic. When it comes to

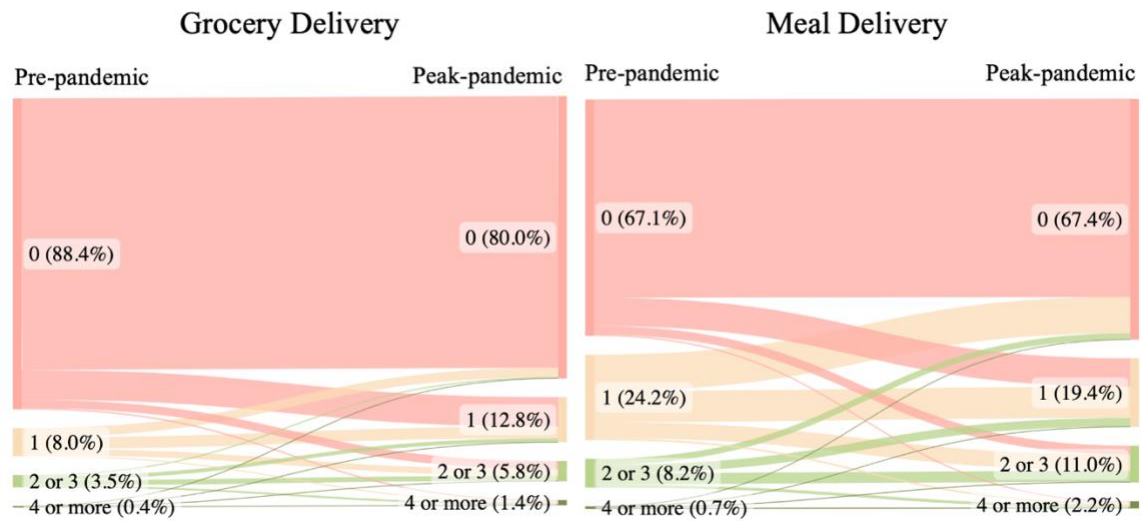
online pickup, there is a slight increase in the use of grocery pickup during the pandemic. Overall, meal pickup patterns remain similar pre- to peak-pandemic.



**FIGURE 2 Grocery and Meal Pickup Frequencies Pre- vs. Peak-Pandemic (N=8,392)**

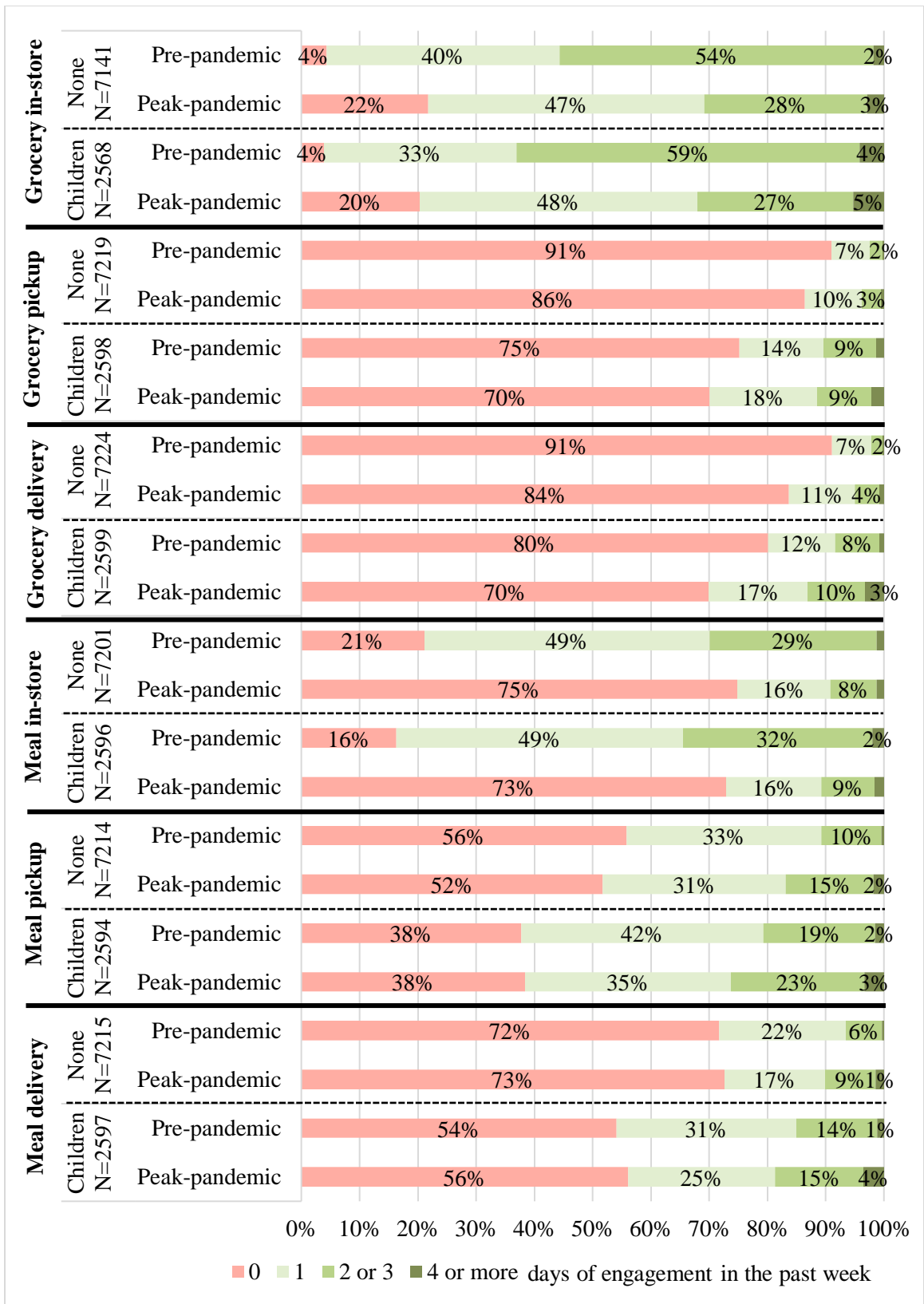
When it comes to grocery delivery, shown in Figure 3, it can be seen that respondents reporting no grocery delivery engagement in the past week decreased from 88.4 percent pre-pandemic to 80.0 percent peak-pandemic. Similar to meal pickup patterns, meal delivery frequencies remained fairly consistent across time periods. There is a slight decrease in the percentage of respondents engaging in meal delivery only once per week and a slight increase in the percentage of respondents engaging multiple times per week during the pandemic peak. Comparing Figure 2 with Figure 3, more respondents reported meal pickup engagement compared to meal delivery, both pre-pandemic and peak-pandemic. For instance, during the pandemic peak, about 50 percent of respondents were engaging in meal pickup at least once per week, whereas only 33 percent of respondents were engaging in meal delivery once per week. Likely, individuals engaged more in online

+ pickup as opposed to online + delivery because in-person pickup eliminates the need to pay for delivery fees, affords the ability to obtain the commodities at a time convenient to the customer, and provides an opportunity to get out of the home and interact with society. Overall, the six dependent variables exhibit distributions conducive to a joint econometric modeling effort capable of representing engagement in all six food access activities as a contemporaneous consumption choice bundle.



**FIGURE 3 Grocery and Meal Delivery Frequencies Pre- vs. Peak-Pandemic (N=8,392)**

A comparison of pre- versus peak-pandemic modality engagement was also conducted for various subgroups. Engagement frequency comparisons are shown in Figures 4-7 for the presence of children in the household, household income, household vehicle ownership, and gender.

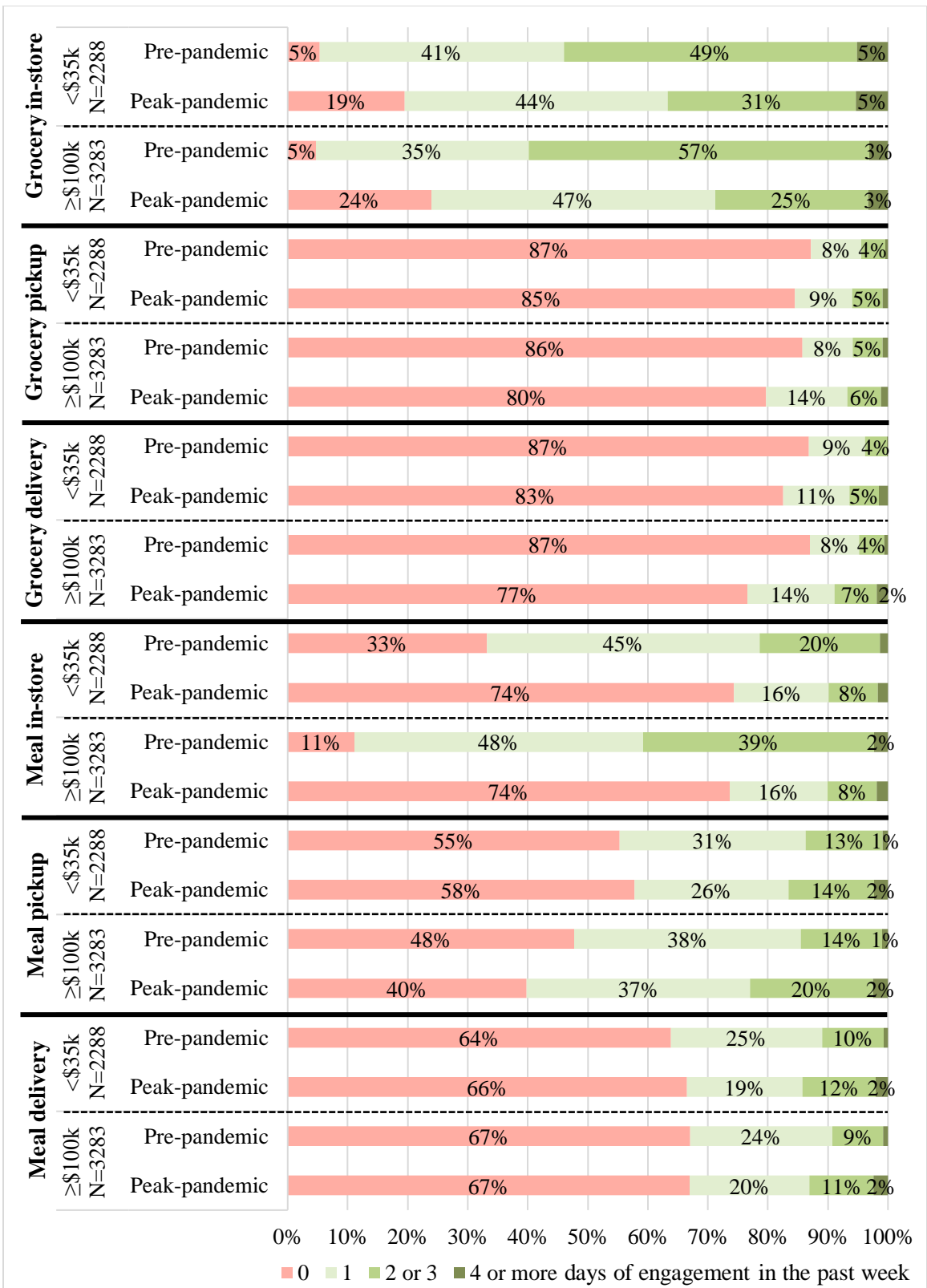


**FIGURE 4 Modality Frequencies Pre- vs. Peak-Pandemic by Children in Household**



Figure 4 illustrates clear differences in engagement frequencies for online grocery and meal modalities when comparing households with and without children. In-store grocery shopping patterns for these households are very similar, with decreases in in-store grocery engagement during the peak-pandemic period. However, pre-pandemic grocery pickup and delivery are both more popular in households with children. About 25 percent of households with children engaged in grocery pickup at least once per week before the pandemic compared to only 9 percent of households without children. Similarly, about 20 percent of households with children engaged in grocery delivery at least once per week before the pandemic compared to 9 percent of households without children. The pandemic leads to increased online grocery modality use for households both with and without children. Both meal pickup and delivery are utilized more frequently by households with children as well, and the onset of the pandemic does not significantly change these patterns.

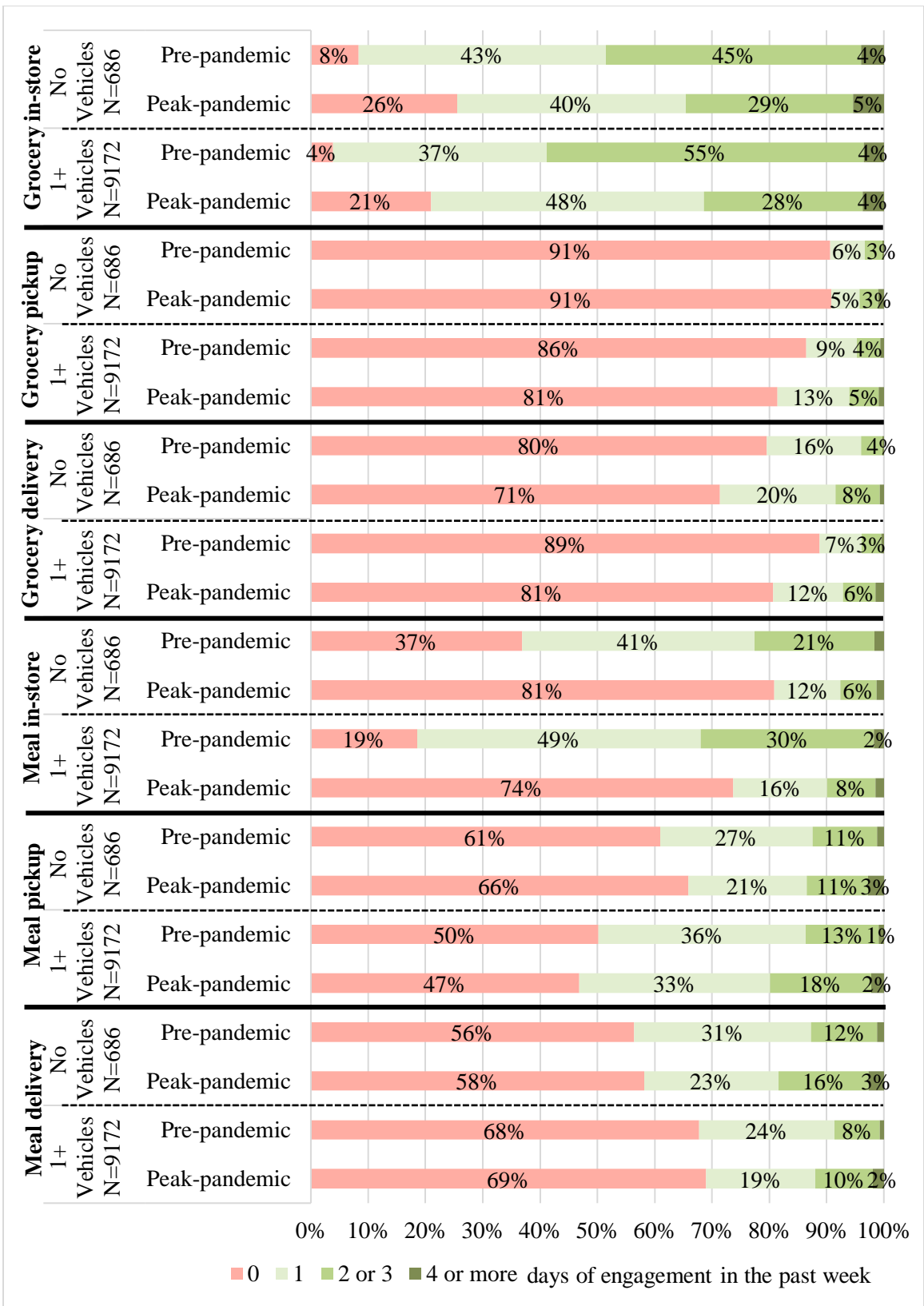
Figure 5 compares household income by modality engagement frequency during pre- and peak-pandemic periods. Looking at grocery engagement, those from lower income households (households making less than \$35,000 a year) engaged more frequently in in-store grocery shopping and less frequently in online grocery shopping once the pandemic hit compared to those from higher-income households (households making \$100,000 or more per year). Significant differences in in-store meal engagement existed before the pandemic, with about a third of those from lower-income households eating at a restaurant one day per week compared to just less than 90 percent of engagement at least one day per week by respondents from higher-income households incomes.



**FIGURE 5 Modality Frequencies Pre- vs. Peak-Pandemic by Household Income**

Interestingly, during the peak-pandemic period, in-store meal engagement frequency is very similar for the two groups. Looking at online meal pickup, higher-income households engaged more frequently in the pre-pandemic period compared to lower-income households and increased the use of online meal pickup at least one day per week by 8 percent when comparing pre- to peak-pandemic engagement. On the other hand, lower-income households decreased their use of online meal pickup, with the frequency of engaging at least one day per week declining by 3 percent during the peak-pandemic period.

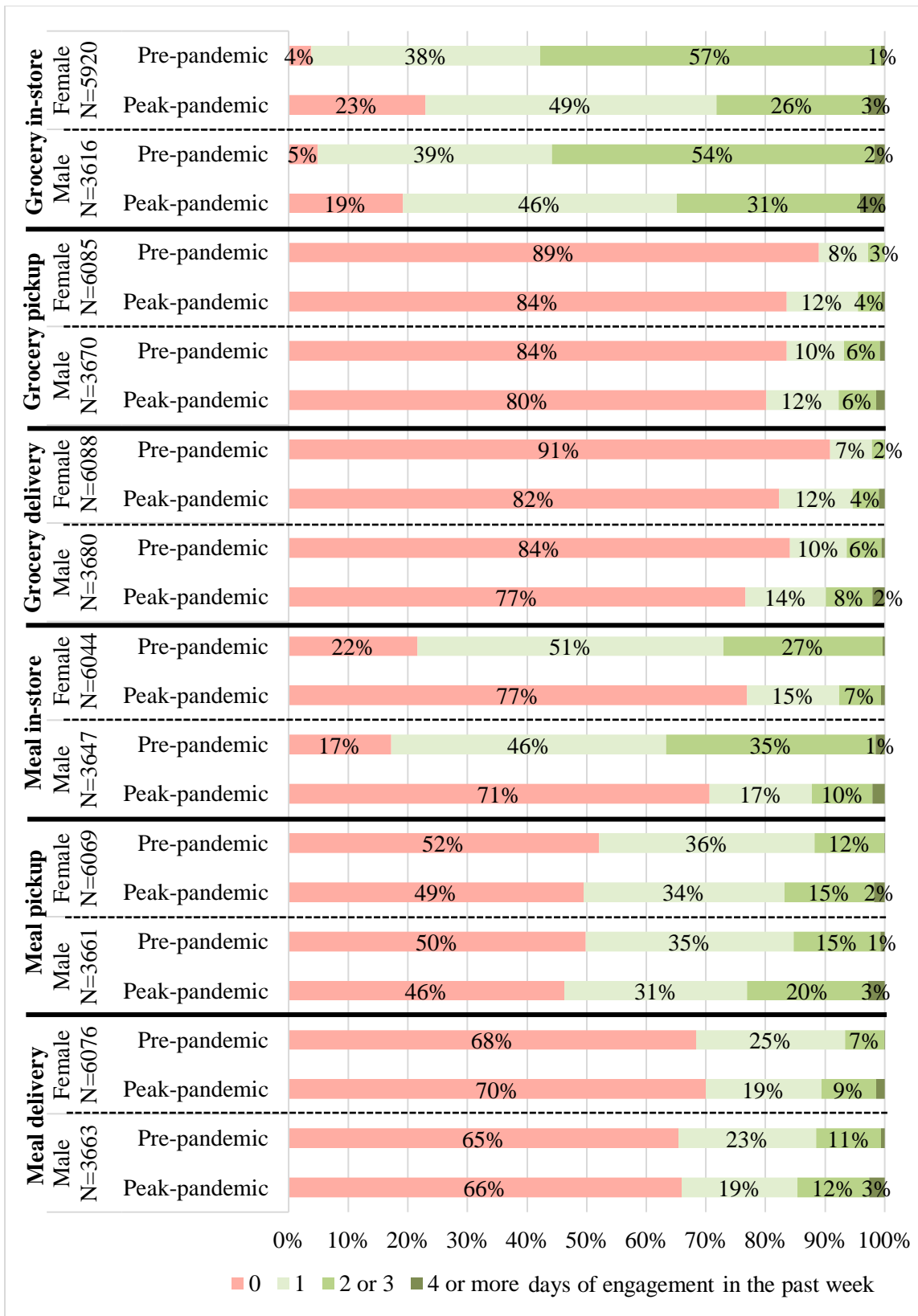
Figure 6 depicts a comparison of modality engagement frequency pre- and peak-pandemic for those with zero household vehicles and those with one or more household vehicles. In-store grocery, grocery pickup, in-store meal, and meal pickup are all engaged in less frequently by those from zero vehicle households both pre- and peak-pandemic, likely because transportation to a store or restaurant is more difficult to facilitate without a vehicle. Pre-pandemic grocery delivery was engaged in by about 19 percent of respondents with no household vehicles at least one day per week compared to about 11 percent of respondents from households with vehicles. Similarly, meal delivery is more frequently utilized by those without household vehicles both pre- and peak-pandemic. These findings show the importance of delivery modalities in providing access to food for those without access to vehicles, especially during a disruption when public transit may not be safe or accessible. These results also indicate that the growing accessibility and utilization of online modalities and services could potentially reduce the demand for vehicle ownership.



**FIGURE 6 Modality Frequencies Pre- vs. Peak-Pandemic by Household Vehicles**

Figure 7 compares modality engagement frequency pre- and peak-pandemic by gender (females versus males). Males and females show highly similar frequencies of in-store grocery shopping pre-pandemic. Males shopped more for groceries peak-pandemic than females, with about 81 percent of males shopping in-store for groceries at least one day in the past week compared to 77 percent of females. Males also shopped more frequently for meals in-store compared to females both pre- and peak-pandemic. Females scored greater scores for COVID-19 risk perceptions, and this may at least partially explain the decreased in-store engagement frequencies. Grocery pickup and grocery delivery were utilized less frequently by females pre- and peak-pandemic, compared to males. Meal pickup and meal delivery modalities are also used less frequently by females in both time periods examined. However, these differences in engagement frequency are less distinct than the patterns observed for groceries.

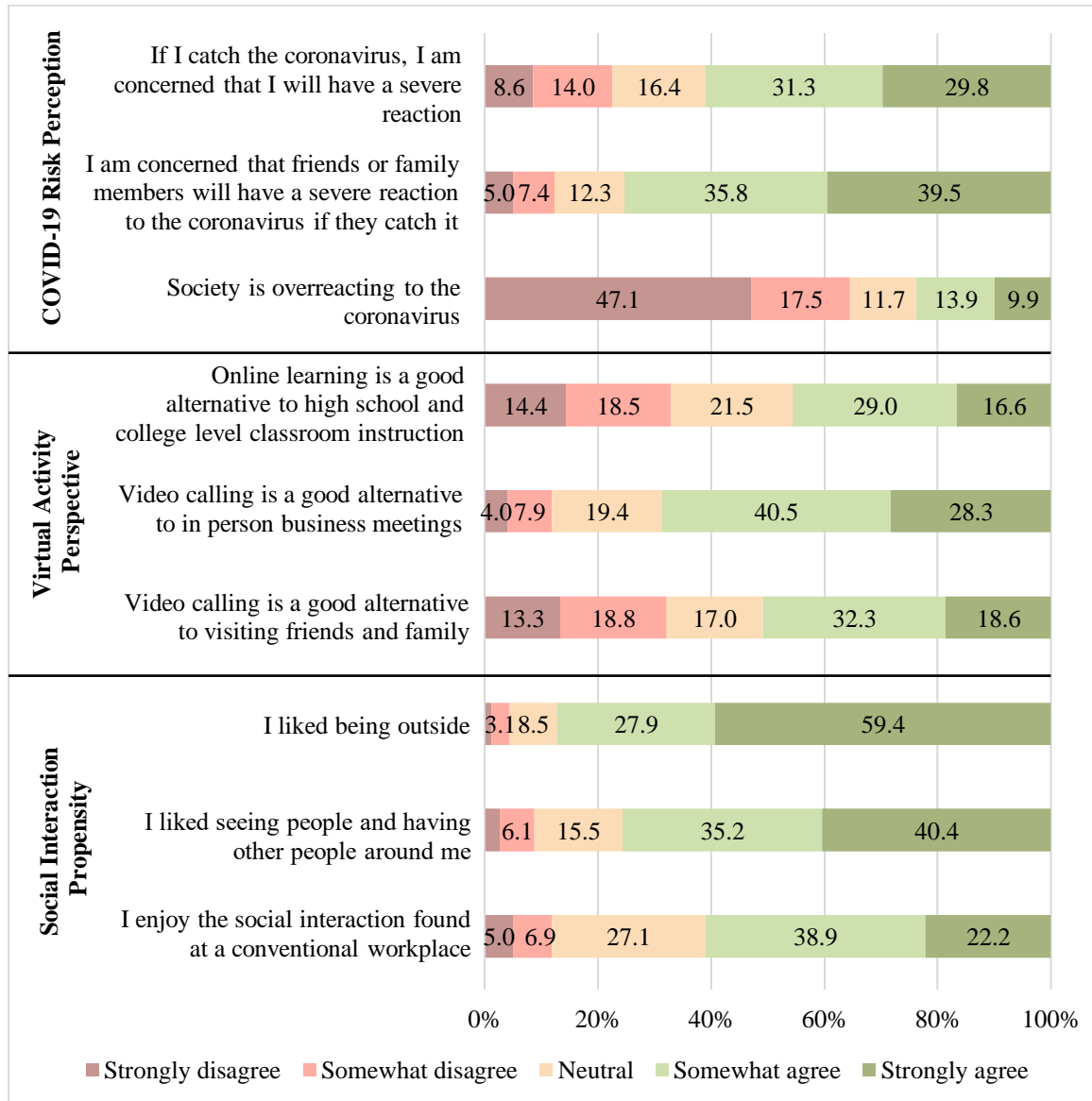
The survey included a rich set of attitudinal statements that captured respondent attitudes, values, perceptions, and preferences. To measure the effect of socio-economic and demographic attributes on the frequency of participation in different activities and modalities, it is helpful to explicitly account for attitudes and preferences so that the magnitudes of coefficients associated with socio-economic and demographic explanatory variables are not confounded by the influence of attitudinal factors.



**FIGURE 7 Modality Frequencies Pre- vs. Peak-Pandemic by Gender**

In this study, three attitudinal factors are formulated and included in the model specification. They are *COVID-19 risk perception*, *virtual activity perspective*, and *social interaction propensity*. Three attitudinal statements comprise each factor; thus, the three latent attitudinal constructs collectively account for nine attitudinal statements. Responses to the three statements that comprise a single factor are highly correlated with one another. The attitudinal statements associated with a latent factor were identified through a review of prior research and based on behavioral intuitiveness in attitudes most likely to influence food access activities and modalities. Figure 8 shows the latent factors, the attitudinal statements on which they are loaded, and the sample distribution for each attitudinal indicator (respondents indicated their level of agreement with each statement on a Likert scale of *strongly disagree* to *strongly agree*). The statement distributions considered in each latent variable show consistent and logical patterns. This signifies that they are reasonable as indicators of the selected latent variables. Some patterns are noteworthy. For example, 47 percent of respondents strongly disagreed that society is overreacting to the virus (recall that the data was collected at the height of the pandemic in the spring and summer of 2020). Respondents also expressed considerable concern that friends or family would have a severe reaction to the virus, with nearly three-quarters somewhat or strongly agreeing with that concern. Although there was only tepid enthusiasm for online learning (as a good alternative to classroom instruction), the enthusiasm for video calling as a good alternative to business meetings was quite substantial (79 percent somewhat agree or strongly agree that video calling is a good alternative). A vast majority of respondents (nearly 88 percent) indicated that they like being outside, which may explain (to some degree) why people engaged in grocery shopping in-person at a much higher rate than using

virtual modalities. On the other hand, the eagerness for social interactions at the workplace is more measured, which is a likely explanation for why so many workers have embraced work-from-home and hybrid work modalities.



**FIGURE 8 Response Distributions for Attitudinal Indicators of Latent Constructs (N=8,392)**

The survey included three attitudinal statements that capture the degree to which respondents consider the virus to present a threat or risk. One statement captures the degree of perceived risk to a respondent’s own health, and a second statement captures the degree



of perceived risk to the health of family and friends. A third statement asks if respondents believe society is overreacting to the coronavirus. These three statements may be viewed as "COVID-19 risk perception" variables; likely, individual risk perceptions are closely associated with the modality of choice in accessing food. The following preliminary analysis analyzes the data to determine if this or other meaningful patterns are present in order to establish if additional modeling efforts are justified.

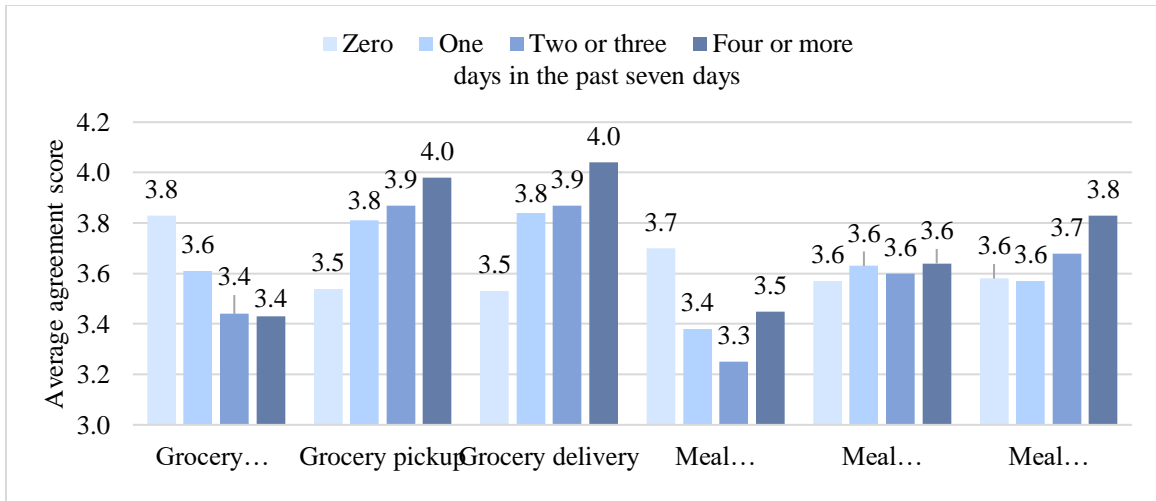
### **3.3. Descriptive Analysis of Endogenous Variables**

The purpose of preliminary descriptive analysis is to explore the data to identify indications of meaningful patterns. In this research, patterns indicating an inability to adapt to disruption or of vulnerability to food insecurity are of important interest. This process does not involve statistical tests to determine the significance of any relationships or patterns, as it serves as an initial step before progressing to more complex modeling techniques. These more advanced modeling techniques, presented in Chapter 4, include statistical testing and are utilized to obtain a deeper understanding of the data.

#### *COVID-19 Risk Perception*

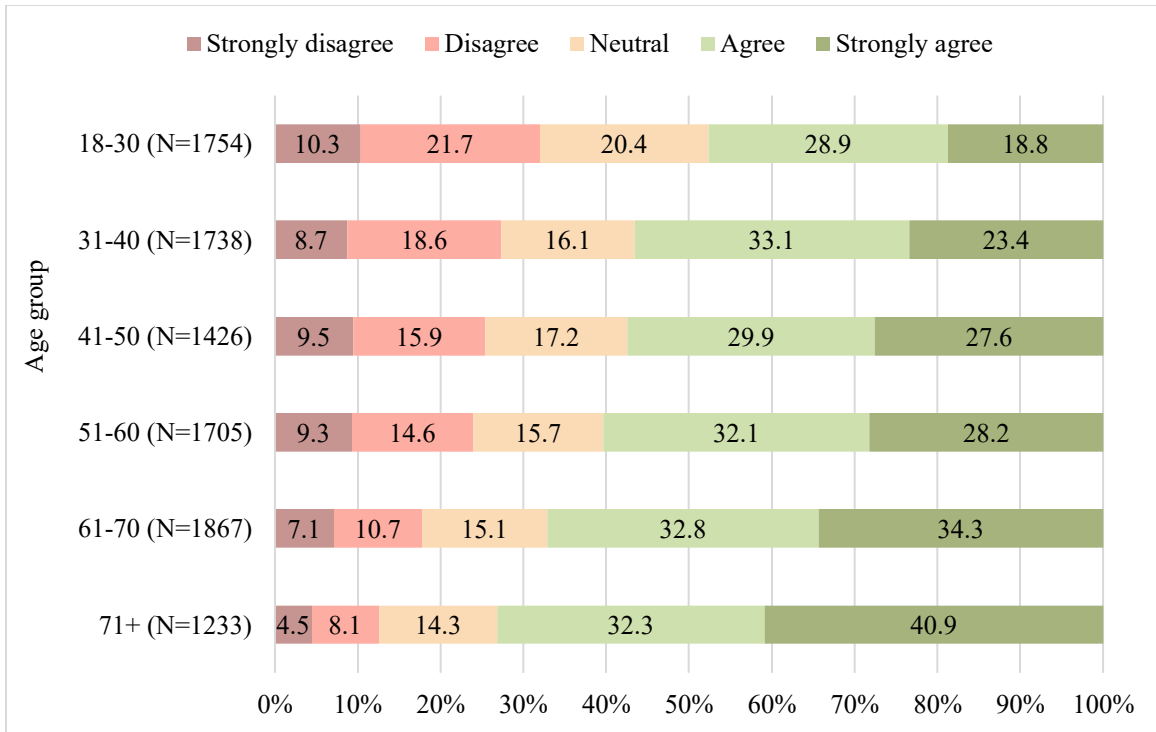
When comparing attitudinal statements about COVID-19 risk perceptions against the six endogenous variables, analysis results align with expectations, showing that increased risk perception leads to decreased in-person shopping and increased online shopping. For example, Figure 9 illustrates average agreement scores with the phrase, "If I catch the coronavirus, I am concerned I will have a severe reaction" by respondents' weekly shopping frequency of the six modalities. Agreement scores can range from 1 to 5, with

low scores indicating strong disagreement and high scores indicating strong agreement. As shown in Figure 9, those who agreed more strongly with being concerned about personally having a severe reaction to the virus shopped more frequently online for groceries and meals. Inversely, those who agreed less strongly with having these concerns tend to shop more frequently in a store for food.



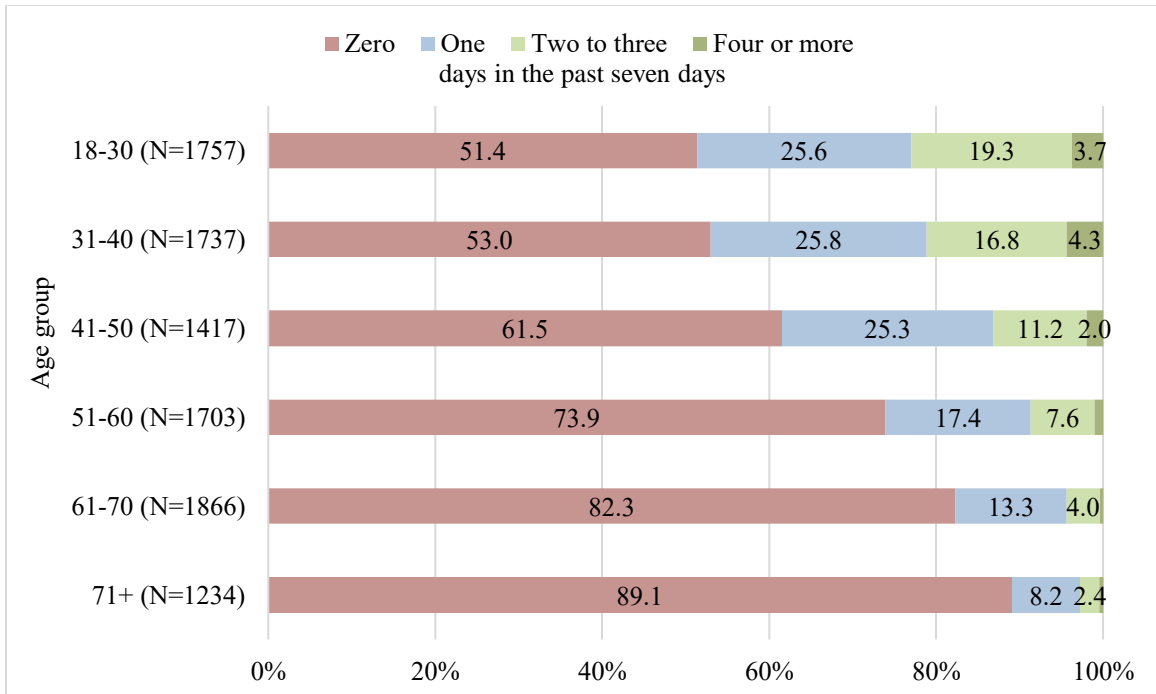
**FIGURE 9 Agreement with the Phrase “If I catch the coronavirus, I am concerned that I will have a severe reaction” by Shopping Modality Frequency (N=8,392)**

These trends do not always hold true when examining cross-tabulations of subgroups by attitudes and modality engagement. Specifically for the subsamples of age and gender, distinct patterns can be observed. Figure 10 compares age groups against agreement with the same statement about personal health concerns related to catching the coronavirus. Nearly 41 percent of respondents 71 years or older strongly agreed with having these concerns about their personal health. However, less than half, or 18.8 percent of those aged 18 to 30 years old, strongly agreed with the statement.



**FIGURE 10 Age Group by Agreement with the Phrase “If I catch the coronavirus, I am concerned I will have a severe reaction.”**

As shown in Figure 9, those with higher risk perceptions tend to use online food procurement modalities more frequently. Additionally, Figure 10 depicts how those in older age groups have higher COVID-19 risk perceptions. Therefore, it is logical to hypothesize that older individuals would use safer online modalities for purchasing food frequently. However, when comparing age and online grocery and meal shopping modality engagement, older adults showed less inclination to use these online platforms compared with younger subgroups. Figure 11 illustrates that 89.1 percent of those 71 years or older did not order a meal for delivery in the past week compared to 51.4 percent of those aged 18 to 30.



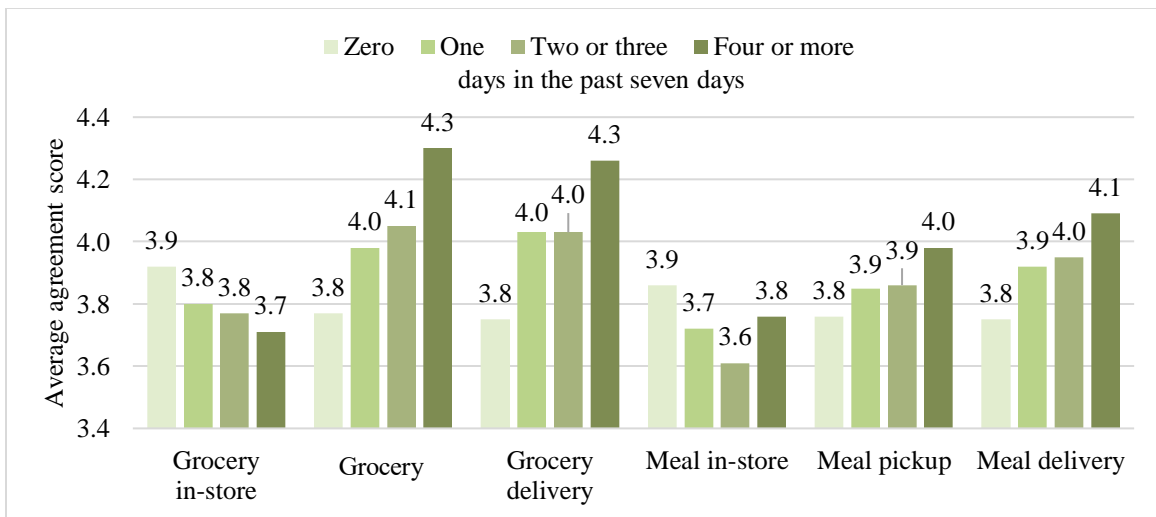
**FIGURE 11 Age Group by Frequency of Shopping for Meal Delivery in the Past Week**

These findings suggest that some of those concerned about catching the coronavirus likely faced limitations when it came to shopping for food online, reducing their online shopping engagement frequency and preventing some individuals from realizing the health and safety benefits online modalities had to offer. Individuals falling into these subcategories, specifically those 61 years or older and non-workers, were likely less able to adapt during the disruption.

#### *Virtual Activity Perspective*

Cross-tabulation analysis of virtual activity perspective attitudinal statements and the six endogenous variables resulted in expected outcomes of increased in-person shopping for those with more negative virtual activity perspectives and increased online shopping for those with more positive virtual activity perspectives. This is evidenced in Figure 12, for

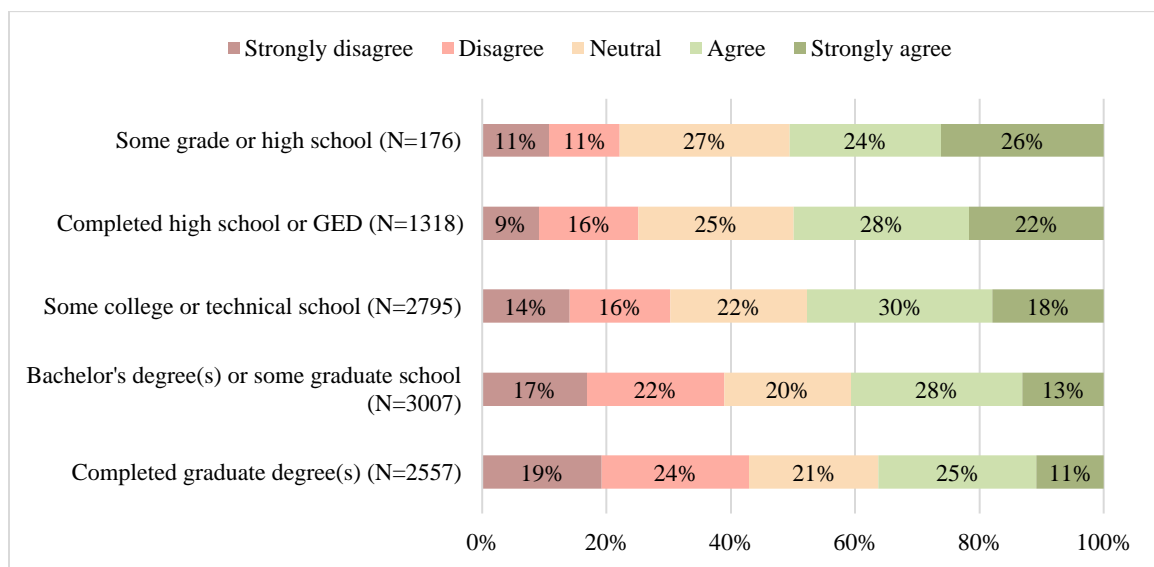
example, which depicts average agreement with the phrase, “Video calling is a good alternative to in-person business meeting” by weekly frequency of engagement in the six outcome variables. As can be seen in Figure 12, average agreement scores when looking at the mode of in-store grocery shopping decrease by 0.2 as the frequency of in-store grocery shopping increases. Those who more strongly agree that video calling is a good alternative to in-person business meetings purchase groceries in a store less frequently. Similarly, average agreement scores for the modes of grocery pickup and delivery increase by 0.5 as days of engagement increase from zero to four or more, depicting that those who agree with the phrase more strongly are more likely to engage in online activities more frequently.



**FIGURE 12 Agreement with the Phrase, “Video calling is a good alternative to in-person business meeting” by weekly shopping modality frequency (N=8,392)**

When analyzing subsample characteristics against attitudes, many historically disadvantaged subgroups tend to agree with the statement, “Online learning is a good replacement for high school or college-level classroom instruction” including individuals from lower-income households, people with lower educational attainment, females, non-

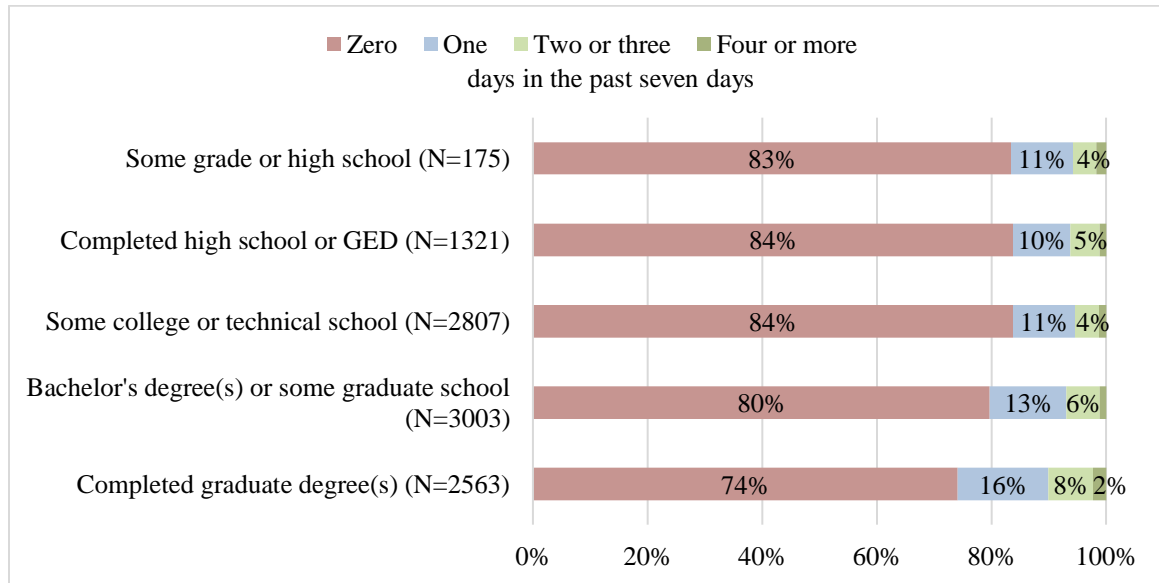
workers, non-Whites, Blacks, Hispanics and those in low-density locations. Figure 13 shows the cross-tabulation between agreement with this statement and educational attainment, and a clear pattern of decreasing agreement is seen in connection with increased educational attainment. For instance, 26 percent of those with less than a high school degree strongly agreed that online learning was a good replacement for in-person instruction, whereas only 11 percent of those completing graduate degree(s) strongly agreed.



**FIGURE 13 Educational Attainment by Agreement with the Phrase “Online learning is a good replacement for high school or college-level classroom instruction.”**

As previously stated, Figure 11 illustrates a pattern of increased online shopping associated with increasingly positive virtual activity perspectives, and Figure 12 suggests that those with lower educational attainment are more likely to have more positive virtual activity perspectives. However, those with lower educational attainment are not found to be among the subgroups more frequently purchasing food via online modalities. Figure 13 depicts the cross-tabulation of educational attainment and frequency of grocery delivery in

the past week. While 26 percent of respondents with one or more graduate degrees purchased groceries for delivery at least one day in the past week, only 17 percent of those with some grade or high school education did the same.

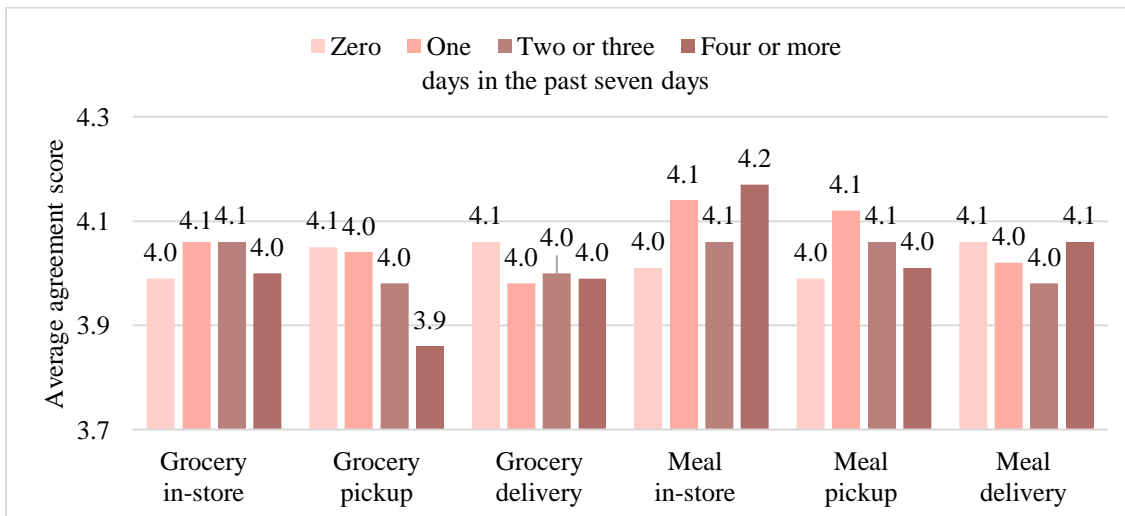


**FIGURE 14 Educational Attainment by the Frequency of Grocery Delivery Shopping in the Past Week**

There is a clear pattern of increasingly frequent grocery delivery with increasing educational attainment despite the more positive attitudes towards online alternatives by those with lower educational attainment. Similarly, while non-workers, those in low-density locations, and females have positive virtual activity perspectives, they also use these modalities less frequently than their counterparts. These subgroups were likely less able to adapt to using online modalities during the pandemic, possibly due to barriers associated with the digital divide. These groups may have been put at a disadvantage regarding food access as a result and may therefore have been more vulnerable to food insecurity.

*Social Interaction Propensity*

Finally, attitudinal indicators of social interaction propensity are cross-examined against the six endogenous outcome variables, and it is generally found that those who liked being around others, enjoyed being outside, and liked traditional in-office work interactions are more likely to shop in-store and less likely to shop online for both groceries and meals. For example, Figure 15 shows average agreement scores for the phrase “I liked seeing people and having other people around me” versus weekly shopping modality frequency. Patterns for meal modalities are more pronounced than for grocery modalities, but for both options, those who agree about enjoying seeing people and having them around are more likely to shop in-person for food more frequently. Similarly, those who more strongly disagreed with the phrase were more likely to shop for food online more days of the week.

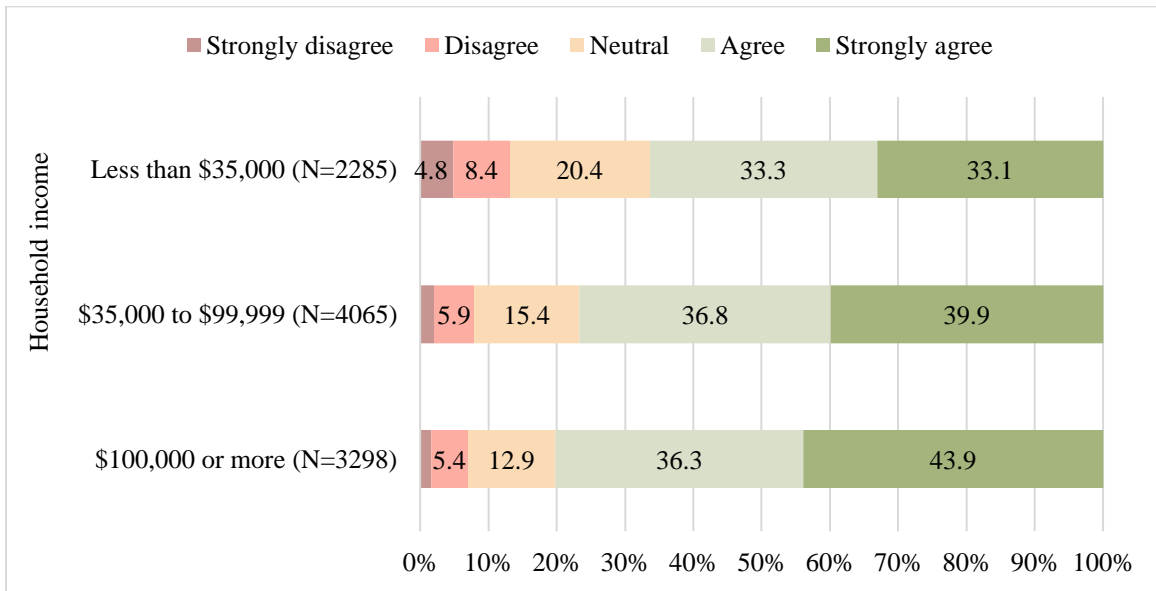


**FIGURE 15 Agreement with the Phrase, “I liked seeing people and having other people around me.” by weekly shopping modality frequency (N=8,392)**

Subgroup comparison of agreement with the phrase, “I liked seeing people and having other people around me” found that those in households with higher incomes, those aged 61 and older, females, Whites, non-Blacks, those with higher educational attainment,

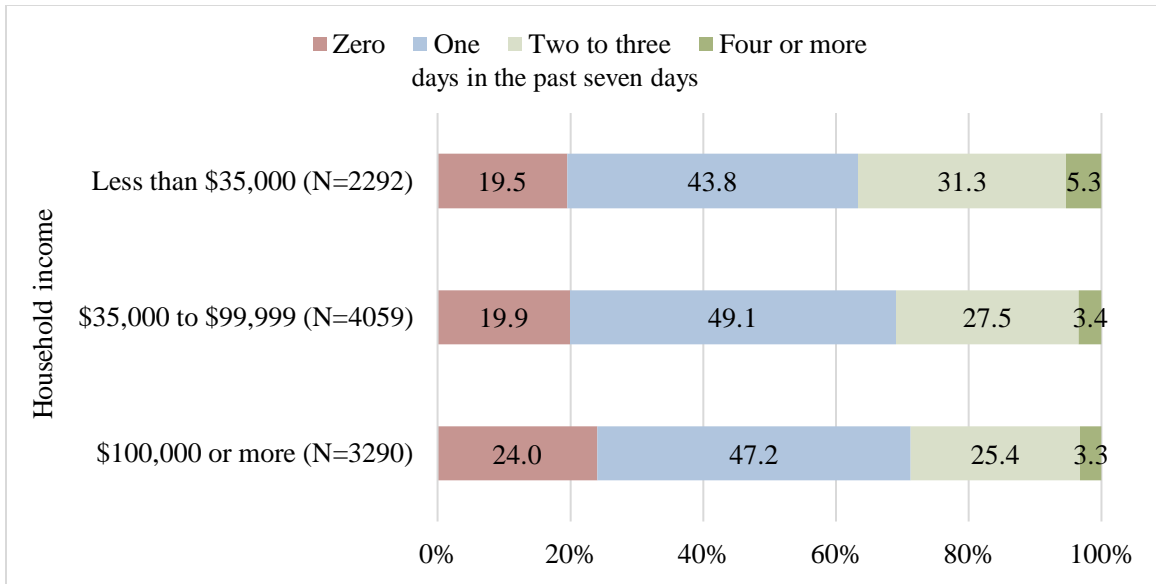


and workers more strongly agreed with the phrase than their counterparts. Figure 16 depicts a cross-tabulation analysis of income and agreement with the phrase. Almost 44 percent of those from households making \$100,000 or more a year strongly agreed, whereas about 33 percent of those from households making \$35,000 or less per year strongly agreed.



**FIGURE 16 Household Income by Agreement with the Phrase “I liked seeing people and having other people around me.”**

Figure 15 shows increased in-store shopping for those with greater social propensity, and Figure 16 illustrates a tendency for those from higher-income households to have more positive social propensities. However, the findings do not show that those from higher income households shop in-store more frequently than their counterparts, as one may assume. Figure 17 depicts the number of days in the past week of in-store grocery shopping by household income. Nearly one-quarter of those with household incomes of \$100,000 or more did not shop in-store for groceries in the past week, compared to 19.5 percent with household incomes of less than \$35,000.



**FIGURE 17 Household Income by Frequency of In-store Grocery Shopping in the Past Week**

Figure 17 shows that those with lower household incomes shop in a store more frequently despite having lower social propensities than higher income households. Non-whites, those with lower educational attainment, and non-workers also disagreed more than their counterparts that they “liked seeing people and having people around” but engaged more frequently in in-store grocery shopping than their counterparts.

While those with higher household incomes and workers engaged less frequently in in-store grocery shopping, they engaged more frequently in in-store meal purchases than their counterparts. This suggests that some of those seeking out social interactions may pursue these activities by dining in at restaurants rather than shopping for groceries in person. In contrast, those most frequently engaging in in-store grocery shopping tend to agree less with desiring social interaction, suggesting these subgroups are frequenting the grocery store out of necessity rather than social interest. These findings suggest that subgroups including those with lower household incomes, Non-whites, those with lower

educational attainment, and non-workers are frequenting grocery stores out of necessity. These groups were likely less able to adapt to using online modalities during the pandemic, potentially decreasing their access to safe food options.

### *Summary*

Based on the preliminary analysis, there are discrepancies in the frequencies of use of in-person versus online modalities among different subgroups. Initial findings indicate that those from disadvantaged subgroups may be most vulnerable to decreased food access in a disruption scenario, even after considering how attitudes may impact behavior. While these findings hint at potential inequities, they do not account for the potential interdependencies and relationships that exist among variables. A more sophisticated modeling effort is warranted from the findings of this preliminary analysis and must be undertaken to better understand the complex interconnections at play, which is presented in the following sections.

## **CHAPTER 4**

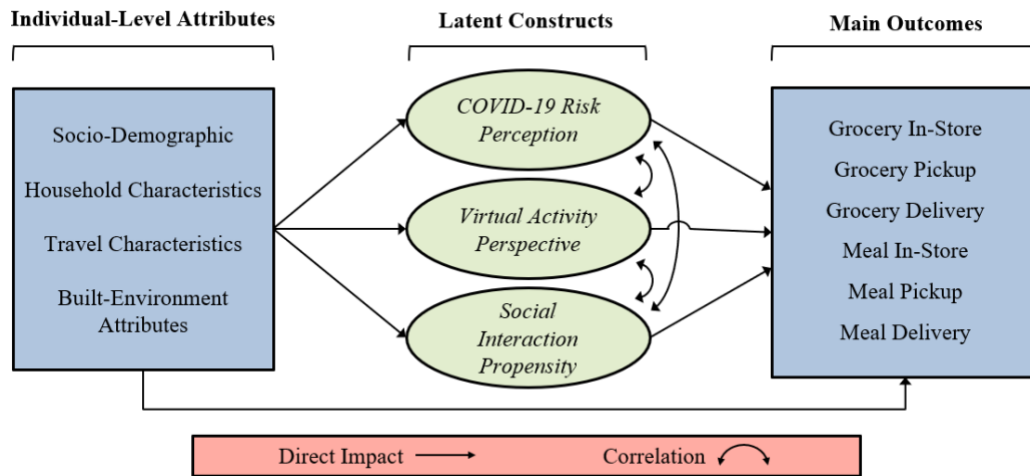
### **METHODOLOGY**

This chapter presents an overview of the modeling framework and methodology. The thesis aims to understand engagement in various activity modalities for accessing food (groceries and meals), with a focus on how those with various individual-level attributes were impacted by the pandemic. The data set includes six endogenous variables stemming from two commodity types that can both be accessed via three modalities. While it is possible to model the six dependent variables independently, there is a high likelihood that there are correlated unobserved factors that simultaneously affect the six endogenous outcome variables of interest. Moreover, it is likely that decisions about participation in the respective activity modalities are not made in isolation from one another. Treating these six endogenous choice variables as representative of an overall integrated lifestyle approach (choice bundle) to accessing food would help model the phenomenon in a comprehensive and holistic framework. For this reason, this thesis employs a simultaneous equation modeling framework capable of accounting for error correlations and endogeneity of attitudinal constructs.

#### **4.1. Model Structure**

A simplified representation of the model structure is shown in Figure 18. The analytical framework aims to provide the ability to specify and estimate a joint model that considers six main outcome variables associated with people's in-store shopping and online purchase frequencies of groceries and meals. Note that the indicators for each latent construct are

not shown for ease of representation. Each latent construct is formulated based on three attitudinal statements, as depicted in Figure 8.



**FIGURE 18 Modeling Framework**

The right-hand side of Figure 18 shows the six endogenous variables of interest. Each variable is treated as an ordered choice, with the frequency (represented by number of days within the past week that grocery or meal purchase activities were pursued for each in-person or virtual modality) serving as an ordered response. Thus, the model is formulated as a multivariate ordered response model system with error correlations engendered through the recognition that the latent constructs themselves are stochastic variables with error components. By accounting for error correlations between the three latent constructs, error correlations between the endogenous choice dimensions can be inferred and computed. The three latent constructs are themselves endogenous variables (influenced by socio-economic and demographic attributes) and they in turn influence the outcome variables of interest. Socio-economic and demographic variables (exogenous

attributes) may directly affect the outcome variables (frequency of grocery and meal activities by various modalities) and/or affect them indirectly through the latent factors (which serve as mediating variables). Factor scores are continuous variables, while the six endogenous variables represent ordered discrete outcomes. The entire model structure can be estimated in an integrated econometric framework using the Generalized Heterogenous Data Model (Bhat, 2015). The latent constructs are modeled through a structural equations model (SEM) component and measurement equations model (MEM) component of the GHDM; the latent constructs appear as exogenous variables in the multivariate ordered-response probit (MORP) model of the six main outcomes. However, the entire model system is estimated in one step through the GHDM approach.

#### 4.2. Model Estimation Methodology

As the outcomes and the indicators are ordinal in nature, the GHDM model for this study is formulated for exclusively ordinal outcomes. Consider the case of an individual  $q \in \{1, 2, \dots, Q\}$ . Let  $l \in \{1, 2, \dots, L\}$  be the index of the latent constructs and let  $z_{ql}^*$  be the value of the latent variable  $l$  for the individual  $q$ .  $z_{ql}^*$  is expressed as a function of its explanatory variables as,

$$z_{ql}^* = \mathbf{w}_{ql}^T \boldsymbol{\alpha} + \eta_{ql}, \quad (1)$$

where  $\mathbf{w}_{ql}$  ( $D \times 1$ ) is a column vector of the explanatory variables of latent variable  $l$  and  $\boldsymbol{\alpha}$  ( $D \times 1$ ) is a vector of its coefficients.  $\eta_{ql}$  is the unexplained error term and is assumed to follow a standard normal distribution. Equation (1) can be expressed in matrix form as,

$$\mathbf{z}_q^* = \mathbf{w}_q \boldsymbol{\alpha} + \boldsymbol{\eta}_q, \quad (2)$$

where  $\mathbf{z}_q^*$  ( $L \times 1$ ) is a column vector of all the latent variables,  $\mathbf{w}_q$  ( $L \times D$ ) is a matrix formed by vertically stacking the vectors  $(\mathbf{w}_{q1}^T, \mathbf{w}_{q2}^T, \dots, \mathbf{w}_{qL}^T)$  and  $\boldsymbol{\eta}_q$  ( $D \times 1$ ) is formed by vertically stacking  $(\eta_{q1}, \eta_{q2}, \dots, \eta_{qL})$ .  $\boldsymbol{\eta}_q$  follows a multivariate normal distribution centered at the origin and having a correlation matrix of  $\boldsymbol{\Gamma}$  ( $L \times L$ ), i.e.,  $\boldsymbol{\eta}_q \sim MVN_L(\mathbf{0}_L, \boldsymbol{\Gamma})$ , where  $\mathbf{0}_L$  is a vector of zeros. The variance of all the elements in  $\boldsymbol{\eta}_q$  is fixed as unity because it is not possible to uniquely identify a scale for the latent variables. Equation (2) constitutes the structural component of the framework.

Let  $j \in \{1, 2, \dots, J\}$  denote the index of the outcome variables (including the indicator variables). Let  $y_{qj}^*$  be the underlying continuous measure associated with the outcome variable  $y_{qj}$ . Then,

$$y_{qj} = k \text{ if } t_{jk} < y_{qj}^* \leq t_{j(k+1)}, \quad (3)$$

where  $k \in \{1, 2, \dots, K_j\}$  denotes the ordinal category assumed by  $y_{qj}$  and  $t_{jk}$  denotes the lower boundary of the  $k^{\text{th}}$  discrete interval of the continuous measure associated with the  $j^{\text{th}}$  outcome.  $t_{jk} < t_{j(k+1)}$  for all  $j$  and all  $k$ . Since  $y_j^*$  may take any value in  $(-\infty, \infty)$ , we fix the value of  $t_{j1} = -\infty$  and  $t_{j(K_j+1)} = \infty$  for all  $j$ . Since the location of the thresholds on the real line is not uniquely identifiable, set  $t_{j2} = 0$ .  $y_j^*$  is expressed as a function of its explanatory variables and other observed dummy variable endogenous outcomes (only in a recursive fashion, if specified),

$$y_{qj}^* = \mathbf{x}_{qj}^T \boldsymbol{\beta} + \mathbf{z}_q^{*T} \mathbf{d}_j + \xi_{qj}, \quad (4)$$

where  $\mathbf{x}_{qj}$  is an  $(E \times 1)$  vector of size of explanatory variables including a constant as well as including the possibility of other dummy variable endogenous outcome variables.  $\boldsymbol{\beta}$   $(E \times 1)$  is a column vector of the coefficients associated with  $\mathbf{x}_{qj}$  and  $\mathbf{d}_j$   $(L \times 1)$  is the vector of coefficients of the latent variables for outcome  $j$ .  $\xi_{qj}$  is a stochastic error term that captures the effect of unobserved variables on  $y_{qj}^*$ .  $\xi_{qj}$  is assumed to follow a standard normal distribution. Jointly, the continuous measures of the  $J$  outcome variables may be expressed as,

$$\mathbf{y}_q^* = \mathbf{x}_q \boldsymbol{\beta} + \mathbf{d} \boldsymbol{\zeta}_q + \boldsymbol{\xi}_q, \quad (5)$$

where  $\mathbf{y}_q^*$   $(J \times 1)$  and  $\boldsymbol{\zeta}_q$   $(J \times 1)$  are the vectors formed by vertically stacking  $y_{qj}^*$  and  $\xi_{qj}$ , respectively, of the  $J$  dependent variables.  $\mathbf{x}_q$   $(J \times E)$  is a matrix formed by vertically stacking the vectors  $(\mathbf{x}_{q1}^T, \mathbf{x}_{q2}^T, \dots, \mathbf{x}_{qJ}^T)$  and  $\mathbf{d}$   $(J \times L)$  is a matrix formed by vertically stacking  $(\mathbf{d}_1^T, \mathbf{d}_2^T, \dots, \mathbf{d}_J^T)$ .  $\boldsymbol{\xi}_q$  follows a multivariate normal distribution centered at the origin with an identity matrix as the covariance matrix (independent error terms).  $\boldsymbol{\xi}_q \sim MVN_J(\mathbf{0}_J, \mathbf{I}_J)$ . It is assumed the terms in  $\boldsymbol{\xi}_q$  are independent because it is not possible to uniquely identify all correlations between the elements in  $\boldsymbol{\eta}_q$  and all correlations between the elements in  $\boldsymbol{\zeta}_q$ . Further, because of the ordinal nature of the outcome variables, the scale of  $\mathbf{y}_q^*$  cannot be uniquely identified. Therefore, the variances of all elements in  $\boldsymbol{\xi}_q$  is fixed to one. The reader is referred to Bhat (2015) for further nuances regarding the identification of coefficients in the GHDM framework.



Substituting Equation (2) in Equation (5),  $\mathbf{y}_q^*$  can be expressed in the reduced form

as

$$\mathbf{y}_q^* = \mathbf{x}_q \boldsymbol{\beta} + \mathbf{d} (\mathbf{w}_q \boldsymbol{\alpha} + \boldsymbol{\eta}_q) + \boldsymbol{\xi}_q, \quad (6)$$

$$\mathbf{y}_q^* = \mathbf{x}_q \boldsymbol{\beta} + \mathbf{d} \mathbf{w}_q \boldsymbol{\alpha} + \mathbf{d} \boldsymbol{\eta}_q + \boldsymbol{\xi}_q. \quad (7)$$

On the right side of Equation (7),  $\boldsymbol{\eta}_q$  and  $\boldsymbol{\xi}_q$  are random vectors that follow the multivariate normal distribution and the other variables are non-random. Therefore,  $\mathbf{y}_q^*$  also follows the multivariate normal distribution with a mean of  $\mathbf{b} = \mathbf{x}_q \boldsymbol{\beta} + \mathbf{d} \mathbf{w}_q \boldsymbol{\alpha}$  (all elements of  $\boldsymbol{\eta}_q$  and  $\boldsymbol{\xi}_q$  have a mean of zero) and a covariance matrix of  $\boldsymbol{\Sigma} = \mathbf{d} \boldsymbol{\Gamma} \mathbf{d}^T + \mathbf{I}_J$ .

$$\mathbf{y}_q^* \sim MVN_J(\mathbf{b}, \boldsymbol{\Sigma}). \quad (8)$$

The parameters that are to be estimated are the elements of  $\boldsymbol{\alpha}$ , strictly upper triangular elements of  $\boldsymbol{\Gamma}$ , elements of  $\boldsymbol{\beta}$ , elements of  $\mathbf{d}$  and  $t_{jk}$  for all  $j$  and  $k \in \{3, 4, \dots, K_j\}$ .

Let  $\boldsymbol{\theta}$  be a vector of all the parameters that need to be estimated. The maximum likelihood approach can be used for estimating these parameters. The likelihood of the  $q^{\text{th}}$  observation will be,

$$L_q(\boldsymbol{\theta}) = \int_{v_1=t_{1y_{q1}}-b_1}^{v_1=t_{1(y_{q1+1})}-b_1} \int_{v_2=t_{2y_{q2}}-b_2}^{v_2=t_{2(y_{q2+1})}-b_2} \dots \int_{v_J=t_{Jy_{qJ}}-b_J}^{v_J=t_{J(y_{qJ+1})}-b_J} \phi_J(v_1, v_2, \dots, v_J | \boldsymbol{\Sigma}) dv_1 dv_2 \dots dv_J, \quad (9)$$

where,  $\phi_J(v_1, v_2, \dots, v_J | \boldsymbol{\Sigma})$  denotes the probability density of a  $J$  dimensional multivariate normal distribution centered at the origin with a covariance matrix  $\boldsymbol{\Sigma}$  at the point  $(v_1, v_2, \dots, v_J)$ . Since a closed form expression does not exist for this integral and evaluation

using simulation techniques can be time consuming, the One-variate Univariate Screening

technique proposed by Bhat (2018) was used for approximating this integral. The estimation of parameters was carried out using the *maxlik* library in the GAUSS matrix programming language.

## CHAPTER 5

### MODEL ESTIMATION RESULTS

This section presents a detailed description of the model estimation results. First, the latent construct structural equation model (SEM) component is presented together with the measurement equation model (MEM) model component depicting factor loadings. Second, results are presented for the multivariate ordered probit (MORP) model of endogenous outcomes of interest.

#### 5.1. Latent Constructs Model Component

The results of the latent constructs model components are shown in Table 2. The top half of the table shows the structural equation model component, depicting the influence of socio-economic and demographic variables on the three latent constructs. This component is estimated as a multivariate regression incorporating error correlations.

The interpretation of the model coefficients is behaviorally reasonable and consistent with expectations. Consistent with findings reported by Alsharaway et al. (2021), men exhibit a lower level of COVID-19 risk perception. Women view virtual activity modalities more positively than men (Bidmon & Terlutter, 2015; Mundorf et al., 2009) and exhibit a greater social interaction propensity (Umberson et al., 1996). Given the extensive media coverage that older individuals were more susceptible to severe reactions to COVID-19, it is not surprising to see younger individuals exhibit a lower risk perception (Hu et al., 2020). They also exhibit a lower social interaction propensity, suggesting that younger individuals – who are more technology savvy and able to use virtual social interaction platforms effectively to stay in touch with family and friends

(Auxier & Anderson, 2021) – do not feel as much of a need to interact in-person (when compared with older individuals). Older individuals are less likely to embrace virtual activity platforms, consistent with the technology-savvy nature of younger generations (Charness et al., 2020). Those with a higher educational attainment exhibit higher levels of COVID-19 risk perception, presumably due to their greater awareness and trust in official sources of information (Pfortner et al., 2022). Those with a lower educational attainment exhibit a lower social interaction propensity.

The results show differences among races, with Whites less enamored and Blacks more enthusiastic about virtual activity platforms. Blacks and Asians depict a higher level of COVID-19 risk perception, which may affect their proclivity to engage in out-of-home activities and access goods and services in-person. Non-Whites exhibit a lower social interaction propensity. Workers depict a lower COVID-19 risk perception, a finding that merits further investigation of underlying reasons. With respect to household characteristics, lower-income individuals exhibit a lower social interaction propensity, individuals residing in middle-income households are more likely to embrace virtual activity platforms, and the rich, making \$100,000 or more, exhibit higher levels of social interaction propensity. Higher-income individuals generally engage in more social and recreational activities outside the home (Nordbakke, 2019); hence, this finding is consistent with expectations. Finally, the presence of children is associated with an elevated perspective of virtual activity platforms, presumably because these households have had to use such technologies to a greater degree when schools shut down and pivoted to online learning modalities.

**TABLE 2 Determinants of Latent Variables and Loadings on Indicators (N=8,392)**

Explanatory Variables (base category)		Structural Equations Model Component					
		COVID-19 Risk Perception		Virtual Activity Perspective		Social Interaction Propensity	
		Coef	t-stat	Coef	t-stat	Coef	t-stat
<b><i>Individual characteristics</i></b>							
<i>Gender (*)</i>	Female	na	na	0.22	8.06	0.14	4.45
	Male	-0.23	-8.68	na	na	na	na
<i>Age (*)</i>	18-40 years	-0.13	-5.20	na	na	-0.22	-6.92
	65 years or older	na	na	-0.25	-7.80	na	na
<i>Education (*)</i>	High school or less	na	na	na	na	-0.35	-8.21
	Bachelor's degree(s)	0.17	6.08	na	na	na	na
	Graduate degree(s)	0.25	8.06	na	na	na	na
<i>Race and ethnicity (*)</i>	Non-White	na	na	na	na	-0.41	-10.76
	Non-Hispanic White	na	na	-0.24	-7.25	na	na
	Black	0.23	5.47	0.44	8.92	na	na
	Asian	0.20	3.54	na	na	na	na
<i>Employment (non-worker)</i>	Worker	-0.17	-6.56	na	na	na	na
<b><i>Household characteristics</i></b>							
<i>Household income (*)</i>	Up to \$50,000	na	na	na	na	-0.39	-10.35
	\$50,000 to \$100,000	na	na	0.07	2.81	na	na
	\$100,000 or more	na	na	na	na	0.19	4.76
<i>Children in home (no children)</i>	One or more	na	na	0.21	7.20	na	na
<b><i>Correlations between latent constructs</i></b>							
COVID-19 risk perception		1	na	0.43	8.45	0.06	3.32
Virtual activity perspective		na	na	1	na	0.01	0.99
Social interaction propensity		na	na	na	na	1	na
<b>Attitudinal Indicators</b>		<b>Loadings of Latent Variables on Indicators (Measurement Equations Model Component)</b>					
If I catch the coronavirus, I am concerned that I will have a severe reaction.		1.03	55.14	na	na	na	na
I am concerned that friends or family members will have a severe reaction to the coronavirus if they catch it.		0.77	47.17	na	na	na	na
Society is overreacting to the coronavirus.		-1.40	-52.66	na	na	na	na
Online learning is a good alternative to high school and college level classroom instruction.		na	na	0.68	42.90	na	na
Video calling is a good alternative to in-person business meetings.		na	na	0.62	33.31	na	na
Video calling is a good alternative to visiting friends/family.		na	na	0.66	39.60	na	na
I liked being outside.		na	na	na	na	0.55	21.82
I liked seeing people and having other people around me.		na	na	na	na	0.60	20.19
I enjoy the social interactions at a conventional workplace.		na	na	na	na	0.49	24.54

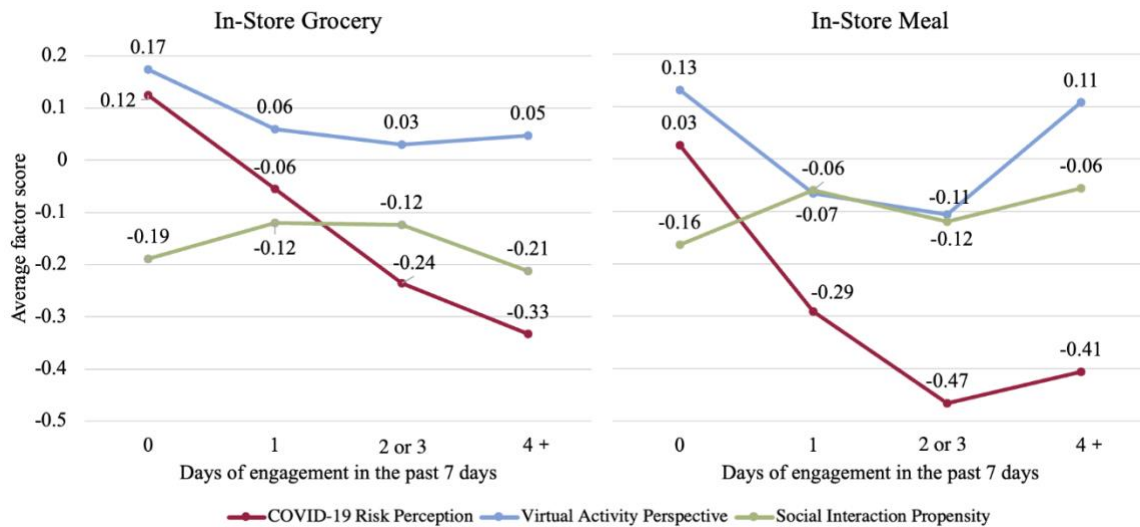
Note: Coef = coefficient; na = not applicable

\*Base category is not identical across the model equations and corresponds to all omitted categories.

Two of the three error correlations are significant, thus supporting the use of a joint econometric model formulation for this study. All correlations are positive. This means that unobserved factors contributing to one attitudinal construct also elevate the level of the other attitudinal constructs. For example, unobserved factors that contribute to elevated levels of COVID-19 risk perception are also likely to engender more positive feelings about using virtual activity platforms. Similarly, unobserved factors contributing to a higher social interaction propensity are likely to also contribute to elevated feelings of risk stemming from COVID-19. The bottom half of Table 2 presents the factor loadings for the measurement equations model (MEM) component. All factor loadings are intuitive and statistically significant. All coefficients are positive, implying that the indicators lead to an elevation of the particular latent construct. The one exception is the loading of the statement on whether the individual feels society is overreacting to the virus. As expected, this has a negative loading for the COVID-19 risk perception factor. If an individual agrees with this statement, the person has a low COVID-19 risk perception (hence, believes that society is overreacting). All other factor loadings offer similar behaviorally intuitive interpretations.

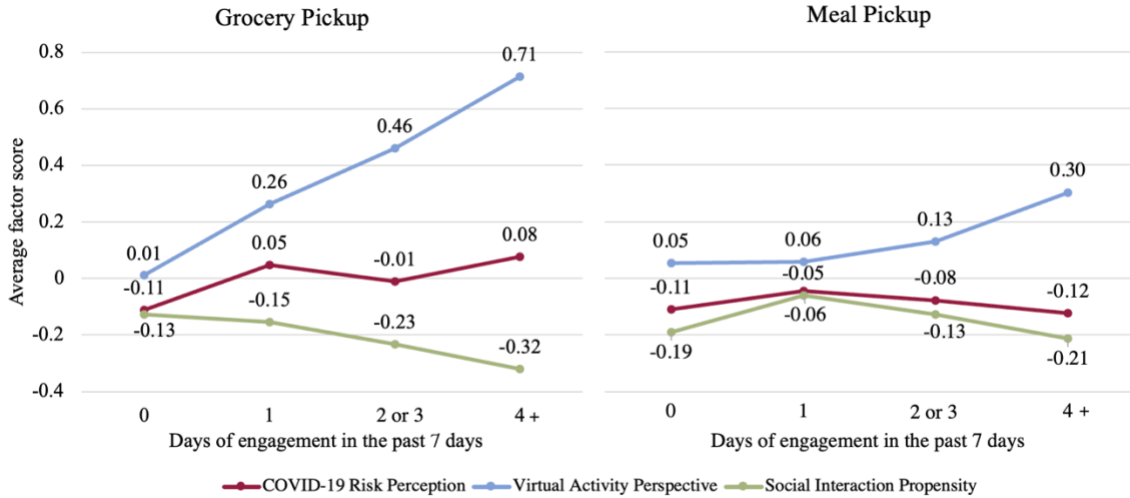
Average factor scores for the latent constructs were calculated and are shown by days of engagement for the six outcome variable activities. Figure 19 compares the scores for in-store grocery versus in-store meal engagement frequency. The patterns are intuitive for most of the latent constructs. For instance, when looking at in-store grocery shopping, we can see that average factor scores for COVID-19 risk perceptions and virtual activity perspectives are greater for those who engage less frequently, and lower for those who engage more frequently. The patterns are less clear when looking at the 4 or more days of

engagement for meals but tend to follow a similar pattern. The social interaction propensity average factor scores are also generally greater for in-store meal shopping as the frequency of engagement increases, which illustrates these individuals' desire to be in-store interacting with others.



**FIGURE 19 Latent Construct Factor Scores by In-store Grocery and Meal Engagement Frequency (N=8,392)**

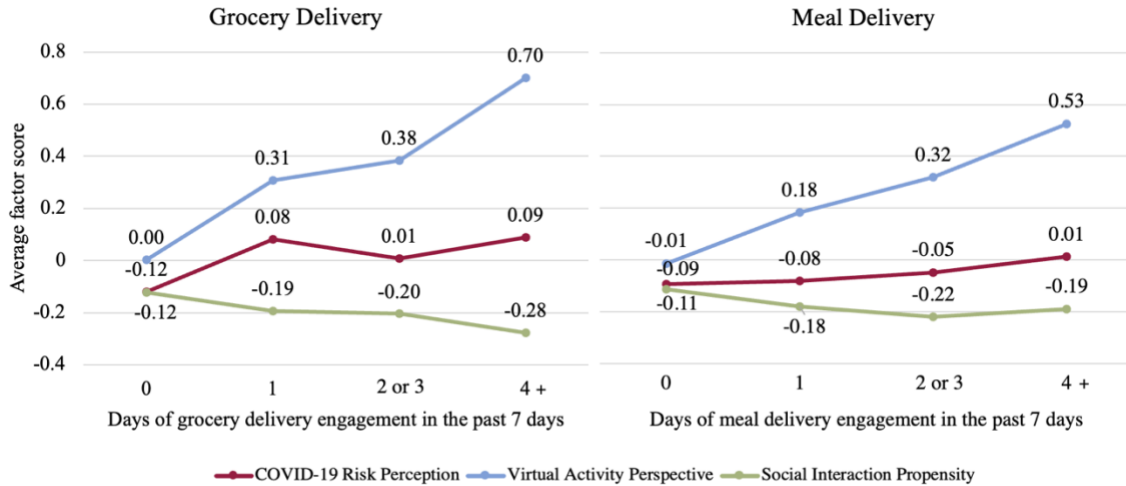
Figure 20 shows the average factor scores for grocery and meal pickup activity. COVID-19 risk perceptions increase with increased grocery pickup engagement, which is in alignment with expectations. COVID-19 risk perception and patterns are not clear for meal pickup engagement, which potentially points to the difference in necessity between grocery and meal activities. Virtual activity perspective average factor scores increase with increased pickup engagement for both groceries and meals, showing how acceptance increases the use of these technologies. Average social interaction propensity factor scores steadily decrease with increased grocery pickup engagement frequency and show a less pronounced but similar pattern for meal engagement.



**FIGURE 20 Latent Construct Factor Scores by Grocery and Meal Pickup Engagement Frequency (N=8,392)**

Finally, Figure 21 compares average factor scores for the three latent constructs with grocery and meal delivery. The same patterns as seen for pickup modalities are illustrated for delivery use, although these patterns are slightly more pronounced for delivery. It is again observed that a greater frequency of engagement in grocery and meal delivery is associated with greater COVID-19 risk perceptions and more positive virtual activity perspectives. Average factor scores for social interaction propensity decrease with increased online delivery use frequency, supporting the hypothesis that some value in-store trips as opportunities for socialization.





**FIGURE 21 Latent Construct Factor Scores by Grocery and Meal Delivery Engagement Frequency (N=8,392)**

## 5.2. Multivariate Model of Behavioral Outcomes

Table 3 presents estimation results for the multivariate ordered probit (MORP) model of six endogenous outcomes representing food access modalities. A key finding is that attitudinal constructs significantly influence grocery and meal activity engagement. Higher COVID-19 risk perception is associated with a lower propensity to engage in grocery shopping in-store, eating meals in-store (restaurants), and picking up meals in-person. In other words, those with higher COVID-19 risk perceptions are less likely to engage in these activity modalities, potentially affecting their ability to access meals and food affordably. Meal and grocery delivery fees can be cost-prohibitive for many. Table 2 shows that minorities (Blacks and Asians) are more prone to elevated COVID-19 risk perceptions, meaning minorities are less likely to access food (groceries and meals) in-person during a public health crisis. The disruption disrupts food access for minorities disproportionately more than for other groups. Elevated and more positive perspectives of the efficacy of virtual activity engagement platforms are associated with a greater proclivity to engage in

food access activities through virtual (online) means (followed by food delivery or pickup). Those with a more significant social interaction propensity are more likely to engage in in-person shopping and pickup. These findings are consistent with expectations and indicate that attitudes play a significant role in shaping disruption-era behaviors.

The rest of Table 3 provides the coefficients associated with socio-economic and demographic attributes. Females are less likely to engage in all six activity modalities. This finding suggests that men were more likely to shop for groceries and meals both online and in-person during the pandemic. Males exhibited lower levels of COVID-19 risk perceptions (see Table 2), and generally adopted technology platforms to a greater degree than females (Rana et al., 2022). This helps explain why males were more likely to shop in-store and use online shopping/ordering platforms.

The age group of 51-60 is positively associated with in-store grocery shopping, while younger individuals are more likely to embrace virtual modalities – except for eating meals in-store. Younger individuals may consider eating meals in-person an important social activity and be less worried about the risk of COVID to their health (Rosi et al., 2021). They are also more technology-savvy and likely to use virtual activity platforms to order goods and services. Middle-aged people engaged in more pickup and delivery modalities, presumably because of the higher presence of children and the need to juggle elevated household and childcare obligations and constraints during the pandemic.

**TABLE 3 Estimation Results of Grocery and Meal Model Components (N=8,392)**

Explanatory Variables (base category)		Main Outcome Variables (4-level: zero to four or more times per week)											
		Grocery in-store		Grocery pickup		Grocery delivery		Meal in-store		Meal pickup		Meal delivery	
		Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
<b>Latent constructs</b>													
	COVID-19 risk perception	-0.40	-40.04	—	—	0.03	2.33	-0.38	-32.45	-0.04	-2.42	—	—
	Virtual activity perspective	na	na	0.36	23.10	0.53	39.98	0.03	1.68	0.15	9.29	0.43	40.10
	Social interaction propensity	0.08	4.98	na	na	na	na	0.11	5.57	0.08	4.63	—	—
<b>Individual characteristics</b>													
<i>Gender (not female)</i>	Female	-0.09	-3.61	-0.24	-6.24	-0.42	-10.98	-0.14	-4.70	-0.12	-4.40	-0.25	-8.15
<i>Age (*)</i>	18-30	na	na	0.49	9.44	0.34	6.49	0.15	4.65	na	na	0.75	18.42
	18-40	na	na	na	na	na	na	na	na	0.26	8.68	na	na
	31-40	na	na	0.53	10.26	0.41	7.42	na	na	na	na	0.62	14.43
	41-50	na	na	0.31	5.61	—	—	na	na	na	na	0.39	8.43
	51-60	0.11	3.26	na	na	na	na	na	na	na	na	na	na
<i>Race and ethnicity (*)</i>	Non-Hispanic White	-0.17	-5.02	na	na	na	na	na	na	-0.12	-3.84	na	na
	Non-Hispanic	na	na	—	—	na	na	na	na	na	na	na	na
	Non-White	na	na	na	na	-0.07	-1.72	na	na	na	na	—	—
	Asian	na	na	na	na	na	na	-0.16	-2.35	na	na	na	na
	Black	0.21	4.77	na	na	na	na	na	na	na	na	na	na
	Hispanic	na	na	na	na	na	na	0.08	1.67	na	na	na	na
<i>Employment (*)</i>	Worker	na	na	na	na	0.10	2.35	na	na	na	na	0.28	8.84
	Non-worker	—	—	-0.11	-2.78	na	na	-0.16	-5.03	-0.17	-6.11	na	na
<i>Education (*)</i>	High school or less	0.07	1.92	na	na	-0.14	-2.86	0.12	2.84	na	na	na	na
	Graduate degree(s)	na	na	0.22	5.38	na	na	na	na	na	na	na	na
<i>COVID-19 test results (*)</i>	Positive	na	na	0.42	3.22	0.25	1.93	na	na	0.22	2.25	0.41	3.92
	Negative	na	na	na	na	na	na	0.13	3.88	na	na	na	na
<b>Household characteristics</b>													
<i>Household income (*)</i>	Less than \$25,000	na	na	na	na	-0.57	-9.36	na	na	na	na	na	na
	Less than \$35,000	0.07	2.14	na	na	na	na	na	na	na	na	na	na
	Less than \$50,000	na	na	na	na	na	na	na	na	-0.09	-2.74	—	—
	\$25,000-\$50,000	na	na	na	na	-0.45	-8.64	na	na	na	na	na	na
	\$50,000-\$100,000	na	na	na	na	-0.36	-8.16	na	na	na	na	na	na
	\$100,000 or more	-0.10	-3.35	na	na	na	na	0.08	2.38	0.10	3.02	na	na
<i>Household size (&gt;1)</i>	One	-0.09	-2.85	na	na	na	na	na	na	-0.22	-6.17	na	na

**TABLE 3 (CONTINUED) Estimation Results of Grocery and Meal Model Components (N=8,392)**

Explanatory Variables (base category)		Main Outcome Variables (4-level: zero to four or more times per week)											
		Grocery in-store		Grocery pickup		Grocery delivery		Meal in-store		Meal pickup		Meal delivery	
		Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
<i>Household vehicles</i> (*)	Zero	na	na	-0.42	-6.07	0.11	1.75	-0.21	-3.18	-0.37	-6.63	0.15	2.73
	Three or more	0.09	2.86	na	na	na	na	na	na	na	na	na	na
<i>Home type</i> (*)	Stand-alone home	-0.11	-4.25	na	na	-0.26	-6.86	na	na	na	na	-0.10	-3.00
	Apartment	na	na	-0.15	-3.61	na	na	na	na	na	na	na	na
<i>Household structure</i> (*)	Children present	na	na	0.25	5.73	0.23	4.68	na	na	0.11	3.55	0.13	3.30
	Single parent	na	na	na	na	0.24	3.71	na	na	na	na	0.20	3.35
<b>Built envr and travel characteristics</b>													
<i>Employment density</i> (*)	<3000 jobs/km <sup>2</sup>	na	na	-0.35	-4.78	na	na	na	na	na	na	na	na
<i>Housing density</i> (*)	<3000 units/km <sup>2</sup>	na	na	na	na	na	na	-0.21	-3.67	-0.12	-2.29	na	na
<i>Population density</i> (*)	<3000 person/km <sup>2</sup>	na	na	na	na	na	na	na	na	na	na	-0.22	-5.66
<i>Retail jobs density</i> (*)	<200 jobs/km <sup>2</sup>	na	na	na	na	-0.33	-8.24	na	na	na	na	-0.10	-2.46
<i>Commute distance</i> (<40)	40 mi or more	na	na	0.30	3.27	na	na	na	na	na	na	na	na
<b>Thresholds</b>	1 2	-1.13	-24.45	0.73	7.57	0.27	4.20	0.35	5.30	-0.35	-5.62	0.55	10.52
	2 3	0.24	5.27	1.46	15.17	1.01	15.52	1.09	16.49	0.60	9.60	1.37	25.75
	3 4	1.71	34.58	2.36	22.67	1.97	27.11	2.07	28.53	1.79	26.23	2.48	40.64
<b>Correlation</b>	Grocery in-store	1.00		-0.05		-0.08		0.13		-0.01		-0.06	
	Grocery pickup	na		1.00		0.16		-0.03		0.05		0.13	
	Grocery delivery	na		na		1.00		-0.07		0.06		0.19	
	Meal in-store	na		na		na		1.00		0.00		-0.05	
	Meal pickup	na		na		na		na		1.00		0.05	
	Meal delivery	na		na		na		na		na		1.00	
<b>Data Fit Measures</b>		GHDM						Independent Model					
Log-likelihood at convergence		-41060.75						-42009.66					
Log-likelihood at constants		-44633.9											
Number of parameters		173						121					
Likelihood ratio test		0.080						0.059					
Average probability of correct prediction		0.0112						0.0109					

Note: Coef = coefficient; na = not applicable; "—" = not statistically significantly different from zero at the 90% confidence level and removed from the specification.

\*Base category is not identical across the model equations and corresponds to all omitted categories.

Built environment information is: Employment density at 95 percentile: 3000 jobs/km<sup>2</sup>; Housing density at 95 percentile: 3000 housing units/km<sup>2</sup>; Population density at 75 percentile: 3000 person/km<sup>2</sup>; Retail jobs density at 75 percentile: 200 jobs/km<sup>2</sup>

Non-Whites (racial minorities) are less likely to order groceries for delivery. As mentioned earlier, minorities are also more likely to feel that COVID-19 presents a risk to their health. As a result, they are less likely to engage in in-person shopping activities. The race effect shows that minorities are also less likely to have groceries delivered. In other words, minority groups may experience diminished access to food during a public health pandemic by virtue of their reluctance to engage in in-person shopping activities and their lower levels of technology savviness/access and ability to pay for delivery. These findings align with food insecurity findings from the United States Census Bureau Pulse Survey (2021). Communities must provide these groups with resources, so they do not experience a food access challenge during a pandemic.

Workers are more likely to have groceries and meals delivered, presumably because of their technology savviness, constrained work schedules, and greater awareness of virtual platforms to access goods and services. Non-workers consistently depict a lower propensity to engage in in-store and pickup modalities, likely due to household obligations and childcare responsibilities. Highly educated individuals exhibit a greater propensity to order groceries online for pickup, while those with lower educational attainment are more likely to shop in-store (increasing their risk exposure) and less likely to have groceries delivered (even after controlling for income constraints). These findings suggest that individuals at the lower end of the educational spectrum may experience challenges accessing and affording virtual mechanisms for acquiring groceries. Those who experienced COVID-19 (indicated by positive test results) may be more cautious and hence show a greater proclivity for procuring groceries and meals online than in-person.

Household characteristics show a similar pattern of behaviorally intuitive results. The low-income group was least likely to purchase groceries through online + delivery mechanisms. This suggests that low-income individuals face considerable technological and income barriers to taking advantage of virtual activity modalities for accessing food (Guzman et al., 2021; Kim & Wang, 2021). The low-income group also exhibits a higher propensity to shop for groceries in-store, increasing their exposure to the virus. Middle-income groups also depict a lower propensity to shop for groceries online for delivery, essentially implying that delivery-based grocery access is rather limited to the rich (Dias et al., 2020). Single adults are less likely to shop in-store and pickup meals, which merits further investigation for underlying reasons.

From a *transportation* standpoint, access to vehicles matters. Individuals in households with zero vehicles exhibited a greater propensity to have groceries and meals delivered, a finding previously reported by Kim & Wang (2021). However, they had to incur additional delivery fees for that service. They are less likely to engage in in-person pickup and in-store shopping/meal modalities, which is not surprising given their modal constraints (Dias et al., 2020). On the other hand, higher vehicle ownership is associated with a greater propensity to shop in-store. While virtual delivery-based activity modalities help individuals without a car access food through delivery services, affordability may be an issue – particularly if the disruption is long.

Households with children were more likely to purchase groceries for pickup (Dias et al., 2020) and groceries for delivery (Dias et al., 2020; Kim & Wang, 2021). They were also more likely to purchase meals for pickup and delivery (Dias et al., 2020). This finding is likely due to the time pressures and constraints associated with the presence of children

in homes. Single parents were more likely to engage in higher levels of grocery and meal deliveries, likely for similar reasons. Lower housing density was negatively associated with purchasing meals for pickup (Dias et al., 2020) or in-store dining, presumably because fewer restaurants are nearby. A lower population density is negatively associated with meal delivery. This finding may be explained by restaurants not serving far away low-density or rural areas. Finally, retail job density is negatively associated with grocery delivery and meal delivery (Dias et al., 2020). In areas with high retail job density, grocery and meal establishments are likely in close proximity, thus enabling easy access to in-store or in-person pickup modalities. Finally, those commuting 40 miles or more were more likely to purchase groceries for pickup, potentially due to time constraints.

A number of error correlations are statistically significant, supporting the specification and estimation of a joint simultaneous equations model that considers all six endogenous outcomes as a bundle of choices. The correlations are behaviorally intuitive; generally, correlations between in-store modality and pickup/delivery modalities are negative, while correlations between pickup and delivery modalities are positive. This means that unobserved factors that elevate in-person in-store activity engagement are likely to be negatively correlated with unobserved factors that contribute to online activity engagement. On the other hand, unobserved factors that contribute to elevating one form of virtual activity engagement are also likely to elevate the other form. There are likely unobserved factors related to technology access and savviness, time pressure, and willingness to try new things that simultaneously impact alternative activity engagement modalities.

## CHAPTER 6

### **POLICY IMPLICATIONS FOR ADDRESSING FOOD ACCESS DISPARITIES**

Policies are needed to address disparities in food access during extreme, prolonged disruptions. The findings from this study show that assistance should be especially targeted towards those with low household incomes, those living in low-density locations, racial minorities, females, and those with lower educational attainment. It is suggested that these recommendations are planned for before the event of a future crisis, as data collection and stakeholder engagement must be conducted and because potential restrictive policies, economic stressors, and other disaster scenario outcomes may make action increasingly difficult to enact (Rena et al., 2022).

Caution must also be exercised in interpreting the policy implications discussed in the following subsections. While the findings and recommendations provide valuable insights, it is important to consider the limitations and potential unintended consequences of implementing policies in response to food insecurity during disruptions. The complexities of supply chain issues, food shortages at stores, and other contextual factors may pose challenges that cannot be fully addressed through policy interventions alone. Furthermore, the financial considerations and feasibility of implementing policies should be carefully assessed to ensure their sustainability and effectiveness in the long run. When considering additional policies to increase food access, it is important to acknowledge the presence of aid programs such as the FFCRA, CARES Act, and American Rescue Plan that were implemented during the pandemic with the aim of reducing food insecurity (Library of Congress, 2020). These programs included aid supplements such as stimulus checks and the Child Tax Credit, which have had impacts on finances and the ability to access food.



Therefore, it is crucial to carefully evaluate the effectiveness and consequences of existing aid programs before implementing new policies. It is also necessary to ensure that proposed policies build upon the positive impacts and lessons learned from previous interventions. Taking into consideration the complexities of aid programs already in place can help inform the development of comprehensive and sustainable policies to address food access challenges in the future.

Table 4 includes the explanatory variables and associated signs of coefficients (positive or negative) for those most vulnerable to food insecurity during the pandemic. The far right column of the table briefly overviews policy implications associated with the finding. With the caveats discussed in mind, the following sections of the chapter include policy implications for increasing access to food for those most at risk of food insecurity during future disruptions.

### **6.1 Aid Interventions for Overcoming Health Risks Due to Social Isolation**

Social isolation and loneliness present mortality risks similar to, if not greater than, those of other public health issues, including obesity and air pollution (Holt-Lunstad, 2021). Loneliness was believed to impact 20 to 45 percent of individuals in western countries prior to the pandemic (Aleman & Sommer, 2022), and the social isolation that accompanied social distancing and stay-at-home orders exacerbated the issue. In-store grocery shopping is a regular errand that provides social interaction for those who may face social isolation or loneliness. As noted in Table 4, those with greater social interaction scores were more likely to shop in-store for both groceries and meals despite the increased risk to health and safety, likely in some cases to experience socialization.

**TABLE 4 Vulnerable Population Estimation Coefficient Signs and Policy Implications**

Explanatory Variables	Main Outcome Variable Coefficient Signs						Policy Implications
	Grocery			Meal			
	In-store	Pickup	Delivery	In-store	Pickup	Delivery	
<i>Latent constructs</i>							
Social interaction propensity	+	na	na	+	+	na	Provide safe, affordable, and accessible social outlets to reduce the need for unsafe socialization in future disruptions
Virtual activity perspective	na	+	+	+	+	+	Provide tools and training to overcome the digital divide, as this is shown to increase online modality use
<i>Individual characteristics</i>							
Female	-	-	-	-	-	-	Account for gender-based transportation constraints in emergency disruption planning and provide tools and training to overcome the digital divide when applicable
Non-white	na	na	-	na	na	na	Provide translation services for online food access services, food aid programs, and emergency planning
Black	+	na	na	na	na	na	
High school educational attainment or less	+	na	-	+	na	na	Provide tools and training to overcome the digital divide
<i>Household incomes</i>							
<\$25,000	na	na	-	na	na	na	Expand the reach of the SNAP Online Purchasing Pilot, (partially) subsidize online fees during disruptions, and increase food aid program funding if appropriate
<\$35,000	+	na	na	na	na	na	
<i>Built envr characteristics</i>							
<3000 person/km <sup>2</sup>	na	na	na	na	na	-	Offer mobile food pantry programs and (partially) subsidize online food delivery fees for those in need
<3000 jobs/km <sup>2</sup>	na	-	na	na	na	na	
<200 retail jobs/km <sup>2</sup>	na	na	-	na	na	na	

Note: Coef = coefficient; na = not applicable or not statistically significantly different from zero at the 90% confidence level and removed from the specification. Built environment information is: Employment density at 95 percentile: 3000 jobs/km<sup>2</sup>; Population density at 75 percentile: 3000 person/km<sup>2</sup>; Retail jobs density at 75 percentile: 200 retail jobs/km<sup>2</sup>

It is important to acknowledge that limited data made it difficult to differentiate between individuals who desire social interaction and derive these benefits from a workplace or home interactions, compared to those who desire socialization but lack opportunities to fulfill that need. Taking limitations into consideration, the following aid interventions are recommended to mitigate risky behavior due to social isolation in future disruptions:

- Educate the public on safe virtual social interaction opportunities
- Pass adaptable guidelines or policies that prioritize health and safety while recognizing the importance of in-person social interaction

Many online platforms for safe socialization exist, including online support groups. Connecting those who may feel socially isolated during disruptions with these resources can increase opportunities for safe socialization from home. Additionally, adaptable guidelines and policies are needed to promote in-person social connection while maintaining health and safety as the top priority. These policies must evolve as knowledge of disruptions evolves and must be highly inclusive and accessible. Increased opportunities for safe socialization may decrease the frequency with which individuals put themselves in high-risk situations to socialize.

## **6.2 Aid Interventions to Address Food Insecurity Due to the Digital Divide**

The digital divide limits individuals without access to technological resources such as phones, computers, or the internet, as well as those unfamiliar or uncomfortable with using these technologies from taking part in virtual modality engagement, including but not limited to ordering groceries or meals for pickup and delivery. Research has shown that

historically disadvantaged populations such as older adults, minorities, females, those with lower educational attainment, and those with lower incomes are more likely to be vulnerable to disparities in digital access (Van Dijk, 2017). The preliminary analysis combined with findings in Tables 3 and 4 reveals that although subgroups, including those with lower household incomes, those with lower educational attainment, racial minorities, females, and non-workers, generally have positive virtual activity participation attitudes compared to their counterparts, they are not using the online alternatives to an equal extent. These findings indicate that disparities in access to technology may be a contributing factor to decreased technological use. This decreased access has the potential to further exacerbate historical inequities (Van Dijk, 2017). The following recommendations aim to help reduce inequities by providing education and tools necessary to connect those who may be food insecure with the resources needed to access food safely during disruptions:

- Provide the technological resources required to empower individuals who are digitally challenged and experiencing food insecurity
- Offer education and support to acquire proficiency in utilizing digital tools for accessing food-related resources

Providing technological resources such as computers or the essential service of internet access can increase food provision options for those lacking the necessary tools to order food online in future disruptions, especially when in-store trips put health or wellbeing at risk (Bezigan & Lachapelle, 2021; Lai & Widmar, 2020). Providing educational classes or training on the use of online technologies reduces technological barriers, increasing access for those limited by a lack of education (Van Dijk, 2017). The challenge of providing technological education or training while adhering to social

distancing mandates underscores the need to offer such training proactively before disruptions occur or to have support systems in place, such as family or friends, who can assist those in need. Incorporating social support from family and friends can increase interest and motivation in learning how to use these technological tools. Ensuring access to these resources or educational opportunities for elderly, physically handicapped, or otherwise homebound individuals is especially important to ensure the most vulnerable populations have access to food, especially during disruptions.

### **6.3 Aid Interventions by Subgroup**

Many recommended aid interventions are useful across socio-demographic and economic as well as built environment subgroup categorizations. Other recommendations are targeted to specific subgroups to effectively address the population's needs. This section first discusses general recommendations, followed by specific interventions for populations with individual needs. General aid interventions recommended for implementation during disruptions that aim to increase access to food for all are as follows:

- Expand the reach of the SNAP Online Purchasing Pilot and allow SNAP funds to be used for online purchasing fees
- Pass policies or adapt assistance programs to (at least partially) subsidize online food purchasing fees during disruptions
- Include diverse stakeholders and those especially vulnerable to food insecurity in emergency disruption preparation plans

SNAP was shown to help reduce food insecurity during the pandemic (Bryant & Follett, 2022; Reimold et al., 2021), and increasing funding to SNAP and similar programs can mitigate food insecurity for the most vulnerable in future disruptions. Continuing to

fund and expand the SNAP Online Purchasing Pilot can increase reliable access to online food options. This program allows SNAP participants to purchase eligible food online through a list of approved retailers (USDA Food and Nutrition Service, 2023). However, SNAP funds cannot be used to pay for delivery fees, and the program is only available at limited stores, making the program's reach constrained. Passing state or federal government policies to assist in paying for online food pickup or delivery fees will increase online food access during disruptions, which is especially critical to ensure access for the most vulnerable.

Emergency and disruption plan preparation must include members from all diverse stakeholder subgroups, especially those most vulnerable to food insecurity. Research has shown that stakeholder engagement is necessary when planning, as it helps pinpoint context-specific factors and root causes of food insecurity challenges (Garba et al., 2022) and provides real-life knowledge when data is scarce or non-existent (Tendell et al., 2015). Stakeholder engagement is also advantageous for building trust and program buy-in throughout communities (Rela et al., 2022). Diverse stakeholder engagement can help address the needs of a wide array of vulnerable subgroups.

### *Racial Minorities*

As seen in Tables 3 and 4, Blacks were more likely to shop in-store for groceries than other races during the pandemic peak, and non-whites were less likely to use grocery delivery services. To help prevent food insecurity for racial minorities in future disruptions it is recommended that translation services are provided for online food purchasing websites when deploying food assistance programs, when marketing aid efforts, and during stakeholder engagement in disruption preparation planning. This will increase the

widespread reach of assistance, improve understanding of diverse population needs, and encourage participation in planning for disruption by those whose first language is not English. Challenges and needs vary by culture and population, meaning location-specific research may be necessary to comprehend and provide best practices for individual communities (Garba et al., 2022).

#### *Low-Density Locations*

Homes in low-density or rural neighborhoods may experience increased food insecurity due to factors such as fewer grocery stores and restaurants being located nearby and decreased access to home food delivery services (Beese et al., 2022). Table 4 shows this thesis' findings that a lower density of jobs and people lead to decreased use of online grocery options and meal delivery, respectively. One option for increasing food access for those in low-density areas is to provide mobile food pantry programs that deliver prepackaged food to those in need (Carson and Boege, 2020). These programs should be targeted toward those most vulnerable to food insecurity. Another option is to, at least partially, subsidize online purchasing fees for customers living in low-density or rural communities or food deserts during disruptions (Xu & Saphores, 2022).

## CHAPTER 7

### SUMMARY AND CONCLUSIONS

The COVID-19 pandemic was a severe and prolonged disruption that led to a public health crisis that impacted people's lives in many ways. During this disruption, many businesses and establishments restricted their operations, and policies were implemented to limit the virus's spread. This thesis focuses on studying access to food (groceries and meals) during the pandemic, with an emphasis on identifying segments of the population that may be particularly vulnerable and unable to sufficiently *adapt* to access food to the same degree as in a pre-pandemic era.

This thesis utilizes data collected in the first wave of a large national panel survey aimed at capturing behavioral changes over the course of the pandemic. The data set, derived from the COVID Future Panel Survey, includes more than 8,300 observations and contains detailed data about how frequently people engaged in various activities by different modalities (in-person and online) before and during the pandemic. This thesis defines food access as the ability to obtain groceries and meals. Both food types may be purchased in-store or ordered online for possible pickup in-person or delivery to the consumer. Thus, there are two commodity types and three possible modalities, leading to six possible avenues for obtaining food. Engaging in any food access activity modalities constitutes a choice; hence, the six possible food access modalities may be treated as a bundle of choices.

The study models the frequency with which individuals engage in the six possible modalities in a simultaneous equations modeling framework that accounts for error correlations across the dimensions of interest. The simultaneous equations model system



incorporates a series of latent constructs that capture attitudes and perceptions, including COVID-19 risk perceptions, perceptions of the effectiveness of virtual activity platforms, and social interaction propensity. The model system showed that attitudes and perceptions, together with a host of socio-economic and demographic attributes, significantly affect participation in different activity modalities. Moreover, the presence of significant error correlations and the model goodness-of-fit measures show that the joint simultaneous equations modeling approach is warranted when considering a set of closely related endogenous variables.

Certain groups exhibited a greater proclivity to engage in in-store shopping even after accounting for the attitudinal proclivities and lifestyle preferences for social interactions. It appears that these groups continued to shop in-store and place themselves in harm's way because alternative online-based options were out of reach or unaffordable. Groups continuing to shop in-store during the pandemic included Hispanics and Blacks. These minority groups also experience a greater digital divide, making it difficult to access online platforms and utilize them effectively to access goods and services. In the case of food deliveries, the cost must be considered; the model showed that lower-income individuals are less likely to procure groceries via delivery mechanisms, presumably because of delivery fees. Females and those with lower educational attainment also exhibit lower levels of virtual food access, suggesting that they are particularly vulnerable should stores restrict operations for prolonged periods. Additionally, those living in lower-density locations are less likely to purchase food for pickup or delivery, likely due to fewer stores serving these areas and high fees for available services.

For purposes of this study, modality engagement frequency is considered as one possible surrogate measure of food access vulnerability during a severe, prolonged disruption. That is to say that, decreased frequency of use of online food services may *potentially* indicate decreased access to safe food options during the pandemic. Similarly, increased in-store grocery shopping may *potentially* indicate a lack of options to access food safely online. More explicit data needs to be collected to truly understand food vulnerability during disruptions. With these limitations in mind, the conclusions of this thesis are as follows:

- In-store grocery shopping was utilized by marginalized subgroups during the COVID-19 pandemic, even by those depicting a low propensity to engage, highlighting its essential nature for food access. Meanwhile, advantaged subgroups who showed preferences for meal activity chose to dine in frequently, demonstrating how meal shopping is more of a choice than grocery shopping.
- Online delivery modalities are subject to greater influence from financial, racial, and educational limitations compared to online pickup modalities. This may limit access to food via delivery methods during a disruption, emphasizing the versatility that pickup options can offer.
- Attitudes and perceptions play a significant role in shaping the frequency of modality engagement. Increased concern about the COVID-19 disruption led to decreased use of in-store modalities, illustrating how alternative, accessible, and affordable online methods for food acquisition are necessary for maintained access to food access during a disruption.

- Racial minorities, those in lower-income households, and, those with less educational attainment were more likely to shop in-store during the pandemic. Females, racial minorities, those in lower-income households, those with less educational attainment, and those from lower-density locations were less likely to use online food modalities. Assuming modality engagement frequency as a surrogate measure of food access vulnerability, these marginalized populations may be at increased risk of food insecurity during future disruptions.

Vulnerable groups need to be provided with technological resources to participate in the online economy and leverage virtual platforms for procuring essential goods and services, including food. Policy suggestions spanning socio-demographic and economic characteristics, as well as built environment attributes and attitudes, are presented.

Looking specifically at transportation, this thesis highlights the significant implications of online services on accessibility, especially for mobility-limited subgroups. Accessibility is being redefined to not only include physical access to infrastructure but also to incorporate online options which provide access to essential services. This expanded definition acknowledges the growing importance of online services in improving accessibility for vulnerable or mobility-limited populations, especially during disruptions or times of crisis. Additionally, this thesis shows that those from households with zero vehicles are more likely to purchase food for delivery and less likely to purchase food in-person or for pickup. As the use of online services increases, it is likely that the necessity of owning a car will be diminished. Continued data collection is needed to capture these changing dynamics.

Designing transportation networks that meet evolving human demands is becoming increasingly complex, partially due to the rapid adoption of online services, including food pickup and delivery options. Transportation infrastructure is critical in providing access to food, and there are significant impacts of increased online food access activity on traffic patterns and demand for transportation infrastructure, both by customers and supply-side entities. Factors such as time of day, day of the week, weather, and personal preferences influence the choice between in-person and online food shopping as well as grocery versus meal preferences. To effectively design future transportation infrastructure, data collection efforts and transportation planning strategies must account for these technological changes and increased online activity engagement. Quality data about pickup and delivery modalities and their spatial and temporal characteristics are necessary for planning and operating transportation infrastructure to support these activities. Travel modeling must account for changes in traffic patterns and demand for transportation infrastructure associated with increased online activity engagement on both the supply and demand sides of planning. The importance of transportation infrastructure in ensuring access to food is evident, underscoring the necessity of planning our future infrastructure to accommodate diverse and dynamic transportation needs.

The research study has several limitations that may impact the generalizability and validity of the findings. Firstly, the study's sample is nationally comprehensive, but the findings are not region-specific, which may limit the applicability of the results to potential regional differences in online food access during the pandemic. As food may be highly culturally and regionally specific, it is recommended that further research investigates how disruptions impact food access on a regional level. Furthermore, confounding food access

variables, including supply chain disruptions, shortages in grocery stores, government food aid programs, and government stimulus checks, were not fully addressed in the study methodology. These confounding factors may impact the interpretation of the findings and the related policy implications. Lastly, this study employs the frequency of engagement in different modalities as a potential proxy for food access, which has certain limitations. Although household-level dynamics were taken into consideration, the data does not account for food purchases made by other household members, which could affect overall food access. Moreover, using data on the days of engagement for modalities may not accurately reflect the quantity of food obtained per day, leading to potential misinterpretation of results. Additional and more explicit data collection on food access is needed in future research on food insecurity during severe and prolonged disruptions.

## REFERENCES

- Ahmed, A. N., Nisar, A., Gul, A., Javed, H. B. Abbas, & Yasmin, R. (2021). Fear of COVID-19 Infection and its Relationship with Health-Related Preventative Practices Among Patients Having Chronic Ailments. *Pakistan Journal of Medical and Health Sciences*, 15(4), 2508-2511.
- Aleman, A., & Sommer, I. (2022). The Silent Danger of Social Distancing. *Psychological Medicine*, 52(4), 789-790.
- Aryani, D. N., Nair, R. K., Hoo, D. X. Y., K, D., Hung, M., Lim, D. H. R., Chew, W. P., & Desai, A. (2021). A Study on Consumer Behavior: Transition from Traditional Shopping to Online Shopping During the COVID-19 Pandemic. *International Journal of Applied Business and International Management*, 6(2), 81-95.
- Auxier, B., & Anderson, M. (2021). Social Media Use in 2021. *Pew Research Center*, 1-4.
- Beese, S., Amram, O., Corylus, A., Graves, J.M., Postma, J., & Monsivais, P. (2022). Expansion of Grocery Delivery and Access for Washington SNAP Participants During the COVID-19 Pandemic. *Preventing Chronic Disease*, 19, E36.
- Belarmino, A., Raab, C., Tang, J., & Han, W. (2021). Exploring the Motivations to Use Online Meal Delivery Platforms: Before and During Quarantine. *International Journal of Hospitality Management*, 96, 102983.
- Bezigani, A., & Lachapelle, U. (2021). Online Grocery Shopping for the Elderly in Quebec, Canada: The Role of Mobility Impediments and Past Online Shopping Experience. *Travel Behaviour and Society*, 25, 133-143.
- Bhat, C. R. (2015). A New GHDM to Jointly Model Mixed Types of Dependent Variables. *Transportation Research B*, 79, 50–77.
- Bhat, C. R. (2018). New Matrix-Based Methods for the Analytic Evaluation of the Multivariate Cumulative Normal Distribution Function. *Transportation Research B*, 109, 238–256.
- Bidmon, S., & Terlutter, R. (2015). Gender Differences in Searching for Health Information on the Internet and the Virtual Patient-Physician Relationship in Germany: Exploratory Results on How Men and Women Differ and Why. *Journal of Medical Internet Research*, 7, e4127.
- Bryant, A., & Follett, L. (2022). Hunger Relief: A Natural Experiment from Additional SNAP Benefits During the COVID-19 Pandemic. *The Lancet Regional Health-Americas*, 10, 100224.

Carson, J. A., & Boege, S. (2020). Innovation in Food Access Amid the COVID-19 Pandemic. *University of New Hampshire*. Retrieved from <https://scholars.unh.edu/cgi/viewcontent.cgi?article=1403&context=carsey>

Carvalho, L. F., Pianowski, G., & Gonçalves, A. P. (2020). Personality Differences and COVID-19: Are Extroversion and Conscientiousness Personality Traits Associated with Engagement with Containment Measures? *Trends in Psychiatry and Psychotherapy*, 42, 179-184.

Chakraborty, P., Mittal, P., Gupta, M. S., Yadav, S., & Arora, A. (2020). Opinion of Students on Online Education During the COVID-19 Pandemic. *Human Behavior and Emerging Technologies*, 3, 357-365.

Charness, N., Fingerman, K., Kaye, J., Kim, M. T., & Khurshid, A. (2019). When Going Digital Becomes a Necessity: Ensuring Older Adults' Needs for Information, Services, and Social Inclusion During COVID-19. *Journal of Aging and Social Policy*, e11694.

Chauhan, R. S., Bhagat-Conway, M. W., Capasso da Silva, D., Salon, D., Shamshiripour, A., Rahimi, E., Khoeini, S., Mohammadian, A. K., Derrible, S., & Pendyala, R. (2021). A Database of Travel-related Behaviors and Attitudes Before, During, and After COVID-19 in the United States. *Scientific*, 8, 245.

Chenarides, L. C., Grebitus, J. L., Lusk, J., & Printezis, I. (2020). Food Consumption Behavior During the COVID-19 Pandemic. *Agribusiness*, 37, 44-81.

Dias, F. F., Lavieri, P. S., Sharda, S., Khoeini, S., Bhat, C. R., Pendyala, R. M., Pinjari, A. R., Ramadurai, G., & Srinivasan, K. K. (2020). A Comparison of Online and In-person Activity Engagement: The Case of Shopping and Eating Meals. *Transportation Research Part C*, 114, 643-656.

Figliozi, M., & Keeling, K. (2019). E-Grocery Home Delivery Impacts on Food Distribution, Access and Equity: a Portland Case Study. *Civil and Environmental Engineering Faculty Publications and Presentations*, 544.

Food Marketing Institute. (2020). *U.S. Grocery Shopper Trends 2020*. <https://www.fmi.org/forms/store/ProductFormPublic/u-s-grocery-shopper-trends-2020>

Garba, N. A., Sacca, L., Clarke, R. D., Bhoite, P., Buschman, J., Oller, V., Napolitano, N., Hyppolite, S., Lacroix, S., Archibald, A., Hamilton, O., Ash, T., & Brown, D. R. (2022). Addressing Food Insecurity during the COVID-19 Pandemic: Intervention Outcomes and Lessons Learned from a Food Delivery Underserved Households. *International Journal of Environmental Research and Public Health*, 19, 8130.

Guzman, L. A., J. Arellana, D. Oviedo, C. Alberto, & M. Aristizábal. (2021). COVID-19, Activity and Mobility Patterns in Bogotá. Are We Ready for a ‘15-minute City’? *Travel Behaviour and Society*, 24, 245-256.

Hansson, L. U., Holmberg, & A. Post. (2022). Reorganizing Grocery Shopping Practices – The Case of Elderly Consumers. *The International Review of Retail, Distribution, and Consumer Research*, 32, 351-369.

Holt-Lunstad, J. (2021). A Pandemic of Social Isolation?. *World Psychiatry*, 20(1), 55.

Hu, Y., R. Wang, X. Zhang, L. Lin, R. Jiang, J. Li, D. Li, C. Liu, Y. Ye, Z. Hou, & Z. Fang. (2020). Perceived Risk of COVID-19 Infection and Among the US Public. *International Journal of Infectious Diseases*, 34, 115-123.

Jacobsen, G. D., & K. H. Jacobsen. (2020). Statewide COVID-19 Stay-at-Home Orders and Population Mobility in the United States. *World Medical & Health Policy*, 12, 347-356.

Jensen, K. L., J. Yenerall, X. Chen, & T. E. Yu. (2021). US Consumers’ Online Shopping Behaviors and Intentions During and After the COVID-19 Pandemic. *Journal of Agricultural and Applied Economics*, 53, 461-434.

Jilcott Pitts, S. B., S. W. Ng, J. L. Blitstein, A. Gustafson, C. J. Kelley, S. Pandya, & H. Weismiller. (2020). Perceived Advantages and Disadvantages of Online Grocery Shopping Among Special Supplemental Nutrition Program for Women, Infants, and Children Participants in Eastern North Carolina. *Current Developments in Nutrition*, 4, nzaa076.

Kim, W., & X. C. Wang. (2021). To be Online or In-Store: Analysis of Retail, Grocery, & Food Shopping in New York City. *Transportation Research Part C*, 126, 103052.

Lai, J., & N. O. Widmar. (2020). Revisiting the Digital Divide in the COVID-19 Era. *Applied Economic Perspectives and Policy*, 42, 458-464.

Lauren, B. N., Silver, E. R., Faye, A. S., Rogers, A. M., Woo-Baidal, J. A., Ozanne, E. M., & Hur, C. (2021). Predictors of Households at Risk for Food Insecurity in the United States During the COVID-19 Pandemic. *Public Health Nutrition*, 24, 3929-3936.

Library of Congress. (2020). H.R.6201 - Families First Coronavirus Response Act. USA.gov. <https://www.congress.gov/bill/116th-congress/house-bill/6201>. Accessed January 26, 2023.

Library of Congress. (2020). H.R.748 – Cares Act. USA.gov. <https://www.congress.gov/bill/116th-congress/house-bill/748>. Accessed January 26, 2023.



Mundorf, N., Dholakia, N., Westin, S., & Brownell, W. (1992). Reevaluating Gender Differences in New Communication Technologies. *Communication Research Reports*, 2, 171-181.

Niles, M. T., Bertmann, F., Belarmino, E. H., Wentworth, T., Biehl, E., & Neff, R. (2020). The Early Food Insecurity Impacts of COVID-19. *Nutrients*, 12, 2096.

Nordbakke, S. T. D. (2019). Mobility, Out-of-home Activity Participation and Needs Fulfillment in Later Life. *International Journal of Environmental Research and Public Health*, 16, 5109.

O'Hara, S., & Toussaint, E. C. (2021). Food Access in Crisis: Food Security and COVID-19. *Ecological Economics*, 180, 106859.

Palmer, F., Jung, S. E., Shahan, M. K., & Ellis, A. (2021). Understanding How the COVID-19 Pandemic Influenced Older Adults' Grocery Shopping Habits. *Journal of Nutrition Education and Behavior*, 53, S54-S55.

Pförtner, T. K., Dohle, S., & Hower, K. I. (2022). Trends in Educational Disparities in Preventive Behaviours, Risk Perception, Perceived Effectiveness and Trust in the First Year of the COVID-19 Pandemic in Germany. *BMC Public Health*, 22, 1-14.

Rena, I. Z., Z. Ramli, M. Z. Firihi, W. Widayati, A. H. Awang, & N. Nasaruddin. (2022). COVID-19 Risk Management and Stakeholder Action Strategies: Conceptual Frameworks for Community Resilience in the Context of Indonesia. *International Journal of Environmental Research and Public Health*, 19(15), 8908.

Rosi, A., van Vugt, F. T., Lecce, S., Ceccato, I., Vallarino, M., Rapisarda, F., Vecchi, T., & Cavallini, E. (2021). Risk Perceptions in a Real-world Situation (COVID-19): How it Changes from 18 to 87 Years Old. *Frontiers in Psychology*, 12, 646558.

Rummo, P. E., Bragg, M. A., & Yi, S. S. (2020). Supporting Equitable Food Access During National Emergencies - The Promise of Online Grocery Shopping and Food Delivery Services. *JAMA Health Forum*, 1(9), e200365-e200365.

Savary, S., Akter, S., Almekinders, C., Harris, J., Korsten, L., Rötter, R., Waddington, S., & Watson, D. (2020). Mapping Disruption and Resilience Mechanisms in Food Systems. *Food Security*, 12, 695-717.

Singu, S., Acharya, A., Challagundla, K., & Byrareddy, S. N. (2020). Impact of Social Determinants of Health on the Emerging COVID-19 Pandemic in the United States. *Sec. Health Economics*, 8, 406.

Tendell, D. M., Joerin, J., Kopainsky, B., Edwards, P., Shreck, A., Lee, Q. B., Kruetli, P., Grant, M., & Six, J. (2015). Food system resilience: Defining the concept. *Global Food Security*, 6, 17-23.

Umberson, D., Chen, M. D., House, J. S., Hopkins, K., & Slaten, E. (1996). The Effect of Social Relationships on Psychological Well-being: Are Men and Women Really so Different? *American Sociological Review*, 61(5), 837-857.

United States Census Bureau. (2021, May). *Week 28 Household Pulse Survey: April 14 – April 26*. Retrieved from <https://www.census.gov/data/tables/2021/demo/hhp/hhp28.html>. Accessed January 25, 2023.

United States Department of Agriculture (USDA). *Food and Nutrition Service. Online Purchasing Pilot, 2023*. <https://www.fns.usda.gov/snap/online-purchasing-pilot>. Accessed February 23, 2023.

United States Department of Agriculture (USDA). (2022). *Food Security in the US: Key Statistics and Graphics*. <https://www.ers.usda.gov/topics/food-nutrition-assistance/food-security-in-the-u-s/key-statistics-graphics/#insecure>. Accessed July 31, 2022.

United States Department of Agriculture (USDA). (2021). *Food Access Research Atlas: Documentation*. <https://www.ers.usda.gov/data-products/food-access-research-atlas/documentation/>. Accessed July 31, 2022.

United States Department of Agriculture (USDA). (2021, March 22). *USDA Increases SNAP Benefits 15% with Funding from American Rescue Plan, March 2021*. <https://www.usda.gov/media/press-releases/2021/03/22/usda-increases-snap-benefits-15-funding-american-rescue-plan>. Accessed January 21, 2023.

U.S. Department of the Treasury. (2021, June 17). *Economic Impact Payments*. <https://home.treasury.gov/policy-issues/coronavirus/assistance-for-american-families-and-workers/economic-impact-payments>. Accessed April 19, 2023.

Van Dijk, J. A. (2017). Digital divide: Impact of access. *The international encyclopedia of media effects*, 1-11.

White House. (2021, November 17). *Child Tax Credit*. <https://www.whitehouse.gov/child-tax-credit/>. Accessed April 19, 2023.

WHO. (2022, July 6). *UN Report: Global Hunger Numbers Rose to as Many as 828 Million in 2021*. <https://www.who.int/news/item/06-07-2022-un-report--global-hunger-numbers-rose-to-as-many-as-828-million-in-2021>. Accessed July 31, 2022.

Wolfson, J. A., & Leung, C. W. (2020). Food Insecurity and COVID-19: Disparities in Early Effects for US Adults. *Nutrients*, 12(6), 1648.

Xu, L., & Saphores, J. D. (2022). Grocery Shopping in California and COVID-19: Transportation, Environmental Justice, and Policy Implications. *Transportation Research Part D: Transport and Environment*, 113, 103537.

Zhang, Y., Trusov, M., Stephen, A. T., & Jamal, Z. (2017). Online Shopping and Social Media: Friends or Foes?. *Journal of Marketing*, 81(6), 24-41.