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How do customers change their purchasing behaviors during the COVID-19 pandemic?

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ABSTRACT

This study focuses on examining how customers’ shopping behaviors have changed during the pandemic and contributing variables. Three primary shopping modes include online purchases, curbside pickup, and in-store shopping. The dependent variables are the changes in customers’ spending in those three modes during the pandemic. The theory of fear appeal was used as the theoretical foundation for selecting independent variables. Based on this theory, two groups of independent variables were identified, fears for health and fears for financial conditions due to COVID-19. Additionally, demographic variables were also included in the analysis. The data from Census Bureau’s Household Pulse Survey Phase 3.1 collected from June 23 to July 5, 2021, was used with 24,998 usable cases. Logistic regression was used to analyze the data to test the effects of independent variables on customers’ shopping behavior changes in the three modes. The results show that both fears for health and fears for financial conditions have effects on the shopping behavioral changes. Due to those fears, residents change their shopping behaviors by considering the shopping modes that allow them to deal with or avoid the risks. Additionally, demographic variables, including age, gender, race, income, and marriage status, also have significant impacts on their shopping decisions.

1. Introduction

The COVID-19 pandemic has changed our usual daily activities. The spread of COVID-19, enhanced safety protocol, and social distancing have some effects on residents’ normal shopping behaviors. Given the pandemic and safety concerns, customers have considered various options for their shopping for groceries. These options represent different levels of personal contact (Grashuis et al., 2020; Alaimo et al., 2021; Hadler et al., 2021; Kim and Im, 2021). More specifically, customers can choose to shop in stores, as usual, adhering to the stores’ restrictions and safety requirements. This option has the usual level of personal contact with more distances between shoppers. Customers who prefer less personal contact can order groceries online and use a curbside pickup service. Finally, customers who want to avoid all personal contact can order everything online and have them shipped to the door. The multiple shopping options allow people to get the groceries they need without facing the safety risks regarding COVID-19 or the inconvenience of the store restrictions and daily travels. It is important to note that customers’ shopping behaviors are not static but very dynamic (BTS, 2021). As the pandemic progresses, their shopping behaviors continue to change depending on many possible factors related to changes in COVID-19 situations, vaccine rollout, and financial situations. Understanding these contributing factors is essential for us to predict the future of our economy, especially business models that retailers can use to best serve the customers’ needs.

Current literature in shopping behaviors during the COVID-19 pandemic has focused mainly on factors affecting customers’ online shopping decisions. Their findings indicated primary factors, including benefits from online shopping, fears of the pandemic, media, and subjective norms (Moon et al., 2021; Showrav et al., 2021; Prasad and Srivastava, 2021; Yan et al., 2021; Lo et al., 2021; Alhainer, 2021; Eger et al., 2021). Other studies emphasized the roles of hedonic motivation, economic situation, and satisfaction and trust with online shopping (Koch et al., 2020; Al-Hattami, 2021). However, most of those studies used data collected at the beginning of the pandemic in 2020, which only captured the customers’ shopping behavior at the initial stage. As the pandemic continues to change dynamically with the threat of a more contagious and fast-spreading Delta variant and the vaccine rollout, the shopping behaviors are expected to shift. How people perceive and feel about the risk of COVID-19 and their past shopping experience may lead...
to changes in their shopping behaviors. It is crucial to capture the customers’ shopping behaviors at a more mature stage since these behaviors are likely to follow patterns, which help predict their behaviors in the future. Furthermore, the current findings focus mainly on the online shopping mode and are based on the assumption that customers choose only one mode of shopping for groceries, and they cannot choose a combination of them. While it is valid for one-time shopping decisions for specific products, it is not the situation in real life, in which customers can decide to use a combination of those modes depending on the type of foods, purchase volume, or travel distance. In other words, if we look at the customers’ shopping behaviors over time, these shopping options are not exclusive. The same customer can choose to use one shopping mode at this time and another mode at another time. Accordingly, unanswered questions are how customers’ shopping behaviors have shifted in each mode over time and what factors have driven these behavioral changes? More specifically, whether the customer chooses to spend more or less on those shopping modes, and what has made them choose to do so.

The purpose of this study is to fill those gaps in the literature by examining customers’ behavior changes in three grocery shopping modes: 1) in-store shopping: shopping at stores with restrictions – regular personal contact; 2) curbside pickup: ordering groceries online and getting them delivered to the car – limited personal contact; 3) online shopping: ordering groceries online and having them shipped to the door – no personal contact. The novel variables in this study are the new dependent variables being studied. We look into the customers’ choices from a new perspective, which is how customers change their shopping behaviors over time. Since these shopping modes are not exclusive, we assume customers can choose to use multiple modes at different times as they see fit, instead of just one mode. The behavioral changes are represented by the changes in their spending in those modes over time during the pandemic. More specifically, we examine three new dependent variables: changes in customers’ spending in in-store shopping, curbside pickup, and online shopping over time amid the pandemic. We use the theory of fear appeal as the theoretical foundation for selecting contributing variables for the shift in shopping behaviors. The theory posits that people’s fears of imminent risks would drive them to make decisions to find a way to deal with the risks (Ahmed et al., 2020; Addo et al., 2020; Eger et al., 2021). Using this theory, in this study, independent variables are categorized into two groups, fears for health and fears for financial conditions. As these fears change, the shopping behaviors will change accordingly. The unknown is the direction and extent of those changes, which we try to find out in this study. Additionally, multiple demographic variables are also included in the analysis, as they have been found to affect shopping choices (Moon et al., 2021; Lo et al., 2021; Taha et al., 2021). Understanding the shifting in customers’ shopping behaviors and contributing variables in a more dynamic and complex environment would allow us to understand better how effective those shopping modes are and how retailers can improve their shopping services to accommodate customers amid the pandemic. The results of this study also provide useful information for predicting the future of our economy post COVID-19. The U.S. market is the main focus of this study, and globalized policies and trends are not considered. The study also focuses on the individuals’ decisions rather than the entire economic impact. We want to understand how U.S. residents make their shopping decisions. Survey data collected recently in July 2021 allows us to capture the shopping behaviors at a more mature stage.

The paper is organized as follows. Section 2 presents a review of the current literature, research gaps, and theoretical foundation. In Section 3, we describe the data source, variables, and statistical method. Section 4 section provides detailed results of the analysis. Finally, in Sections 5 and 6, discussions of the findings and conclusions are provided in the last section, along with recommendations for future research.

2. Literature review and theoretical foundation

2.1. Literature review and research gaps

Much attention has been paid to the customers’ shopping behaviors amid COVID-19. Table 1 summarizes extant studies, their focuses, location, timeline of the data, and major findings. Numerous studies have been conducted to examine factors that influence online shopping during the pandemic. They used survey data in different countries over the world, including the U.S., South Korea, China, Taiwan, India, Bangladesh, Yemen, Germany, Italy, Slovakia, Czech Republic. Some key contributing factors for online shopping identified in those studies are the contactless benefits from online shopping (Showrav et al., 2021; Prasad and Srivastava, 2021; Yan et al., 2021; Lo et al., 2021), fear of COVID-19 and germs (Prasad and Srivastava, 2021; Lo et al., 2021; Alhaimer, 2021; Eger et al., 2021), and media and subjective norms (Moon et al., 2021; Koch et al., 2020; Yan et al., 2021; Taha et al., 2021). In addition, several studies emphasized the impacts of demographic factors on online shopping decisions, such as age, education, region, race, number of children (Moon et al., 2021; Lo et al., 2021; Taha et al., 2021). Koch et al. (2020) also highlighted the role of hedonic motivation and economic situation, whereas Al-Hattami (2021) indicated the impact of perceived task technology fit, satisfaction, and trust. Interestingly, Chen et al. (2021) looked at online shopping decisions from the perspective of past experience in online shopping during the pandemic and travel time to the stores. Alhaimer (2021) focused more on risk factors, especially how the risk of COVID-19 and the risk of violation penalties might affect customers’ choice of online shopping.

Alaimo et al. (2020, 2021) chose a different direction and focused on examining customer satisfaction with online shopping. They found that familiarity with online shopping, education, and ease of use had significant impacts on the shopping satisfaction level. Furthermore, there are limited studies examining shopping mode preferences during the pandemic. Grashuis et al. (2020) found that the trend in COVID-19 had effects on grocery shopping preferences. Customers are less willing to shop in the store when COVID-19 is spreading. On the other hand, the importance of shopping mode reduces as the rate of COVID-19 spread decreases. Hadler et al. (2021) found that in November 2020, 46% of surveyed customers used online grocery shopping, and 27% used grocery delivery services. Young people tended to purchase healthier food, and there was a higher demand for snacks and non-perishable foods. Finally, according to Chang and Meyerhofer (2021), in Taiwan, online shopping was sensitive to media coverage, and customers seemed to purchase more grains, fresh fruit, vegetables, and frozen foods.

While those studies provide useful findings, there are several important unanswered questions regarding customers’ shopping behaviors during the pandemic. First, those studies used the data in 2020; some of them even used data in the very early stage of COVID-19, from March to June 2020 (Alaimo et al., 2020, 2021; Moon et al., 2021; Lo et al., 2021; Prasad and Srivastava, 2021; Koch et al., 2020). Accordingly, these studies only captured customers’ initial shopping behaviors in the early stage of the pandemic. We expect these behaviors would have changed dynamically, given the recent surges of COVID-19 cases due to the fast-spreading Delta variant and the current vaccine rollout efforts. Thus, these findings need further validation with more recent data. As the pandemic continues to develop, the customers’ shopping behaviors will mature and form patterns, even though they still stay dynamic variables such as previous shopping experience, past COVID-19 infection, economic impact payment, job loss, and financial hardship were not considered, which does not capture the full picture of the society during the pandemic. It is crucial to understand how these factors affect customers’ shopping decisions as we are approaching the end of the second year of the pandemic. Second, most of those studies examined factors that had driven customers to use online shopping only. However, as the pandemic continues to change, customers have used various shopping modes, including online shopping, curbside pickup, and 67 (2022) 102963
### Literature review

| References                  | Category                                    | Purpose                                                                 | Location      | Time              | Findings                                                                                          |
|-----------------------------|---------------------------------------------|-------------------------------------------------------------------------|---------------|-------------------|---------------------------------------------------------------------------------------------------|
| Koch et al. (2020)          | Determinants of online shopping             | Investigate online shopping motives of generation Y and Z during the COVID-19 shutdown | Germany       | April 2020        | Media reports and hedonic motivation are better predictors than utilitarian motives               |
| Showrav et al. (2021)       | Determinants of online shopping             | Explore factors influencing the rapid growth of online shopping during COVID-19 | Dhaka City, Bangladesh | September 2020   | Benefits of online shopping is the most significant factor, followed by technological supports and convenience |
| Yan et al. (2021)           | Determinants of online shopping             | Determine key factors influencing consumers online shopping             | China         | 2020              | Contactless characteristics of online shopping, shutdown of offline shopping channels, opinions of people, pandemic-related official information, public panic                                                |
| Al-Hattami (2021)           | Determinants of online shopping             | Study intention to continue using online shopping under COVID-19         | Yemen         | October-November 2020 | Perceived risks of infectious disease and the benefits of online shopping                           |
| Prasad and Srivastava (2021) | Determinants of online shopping             | Investigate customers’ switching behaviors during the Covid-19          | India         | March and August 2020 |                                                                                                  |
| Taha et al. (2021)          | Determinants of online shopping             | Examine the influence of social media on e-shops during the first wave of the pandemic | Italy and Slovakia | Feb to June 2020  | Use of social media, demographic variables                                                          |
| Chen et al. (2021)          | Determinants of online shopping             | Study the influence of COVID-19 on fresh food shopping behavior         | Wuhan, China  | 2020              | Frequencies of online shopping before and during COVID-19 and age have a negative effect; Proportions of online shopping before and during COVID-19 and travel time of in-store shopping have a positive effect. |
| Lo et al. (2021)            | Determinants of online shopping             | Examine shifts in online grocery shopping by sociodemographic characteristics | USA           | March and April 2020 | Age, education, region, race, number of children have significant effects. Top reasons to increase online shopping are to avoid public germs and COVID-19, take advantage of the convenience, and access a better selection |
| Alhaimer (2021)             | Determinants of online shopping             | Investigate various risk factors that alter online shopping behavior    | Kuwait        | 2020              | Risk susceptibility, risk severity, and risk of formal penalties have positive effects; Convenience risk has a negative effect                                      |
| Eger et al. (2021)          | Determinants of online shopping             | Examine trends and impacts of the COVID-19 pandemic on consumer buying behavior | Czech Republic | September 2020    | Fears for health are significant for choosing new items. The reasons for the new purchase were the quality, availability, and convenience of the purchase.                                    |
| Moon et al. (2021)          | Determinants of online shopping             | Examine factors influencing online or offline shopping behavior at the beginning of the pandemic | South Korea  | May 2020          | Age and gender have effects on offline shopping, while subjective norm and vulnerability have effects on online shopping decisions                            |
| Alaimo et al. (2020)        | Customer satisfaction with online shopping  | Investigate characteristics that affect online food shopping during the pandemic emergency | Italy        | March to May 2020 | Familiarity with buying food online, a higher educational level, ease of use of online channels, satisfaction with online shopping experience have significant effects                                           |
| Alaimo et al. (2021)        | Customer satisfaction with online shopping  | Study satisfaction level of consumers in purchasing food online via food shopping channels | Italy        | March to May 2020 | Process dimension, linked to ease of use of online tools in the searching and purchasing phases, generates a higher satisfaction than outcome dimension                                |
| Grabhuis et al. (2020)      | Shopping preferences and types of food       | Examine grocery shopping preferences during the COVID-19 pandemic       | USA           | 2020              | Trend in COVID-19 has effects on grocery shopping preference: when COVID-19 is spreading at an increasing rate, consumers are generally less willing to shop inside the grocery store; when COVID-19 is spreading at a decreasing rate, the relative importance of the purchasing method attribute is lower. 46% used online grocery shopping; 26% used delivery, and 27% used pickup. Young people reported healthier purchases; a tendency toward more snack and non-perishable foods. |
| Hadler et al. (2021)        | Shopping preferences and types of food       | Study how the pandemic has impacted grocery shopping patterns and types of goods purchased | USA           | November 2020     | 46% used online grocery shopping; 26% used delivery, and 27% used pickup. Young people reported healthier purchases; a tendency toward more snack and non-perishable foods.                                  |
| Chang and Meyerhofer (2021) | Shopping preferences and types of food       | Investigate how the pandemic affected the demand for online food shopping services | Taiwan       | 2020              | Demand for grains, fresh fruit and vegetables, and frozen foods increased the most; online food shopping was highly responsive to COVID-19 media coverage and online content |
| The current study           | Shopping behavioral changes over time in multiple shopping modes | Examine how fears for health, fears for financial conditions, and demographic factors affect the customer behavioral changes over time in all three shopping modes | USA           | July 2021         | Contributions: novel dependent variables (changes in customer’s spending in all three shopping modes: in-store, curbside, and online over time), more current data covering the spread of Delta variant, how fears and demographic variables affect the shopping behavioral changes during the pandemic |
and in-store shopping. Very limited studies such as Grashuis et al. (2020) and Hadler et al. (2021) studied factors that affect customers’ shopping behaviors. The authors assumed those shopping modes were exclusive; i.e., customers chose only one of them. While it works for an one time shopping decision for specific products, it does not capture the customers’ behavioral changes over time. In real life, customers can choose to use multiple shopping modes depending on the types of products, purchase volumes, and travel time to the stores. Thus, the same customer may choose to use all three shopping options at different times. What retailers may want to know is how customers shift their shopping behaviors over time, such as whether they choose to spend more in one mode and less in another mode as the pandemic progresses, and which factors influence those decisions. Since those options are not exclusive, it would be more meaningful to analyze the effects separately for each shopping mode rather than in the same model.

In this study, we aim to fill those gaps in the literature to gain new knowledge and understanding of how customers’ shopping behaviors shift in those shopping modes during the pandemic and what factors drive those changes using the most current survey data. Hence, we look into the shopping behaviors from a different perspective, the changes in shopping behaviors over time. The novel variables are three dependent variables we study: the changes in customers’ spending in online shopping, curbside pickup, and in-store shopping. Those three shopping modes are selected as primary choices for customers during the second stage of the pandemic (Grashuis et al., 2020; Alaimo et al., 2021; Hadler et al., 2021; Kim and Im, 2021). We use the current survey data in July 2021, which covers the effects of Delta variant, vaccine rollout, past COVID-19 infection experience, economic relief receipt, and financial hardship due to the pandemic. The difference and uniqueness of this study compared to existing studies are included in the last row of Table 1. The selection of independent variables is grounded based on the theory of fear appeal, which will be described in the next section.

2.2. Conceptual model

In this study, we use the fear appeal theory as the theoretical foundation for developing our conceptual model. Essentially, a fear appeal is a persuasive message to change people’s behaviors through raising the threat of imminent risks or dangers (Maddux and Rogers, 1983). It presents a risk and vulnerability to the risk, and protective action is not guaranteed (De Hoog et al., 2005). Several studies suggested that fear appeal is an important variable mediating purchasing behavior (Eger et al., 2021; Ahmed et al., 2020; Addo et al., 2020; Iyer et al., 2020).

A fear appeal can be categorized into two phases, fear control and danger control. Fear control captures emotional responses to the risk, while danger control reflects adaptive behaviors to deal with or avoid the danger (Ahmed et al., 2020; Addo et al., 2020; Eger et al., 2021). Wegmann et al. (2017) indicated that fear control represents emotional reactions caused by risk, and danger control changes the behavior of customers to avoid that risk. In other words, when customers face imminent risk or danger, they respond with emotional reactions (fear control), and then their behavior will change adaptively to deal with or avoid that risk (danger control). Focusing on online shopping, Aldo et al. (2020) and Eger et al. (2021) found that fear appeal had a significant relationship with the online purchase of products. In other words, customers found online shopping allowed them to deal with the risks of COVID-19.

Thus, in the context of purchasing behaviors, fears for health drive customers’ behavior, which reflects their decisions to select a shopping mode that could reduce the perception of danger and allow them to overcome the risk. In this study, we use the fear appeal theory as the foundation for selecting our independent variables. But we take it to another level by exploring the differences in risk perceptions (fear control) among residents. We look into two types of fears related to COVID-19, fears for health and fears for financial conditions. Fears for health represent the imminent risks that COVID-19 can cause to our health. The current surges due to the fast-spreading Delta variant pose a great risk to residents. Nonetheless, the COVID-19 risk perception may not be the same for everyone. The ones who got infected with COVID-19 in the past may have a different perception of risk than those who did not. Additionally, the residents who received the vaccine may also have a different emotional reaction to the spread of the pandemic than the unvaccinated ones. Due to the controversy of vaccine efficacy and side effects, this risk perception difference is still unknown, requiring further exploration. Finally, as we go through the second year of the pandemic, we can notice differences in people’s preventive behaviors during the pandemic. Perception of COVID-19 risks is certainly not the same among these groups.

The second type of fear is the fears for financial conditions. Economic conditions have been found to be the major driver for the economy to bounce back (Truong, 2021). Due to the significant impacts of the pandemic on the economy, residents are facing some great financial risks that cause hardship for their spending capability. Many people lost their jobs, had to take furloughs for some time, or had to take early retirement. They have to rely on unemployment insurance or social security payments. The U.S. government had issued several economic impact payments to support residents, but not everyone has received the payment at the same time, not to mention that this payment may not be sufficient. Some residents still have difficulties with expenses or spending budget. Fears for financial conditions are the imminent risk that many U.S. residents are facing. The level of risk perception may be different depending on the recent changes in their employment status, payments from the government, and spending capability.

Thus, in this study, the theory of fear appeal allows us to develop our conceptual model. More specifically, the theory allows us to establish the ground for two types of fears representing imminent risks related to COVID-19: fears for health and fears for financial conditions. We use these two categories of independent variables to capture not only residents’ risk perceptions but also the differences among their perceptions. The residents’ emotional actions to those risks would contribute to the shift in their shopping behaviors that allow them to deal with or avoid the risks. In this study, we explore how those two types of fears affect the change in customers’ shopping behaviors in three shopping modes.

In addition, important demographic variables such as age, gender, race, region, education, income, marital status, and the number of children are also included as they have been found to have significant relationships with shopping behaviors (Moon et al., 2021; Lo et al., 2021; Taha et al., 2021). The conceptual model is presented in Fig. 1. Three novel dependent variables include spending changes in online purchases, curbside pickup, and in-store shopping. Independent variables are grouped into three primary categories: fears for health, fears for financial conditions, and demographics.

3. Methodology

In this study, the survey data from Census Bureau’s Household Pulse Survey Phase 3.1 was used. The Household Pulse Survey aims at studying how the pandemic is impacting households across the country from a social and economic perspective. It takes about 20 min to complete the survey. The questionnaire includes questions about how education, employment, health, housing, social security benefits, household spending, consumer spending associated with stimulus payments, intention to receive a COVID-19 vaccination, and shopping decisions have been affected by the ongoing crisis. Phase 3.1 of the Household Pulse Survey began on April 14, 2021, and ended on July 5, 2021 (U.S. Census Bureau, 2021).

The target population is U.S. residents within the age of 18 or higher. The Census Bureau used a random sampling method and contacted individuals, who are U.S. residents within that age range, randomly for the survey invitation. The survey was collected between June 23 and July 5, 2021. The data were protected from cybersecurity risks through screening of the system that transmits the data (U.S. Census Bureau,
The data were de-identified and made available to the public on the Census Bureau’s website.

As for sample size, according to the U.S. Census Bureau (2019), the U.S. population 18 years or older in 2019 was about 250 million. Using this population size, the confidence interval of 95%, and an error margin of 5%, the needed sample size for this study is 385 (Qualtrics, 2021). Additionally, G*Power 3.1 tool was used to calculate the required sample size to achieve the desired power, significance value, and effect size for logistic regression. With the power of 0.8, significance value of 0.05, and effect size of 0.2, the required sample size is 2,089 responses, given the non-normal distributions of the independent variables. Hence, it was decided that the needed sample size for this study was 2,089. After removing cases with excessive missing values, the dataset has 24,998 usable cases, which is sufficient sample size for logistic regression analysis.

The variables and descriptions used in this study are presented in Table 2. Most variables are binary or categorical scales. Age and the number of household members are ratios, while difficulty with expenses is a Likert-scale. The detailed values for binary and nominal variables are included in the Appendix. Three novel dependent variables are CHNGSHP1ML, CHNGSHP2M, and CHNGSHP3ML, representing changes in the spending in online purchase, curbside pickup, and in-store shopping, respectively, in the last seven days. It is worth noting that these are not mutually exclusive choices, and customers can choose to spend more, or less, on grocery purchases in one or more shopping choices.

Since the dependent variables are binary, logistic regression was selected for the statistical analysis. In addition, logistic regression works with categorical independent variables and does not require strict assumptions as with ordinal least square methods, such as multiple regression. Three separate logistic regression models were conducted for those three dependent variables. The multicollinearity was evaluated to ensure no significant dependency among independent variables. Additionally, −2Log likelihood (-2LL), Cox & Snell R-square, and Nagelkerke R-square were used to find the best fit model in those steps, and the Omnibus test was used to evaluate the model improvement. The logistic regression results include coefficient, standard error, Wald chi-square statistic, p-value, and odds ratio. Odds ratio, also called exp(B), was used mainly to interpret the effect of each independent variable on the dependent variable since it is easier to interpret.

4. Results

4.1. Demographic results

Demographic results for the survey respondents are presented in Figs. 2-6. The sample covers ages from 18 to 84, with a majority of respondents from 30 to 74 years old (Fig. 2). It is interesting to note a large number of residents within ages between 56 and 72 years old, groups with high risks. As for education, 29% of the respondents have a bachelor’s degree, followed by 26.3% with a graduate degree (Fig. 3). In addition, 10.4% of them have an associate’s degree, 21% are currently attending college but have not received any degree, and 11% received a high school degree. In terms of income, 18.5% of the respondents earned an annual income from $100 thousand to $150 thousand, followed by 17% earned from $50 thousand to $75 thousand (Fig. 4). It is worth noticing that about 11.6% earned an annual income over $200 thousand.
thousand, and about 10% earned less than $25 thousand.

As shown in Figs. 5 and 59% of the respondents are female, and 41% are male. In addition, 82% are White, 8% are Black, and 5% are Asian. In terms of employment, a majority of them (56%) work for private sectors, followed by 17% working for the government, 13% self-employed, and 12% working for non-profit organizations. Finally, 86% indicated that they had received at least one dose of vaccine, while the other 14% had not received any. Overall, the sample covers sufficient variety and diversity of the U.S. population that does grocery shopping regularly and is affected by the pandemic.

Fig. 6 shows the percentages of the respondents who chose to spend more, or less, on purchases in each shopping mode in the past seven days. Overall, less than half of respondents chose to spend more on grocery purchases in all three modes. More specifically, about 46.1% spent more on online purchases, 42.9% spent more on curbside pickup purchases, and 39.2% spent more on in-store purchases.

4.2. Logistic regression results

Logistic regression was used to analyze the data. As stated before, since we have binary dependent variables and a sufficient sample size, logistic regression is the appropriate method. In order to ensure no multi-collinearity among independent variables, variance inflation factor (VIF) and tolerance were evaluated. SPSS was used to calculate those values, and the results showed that all VIF scores were lower than 10 (the maximum VIF was 2.79), and all tolerance scores were higher than 0.10, indicating no multi-collinearity among independent variables (Hair et al., 2019).

Three logistic regression models using the stepwise method were conducted to test the correlations between independent variables and the three dependent variables. Categorical independent variables were dummy coded in this process. For the interpretation purpose, the second category was used as the reference category for binary variables, and the first category was used as the reference category for nominal variables. Table 3 presents the model fit results for all three models, with the number of steps for each model. $-2 \text{LL}$, Cox & Snell $R^2$, and Nagelkerke $R^2$ were used to find the best fit model in those steps, which was the model with the lowest $-2 \text{LL}$ and highest pseudo $R^2$ values. The Omnibus test was used to check if this model was an improvement from the previous model. In this test, the significant Chi-square indicates a significant performance improvement of the final model. Finally, the classification accuracy shows the overall prediction accuracy of the model. The results show that the model for online purchase spending used 12 steps, the model for curbside pickup spending used 16 steps, and the model for in-store purchase spending used 11 steps. Overall, in all three cases, the final model shows significant improvement in performance from the model in the previous step.

Table 4 presents the significant independent variables for online purchase spending at the significance level of 0.05. The $B$ values show the correlation coefficients and signs of the effects. But we will focus more on the exp($B$), or odds ratio, since it allows us to interpret the magnitude of the effects in terms of the odds for certain shopping modes. The results show that age has a positive effect on online purchase spending. More specifically, an increase of age by one year will increase the odds of someone spending more on online shopping by a factor of 1.008 or 0.8%. On the other hand, as gender changes from female to male, the odds of spending more on online shopping will decrease by a factor of 0.851 or 14.9%; i.e., the odds of online purchase spending for
female residents is 1.175 times of the male residents. In terms of race, the odds of spending more on online purchases by White residents is 1.24 times of Black residents, 1.485 times of Asian residents, and 1.4 times of other races. Furthermore, education has a negative effect on online purchase spending. As the education level increases, the odds of spending more on online shopping will decrease by about 60%. Thus, residents with higher education tend to spend less on online shopping.

The effects of fears for health variables are somewhat mixed. Residents with no infection have an increased odds of online purchase spending by 13.4% compared to those infected with COVID-19 in the past. However, the odds of spending more on online shopping by those infected residents, in their turn, will be 1.61 times of the ones unsure about their health statuses. Additionally, vaccination history has a negative effect, indicating that the odds of spending more on online shopping by residents not vaccinated will be 1.66 times of those with at least one dose. COVID-19 prevention behavior change also has a negative effect. More specifically, the odds of online purchase spending by residents with less preventive behavior is 1.08 times of those with unchanged prevention behavior and 1.28 times of those with increased prevention behavior. In other words, as residents become more preventive of COVID-19, they will be less likely to spend more on online purchases.

In terms of fears for financial conditions, interestingly, both recent household job loss and expected household job loss have positive effects on the shopping decision. More specifically, the odds of online purchase spending increases by 28.2% for residents with past job loss and 29.8% for those with expected job loss. Furthermore, residents with more difficulties with their expenses will have decreased odds of online purchase spending by 53%. On the contrary, the ones who received economic impact payment will have increased odds of online purchase spending by 41.5%. Finally, cash usage has mixed effects on the shopping decision. The odds of spending more on online shopping by residents using more cash is 2.07 times of those using less cash, while the one using the same cash amount will have increased odds of online purchase spending by 108.5%.

Table 5 presents the results for curbside pickup spending with significant independent variables. Regarding demographic variables, the odds of curbside pickup spending by Northeastern will be 1.25 times of the Southern, 1.175 times of the Midwestern, and 1.2 times of Western. Additionally, age has a positive effect on the shopping decision, indicating that as age increases by one year, the odds of curbside pickup spending...
Table 4: Logistic regression results – Online purchase spending.

| Independent variables | B     | S.E   | Wald  | p-value | Exp (B) |
|-----------------------|-------|-------|-------|---------|---------|
| Age                   | .008  | .001  | .000  | 1.008  |
| Gender                | -.162 | .033  | .000  | .851   |
| Race                  | 60.160| .000  |       |         |
| Race(1)               | -.214 | .063  | .001  | .807   |
| Race(2)               | -.396 | .064  | .000  | .673   |
| Race(3)               | -.336 | .078  | .000  | .715   |
| Education             | 21.249| .002  |       |         |
| Education(1)          | -.842 | .384  | .028  | .431   |
| Education(2)          | -.152 | .310  | .002  | .359   |
| Education(3)          | -.110 | .327  | .001  | .332   |
| Education(4)          | -.115 | .329  | .000  | .316   |
| Education(5)          | -.102 | .326  | .002  | .357   |
| Received or plan for all does | -.507 | .217  | .020  | .602   |
| COVID-19 prevention   | 8.136 | .017  |       |         |

Table 5: Logistic regression results – Curbside pick-up spending.

| Independent variables | B     | S.E   | Wald  | p-value | Exp (B) |
|-----------------------|-------|-------|-------|---------|---------|
| Region                | 18.715| .000  |       |         |
| Region(1)             | -.227 | .054  | .000  | .797   |
| Region(2)             | -.161 | .059  | .006  | .851   |
| Region(3)             | -.113 | .054  | .036  | .893   |
| Age                   | .019  | .002  | .000  | 1.020  |
| Gender                | -.120 | .036  | .001  | .887   |
| Race                  | 17.678| .000  |       |         |
| Race(1)               | -.156 | .067  | .021  | .856   |
| Race(2)               | -.157 | .069  | .022  | .855   |
| Race(3)               | -.257 | .080  | .001  | .774   |
| Marriage Status       | 24.337| .000  |       |         |
| Marriage Status(4)    | .240  | .051  | .000  | 1.271  |
| Income                | -.045 | .012  | .000  | .956   |
| Number of kids        | -.039 | .018  | .005  | .962   |
| COVID-19 prevention behavior | 10.780| .000  |       |         |
| COVID-19 prevention behavior (1) | -.115 | .037  | .002  | .891   |

| Independent variables | B     | S.E   | Wald  | p-value | Exp (B) |
|-----------------------|-------|-------|-------|---------|---------|
| Race                  | 91.293| .000  |       |         |
| Race(1)               | -.244 | .060  | .000  | .784   |
| Race(2)               | -.484 | .059  | .000  | .616   |
| Race(3)               | -.322 | .073  | .000  | .724   |
| Marriage Status       | 18.811| .001  |       |         |
| Marriage Status(4)    | .143  | .040  | .000  | 1.154  |
| Income                | .023  | .009  | .014  | 1.023  |
| COVID-19 prevention behavior | 19.508| .000  |       |         |
| COVID-19 prevention behavior (1) | -.388 | .126  | .000  | .678   |
| COVID-19 infection informed by doctor | 18.782| .000  |       |         |

Fears for health variables show some interesting results. The odds of curbside pickup spending by residents with no COVID-19 infection will be 1.17 times of those with past infection. In addition, the odds of spending by residents with decreased preventive behavior will be 1.22 times those with the unchanged behavior. Regarding fears for financial conditions, residents with expected job loss will have higher odds of spending more than curbside pickup purchases than those with no expected job loss (1.387 times). Similarly, the odds of spending by residents who teleworked in the past 7 days will be 1.14 times of those without telework. Additionally, residents receiving economic impact payments and SSA will have increased odds of spending by 27% and 16.9%, respectively. On the other hand, as difficulty with expenses in the past 7 months will have higher odds of in-store purchase spending than those with past 7 months, the odds of curbside pickup spending will decrease by 37.4%. Finally, residents using more cash will have higher odds of curbside pickup spending than those using less cash by 2.07 times.

Finally, Table 6 presents the results for in-store purchase spending. As for demographic variables, only race, marriage status, and income have significant impacts. The results show that the odds of in-store purchase spending by White residents will be 1.275 times of Black residents, 1.623 times of Asian residents, and 1.38 times of other races. As for marriage status, separated residents will have higher odds of spending more on in-store purchases than married residents (1.514 times). Furthermore, as income increases by one level, the odds of in-store purchase spending will increase by 2.3%. As for fears for health variables, residents without COVID-19 infection will have higher odds of in-store purchase spending than those with COVID-19 infection will have higher odds of in-store purchase spending by female residents will be 2.113 times of male residents. Race is also a significant predictor. The odds of curbside pickup spending by White residents will be 1.7 times of Black residents, 1.7 times of Asian residents, and 1.51 times of other races. As for marriage status, separated residents will likely spend more on curbside pickup purchases than married residents (the odds will increase by 27.1%). Interestingly, income and number of kids have negative effects on the shopping decision. More specifically, as income increases by one level, the odds of curbside pickup spending will decrease by 4.4%. As the number of kids increases by one, the odds will decrease by 3.8%.

Table 6: Logistic regression results – In-store purchase spending.

| Independent variables | B     | S.E   | Wald  | p-value | Exp (B) |
|-----------------------|-------|-------|-------|---------|---------|
| Race                  | 91.293 | .000  |       |         |
| Race(1)               | -.244 | .060  | .000  | .784   |
| Race(2)               | -.484 | .059  | .000  | .616   |
| Race(3)               | -.322 | .073  | .000  | .724   |
| Marriage Status       | 18.811 | .001  |       |         |
| Marriage Status(4)    | .143  | .040  | .000  | 1.154  |
| Income                | .023  | .009  | .014  | 1.023  |
| COVID-19 prevention behavior | 19.508| .000  |       |         |
| COVID-19 prevention behavior (1) | -.388 | .126  | .000  | .678   |
| COVID-19 infection informed by doctor | 18.782| .000  |       |         |
| COVID-19 infection informed by doctor (1) | .130  | .047  | .006  | 1.139  |
| COVID-19 infection informed by doctor (2) | -.578  | .212  | .007  | .561   |
| Household job loss    | .156  | .063  | .014  | 1.168  |
| Expected household job loss | .199  | .076  | .009  | 1.220  |
| Economic impact payment received | .399  | .054  | .000  | 1.491  |
| Difficulty with expenses | -.534  | .020  | .000  | .586   |
| Use of cash(1)        | -.374  | .070  | .000  | .688   |
| Use of cash(2)        | .743  | .065  | .000  | 2.102  |
| Constant              | -.116  | .198  | .000  | .313   |
past infection (1.139 times), while the ones unsure about their health status will have decreased odds of spending by 43.9%. In terms of preventive behavior, residents with unchanged behavior will have slightly higher odds of in-store purchase spending than those with decreased prevention behavior (1.084 times), who, in their turns, will have higher odds of spending than those with increased behavior (1.474 times).

Regarding fears for financial conditions, past household job loss and expected job loss have positive effects on the shopping decision. More specifically, the odds of in-store purchase spending by residents with past job loss will be 1.168 times of those without job loss, and the ones with expected job loss will have higher odds than those without (1.22 times). Additionally, residents receiving economic impact payments will have higher odds of spending than those receiving no payment (1.491 times). On the other hand, difficulty with expenses has a negative effect. As the difficulty level increases, the odds of in-store purchase spending will decrease by 41.4%. Finally, residents using the same cash amount will have higher odds of spending more on in-store purchases than the ones using more cash (2.102 times), who, in their turn, will have higher odds of spending than those using less cash (1.453 times).

5. Discussion

The COVID-19 pandemic has some significant impacts on our lives, especially shopping behaviors. This paper aims at exploring variables contributing to changes in U.S. residents’ grocery shopping behaviors amid COVID-19. As shown in Figs. 5 and 46.1% of residents chose to spend more on online purchases than curbside pickup purchases (42.9%) and in-store purchases (39.2%). While the differences are not substantial, these results show that residents seem to prefer online shopping, given the pandemic. We analyzed the survey data collected in July 2021, reflecting the current pandemic trend, especially the presence of the more contagious Delta variant. In this paper, we used the theory of fear appeal to categorize independent variables into two categories, fears for health and fears for financial conditions. Demographic variables were also included in the analysis. The analysis results indicate some interesting and new findings that add value to the body of knowledge in consumer behaviors.

Due to the varied results of logistic regression analyses, a summary of findings is presented in Table 7 for easier interpretation. The results show that certain demographic variables have significant impacts on shopping behaviors. Age has a positive effect on both online shopping and curbside pickup, but not in-store shopping. That means older residents will have higher odds of spending more on online purchases or curbside pickup purchases. Gender also has a significant effect on those two shopping modes. In both cases, female residents will have higher odds of online and curbside pickup spending than male residents. These findings explain that older and female residents may be more cautious with health safety than younger and male residents. As for race, we have the same results for all three shopping modes. White residents will have higher odds of spending more on purchases in all three modes than Black, Asian, and other races. Interestingly, education only has a significant effect on online shopping. The higher the education level residents have, the less likely they will spend more on online purchases. In other words, more educated residents will choose to shop online less, for unknown reasons. On the other hand, separated residents will have higher odds of curbside pickup or in-store purchase spending than married ones. The reason could be that they prefer going out to stores to gain more contact with society. Furthermore, residents with more kids will have lower odds of curbside pickup spending. However, the number of kids does not have significant effects on online or in-store shopping, indicating further studies may be needed. Finally, income has some mixed effects on shopping behaviors. Residents with higher income will have lower odds of curbside pickup spending but higher odds of in-store purchase spending. And income does not have any effect on online shopping. This finding, along with the negative effect of the education level, is certainly interesting and deserves further study to explore how income and education have made people change their shopping behaviors and why.

Regarding fears for health, past COVID-19 infection has significant effects on all shopping modes. In all three modes, residents with past infections will have lower odds of spending more on purchases than those without infection. In other words, the past infection made them more cautious. Interestingly, these residents will have higher odds of online and in-store purchase spending than those unsure about their past health status. We can say that this group of residents may have a very high level of risk perception, due to the uncertainty of their health status, and seem to be more careful with in-store shopping. Nevertheless, it is harder to explain why they will also have lower odds of online spending than those with past infections. In terms of vaccination history, unvaccinated residents will have higher odds of shopping online, which can be explained by their higher risk perception since they feel unprotected by the vaccine. Furthermore, residents’ COVID-19 prevention behavior changes also have impacts on their shopping behaviors. Residents with decreased prevention behaviors will have higher odds of purchasing in all three modes than those with increased or unchanged behaviors. In other words, these residents may become less cautious with the risk of COVID-19 and will likely shop more.

As for fears for financial conditions, the impacts of job loss also indicate some interesting findings. Residents with past job loss or expected job loss will have higher odds of shopping in all three modes than those without job loss. It can be explained that these residents have more free time, and they enjoy shopping to kill time or reduce stress.

| Table 7 | Summary of the findings. |
|---------|--------------------------|
| Groups  | Variables                | Online purchase spending | Curbside pickup spending | In-store purchase spending |
| Demographic variables | Age | Positive effect | Positive effect | Positive effect |
| Gender | Female > Male | Female > Male | Female > Male |
| Race | White > Black, Asia, Others | White > Black, Asia, Others |
| Education | Negative effect | Negative effect | Negative effect |
| Marriage status | Separated > Married | Separated > Married |
| Number of kids | Decreased > Not change | Decreased > Not change |
| Income | Decreased > Increased | Decreased > Increased |
| Fears for health | Past COVID-19 infection | Decreased > Not change |
| Vaccine | Decreased > Increased | Decreased > Increased |
| Prevention behavior | Yes > No | Yes > No |
| Household job loss | Yes > No | Yes > No |
| Expected job loss | Yes > No | Yes > No |
| Teledwork | Yes > No | Yes > No |
| Economic payment received | Yes > No | Yes > No |
| SSA received | Yes > No | Yes > No |
| Difficulty with expenses | Negative effect | Negative effect |
| Use of cash | Increased > Decreased | Increased > Decreased |
| Table 7 | Summary of the findings. |
Additionally, residents that have teleworked in the past seven days will have higher odds of curbside pickup spending than those without telework. Thus, they tend to be cautious with the risk COVID-19 and try to avoid going in the stores but still enjoy going outside to gain more contact with society. Additionally, residents receiving economic impact payments tend to shop more in all three modes than those not receiving the support, while the ones receiving SSA payments will likely spend more on curbside pickup purchases than those without. These findings indicate that financial supports from the government do provide residents with more financial resources, which encourages them to spend more on shopping. On the contrary, residents with more difficulty with expenses will likely shop less in all three shopping modes. Clearly, these hardships affect their shopping capabilities. Finally, residents using more cash tend to shop more in all three modes than those using less cash. This finding makes sense since lack of cash certainly affects their shopping capabilities. On the other hand, the results also show that residents using the same amount of cash will likely shop more than those using more. This result could be explained by the assumption that the ones with unchanged cash use may have better control of their cash and can afford to shop more.

6. Conclusions and recommendations

This paper explores U.S. residents’ shopping behaviors amid COVID-19 and important variables that have impacts on their shopping decisions. The primary theoretical contribution of this paper is to examine the changes in customers’ spending in all three shopping modes over time rather than a shopping decision at one point in time. Unlike the extant literature, we assume that customers can choose to use multiple shopping modes to purchase products at different times. As the pandemic progresses, their shopping behaviors shift, and their spending on those modes changes accordingly. We use novel dependent variables, which are the changes in spending over time in all three shopping modes: in-store, curbside, and online. Based on the fear appeal theory, fears for health and fears for financial conditions are used as two primary categories of independent variables, along with demographic variables, to explain how customers have shifted their shopping behaviors. The results show that due to the risk of COVID-19, more residents chose to spend more on online purchases than other shopping modes (curbside pickup or in-store shopping). These shopping behaviors are impacted by demographic variables, fears for health, and fears for financial conditions. Age, gender, race, marriage status, and income are common demographic variables that have significant relationships with the residents’ shopping decisions. These findings are consistent with the results of existing studies (Moon et al., 2021; Lo et al., 2021; Taha et al., 2021). In terms of fears for health, past COVID-19 infection and change in prevention behaviors are significant contributing variables that impact how the residents choose to purchase groceries. Interestingly, vaccination history only has a significant impact on online shopping. As for fears for conditions, job loss (in the past or expected), economic impact payment, difficulty with expenses, and the use of cash all have significant impacts on shopping behaviors. These findings are consistent with the fear appeal theory, indicating that residents respond to the risk of COVID-19 with emotional actions, including fears for health and fears for financial conditions. Consequently, they change their shopping behaviors by considering the shopping modes that allow them to deal with or avoid the risk.

These findings have important theoretical contributions to the consumer behavior literature by discovering the effects of those new variables on the residents’ shopping behavioral changes over time. How U.S. residents shift their purchasing behaviors depends not only on their demographics but also on their fears for health and fears for financial conditions. As the pandemic progresses with new variants, more people receive the vaccine, and more people face financial hardship, they will change their shopping behaviors accordingly to deal with the risks. Our findings add an important contribution to the fear appeal theory that the fear control reflects not only how residents respond emotionally to the imminent risk but also the differences in their risk perception. These differences in risk perception play an important role in driving the changes in residents’ purchasing behaviors to deal with or avoid the risk.

Another important finding is that both fears for health and fears for financial conditions play equally important roles in their shopping decisions. For example, past COVID-19 infection makes residents less likely to purchase groceries in-store or even curbside pickup than those without infection, partly because they have more fears for health given their past experience with the virus. But the results also indicate that those residents will be less likely to shop online, which can be explained by the impact of fears for financial conditions. In other words, residents with past infections could also face financial difficulties, which impact their shopping capabilities. On the other hand, the ones with job loss tend to purchase more than those without, regardless of shopping mode, indicating their need to shop when they have more free time and, possibly, greater stress of being home too much during the pandemic. This impact is part of fears for health caused by the pandemic. Thus, how residents change their shopping behaviors should be explained by considering both fears for health and fears for financial conditions in a dynamic relationship rather than a unilateral one.

Retailers can use these findings to establish appropriate strategies for shopping channel networks to support customers during the pandemic. More specifically, they should focus on providing more contactless shopping options for customers, especially the ones with great fears for health. Since some customers still enjoy shopping in stores, safety precautions and protocols should be enhanced to assure customers of health safety. Several stores have set up self-checkout counters, which seem to encourage more customers to come into the stores. In addition, pricing could also be adjusted to support customers with financial hardship. More grocery options could also be added to online purchasing. Of course, retailers should be aware of the potential channel conflicts.

Future research could expand this study and focus on the effects of mental health. Residents are living under a lot of pressure, which causes changes in their shopping behaviors. Additionally, the effectiveness of various shopping modes can be evaluated to see which modes work better during the pandemic for which types of products. A cluster analysis could also be done to cluster customers into different segments by their demographics and types of products. The results can show the difference across those segments in terms of customers’ behavioral changes and their demographics. Finally, a cross-country comparison can be made to compare changes in customers’ shopping behaviors across countries.

APPENDIX

| Name   | Value | Label        |
|--------|-------|--------------|
| REGION | 1     | Northeast*   |
|        | 2     | South        |
|        | 3     | Midwest      |
|        | 4     | West         |

(continued on next page)
### (continued)

| Name          | Value | Label                      |
|---------------|-------|----------------------------|
| GENDER        | 1     | Male                       |
|               | 2     | Female*                    |
| RACE          | 1     | White*                     |
|               | 2     | Black                      |
|               | 3     | Asia                       |
|               | 4     | Others                     |
| EDUCATION     | 1     | Less than high school*     |
|               | 2     | Some high school           |
|               | 3     | High school graduate       |
|               | 4     | Some college, degree not received |
|               | 5     | Associate’s degree         |
|               | 6     | Bachelor’s degree          |
|               | 7     | Graduate degree            |
| MS            | 1     | Now married*               |
|               | 2     | Widowed                    |
|               | 3     | Divorced                   |
|               | 4     | Separated                  |
|               | 5     | Never married              |
| INCOME        | 1     | Less than $25,000*         |
|               | 2     | $25,000 - $34,999          |
|               | 3     | $35,000 - $49,999          |
|               | 4     | $50,000 - $74,999          |
|               | 5     | $75,000 - $99,999          |
|               | 6     | $100,000 - $149,999        |
|               | 7     | $150,000 - $199,999        |
|               | 8     | $200,000 and above         |
| RECVDVACC     | 1     | Yes                        |
|               | 2     | No*                        |
| DOSES         | 1     | Yes                        |
|               | 2     | No*                        |
| COVPRVNT      | 1     | Decreased prevention behavior* |
|               | 2     | Not change                 |
|               | 3     | Increased prevention behavior |
| HADCOVID      | 1     | Yes*                       |
|               | 2     | No                         |
|               | 3     | Not sure                   |
| WRKLOSSRV     | 1     | Yes                        |
|               | 2     | No*                        |
| EXPCTLOSS     | 1     | Yes                        |
|               | 2     | No*                        |
| KINDWORK      | 1     | Government*                |
|               | 2     | Private                    |
|               | 3     | Non-profit                 |
|               | 4     | Self-employed              |
|               | 5     | Family business            |
| TW_YN         | 1     | Yes                        |
|               | 2     | No*                        |
| UI_APPLRYRV   | 1     | Yes                        |
|               | 2     | No*                        |
| UI_RECVRV     | 1     | Yes                        |
|               | 2     | No*                        |
| SSA_RECV      | 1     | Yes                        |
|               | 2     | No*                        |
| SSA_APPLRYRV  | 1     | Yes                        |
|               | 2     | No*                        |
| EIP_YN        | 1     | Yes                        |
|               | 2     | No*                        |
| EIPRV         | 1     | Spend it                   |
|               | 2     | Save it*                   |
|               | 3     | Pay off debt               |
| EXPNS_DIF     | 1     | Not at all difficult*      |
|               | 2     | A little difficult         |
|               | 3     | Somewhat difficult         |
|               | 4     | Very difficult             |
| CASHUSE       | 1     | Increased*                 |
|               | 2     | Decreased*                 |
|               | 3     | No change                  |
| CHNGSHP1ML    | 1     | More                       |
|               | 2     | Less*                      |
| CHNGSHP2ML    | 1     | More                       |
|               | 2     | Less*                      |
| CHNGSHP3ML    | 1     | More                       |
|               | 2     | Less*                      |

*: reference category.
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