Purchase Behaviors During Emergencies: Exploratory Analyses and Predictive Models

Varol O. Kayhan
University of South Florida

Philip J. Trocchia
University of South Florida

Alison Watkins
University of South Florida

In this study, we distinguish between traditional emergency events (i.e., those that occur frequently) and novel emergency events (i.e., those that occur rarely in one's lifetime). We examine consumers' shopping behaviors during both types of emergency events. Using data from a U.S. supermarket chain, we answer three research questions. First, we conduct multiple cluster analyses and identify three distinct shopping behaviors during emergency events, namely strategic, routine, and stocking. Second, we examine how consumers change their shopping behaviors toward novel emergency events and find that majority of consumers continue to engage in routine shopping behaviors. Third, we examine how to predict shopping behaviors before emergency events and show that all three types of shopping behaviors can be predicted with reasonable levels of accuracy based on consumers' spending before emergency events.

Keywords: emergency events, hurricanes, COVID-19, shopping behaviors, machine learning

INTRODUCTION

Individuals sometimes need to make quick purchases of goods and services without prior anticipation. Such emergency purchasing emanates when individuals encounter an imminent, disruptive, threatening, and unanticipated event. While some of these emergency purchases occur because of minor unexpected events (such as purchasing an umbrella in a sudden rainstorm or a stain remover after a clothing mishap), they might also come from major events such as disasters triggered by natural hazards (e.g., hurricanes, winter storms, etc.), public health crises such as the coronavirus disease of 2019 (COVID-19), or political conflicts (e.g., a coup).

In the context of this paper, we define an emergency event as an unexpected, unforeseen, and sudden circumstance that impacts health, life, or property of large groups of individuals (Alexander, 2002; S. A. Thomas, 2007). We distinguish between two types of emergency events. *Traditional emergency events* are those that occur somewhat frequently, on a regular basis, and for which most individuals have gained some measure of familiarity. For example, we consider many disasters triggered by natural hazards, such as hurricanes, snowstorms, and tornadoes, as traditional emergency events because of the frequency with which these events occur in particular geographic regions. On the other hand, *novel emergency events* are those that occur very rarely (e.g., once or twice in a lifetime). We consider pandemics, biochemical warfare, nuclear disasters, and military attacks as novel emergency events since, for most people, they occur on an infrequent basis. This distinction is important because consumers might adopt different shopping behaviors for novel emergency events compared to traditional emergency events.

Prior literature examines consumers' shopping behaviors during both traditional and novel emergency events. For example, it has already been shown that consumers engage in stockpiling behaviors during disasters triggered by natural hazards as well as the COVID-19 pandemic (Elmore, 2017; Hall, Prayag, Fieger, & Dyason, 2020; Larson & Shin, 2018; Yuen, Wang, Ma, & Li, 2020; Zulauf, Cechella, & Wagner, 2021). However, other types of shopping behaviors besides stockpiling during emergency events have not garnered enough interest from researchers. For example, we do not know the types or prevalence of other shopping behaviors observed during emergency events compared to stockpiling behaviors. Further, most of the existing work focuses on a single emergency event, which makes many of the studies cross-sectional in nature. Therefore, we do not know how consumers might switch between different shopping behaviors depending on the type of emergency events. Last, prior work outlines different strategies on how to prevent stockpiling behaviors (cf. Carlson, 2021) but does not shed much light on determining a consumer's likelihood of stockpiling at the onset of an emergency event. This is important because better intervention techniques can be developed if we can predict each consumer's likelihood of stockpiling even before an emergency event happens. We try to address these gaps in extant work.

The goals of this paper are threefold. First, we identify different types of shopping behaviors when the public is notified about each type of emergency event. We accomplish this by comparing shoppers' behaviors before and after a public notification of an emergency event. This helps us identify not only the different types of shopping behaviors during emergency events, but also their prevalence. Second, we examine how consumers might alter their shopping behaviors from traditional to novel emergency events. This helps us shed light on consumers' decision making under uncertainty such that we examine the type of shopping behavior adopted by a consumer for a novel emergency event compared to a traditional emergency event encountered by the same consumer. Finally, we build models to predict shopping behaviors that will be observed after the public is notified of emergency events. This helps us make recommendations to retailers so they can proactively manage shoppers during these events. In summary, we address the following research questions:

RQ1: *When public is notified about an upcoming emergency event: (a) What categories of shopping behaviors for emergency items are observed? (b) What percentage of shoppers belong in each category? and (c) What is the average expenditure in each category?*

RQ2: *How do consumers change their shopping behaviors toward novel emergency events?*

RQ3: *How can we predict emergency shopping behaviors that will be observed after the public is notified of emergency events?*

We answer these research questions using data obtained from a large supermarket chain with stores located in the Southern and Midwestern regions of the United States. The data includes purchases of rewards card holders before and after public announcements of several emergency events in Florida and four states in the midwestern United States (heretofore referred to as the Midwest).

This paper is organized as follows. In the next section, we review extant work on shopping behaviors during emergency events. In the following section, we discuss our data source and data set. In the Results section, we present the findings of our research questions. Finally, we summarize our findings and discuss their limitations and implications.

BACKGROUND

The impact of emergency events on shopping behaviors has been studied previously. Not surprisingly, emergency events cause a significant change in purchase behaviors (cf. Loxton et al., 2020; Young, 2020). One of the most commonly reported shopping behaviors during an emergency event is stockpiling. For instance, Hurricane Irma caused a 40% increase in grocery store purchases compared to the same week a year before the hurricane's landfall (Elmore, 2017). Similarly, COVID-19 caused severe stockpiling among shoppers (Hall et al., 2020).

Prior work offers several reasons to explain the stockpiling behavior such as impulsive and compulsive tendencies of shoppers (Kennett-Hensel, Sneath, & Lacey, 2012; Sneath, Lacey, & Kennett-Hensel, 2009). Furthermore, shoppers' fear of or general anxiety about emergency events has been identified as a salient reason behind stockpiling (Arndt, Solomon, Kasser, & Sheldon, 2004; Larson & Shin, 2018; Yuen et al., 2020). If shoppers buy more and stockpile during emergency events, they are more likely to feel a sense of security, comfort, momentary escape, and reduced stress (Kennett-Hensel et al., 2012; Sneath et al., 2009). Also, shoppers stockpile because they have greater concerns for accessing stores during emergencies (Larson & Shin, 2018). Other notable reasons for stockpiling are perceived product scarcity (Gupta & Gentry, 2016; Gupta & Gentry, 2019; Sheu & Kuo, 2020; Sterman & Dogan, 2015; J. A. Thomas & Mora, 2014), social influence (Frank & Schvaneveldt, 2016), and fear of missing out (Kang, He, & Shin, 2020).

In summary, explanations for stockpiling behavior during emergency events have been well-documented. Interested readers can refer to Yuen et al. (2020) for a more comprehensive review of some of the reasons for stockpiling. However, extant work provides no discussion regarding other types of shopping behaviors or the prevalence of other types of behaviors relative to stockpiling in times of emergency. More importantly, prior work offers no insight into how shopping behaviors change if consumers encounter a novel emergency event. For example, we do not know whether consumers switch between different types of shopping behaviors if there is a new emergency event with which they are not familiar. Finally, existing work does not shed light on a consumer's likelihood of adopting a specific type of shopping behavior during an emergency event so that retailers and policy makers can make necessary interventions. We address these gaps in the literature.

DATA

Secondary Data Source

To address our research questions, we obtained data from DecaData, a provider of Granular USA food and beverage retail data. We obtained the grocery shopping data of reward card holders for hurricanes Matthew and Irma in Florida, an early winter storm in Midwest, and COVID-19 in both Florida and Midwest. These emergency events and their occurrences in the timeline are presented in Table 1. As discussed earlier, we consider hurricanes and winter storm as traditional emergency events, and COVID-19 as a novel emergency event.

TABLE 1
TIMELINE OF EMERGENCY EVENTS IN THE DATA SET

YEAR	FLORIDA	MIDWEST
2016	**HURRICANE MATTHEW**	
2017	**HURRICANE IRMA**	
2018		**EARLY WINTER STORM**
2020	**COVID-19**	**COVID-19**

For each event, we divide the related data set into two categories, namely pre-notification and post-notification, based on the time of purchases. Pre-notification data comprise all purchases made prior to the public notification of an emergency event. Post-notification data comprise all purchases made after the public notification. Therefore, pre-notification data enables us to create a baseline shopping behavior, while the post-notification data shows the change from baseline.

We performed rigorous data cleaning and transformation on both pre- and post-notification data. To be included in a data set, a rewards card member had to make purchases during both pre-notification and post-notification time windows. All other card members who did not make any purchases during either of these time windows were excluded from our data sets. Further, we excluded all rewards cards that were used for bulk purchases in one store because of the possibility that those cards were used by store clerks to provide discounts to non-members. To do this, we eliminated all rewards cards that purchased more than six standard deviations away from mean purchases of all members.

Florida Data

Hurricane Matthew impacted Florida between October 6 to October 7, 2016. A state of emergency for the hurricane was declared in Florida on October 3, 2016. Despite its early threatening behavior, Hurricane Matthew impacted only a specific region of Florida. We obtained the zip codes of these regions from a report published by Dun and Bradstreet (2016) for insurance purposes. When matched to our data, we found 17 zip codes with 21 stores in the data set. We used only these locations for the analysis of hurricane Matthew. Pre-notification period, which is the baseline, is between September 15 and October 1, 2016 (i.e., two weeks prior to the public notification). Post-notification period, which is the change from baseline, is between October 2 and October 7, 2016.

Irma developed from a tropical wave near the Cape Verde Islands on August 30, 2017, and became a Category 5 hurricane by September 5, 2017. Unlike Matthew, hurricane Irma threatened the majority of Florida. Therefore, we included the data from all stores for the analysis of Irma. In this case, the pre-notification period, or baseline, is between August 25 and September 4, 2017. The post-notification period, or change from the baseline, is between September 5 and September 9, 2017.

We identified March 1, 2020 as the date delineating pre- and post-notification data for COVID-19 in Florida, because the first two Floridians tested positive for COVID-19 on this date (ClickOrlando.com, 2020). Therefore, pre-notification period is between February 15 and February 28. 2020, while post-notification period is between March 1 and March 23, 2020. We included all stores in Florida for the analysis for COVID-19.

Midwest Data

Our data set included purchases made before and during a major storm in late November 2018, which is considered an ‘early winter storm’ or ‘early blizzard.’ The storm hit between November 25 and 26, 2018. In this case, the pre-notification period was between November 18 and November 23, 2018, while the post-notification was between November 24 and 25, 2018. We included only those zip codes that were affected by the storm to the analysis.

For Midwest, the COVID-19 pre- and post-notification period was the same as that of Florida. This was because it was reported that coronavirus reached Iowa around March 2, 2020 (Rodriguez, 2020). Similar to Florida, we included all zip codes in Midwest for the analysis of COVID-19.

Emergency Items

Shoppers included in the data set made purchases from a very diverse set of product categories. We used a more targeted approach by focusing on only those items that are most frequently bought during an emergency event. To do this, we used a list of recommended items to purchase before a hurricane or snowstorm (see Maxouris (2022) as well as “weather preparedness” at http://www.directenergy.com/ learning-center/ for a list of these items). We grouped the items provided in this list into four higher-level categories: water, shelf stable foods, energy, and safety. As the name implies, the water category only included bottled water purchases. The shelf stable foods included candy, nuts, dried fruit, canned fish and meat, canned fruit and vegetables, canned soup and pasta, breakfast cereals, cookies, crackers, peanut butter, jelly, and shelf stable drinks. The energy category included batteries, candles, flashlight, and fuel (such as propane, charcoal, and fireplace logs). The safety category included ice, cleaning supplies, first aid, insecticides, paper products, and toilet paper.

Primary Data Source

To investigate Research Question 2, we conducted a survey using Qualtrics on Amazon's Mturk platform. Mturk has been widely used in the academic literature and is accepted as a valid source of consumer information (Hunt & Scheetz, 2019). Surveys were distributed to shoppers in Florida and select Midwest US states (Illinois and Missouri) for which we had secondary data from the supermarket chain. Our initial sample consisted of 485 subjects. We eliminated 99 of these due to failing our attention check question (Mark 'Very Important' for one matrix item) and/or for taking the survey in an inordinately short period of time (90 seconds or less). We ultimately had a total of 386 usable responses in four categories: 97 in Florida regarding hurricane purchases; 99 in the Midwest for winter storm purchases, 99 in Florida for COVID-19 purchases, and 91 in Midwest for COVID-19 purchases.

RESULTS

Research Question 1

Recall, RQ1 seeks to identify (a) different categories of shopping behaviors, (b) the percentage of shoppers in each category, and (c) the average expenditure in each category during emergency events. To address these questions, we ran a series of cluster analyses. The data set used in this analysis included those shoppers who did not participate in more than one emergency event. For example, we made sure that shoppers identified for hurricane Matthew did not shop for hurricane Irma or COVID-19 in Florida (and vice versa). Similarly, shoppers included in the early winter storm did not shop for COVID-19 in Midwest (or vice versa). This enabled us to ensure the independence of samples. Therefore, we could treat each emergency event as being independent of other events, and thus examine if similar shopping behaviors exist across different events using independent samples. As a result, we identified a total of 535,422 shoppers who shopped before and during each emergency event (but not across multiple events).

To run the cluster analyses, we performed a series of data transformations. First, we identified each shopper's expenditure (in dollars) on the four emergency item categories (described in the previous section) during the pre- and post-notification periods of each event. We consider the pre-notification period purchases as the baseline shopping behavior. Then, we identified the difference between the pre- and post-notification periods. We consider this difference as each shopper's deviation from their baseline during an event. Next, we used this difference on the four emergency item categories to run a separate cluster analysis for each event.

Hurricane Matthew

We identified a total of 40,402 shoppers who shopped before and during hurricane Matthew (but did not shop in any other emergency events in our data set). We ran multiple cluster analyses (by changing the number of clusters from 2 to 10) on these shoppers based on their purchase amounts (in dollars) on the four emergency item categories. To determine the optimal number of clusters, we calculated the *silhouette score* of each cluster. Silhouette score is derived from *elbow analysis* which is commonly used to identify the best number of clusters in a cluster analysis (Géron, 2019). The silhouette score ranges from -1 to 1 such that scores close to 1 represent good clusters, scores close to 0 indicate presence of cluster members that are close to cluster boundaries, and scores close -1 indicate suboptimal clusters (Géron, 2019). The silhouette scores of the cluster analyses are presented in Figure 1. As shown in the figure, the three-cluster solution (i.e., k=3) was the best cluster analysis since it had the highest silhouette score.

The three clusters, the percent of shoppers in these clusters, and cluster centers are presented in Table 2. As shown in the table, we refer to the first cluster as *strategic shoppers*, hereafter, because shoppers in this cluster spent, on average, a total of $28.02 less than the baseline values. This means that these shoppers bought less during the post-notification period compared to their baseline (i.e., pre-notification period). They made up 13.9% of all shoppers identified for hurricane Matthew in our data set. A possible reason that might explain this behavior is that these shoppers might have bought their emergency items in advance. Recall, our data set includes only those shoppers who were present in the supermarket during the pre- and post-notification periods of emergency events. This means, these shoppers made purchases during the post-notification period, but made fewer purchases compared to their baseline. Therefore, these shoppers might be closely aligned with the personality characteristic of conscientiousness since they exhibit a certain level of preparedness by not purchasing essential emergency items despite being in the supermarket. According to the big five personality model (cf. De Raad, 2000), individuals exhibiting high degrees of conscientiousness are more self-disciplined, responsible, and most comfortable when they are well-prepared (Arthur Jr & Graziano, 1996). Further, these consumers might have higher levels of internal locus of control since these types of individuals are more likely to take precautionary steps, such as stocking up on emergency supplies in advance, in order to avoid stockouts of important items under emergency conditions (Phares, 1976).

FIGURE 1
SILHOUETTE SCORE OF CLUSTER ANALYSES CONDUCTED FOR HURRICANE MATTHEW

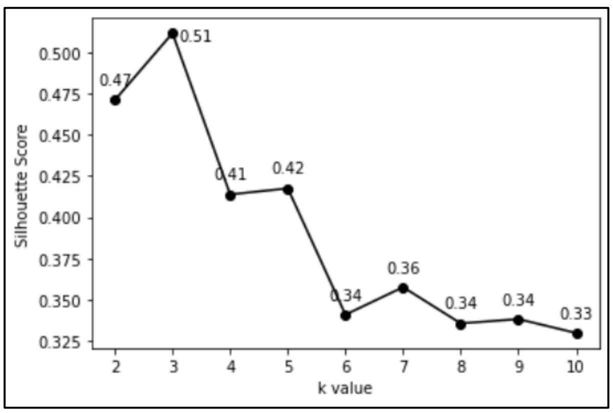

TABLE 2
CLUSTER ANALYSIS ON DIFFERENCE FROM BASELINE FOR HURRICANE MATTHEW (N=40,402)

Cluster #	Cluster name and prevalence	% of total sales (before)	% of total sales (during)	Cluster Centers				TOTAL
				Water	Shelf stable foods	Energy	Safety	
1	Strategic (13.9%)	41.6%	11.1%	-$0.52	-$26.76	$0.40	-$1.14	-$28.02
2	Routine (72.9%)	48.6%	49.0%	$0.25	$0.12	$0.39	$0.16	$0.92
3	Stocking (13.2%)	9.7%	39.8%	$1.43	$29.44	$1.37	$1.60	$33.84

Silhouette score: 0.51

The second cluster, which we refer to as *routine shoppers*, hereafter, spent, on average, a total of $0.92 more than the baseline values. Therefore, these shoppers did not change their baseline behaviors with respect to purchasing emergency items, and shopped the same way they did for their baseline. They made up 72.9% of all shoppers identified for hurricane Matthew. The behaviors of these shoppers can be explained using the concept of *unrealistic optimism*. Unrealistic optimism concerns one's assertion that his/her chances of experiencing a negative event is less than average (Weinstein, 1980). Therefore, individuals are unable to make fair assessments of future risks. As a result, people think that they are less likely to get in an accident, be a victim of crime, get a disease, or have cancer in the future (Weinstein, 1982; Weinstein & Klein, 1996). In fact, the severity of a negative event and optimism is correlated such that individuals believe that their chances of experiencing a negative event is less likely if this event is perceived as more serious or severe. Such optimism, or inaccurate risk assessment, reduces the motivation to take preventive measures (Dunning, Heath, & Suls, 2004). Therefore, individuals do not take any action and become complacent. There are different explanations of this optimism, some of which include incomplete information about the context, not experiencing similar negative events previously, and perceived controllability of events (Dunning et al., 2004; Weinstein, 1984). Unrealistic optimism has been observed for disasters triggered by natural hazards in addition to many other contexts. For example, Spittal et al. (2005) report that individuals believe they are more prepared for an earthquake than others, and they are less likely to suffer injuries from an earthquake compared to others. Similarly, unrealistic optimism was reported for hurricane preparedness even after individuals experienced a hurricane (Trumbo, Meyer, Marlatt, Peek, & Morrissey, 2014). In a recent study, unrealistic optimism was observed for the COVID-19 pandemic as well such that individuals assessed their risks of severe disease much less than others (Gassen et al., 2021).

Shoppers in the third cluster made up the remaining 13.2% of all shoppers for hurricane Matthew. We refer to these shoppers as *stocking shoppers*, hereafter, because they spent, on average, a total of $33.84 more than their baseline values. Therefore, these shoppers bought more emergency items during the post-notification period compared to their baseline, or pre-notification period. Some of the explanations of stocking behaviors include anxiety about an emergency, sense of security obtained through purchasing, comfort, momentary escape, perceived product scarcity, social influence, and fear of missing out (see Yuen et al. (2020) for a comprehensive review).

Other Emergency Events

We conducted the same cluster analysis for the remaining emergency events in our data set. We used the same number of clusters (i.e., k=3) for hurricane Irma and the early winter storm. This not only provided the highest silhouette scores, but also enabled us to identify the same types of shopping behaviors observed for hurricane Matthew. However, shopping behaviors during COVID-19 differed. To identify the strategic and routine shopping behaviors during COVID-19, we had to create four clusters for Florida shoppers and five clusters for Midwest shoppers. This led to varying degrees of stocking behaviors. We used only one name (i.e., stocking) to represent these shopping behaviors in the analyses for consistency purposes.

The results of these analyses are presented in Table 3 (for hurricane Irma), Table 4 (for early winter storm), Table 5 (for COVID-19 in Florida), and Table 6 (for COVID-19 in Midwest). The silhouette scores of these analyses were all above 0.4 and close to the silhouette score observed for hurricane Matthew.

TABLE 3
CLUSTER ANALYSIS ON DIFFERENCE FROM BASELINE FOR HURRICANE IRMA (N=12,030)

Cluster #	Cluster name and prevalence	% of total sales (before)	% of total sales (during)	Cluster Centers				(TOTAL)
				Water	Shelf stable foods	Energy	Safety	
1	Strategic (17.5%)	45.3%	9.2%	-$0.39	-$22.07	$0.06	-$1.41	-$23.80
2	Routine (68.9%)	43.4%	48.9%	$1.61	$3.67	$0.36	$0.19	$5.82
3	Stocking (13.6%)	11.3%	41.8%	$3.50	$43.69	$1.20	$2.27	$50.66

TABLE 4
CLUSTER ANALYSIS ON DIFFERENCE FROM BASELINE FOR MIDWEST WINTER STORM (N=30,134)

Cluster #	Cluster name and prevalence	% of total sales (before)	% of total sales (during)	Cluster Centers				(TOTAL)
				Water	Shelf stable foods	Energy	Safety	
1	Strategic (15.5%)	46.1%	12.1%	-$0.47	-$28.51	-$0.20	-$1.00	-$30.18
2	Routine (66.8%)	46.1%	41.9%	-$0.10	-$3.31	-$0.05	-$0.21	-$3.68
3	Stocking (17.7%)	7.8%	46.0%	$0.19	$13.58	$0.05	$0.20	$14.02

TABLE 5
CLUSTER ANALYSIS ON DIFFERENCE FROM BASELINE FOR COVID-19 IN FL (N=66,076)

Cluster #	Cluster name and prevalence	% of total sales (before)	% of total sales (during)	Cluster Centers				(TOTAL)
				Water	Shelf stable foods	Energy	Safety	
1	Strategic (13.1%)	29.8%	5.9%	-$0.35	-$19.35	-$0.07	$0.18	-$19.59
2	Routine (60.9%)	40.1%	32.1%	$0.95	$4.46	$0.13	$1.73	$7.27
3	Stocking Level 1 (20.9%)	22.4%	40.3%	$3.35	$36.79	$0.48	$5.61	$46.23
4	Stocking Level 2 (5.1%)	7.7%	21.7%	$6.40	$96.20	$0.98	$11.00	$114.58

TABLE 6
CLUSTER ANALYSIS ON DIFFERENCE FROM BASELINE FOR COVID-19 IN MIDWEST (N=386,780)

Cluster #	Cluster name	% of total sales (before)	% of total sales (during)	Cluster Centers				(TOTAL)
				Water	Shelf stable foods	Energy	Safety	
1	Strategic (10.2%)	22.6%	4.9%	-$0.09	-$23.51	$0.05	$0.88	-$22.68
2	Routine (53.0%)	33.9%	23.4%	$0.37	$4.30	$0.09	$1.16	$5.91
3	Stocking Level 1 (24.8%)	24.2%	33.8%	$1.24	$33.72	$0.31	$3.42	$38.70
4	Stocking Level 2 (9.7%)	14.4%	26.4%	$2.55	$78.92	$0.65	$7.08	$89.20
5	Stocking Level 3 (2.5%)	4.9%	11.5%	$4.74	$159.86	$1.29	$12.54	$178.43

As seen in the tables, shoppers in each of these emergency events adopted the same type of shopping behaviors identified for hurricane Matthew. Exceptions were for COVID-19 purchases in both Florida and Midwest. Even though we still observed the strategic and routine shopping behaviors, there were different levels of stocking behaviors in both events.

Research Question 2

RQ2 concerns the manner in which consumers alter their shopping behaviors for novel emergency events. There are two competing hypotheses that may potentially explain changes in shoppers' behaviors. The first of these suggests that consumers will adopt the same shopping behavior they employed in traditional emergency events. The rationale for this assertion is rooted in System 1 processing of the dual-process theory of decision-making (Kahneman, 2011; Stanovich & West, 2000). Accordingly, System 1 processing is fast, parallel, automatic, effortless, associative, slow learning, and emotional (Kahneman, 2003), and allows individuals to make decisions using intuitions or impressions in memory. Therefore, when individuals encounter an emergency event multiple times, they develop automatic and intuitive responses for that event over time. Once developed, these responses might also determine consumers' shopping behaviors during a novel emergency event. Therefore, a consumer's purchasing decisions for a novel emergency might be intuitive, fast, and emotional based on associations developed during traditional emergencies.

The second competing hypothesis suggests that consumers will adopt a different shopping behavior for novel emergency events. The rationale for this hypothesis is still rooted in the dual-process of theory of decision-making, though in this case, consumers use System 2 processing. System 2 processing is slow, serial, controlled, effortful, rule governed, fast learning, and emotionally neutral (Kahneman, 2003). Therefore, when individuals encounter a novel emergency, they might evaluate this emergency event in its own right, and thus, tailor their purchases to the perceived needs of this emergency event. In this case, shopping behaviors are based on reasoning and inference rather than associations developed for traditional emergencies.

In order to test these competing hypotheses, we focused on shoppers in Florida. We identified those who shopped during all three emergency events in Florida (i.e., hurricane Matthew, hurricane Irma, and COVID-19). We identified a total 11,456 such shoppers. We also examined only one emergency item category, namely energy, which consisted of batteries, candles, flashlight, and fuel. We specifically selected this category, because, while these items are essential for a hurricane, they are not as important for COVID-19. Therefore, if we observed that shoppers who stocked up on energy during hurricanes Matthew and Irma also stocked up on energy during COVID-19, then it meant they used System 1 processing. This provides support for the first competing hypothesis. Otherwise, if shoppers who stocked up on energy during hurricanes Matthew and Irma adjusted their energy purchases for COVID-19, then it meant they used System 2 processing. This provides support for the second competing hypothesis.

We ran three separate cluster analyses—one for each emergency event. We only focused on the energy category for these cluster analyses. The results of these analyses are presented in Table 7.

A total of 6.8% (or 785 out of 11,456) engaged in stocking (both Level 1 and 2) behaviors during hurricane Matthew. Out of these 785 shoppers, 85 engaged in stocking behaviors in Irma as well. Among these 85 shoppers, only 11 shoppers engaged in stocking during COVID-19. Therefore, a total of 11 shoppers stocked up on energy supplies during Matthew, Irma, and COVID-19 consistently. Because there was no need to stock up on energy supplies during COVID-19 (compared to baseline), it is possible that these 11 shoppers (or 13% of 85 shoppers) used System 1 processing during COVID-19.

TABLE 7
CLUSTER ANALYSES ON THREE EMERGENCY EVENTS IN FLORIDA (N=11,456)

Cluster #	Cluster name	Matthew		Irma		COVID-19	
1	Strategic	-$10.84	2.0%	-$16.26	1.5%	-$17.17	1.6%
2	Routine	$0.05	91.1%	$0.07	94.2%	$0.11	95.5%
3	Stocking Level 1	$11.08	5.8%	$15.35	4.3%	$18.03	2.9%
4	Stocking Level 2	$29.84	1.0%	NA	NA	NA	NA

However, this also means that the remaining 74 shoppers (87% of 85) engaged in strategic or routine shopping behaviors during COVID-19. This means that these shoppers used System 2 processing because they purchased less energy supplies during COVID-19 (compared to baseline) even though they purchased more during Matthew and Irma.

Please note that the above analysis is based on only 85 consumers (out of 11,456). Therefore, these findings need to be validated in a qualitative study. One of the reasons for the low number is that most shoppers engaged in routing shopping behaviors across the three emergency events. For example, 10,441 shoppers (out of 11,456) were routine shoppers during hurricane Matthew. Out of these, 9,918 were also routine shoppers during hurricane Irma. Further, among the 9,918 shoppers, 9,550 were routine shoppers during COVID-19. Therefore, majority of routine shoppers engaged in the same shopping behaviors across the three events. Routine shopping behaviors might not inform us about System 1 or System 2 processing. Rather, they might signal indifference, or unrealistic optimism, toward emergency events in general.

As a further test of whether shoppers generally use System 1 or System 2 processing, we collected survey data to focus on consumer perceptions of whether there would be shortages of energy-related products. Because media coverage pertaining to the COVID-19 pandemic showed no real threat of an energy shortage, we argue that consumers expressing a fear of shortage of energy supplies would provide an indication of System 1 processing, rather than thoughtful and deliberate System 2 processing. In our survey, we focused on five items (i.e., flashlights, batteries, candles, matches, and fuel (propane, gas, diesel, and/or wood)) as energy-related items. We asked the question, "Please let us know how likely you thought there would be shortages of the following goods and services when you shopped during:" (one of the following) "COVID-19 pandemic" for Florida residents, "COVID-19 pandemic" for Midwest residents, "hurricane" for Florida residents, or "winter storm" for Midwest residents. Responses ranged from "very low likelihood" (1) to "very high likelihood" (5). Individual values for the five energy types were then summed in SPSS; the new scale ranged from 5 (very low likelihood to experience shortages in each energy category) to 25 (very high likelihood). One-way ANOVA revealed that study participants were more likely to perceive shortages of energy items during Midwest winter storms and Florida hurricanes than during COVID-19 in the same geographic regions with statistical significance. In terms of inferential statistics, there were no significant differences in perceptions of energy shortages between the Florida and Midwest participants when asked about COVID-19 (mean for Florida COVID-19 = 13.2 versus mean for Midwest COVID-19 = 12.7; sig. = .930). However, there were significant differences between respondents in Florida who responded to perceptions of energy shortages under hurricane conditions versus COVID-19 conditions (mean for Florida COVID-19 = 13.2 versus mean for Florida hurricane = 18.7; sig < .01) as well as between respondents in the Midwest who responded to perceptions of energy shortages under winter storm conditions (mean for Midwest COVID-19 = 12.7 versus Midwest Winter Storm = 15.8; sig < .01).

We further tested consumer perceptions pertaining to emergency purchase situations by presenting Mturk respondents with the item, "Think about when you first heard about the COVID-19 pandemic. Please let us know how important it was for you to stock up on the following items when preparing for:" (one of the following) COVID-19 pandemic for Florida residents, COVID –19 pandemic for Midwest residents, hurricane for Florida residents, or winter storm for Midwest residents. Responses ranged from "Not Important at All" (1) to "Extremely Important" (5). As before, we summed the responses to create a new scale, which ranged from 5 (not important at all to stock up in each energy category) to 25 (extremely important to stock up in each energy category). One-way ANOVA revealed that study participants were more likely to stock up on the same energy items as above (flashlights, batteries, candles, matches, and fuel (propane, gas, diesel, and/or wood) during Florida hurricanes than during Midwest snowstorms and during COVID-19 in both geographic regions with statistical significance (mean for Florida hurricane = 18.3 versus Florida COVID-19 = 14.0 versus Midwest COVID-19 = 13.4 versus Midwest winter storm = 15.9; sig < .01). There were no significant differences between Midwest winter storm and either of the COVID-19 conditions (sig. > .10).

Research Question 3

To address RQ3, we created a model to predict shopping behaviors during the post-notification period of hurricane Matthew based on purchases made during pre-notification period of Matthew. We used seven input variables as predictors. Four of these concerned the baseline spending on emergency items (i.e., water, shelf stable foods, energy, and safety supplies), one concerned the total spending on these four emergency items, another one concerned the total spending on non-emergency items, and the last one concerned the ratio of total spending on emergency items to overall spending. Note that all variables captured the amount spent (in dollars) during the pre-notification period of Matthew (i.e., baseline spending). The target (i.e., output) variable was shopping behaviors during the event (i.e., the post-notification period). Because we identified three shopping behaviors (i.e., strategic, routine, and stocking), this was a multi-class classification task.

Recall, the proportions of shopping behaviors identified for hurricane Matthew were disproportionate. This created an imbalanced data set: strategic and routine shopping behaviors accounted for 13.9% and 13.2% of all shopping behaviors, respectively. Accuracies of predictive models defaulted to the baseline value (72.9%), which was the proportion of routine shoppers. Therefore, we created a balanced data set using oversampling. To do this, we randomly sampled 3,000 shoppers from each category. To ensure the robustness of findings, we repeated this ten times to create ten different data sets (with replacement).

We used 10 different algorithms to run a 10-fold cross validation on each data set to determine which algorithm performed the best in predicting shopping behaviors. The algorithms included logistic regression, nearest neighbor, decision tree, neural network, support vector machine (with linear kernel), random forest, adaptive boosting, gradient boosting, stochastic gradient descent, and an ensemble model of all these models using hard voting. The best model was a random forest model (with 500 estimators) with an average accuracy of 70.3%. (Note that the baseline accuracy is 33.3% since each category is balanced in the data sets). Because we performed 10-fold cross-validation on ten different data sets, 100 models were created for each algorithm. Therefore, the average accuracy was the average of these 100 models.

To see if there was a better random forest model with different settings, we ran a randomized grid search. We built 20 additional random forest models by randomly selecting the number of estimators from values between 50 and 1000. Average accuracy values ranged between 70.2% to 70.4%. We tried a second grid search by changing the maximum depth of decision trees used in random forest models (from random values between 5 and 50), though the average accuracy values did not change. These two searches demonstrated that there was not a significantly better model than the one with 500 estimators.

We also examined which variables were most important in predicting the shopping behaviors. To do this, we obtained the variable importance metric of each individual variable in each model and averaged them across 100 models. Variables from most important to least (along with their importance scores in parentheses) were as follows: 1) shelf stable foods (0.31); 2) total spending on non-emergency items (0.25); 3) total spending on the four emergency items (0.20); 4) ratio of total spending on emergency items to overall spending (0.16); 5) safety supplies (0.04); 6) water (0.03); 7) and energy (0.01). Note that the values in parenthesis add up to 1.00, which indicates the importance of each variable relative to one another. Even though we cannot definitively say how these variables predict shopping behaviors (due to non-linear and rule-based nature of the relationships between these variables and shopping behaviors), we can see that the first four of these variables have more predictive power than the last three.

Next, we obtained the classification matrix of the model with 500 estimators on each test data set. Therefore, we had 100 classification matrixes. For each classification matrix, we calculated the recall values, or true positive rates, for the three shopping behaviors predicted by the model. The average recall values for each category are summarized in Table 8.

Because recall concerns correct predictions in each category (i.e., True positive / (True Positive + False negative)), we were able to correctly predict, on average, 94.2% of all strategic shopping behaviors during hurricane Matthew. Similarly, we were able to correctly predict 56.1% of routine and 60.8% of stocking behaviors.

TABLE 8
PREDICTIVE MODELS' RESULTS FOR ALL EMERGENCY EVENTS.

	Matthew	**Irma**	**Winter storm**	**COVID-19 FL**	**COVID-19 MW**
Model training:	Yes	No	No	No	No
Model used for testing:	Matthew model	Matthew model	Matthew model	Matthew model	Matthew model
Accuracy:	70.3%	54.6%	58.3%	46.9%	42.4%
Baseline:	33.3%	68.9%	66.8%	60.9%	43.5%
Recall: Strategic	94.2%	75.8%	95.2%	70.4%	84.3%
Recall: Routine	56.1%	53.0%	55.7%	48.8%	47.7%
Recall: Stocking	60.8%	35.5%	35.7%	30.7%	23.3%

To determine the reliability and validity of our predictions, we used the same random forest model (built for hurricane Matthew) to predict the shopping the behaviors during the post-notification period of hurricane Irma. Because we know the actual shopping behaviors for this period for Irma, we could determine the accuracy of the model for hurricane Irma. Note that we did not train a new model for hurricane Irma, but rather used the model trained on hurricane Matthew to make predictions for hurricane Irma. In this case, the average accuracy dropped to 54.6% (the baseline was 68.9% for routine shopping behaviors). Even though the average accuracy was below the baseline, we were able to make correct predictions in each shopping behavior category. The model's recall values for strategic, routine, and stocking behaviors were 75.8%, 53.0%, 35.5% respectively.

We repeated the same procedure for COVID-19 in Florida. The average accuracy further dropped to 46.9% (the baseline was 60.9% for routine shopping behaviors). Though, the average recall values were 70.4%, 48.8%, and 30.7% for strategic, routine, and stocking behaviors, respectively. Next, we repeated this for the winter storm in Midwest. Note that the original model is trained for hurricane Matthew. Therefore, the model not only transcends states, but also emergency events. The average accuracy was 58.3% (the baseline was 66.8% for routine shopping behaviors). Though, the model's recall values for strategic, routine, and stocking shoppers were 95.2%, 55.7%, and 35.7%, respectively.

Finally, repeating the same procedure for COVID-19 in Midwest generated the recall values of 84.3%, 47.7%, and 23.3% for strategic, routine, and stocking shopping behaviors, respectively. In this case, the average accuracy was 42.4% even though the baseline was 43.5% (for stocking shopping behaviors). These values are summarized in Table 8.

DISCUSSION

Summary of Findings

The first research question addressed the categories of shopping behaviors for emergency preparedness items observed during the post-notification period of emergency events, the percent of shoppers in each category, and their relative expenditures. We find that there are three predominant shopping behaviors observed during post-notification periods. Among the different emergency events examined in this study (whether traditional or novel), 10.2% to 17.5% of consumers adopted strategic shopping behaviors, and thus purchased fewer emergency items during post-notification periods compared to pre-notification periods (i.e., baselines). These consumers still went into the store to make purchases during emergency events, though their purchases were less than their baseline purchases, signaling targeted buying to address specific needs. While these shoppers account for 22.6% to 46.1% of total sales during pre-notification, these values drop to 4.9% to 12.1% of total sales during post-notification.

The second type of shopping behavior observed is routine shopping, which was adopted by 53.0% to 72.9% of consumers analyzed in our data sets. These shoppers did not necessarily change their shopping behaviors from their baseline behaviors, signaling a certain level of indifference, or unrealistic optimism, toward emergency events. The expenditures of these shoppers were also nearly the same during the pre- and post-notification periods. For example, these shoppers accounted for 33.9% to 48.6% of total sales during pre-notification and 23.3% to 49.0% of total sales during post-notification.

The last type of shopping behaviors observed is stocking behaviors, which was adopted by 13.2% to 37% of consumers. These shoppers made more purchases during post-notification compared to pre-notification periods. Their expenditures were also higher during post-notification periods: 39.8% to 71.7% of total sales compared to 7.8% to 43.5% of total sales during pre-notification periods.

The second research question concerned how consumers change their shopping behaviors from traditional to novel emergency events. Our analyses show that most consumers adopted routine shopping behaviors for traditional emergency events and continued to engage in routine shopping behaviors for novel emergency events. Only a small fraction of consumers showed evidence of System 1 and System 2 processing. Among these consumers, majority of them used System 2, which concerned thoughtful purchasing. The analysis of our survey data confirmed these findings: most shoppers adapted their shopping behaviors based on the needs of each emergency event. Please note that these findings do not contradict some of the irrational purchases observed in the midst of COVID-19, such as the toilet paper shortage (cf. Kirk & Rifkin, 2020). This is because our analysis of COVID-19 data concerns shopping behaviors in early March 2020, while these types of irrational purchases were observed much later than that (cf. Kirk & Rifkin, 2020).

Finally, the third research question concerned predicting shopping behaviors at the onset of emergency events (i.e., during post-notification periods). Our analyses show that we can predict strategic shopping behaviors with recall values ranging from 70.4% to 95.2%, routine behaviors with recall values ranging between 47.7% to 56.1%, and stocking behaviors with recall values from 23.3% to 60.8%. These values show that the model, originally trained on shoppers during the post-notification period of hurricane Matthew, can correctly predict shopping behaviors for different emergency events.

Limitations

This study is not without limitations. First, our data sets include the purchases of rewards card members only. Therefore, it is possible that the findings observed for rewards card members might not generalize well to those who do not own or use rewards cards. Second, we assume that the rewards card members in our data sets make most of their emergency items purchases at the supermarket chain from which the data is obtained. Though, it is possible that they could be making purchases at other stores or through other channels such as online shopping. We are unable to account for such purchases in this study. Third, we do not know the demographics of the rewards card members examined in this study. Therefore, it is possible that some of the members might not be the heads of households or are not responsible for purchasing emergency items for their households.

These limitations possibly might be offset by large sample sizes used in our analyses. For example, the sample sizes used for RQ1 and RQ3 ranged from 12,030 (for hurricane Irma) to 368,780 (for COVID-19 in Midwest). Similarly, we used a total of 11,456 consumers to address RQ2. Therefore, even if the data sets might include purchases that are not representative of regular household shopping, they still might shed light on patterns observed during post-notification periods of emergency events.

Implications

Our results show that even though a majority of consumers adopt routine shopping behaviors, many others either do not purchase essential items or stock up more than others during post-notification periods of traditional and novel emergency events. Some of these behaviors can be considered sub-optimal for emergency preparedness. While one group of consumers (e.g., strategic shoppers) might be more prepared than others, routine shoppers might be underprepared for an emergency event if they do not purchase the essential items during post-notification periods. On the other hand, another group of consumers (e.g., stockpiling shoppers) might be overprepared by way of hoarding. If the optimal outcome is making sure that all consumers are adequately prepared for emergency events, then retailers might have to determine who is more likely to underprepare or overprepare based on their prior purchasing patterns. Therefore, they might have to use several strategies. The first is the use of predictive algorithms as demonstrated in this study. Based on predictions made by such algorithms, retailers can determine purchasing behaviors beforehand and prevent shoppers from under- or over-preparing by offering incentives. For example, they can prepare emergency preparedness kits and let strategic and routine shoppers know of the availability of these kits through targeted marketing during post-notification periods. Similarly, they can target stockpiling shoppers and offer them coupons and discounts during regular times (before emergency events) so that these types of shoppers can prepare early and do not feel the need to stockpile during post-notification periods. Regardless, retailers can encourage early preparedness for emergency through custom but direct marketing.

Second, policy makers can also consider expanding tax-free shopping before the start of seasonal emergency events. For example, the state of Florida has a week-long tax-free shopping of emergency items at the beginning of each hurricane season. This can not only be extended for a longer period of time, but also implemented in other states that are prone to seasonal emergency events. Retailers can also implement some of the direct marketing tactics discussed above during these times to encourage early preparedness.

Third, retailers can use the insurance industry as an example to create new services concerning emergency preparedness kits. For example, one of the reasons consumers might not want to invest in pre-prepared emergency kits could be the limited shelf life of items (such as batteries or food) sold in these kits. Many of the items in these kits might expire if no emergency event threatens consumers in that season. However, consumers can buy these items similar to buying insurance policies: they can pay upfront to guarantee the timely delivery of these kits at the onset of emergency events. Therefore, if an emergency event is declared for a geographical region, retailers can deliver these kits directly to consumers from warehouses during post-notification periods of these events. Such a service can not only reduce the number of under- and over-prepared shoppers, but also prevent shoppers from spending money on unused emergency preparedness kits. Further, this can help retailers reduce foot traffic in stores at the onset of emergency events so that stores are not overwhelmed during those times.

CONCLUSION

In this study, we investigate three research questions about shopping behaviors. For the first research question, we identify the different categories of shopping behaviors observed for traditional and novel emergency events, determine the percent of shoppers in each category, and find their expenditure during pre- and post-notification of these events. For the second research question, we discuss how consumers change their behaviors for novel emergency events compared to traditional emergency events. For the third research question, we show how to predict a consumer's shopping behavior during the post-notification period of an emergency event.

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