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PERCEIVED RISK AND DEMOGRAPHIC FACTORS ON CONSUMERS' CHOICE IN TIMES OF CRISIS

Risco percebido e fatores demográficos na escolha dos consumidores em tempos de crise

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Abstract
In order to develop effective communication strategies during crises, this study explores how psychological factors (e.g., perceived risk) and demographic variables affect consumers' choice of consumption channels during the business reopening period amid the COVID-19 pandemic by analyzing survey data collected from 1,033 U.S. adults with predictive analytics. There are a number of important findings. First, the results of cluster analysis suggested that the U.S. consumers can be categorized into two clusters, high perceived risk and high concern group, and low perceived risk and low concern group. Cluster membership is associated with gender, ethnicity, and household income. Second, the results of decision tree analysis showed that perceived risk for food delivery and take out is the most important factor that predicts consumers' ordering food delivery and takeout behaviors. Third, the results of decision tree

Resumo
A fim de desenvolver estratégias de comunicação eficazes durante as crises, este estudo explora como fatores psicológicos (por exemplo, risco percebido) e variáveis demográficas afetam a escolha dos canais de consumo dos consumidores durante o período de reabertura de negócios em meio à pandemia de COVID-19, analisando dados de pesquisa coletados de 1.033 Adultos dos EUA com análise preditiva. Há uma série de descobertas importantes. Em primeiro lugar, os resultados da análise de cluster sugeriram que os consumidores dos EUA podem ser categorizados em dois grupos, alto risco percebido e grupo de alta preocupação, e baixo risco percebido e grupo de baixa preocupação. A associação ao cluster está associada a gênero, etnia e renda familiar. Em segundo lugar, os resultados da análise da árvore de decisão mostraram que o risco percebido para entrega e retirada de comida é

analysis suggested that perceived risk for instore consumption activities is the most important predictor for predicting consumers' in-store consumption activities, such as visiting a non-grocery retail store and going out to eat. The results of this study support consumer demographic theory and consumer perceived risk theory. Practical suggestions about how to minimize perceived risks with effective crisis communication strategies are provided.
Keywords: COVID-19; Consumer Behaviors; Consumers' Choice; Consumer Demographics; Perceived Risk; Predictive Analytics; Crisis Communication Strategies.

o fator mais importante que prediz os comportamentos dos consumidores em relação aos pedidos de entrega e de retirada de comida. Em terceiro lugar, os resultados da análise da árvore de decisão sugeriram que o risco percebido para as atividades de consumo dentro da loja é o preditor mais importante para prever as atividades de consumo na loja, como visitar uma loja de varejo que não seja mercearia e sair para comer. Os resultados deste estudo suportam a teoria demográfica do consumidor e a teoria do risco percebido pelo consumidor. São fornecidas sugestões práticas sobre como minimizar os riscos percebidos com estratégias eficazes de comunicação de crise.
Palavras-chave: COVID-19; Comportamentos do Consumidor; Escolha do Consumidor; Demografia do consumidor; Risco percebido; Análise preditiva; Estratégias de Comunicação de Crise.

INTRODUCTION

The unexpected COVID-19 pandemic has disrupted consumer behaviors in a very short period of time. Due to public health concerns, a majority of businesses were shut down and stores were closed from mid-March to the end of May in 2020 in the U.S. Many industries, such as travel, retail, and restaurants, were impacted. For example, non-grocery retail stores were closed during the three-month business shutdown period. Consumers needed to shop online for non-grocery items. In addition, customers could not eat inside the restaurants. Only take-out services were allowed for all restaurants. Until the last week of May, stores were not allowed to reopen with limited capacities. Thus, consumer behaviors were disrupted in the COVID-19 pandemic era, especially in the early stage of the pandemic. Even now, some pandemic-induced consumption trends (e.g., explosion of e-commerce, ordering grocery online) that emerged earlier still persist (Atchley, 2021; Wu, 2022c). Nevertheless, some consumers do go back to brick-and-mortar stores or utilize multi-channel shopping.

In order to predict the new normal, researchers would like to know the factors that may predict consumers' choice of consumption channels/outlets. Previous studies suggested that both psychological (e.g., Moon et al., 2021; Sheth, 2020; Wu, 2020) and demographic (Byrd et al., 2020; Hasan et al., 2021) factors can explain how consumers make consumption decisions and how they changed their behaviors amid the COVID-19 pandemic. For example, Wu (2020) identified four trends that emerged in the early stage of the pandemic, including online shopping, panic buying, shifting popular product categories, and consumers becoming more price-sensitive, and further analyzed the underlying psychological factors that drive these behaviors. The author argued that panic buying behavior is caused by emotions, such as fear and anxiety. In addition, consumers would first like to satisfy lower levels of needs, such as safety needs first based on Maslow's (1970) hierarchy of needs theory. Thus, consumers tend to purchase more staples than luxury goods amid the pandemic. Sheth (2020) also analyzed the immediate impact of COVID-19 on consumer behaviors and identified eight patterns, including: hoarding, improvision, pent-up demand, embracing digital technology, store comes, blurring of work-life boundaries, reunions with friends and family, and discovery of talent. The author argued that some of the patterns may persist; however, some of them may go away. As the author noted, "all consumption is time bound and location bound" (p. 283). Thus, organizations need to be flexible, in order to match evolving demand and supply. Obviously, the unexpected COVID-19 has disrupted the whole range of consumer behaviors. These changes have generated new research opportunities and areas.

Byrd et al. (2020) examined how demographic variables, such as gender, race/ethnicity, and age, affected consumers' risk perceptions about restaurant food and its packaging by surveying 958 consumers from May 5-7, 2020 in the U.S. They found that women were more concerned about contracting COVID-19 from all types of food, restaurant food, and restaurant food packaging than men were. Elderly consumers were more concerned about contracting COVID-19 from some types of restaurant food and packaging, such as dine-in restaurant food and cold/raw/uncooked restaurant food, than younger consumers were. Consumers' race/ethnicity is also an important factor that may affect their concerns about food safety. Except for restaurant dine-in and food delivered by the restaurants, African Americans were the most concerned about COVID-19 risks from all type of food, restaurant food, and restaurant food packaging. Relatively, white Americans were the least concerned among all race/ethnic groups. Previous studies (e.g., Byrd et al., 2020; Moon et al., 2020; Sheth, 2020; Wu, 2020) have provided some snapshots about COVID-19 impacts on consumer behaviors and factors (e.g., psychological and demographic factors) that may affect consumer behaviors amid the pandemic.

However, none of the previous studies specifically examined factors that affect consumer behaviors in the early stage of business reopening period in the U.S. after a three-months lockdown period. Nevertheless, it's important and interesting to take a closer look at consumer behaviors during this period of time, because consumers have more choices about shopping channels/outlets (e.g., going to a non-grocery retail stores vs. continuously shopping online; dinning in a restaurant vs. ordering takeout or food delivery). This study attempts to build on previous studies by exploring how psychological factors (e.g., concern, perceived risk) and demographic variables (e.g., gender, age, race/ethnicity, income, work status, education) affect U.S. consumption behaviors during the reopening period with predictive analytics methods (e.g., cluster analysis and decision tree analysis). By doing so, data-driven insights about consumer behaviors during crises can be provided.

Protection motivation theory (PMT) (Rogers, 1975), consumer perceived risk theory (Mitchell, 1999; Mothersbaugh et al., 2020), and consumer demographics theory (Sheth, 1977; Martins & Brook, 2010; Martins et al., 2012; Pollard et al., 1991) provide the theoretical foundation for this study. The next section of this paper reviews these theories and related studies.

THEORETICAL FRAMEWORK

Consumers' Concern and Perceived Risk

Protection motivation theory (PMT) (e.g., Rogers, 1975) and consumer perceived risk theory (e.g., Mitchell, 1999) provide two of the theoretical foundations for this study. The basic assumption of Rogers' (1975) original PMT is that the intention of the public to adopt protective health behaviors is significantly influenced by high levels of emotional concerns or perceived threats. As Rogers (1975) noted, "protection motivation arises from the cognitive appraisal of a depicted event as noxious and likely to occur, along with the belief that a recommended coping response can effectively prevent the occurrence of the aversive event" (p. 99). The basic assumption of PMT is that the intention of the general public to perform protective health behaviors is significantly influenced by high levels of perceived threat, and by perceptions of efficacy. Thus, the two key constructs in the original PMT are perceived threat and efficacy (Aurigemma et al., 2019). Perceived threat means perceived threat vulnerability and perceived threat severity. If people feel the disease is severe (perceived threat severity) and they are likely to be infected (perceived vulnerability), they are more concerned about the impacts of disease infection and are more likely to adopt protective measures. Perceived threat (Rogers, 1975) is called concern for the pandemic in the present study, in order to customize this concept for the COVID-19 pandemic. Efficacy means the extent to which people believe they are able to perform a security action (self-efficacy), and believe performing action would be effective (response efficacy) (Aurigemma et al., 2019; Okuhara et al., 2020; Song & Yoo, 2020).

PMT has provided a theoretical basis for health communication and consumer behaviors studies. For example, many COVID-19 related studies (Khosravi, 2020; Kowalski & Black, 2021; Okuhara et al.; Song & Yoo, 2020; Wu, 2022a) were conducted to examine consumers' protective health behaviors ((Khosravi, 2020; Kowalski & Black, 2021; Okuhara et al.; Song & Yoo, 2020) or consumption behaviors (e.g., Wu, 2022c) by using PTM (Rogers, 1975) as the guiding theory. As Khosravi (2020) argued, people's risk perception of the pandemic is one of the factors that contribute to their participation in adopting preventive measures, based on Rogers' (1975) protection motivation theory (PMT). Nevertheless, majority of the previous studies conducted amid the pandemic mainly focus on protective health behaviors, instead of consumption behaviors. Concerning consumer behaviors studies, Wu's (2022c) recent study examined how U.S. consumers' perceived threat/concern affect their consumption behaviors (e.g., increased online shopping, online grocery shopping, panic buying/hoarding, work from home, spending more time watching TV) during the business shutdown period.

Wu's (2022c) study has demonstrated the relevance of using PMT as a theoretical framework for consumer behaviors study because the author found that PMT's core concept, perceived threat, is the most significant predictor for consumers' increased online shopping behavior and panic buying/hoarding behavior during the business shutdown period in the U.S. However, Wu's study didn't specifically examine how consumers' protection motivation (e.g., perceived threat/concern) affected consumers' choice of consumption channels/outlets during the business reopening period. To bring additional insights into PMT research, the present study attempts to examine how consumers' perceived threat/concern may affect their consumption behaviors during the business reopening period in the U.S. amid the pandemic. Following Khosravi's (2020) and Wu's (2022a; 2022c) approach, this study focuses on the threat construct, instead of the efficacy construct of PMT, because people tend to have a high level of concern/perceived threat, but are not sure about what could be done to effectively stop the spread of the virus (perceived efficacy) in the early stage of the pandemic.

Similar to PMT's (Rogers, 1975) perceived threat concept, consumer perceived risk theory (Bauer, 1960; Mitchell, 1999; Mothersbaugh et al., 2020) emphasizes how consumers' perceived risk would influence consumer decision making processes and behaviors. The basic assumption of consumer perceived risk theory is that consumers usually go with the options with lower level of perceived risk when they are making purchase decisions, including choosing shopping channels/outlets. Mitchell (1999) argued that the perceived risk concept has been widely used by both academics and practitioners for several decades and will continue to motivate researchers to use its principles. As the author noted, there are different types of risks (e.g., subjective/perceived risk vs. objective/real-world risk). Perceived risk plays a crucial role in affecting consumer behaviors because it is very difficult to measure the accuracy of objective risk. Even if consumers can measure or calculate correctly the risk for a consumption activity, such as a new purchase, it is not the objective risk which motivates the behavior, but the consumer's subjective impression of it (Bauer, 1960, as cited in Mitchell, 1999). Mitchell further argued that "the perceived risk concept can be used in numerous ways by marketing practitioners for developing risk-reducing strategies, new products and product modifications, segmentation tools and improving personal selling" (p. 9). From the marketing communication standpoint, it's important for marketing practitioners to effectively communicate with target audiences in different segments with appropriate messages and channels in order to minimize subjective/perceived risks.

Mothersbaugh et al. (2020) noted that the purchase of products involves the risks that the product may not perform as expected. Such expectations may result in five kinds of cost: social cost, financial cost, time cost, effort cost, and physical cost. The first two are termed social risk. The last three are considered economic risk. They further argued that the perception of these risks differs among consumers, depending on their past experiences and lifestyles. Thus, perceived risk is considered as a consumer characteristic and a product characteristic. They further suggested that retailers need to minimize the perceived risk of shopping, especially if they sell products with either high social or economic risks. To reduce perceived risk, retailers/marketers need to effectively communicate with customers and provide excellent customer services via multiple channels at a timely manner (e.g., 24-hour customer service by phone, live-chat customer services, 100 percent satisfaction guaranteed).

Thinking about the pandemic context, many consumers are concerned about in-store consumption activities and food safety (Bolek, 2021; Byrd et al., 2020), because they are concerned about getting COVID-19 infection. As Byrd et al. (2021) noted, while dinning restrictions were adopted to reduce human contact, consumers may still mistakenly perceive that restaurant foods are risky sources of COVID-19.

Both PMT (Rogers, 1975) and consumer perceived risk theory (Mitchell, 1999; Mothersbaugh et al., 2020) are used by researchers who study consumer behaviors (e.g., Aurigemma et al., 2019; Wu, 2022c) and protective health behaviors (e.g., Khosrai, 2020; Kowalski & Black, 2021; Okuhara et al., 2020; Wu, 2022a). Based on these two theories, concern for the pandemic and consumer perceived risk are used as the psychological variables that predict various consumption activities, including going to a non-grocery store, ordering food take-out or delivery from restaurants, and going out to eat.

Because previous studies (e.g., Byrd et al., 2020; Moon et al., 2020; Wu, 2020) suggested that not only psychological factors, but also demographic factors, can affect consumer behaviors during crises, the next section of this paper reviews consumer demographics theory and discusses its relevance for this study.

Consumer Demographics Theory

Consumer demographic theory (e.g., Sheth, 1977; Martins & Brooks, 2010; Martins et al., 2012; Pollard et al., 1991) provides another theoretical foundation for this study. Martins and Brooks (2010) reviewed the consumer behaviors literature and identified several different perspectives that may explain consumer behaviors, such as the economic, psychological, sociological, and demographic perspectives. They argued that that the demographic perspective is very important because "demographic events are often triggers for the consumption of goods and services during the life cycle" (p. 87). The basic assumption of consumer demographic perspective/theory is that demographic variables, such as gender, age/generation, income, and education, affect consumers' perceptions, motivations, decision making process, lifestyles, behaviors, and the nature of consumer markets (Martins et al., 2012). Demographic variables can be used to segment the consumer population for better marketing strategies, and thus, offer valuable insights into who the consumers are and what they need (Kotler, 1997). As Mothersbaugh et al., (2020) noted, "demographics influence consumption behaviors both directly and by affecting other contributes of individuals, such as their personal values and decision styles" (p. 112). Thus, demographics play a critical role in influencing consumer behaviors.

Martins and Brooks (2010) argued that demographic variables provide an appropriate basis for market segmentation. Consider that consumers' gender (male and female) can affect their consumption decisions and behaviors. For example, males are expected to be more rational and autonomous while females are perceived to be more emotional and connected to others. "In accordance with these premises, males are said to make decisions for their own consumption and large-ticket items and females to make decisions related to household items, children's and their own needs" (p. 86). Age/generation is also an important demographic variable that affects consumer behaviors and protective health behaviors. For example, Nowak and Cacciatore (2022) found that U.S. adults who are 50 years old and older, especially those with higher educational levels, have had the swiftest and highest COVID-19 vaccination uptake since December 2020. Generational cohort defines consumer segments by using coming-of-age year as a proxy determinant (Rogler, 2002). In other words, researchers categorize consumers into different generational cohorts based on their age. Generation has long been regarded as a market segmentation approach due to its utility in predicting consumer behaviors (Kotler & Armstrong, 2010). As Dimock (2019) noted, "generational cohorts give researchers a tool to analyze changes in views over time" (para. 3).

There are different ways to categorize consumers into those generational cohorts. Among different options, Pew Research Center's definition and categorization of generation is widely used by researchers. Thus, Pew Research Center defined 5 generations in the U.S. based on people's year of birth. The five generations are: (1) Generation Z/Post Millennials (born 1997-2012, ages 7-22 in 2019), (2) Generation Y/Millennials (born 1981-1996, ages 23-38 in 2019), (3) Generation X (born 1965-1980, ages 39-54 in 2019), (4) Boomers (born 1946-1964, ages 55-73 in 2019), (5) Silent (born 1928-1945, ages 74-91 in 2019). Pew's generational cohort is used by several social media studies (e.g., Fietkiewicz, 2016; Wu, 2020). For example, Wu's (2022b) research findings suggested that generational cohort is associated with consumers' information and communication (ICT) and social media use behaviors in the U.S. Older generations (especially the "silent generation") are left behind younger generations in terms of ICT and social media use. Thus, there is still a grey divide/generational gap in technology use in the U.S., a developed country, in the pandemic era. In addition, there are generational differences in using specific social media platforms. For example, more Generation X and Generation Y participants use LinkedIn than other generations do. More Generation Z, the youngest generation, are Snapchat, Twitter, and Instagram users than other generations. Therefore, previous studies (Fietkiewicz et al., 2016; Wu, 2022b) do suggest that age/generation can be regarded as an important consumer demographic variable that affects consumers' social media use behaviors.

Income also affects consumer behaviors. As Martins et al. (2012) noted, "the level of people's income influences their propensity to consume and propensity to save" (p. 4). When the household income is low, household choices are driven by satisfying basic needs for food and shelter, instead of saving for the future. When the household income is higher, consumers have more choices about what to spend and how to spend. Income, education, and employment status are usually associated with each other. People with higher education tend to getter better jobs and have higher income. In addition to the commonly used demographic variables (e.g., gender, age, income, education), ethnicity/race also attracts much scholarly attention amid the COVID-19 pandemic, because recent research findings (e.g., Gramlich & Funk, 2020; Laurencin & McClinton, 2020; Lopez et al., 2020) suggested that there is health inequality by ethnicity in the U.S. In addition, minority groups, such as Black Americans and Latinos, are more concerned about the health and financial impacts of the pandemic.

Previous studies (e.g., Fietkiewicz et al., 2016; Kotler, 1977; Matins & Brooks, 2020; Sheth, 1977; Martins et al., 2012; Wu, 2022c) suggested that demographic factors have strong influences on consumer behaviors. A few recent studies (e.g., Byrd et al., 2020; Nowak & Cacciatore, 2022; Papageorge, 2021; Wu, 2022a) have also suggested that demographic factors (e.g., age, gender, race) are associated with people's protective health behaviors and risk perceptions amid the pandemic.

However, very few recent studies examine how both psychological factors (e.g., consumer perceived risk, concern) and demographic factors (e.g., age, gender, race) affect consumer behaviors amid the COVID-19 pandemic, nor use predictive analytics. To bring additional insights into consumer behaviors in times of crisis with empirical analyses, this study attempts to explore psychological and demographic factors that affect consumer behaviors with predictive analytics (e.g., cluster analysis, decision tree).

Research Questions

Four research questions are proposed.

RQ1a: How can U.S. consumers be categorized into different clusters, based on their perceived risks and concern scores?
RQ1b: A follow-up question is: How are cluster memberships associated with consumer demographics (e.g., gender, age, race/ethnicity, income, employment status, education)?
RQ2: What are the most important variables that predict U.S. consumers' visiting a non-grocery store behavior?
RQ3: What are the most important variables that predict U.S. consumers' ordering take-out or delivery from restaurants behavior?
RQ4: What are the most important variables that predict U.S. consumers' going out to eat behavior?

METHODS

Procedure and Samples

The results of this study are based on IPSOS' COVID-19 Panel Survey data. The data of this study was collected from web-based surveys. This Axios/Ipsos survey was conducted from May 29 to June 1, 2020 in the United States. This data collection point was chosen for analysis, because it was in the early stage of reopening after a three-month business shutdown period in the U.S. It means that U.S. adults could have some indoor consumption activities with protective measures (e.g., wearing a mask, social distancing) after experiencing a three-month business shutdown period as well as stay at home advisory. It would be meaningful to explore what are the factors that predict consumers' consumption activities (e.g., visiting a non-grocery retail store, ordering food delivery or take out, in-restaurant dinning) during the reopening period.

Participants were 1,033 U.S. adults, including 519 (50.2%) male and 514 (49.8%) female. Participants' ages ranged from 18 to 94 years old (M = 51.55). Participants' ethnicities include 726 (70.3%) white/non-Hispanic, 84 (8.1%) black/non-Hispanic, 137 (13.3%) Hispanic, 32 (3.1%) 2+ races/non-Hispanic, and 54 (5.2%) other/non-Hispanic. Other/non-Hispanic category includes Asian, American Indian, Native Hawaiian, Pacific Islander, and some other race. Respondents reported diverse educational levels and employment status: 93 (9.0%) have less than high school education, 277 (26.8%) were high school graduates, 269 (26.0%) have some college education, 394 (38.1%) have a Bachelor's degree or higher. About one-half 549 (53.1%) of respondents were working as a paid employee, 79 (7.6%) were self-employed, 405 (39.2%) were not working, including 265 (25.7%) retired.

Scale Development and Data Analysis

In order to measure participants' perceived risks and concerns for the pandemic, three indexes were assessed, including (1) Risk 1: perceived risk for take-out and food delivery, (2) Risk 2: perceived risk for indoor consumption activities, and (3) concerns about the pandemic.

First, two risk indexes were created based on whether the consumption activities were performed as low-contact form (e.g., food delivery, picking up takeout from a restaurant) or instore. All of the two sets of risk-related items were measured by asking participants a question: How much of a risk to your health and wellbeing do you think the following activities are right now? All items are measured by 4-point Likert type scale (after reverse scaling, 1 = no risk, 2 = small risk, 3 = moderate risk, 4 = large risk). The two items which are included in Risk 1 index are (1) having food delivered to your home and (2) picking up takeout from a restaurant. Because only two items are included in this index, there is no need to conduct factor analysis. The reliability score the Risk 1 index is .82 (based on Cronbach Alpha). Risk 2 index is measured by four items. Principal component factor analysis was conducted to ensure that this index is uni-dimensional. Factor loadings for each item are: (1) going to a grocery store (.86), (2) dining in at a restaurant (.89), (3) shopping at retail stores (.90), and (4) going to salons, barber shops, or spas (.88). The Cronbach's Alpha reliability score for the Risk 2 index is .90.

Second, the concern index is measured by six items, including concern for the government's response to the coronavirus outbreak, your ability to pay your bill, the possibility of getting sick, your community re-opening too soon, the coronavirus doing greater damage to people of color, and official responses to the pandemic being biased again certain groups. These items were measured by 5-point scale. (after reverse-scaling, 1 = not at all, 2 = not very concerned, 3 = somewhat concerned, 4 = very concerned, 5 = extremely concerned). Because the dataset which is analyzed in this study is IPSOS' COVID-19 survey panel data, the researcher operationalized the concern index based on IPSOS' definition for concern about the pandemic and its survey items. Principal component factor analysis results suggest that the concern index is uni-dimensional. The factor loading for each item is: concern for the government's response to the coronavirus outbreak (.75), your ability to pay your bill (.81), the possibility of getting sick (.82), your community re-opening too soon (.79), the coronavirus doing greater damage to people of color (.75), and official responses to the pandemic being biased again certain groups (.84). The reliability score for the concern scale is .88 (based on Cronbach Alpha).

Data Transformation and Data Analysis

In order to make the index scores consistent, z-scores were created for the three indexes, because the two trust indexes were measured by 4-point Likert-point scale, while the concern index was measured by 5-point Likert-type scale. Cluster analyses, cross-tab (chi-square) analysis, and decision tree analysis were conducted in SPSS, version 26.

RESULTS AND DISCUSSION

RQ1a: Consumer Clusters Based on Perceived Risk and Concern Scores

To answer RQ1, cluster analyses (e.g., two-step cluster analysis and K-means cluster analysis) were conducted. The variables used in the cluster analyses are Risk 1, Risk 2, and concerns for the pandemic indexes. Cluster analysis is a popular classification/segmentation method which is used by market and consumer researchers. In order to identify the best number for "K", two-step cluster analysis was conducted first. According to IBM (2010a), "two-step clustering will automatically select the number of clusters…A criterion (likelihood-based) is then used to decide which of these solutions is best" (p. 1-3). Then, K-means cluster analysis based on Euclidean distance (Lanz, 2015) was conducted.

The result of two-step cluster analysis suggested that two is the best number for the cluster solution, by using three indexes as variables for cluster classification. In cluster 1, there are 459 (51.5%) of cases. In cluster 2, there are 432 (48.5%) of cases.

The results of K-means cluster analysis suggest that the two groups are: (1) low perceived risks and low concern (cluster 1), and (2) high perceived risks and high concern (cluster 2). Members in cluster 1 have negative z-scores on perceived risk for in-store consumption activities, perceived risk for food delivery and takeout from restaurants, and concern about the pandemic. Members in cluster 2 have positive z-scores on perceived risks for both types of consumption activities and concern.

RQ1b: Relationships Between Cluster Membership and Consumer Demographics

To answer the follow-up question, cross-tab analyses were conducted to examine the relationship between cluster membership and demographic variables (e.g., gender, ethnicity, age/generation, education, employment status, household income). The results show that cluster membership is associated with gender ($\chi^2 = 14.15$, $p < .001$), ethnicity ($\chi^2 = 67.53$ $p < .001$), and household income ($\chi^2 = 14.06$, $p < .001$), but not with other variables (e.g., generation, education, and employment status). Overall, more female participants are in cluster 2 (n = 250, 58.3%) than cluster 1 (n = 179, 41.7%), whereas more male are in cluster 1 (n = 251, 54.3%) than cluster 2 (n = 211, 45.7%). More black Americans are in cluster 2 (n = 65, 84.4%) than in cluster 1 (n = 12, 15.6%). Similarly, more Hispanic Americans are in cluster 2 (n =81, 68.1%) than in cluster 1 (n = 38, 31.9%). More affluent consumers (household income > 100,000) are in cluster 1 (n = 214, 55.4%) than cluster 2 (n = 172, 44.6%).

The result that cluster membership (based on concern and perceived risk) is associated with demographic variables is consistent with previous research findings (e.g., Byrd et al., 2020; Lopez, 2020). Concerning concern for the pandemic by ethnicity, Lopez et al. (2020) found that Black and Latino Americans worry about the pandemic more than others. This study supports Lopez et al. (2020), because more Black Americans and Hispanic Americans are categorized in cluster 2: high concern, high perceived risk group, than cluster 1: low concern low perceived risk group. Concerning consumers' perceived risks, Byrd et al. (2020) found that gender, age, and race are associated with risk perceptions about restaurant foods. Generally speaking, women, older adults, and African Americans are more concerned about restaurant food safety in the early stage of the pandemic. Although the scope of this study is broader than Byrd et al.'s (2020) study, the research findings among these two studies are somewhat similar, because both studies found that gender and race/ethnicity are associated with consumers' perceived risks.

RQ2: Predicting Consumers' Going to a Non-Grocery Store Behavior

To answer RQ2, RQ3, and RQ4, decision tree analysis with CHAID method was conducted. As Srickland (2015) noted, the goal of decision tree "is to create a model that predicts the value of a target variable based on several input variables" (p. 87). Both psychological variables and demographic variables are used as predictors for specific consumption behaviors. The three psychological variables are Risk 1, Risk 2, and concern for the pandemic indexes. The demographic variables are gender, ethnicity, age, education, household income, and employment status. The dependent variables for RQ2, RQ3, and RQ4 are all categorical variables which measure participants' specific consumption activities (1 = Yes; 2 = No).

The result suggests that Risk 2: perceived risk for instore consumption activities, gender, and age are the predictors for consumers' going to a non-grocery store behavior. Among the participants (N = 1,033), 39.3% (n = 405) visited a non-grocery retail store, whereas 60.7% (n = 60.7%) didn't. The first splitting variable is perceived risk for instore consumption activities (χ^2 = 53.08, df = 2, p < .001). Participants were categorized in to three Nodes, Node 1, 2, and 3 based on the z-score of perceived risk for instore consumption activities. In Node 1 (n = 348), 54.3% (n = 189) participants visited a non-grocery retail store. In Node 2 (n = 184), 37.5% (n = 69) did. In Node 3 (n = 498), only 29.5 % (n = 147) did. Overall, more participants scored lower on perceived risk of in-store consumption activities visited a non-grocery retail store last week. This finding supports Mothersbaugh et al.'s (2020) argument that consumers' perceived risk can affect their choice of shopping channels/outlets. This finding is consistent with Wu (2022c). As Wu noted, consumers usually considered online shopping to be safer than in-store shopping amid the COVID-19 pandemic, because it is low contact. That's why more consumers scored lower on perceived risk of in-store consumption activities had the courage to go to physical stores to shop during the business re-opening period.

Age is a splitting variable for Node 1 (χ^2 = 7.82, df = 1, p < .05). Participants who are 39 years old or younger were categorized into Node 4 (n = 91). Participants who are older than 39 years old are categorized into Node 5 (n = 257). This result suggests that less younger participants (< 39 years old) visited a non-grocery store last week than older participants (> 39 years old) did. This result may imply that younger consumers still sticked to online shopping, instead of going back to brick-and-mortar stores immediately after the non-grocery stores were reopened. Interestingly, this result is in accordance with Dimock's (2019) categorization of generational cohorts in the U.S. The cut-off point between Generation Y and Generation X is 39 years old, in 2020. Thus, it implies that younger generations (e.g., Generation Z, Generation Y) still prefer online shopping during the early stage of reopening because they are more used to using digital channels for communication and shopping. This finding supports Prensky's (2001) argument that digital natives who were born after 1980 (e.g., Generation Z, Generation Y) are more technologically savvy than digital immigrants who were born bore 1980 (Generation X, Boomers). It also supports Wu (2022b) that there are generational differences in ICT use. As the author noted, younger generations owned a variety of ICTs and spent more time using Internet in the U.S. If younger generations spend more time using ICTs (e.g., computers, laptop, Internet, smart phones), they are more likely to shop online, instead of going back to retail stores to shop, when they have choices.

Gender is the splitting variable for Node 2 (χ^2 = 6.32, df = 1, p < .05). Female participants were categorized into Node 6 (n =94). Male participants were categorized into Node 7 (n = 90). This result suggests that more males visited a non-grocery retail store than females did. This finding may be explained by the fact that more females are more concerned about the pandemic and have higher levels of perceived risks, because more females are categorized in cluster 2 (high concern, high perceived risk group) in this study. The prediction accuracy for this model is 65.5%. Figure 1 summarizes the decision analysis results.

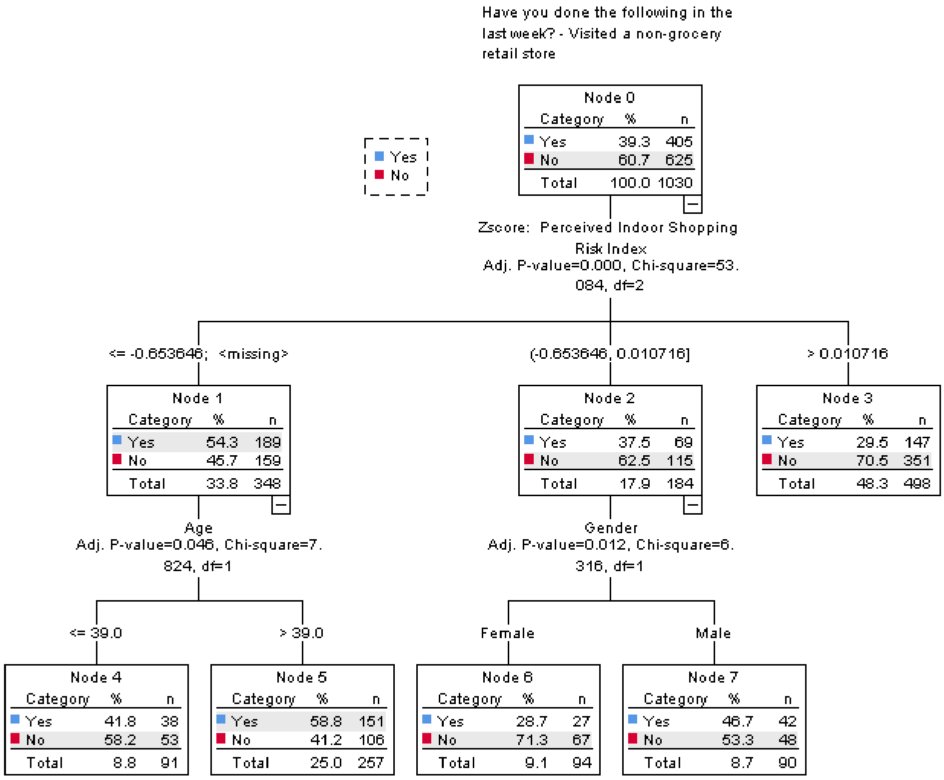

Figure 1. Decision Tree That Predicts Consumers' Visiting a Non-Grocery Retail Store Behavior

RQ3: Predicting Consumers' Ordering Food Delivery and Takeout Behaviors

The result suggests that Risk 1: perceived risk for food delivery and take out index is the most important predictor for participants' ordering takeout behavior. Among the participants (N = 1,029), 69.7% (n = 717) ordered takeout or delivery, whereas 30.3% (n = 312) didn't. Only Risk 1: perceived risk for ordering takeout and delivery from restaurants serves as the splitting variable ($\chi^2 = 57.44$, df = 2, $p < .001$). Participants were categorized in to three Nodes, with Node 1, 2, and 3 based on the z-score of perceived risk for ordering takeout and delivery from restaurants. In Node 1 (z score <= .01; n = 788), 75.3% (n = 593) participants ordered take or delivery from restaurants, whereas 24.7% (n = 195) didn't. In Node 2 (z scores are between .01 and .80, n = 105), 61.0% (n =64) participants did, whereas 39.0% (n = 41) didn't. In Node 3 (z-score > .80; n = 136), 44.1% (n=60) did, whereas 55.9% (n = 76) didn't. This result is interesting, because only a specific psychological factor, perceived risk for food delivery and takeout, instead of any of the demographic variables, serves as the significant predictor for ordering food delivery and takeout behavior. The accuracy rate for this model is 71.2%. See Figure 2.

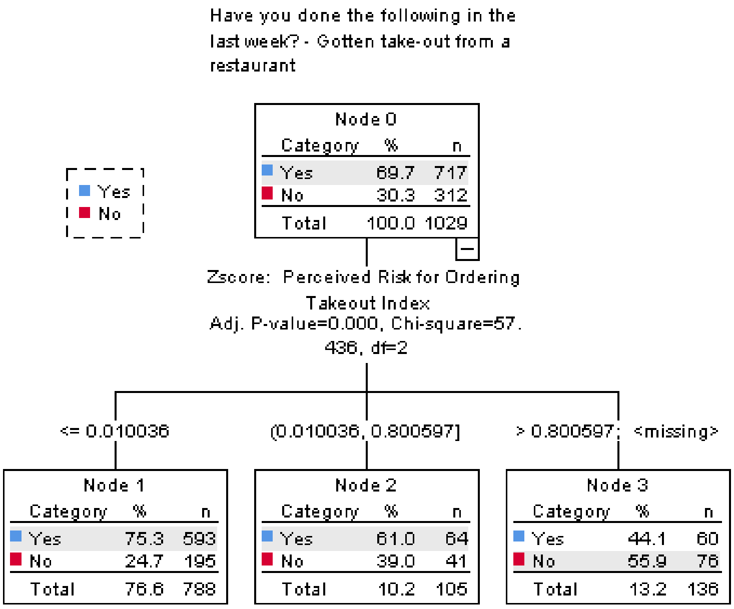

Figure 2. Decision Tree That Predicts Consumers' Ordering Food Delivery and Take-Out Behaviors.

RQ4: Predicting Consumers' Going Out to Eat Behavior

The result indicates that Risk 2: perceived risk for instore consumption index is the most important predictor for participants' going out to eat behavior. Among the participants (N = 1,030), only 18.5% (n = 191) went out to eat last week, whereas 81.5% (n = 839) didn't. Perceived risk for instore consumption index serves as the first splitting variable (χ^2 = 113.41, df = 3, p < .001). Participants were categorized in to four Nodes based on the z-score of perceived risk for instore consumption activities. In Node 1 (z score <= -.99, n = 268), 36.9% (n = 99) participants went out to eat, whereas 63.1% (n = 169) didn't. In Node 2 (z scores between -.99 and -.32, n = 183), 24.0% (n = 44) participants did, whereas 76.0% (n = 139) didn't. In Node 3 (z-scores between -.32 and .34; n = 229), 14.4% (n = 33) did, whereas 85.6% (n = 196) didn't. In Node 4 (z-score > .34; n = 350), 4.3% (n = 15) did, whereas 95.7% (n = 335) didn't. This result suggests that more consumers with lower levels of perceived risk of instore-consumption activities went out to eat last week. This finding supports Mitchell's (1999) consumer perceived risk theory that "perceived risks is more powerful at explaining consumers' behavior since consumers are more often motivated to avoid mistakes than to maximize utility in purchasing" (p. 163). Current employment status is the splitting variable for Node 3 (χ^2 = 11.1, df = 1, p < .05). Participants who were working and non-working - other were categorized into Node 5 (n = 150). Participants who were not working (e.g., retired, disabled, looking for work) were categorized into Node 6 (n = 79). More participants who were working went out to eat than participants who were not working did. The prediction accuracy for this model is 81.5%. See Figure 3.

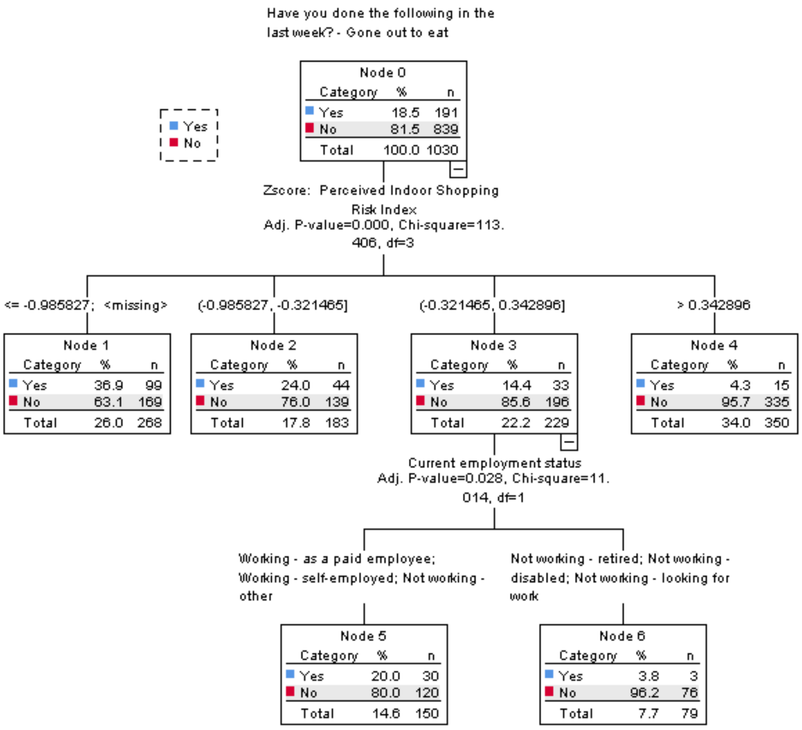

Figure 3. Decision Tree Predicting Consumers' Gone Out to Eat Behaviors

CONCLUSION

Theoretical, Methodological, and Practical Implications

By using predictive analytics methods to analyze Axios/IPSOS' survey data (N = 1, 033) during the business reopening period, this study has provided additional insights into consumer behaviors during crises research. There are a number of significant theoretical, methodological, and practical implications.

Theoretical Implications. First, consumer demographics theory (e.g., Martins et al., 2012; Mothersbaugh et al., 2020) is supported because the results of this study suggests that demographic factors is associated with cluster membership based on concern and perceived risk. As discussed earlier, U.S. adults can be categorized into two clusters: (1) low perceived risks and low concern group and (2) high perceived risks and high concern group. Most importantly, cluster membership is significantly associated with demographic factors (e.g., gender, ethnicity, and household income). The significant association between demographic factors and cluster membership implies that there are differences in perceived risks for consumption activities and concerns about the pandemic among different consumer segments. Thus, the basic assumption that demographics can affect consumer perceptions and values (Mothersbaugh et al., 2020) are supported. As Mothersbaugh et al. (2020) noted, demographics are related to consumers' values, lifestyles, and media usage patterns in important ways. Thus, marketers can segment and describe their markets on the basis of demographics and use the information to develop effective communication strategies and promotional campaigns with appropriate messages and media.

Second, the findings of this supports consumer perceived risk theory (Mitchell, 1999; Mothesbaugh et al., 2020). The results of decision tree analysis suggest that perceived risk for food delivery and take out is the most important predictor that predicts consumers' ordering food delivery and takeout behaviors. In addition, perceived risk for instore consumption activities is the most important predictor for predicting consumers' going to a non-grocery retail store and going out to eat (in-restaurant dinning) behaviors. Psychological variables, especially perceived risks, have more direct impacts on consumer behaviors during crises than demographic variables. However, demographic variables can still serve as secondary predictors (although not as the most impactful predictors) for these consumption behaviors by using decision-tree method to build the prediction model. We need to keep in mind that this study mainly explores factors that predict consumer behaviors during a pandemic. Consumers are afraid of getting COVID-19 virus infections during the pandemic. Thus, it's not surprising that psychological factors, perceived risks, outperform other predictors that affect consumer behaviors, such as choice of consumption channels/outlets.

Interestingly, only perceived risks (e.g., perceived risk for food delivery and takeout, perceived risk for instore consumption activities), not concern, are the significant predictors for consumer behaviors in this study, although a number of previous studies (e.g., Aurigemma et al., 2019; Boss et al., 2015; Khosravi, 2020; Okuhara et al., 2020; Song & Yoo, 2020; Wu, 2022a; 2022c) suggested the relevance of using PMT (Rogers, 1975) as the theory to examine consumers' protective health behaviors amid the pandemic and adoption of some products. When concern for the pandemic, consumers' perceived risks, and demographic variables are entered into the decision tree model together, perceived risk emerges as the most influential predictors for consumer's choice of consumption channels/outlets during the business reopening stage amid the pandemic. Thus, the results of this study support the validity of using consumer perceived risk theory (Bauer, 1960; Mitchell, 1999; Mothersbaugh et al., 2020) to explain how consumer choose consumption channels/outlets during crises.

Methodological Implications. Third, this study has significant methodological contributions by using predictive analytics methods, such as cluster analysis and decision tree, for data analysis. Although cluster analysis is considered as a simple and effective machine learning classification method (Strickland, 2015), very few consumer behaviors studies use this method. To provide evidence-based research findings, this study utilizes two-step cluster analysis and K-means cluster analysis to categorize US survey participants into two clusters based on perceived risk and concern. Then, the results of follow-up cross-tab analyses suggested that there is a significant relationship between consumer demographics and cluster membership. Surprisingly, it is very rare for academic research to use decision tree analysis, although decision tree is considered as a powerful data mining method (Rokach & Maimon, 2008). An advantage of using the decision tree method over other predictive analytics methods is that the algorism can identify the most important factors in prediction (IBM, 2010b). In this study, decision-tree analysis was performed to identify the most influential predictors to explain consumer behaviors during crisis. When psychological variables and demographic variables are entered into the prediction model simultaneously, psychological variables (e.g., perceived risks) outperform demographic factors as predictors in the model.

Practical Implications. Finally, the results of this study have practical implications. Researchers as well as marketing and public relations practitioners all want to know the answer of a question: What do consumers need during crises? The answer is that consumers need a low-risk shopping environment. The results of this study suggest that perceived risks are the most important predictors for consumption activities (e.g., visiting a non-grocery retail store, ordering food delivery and takeout from a restaurant, going out to eat). In order to provide customers a safe consumption environment, restaurants and retail stores are suggested to minimize the risk factors by adopting security measures (e.g., limited dining-in and in-store capacities, wearing a mask, cleaning, contactless payment). When consumers have choices, they would choose the consumption channels/outlets with lower risks. Another practical implication of this study is that there are different consumer segments in the U.S., based on concern for the pandemic and perceived risks.

As the cluster analysis and cross-tab analysis results suggested, gender and race/ethnicity are associated with cluster membership. Thus, organizations may customize their crisis communication strategies and channels (e.g., social media platforms) or partner with social media influencers (e.g., Pöyry, Reinikainen, & Luoma-Aho, 2022) for the consumer segment with high concern, high perceived risk scores (e.g., more females, more black and Hispanic Americans) by emphasizing the security measures that have been implemented in order to reduce target audience's perceived risks. If organizations (e.g., retailers, restaurants) would like to use social media as communication channels, they may take user demographics into account. For example, more females than males are Instagram and Pinterest users (Pew Research Center, 2021). Thus, retailers/restaurants may use these two platforms to communicate with female consumers and tell them about how they implement security measures in their stores/restaurants. Previous studies (e.g., Duggan, 2015; Murphy et al., 2016) also suggested that African and Latino Americans in terms of percentage are more active users of Twitter than white Americans. Thus, organizations may use Twitter to engage with African and Latino Americans.

Limitations and Suggestions for Future Studies

Although there are significant contributions, this study has limitations. First, this study is purely a quantitative study. Future studies may build on this study and use both quantitative, such as survey, and qualitative research methods, such as focus group interviews, in-depth interviews, and observations, to further explore what are other factors that may affect consumer behaviors during crisis. Second, the data of this study was collected in the business reopening stage amid the pandemic. The findings do provide a snapshot about consumer behaviors during crises. However, consumer behaviors are still evolving. Time-series analysis may be conducted periodically, in order to compare the results and track changing consumption trends over time. Specifically, it's noteworthy to foresee what the new normal of consumer behaviors will be alike. By doing so, organizations can adjust their business, communication, and marketing strategies to meet customers' needs in order to move forward in the post-pandemic world.

Research ethic statement

Please be advised that the article was not submitted for review and has not been previously published in another journal.
An earlier version of this paper was presented as **Top Paper** at 2022 Eastern Communication Association (ECA) Annual Convention, Applied Communication Division, Philadelphia, PA. The data of this study is downloaded from a university database system with proper citation.

Author contribution statement

The sole author of the article was responsible for the entire elaboration of the research.

Declaration of conflicting interests

The author declares that there is no conflict of interest with this publication.

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