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LOOKING BACK AND MOVING FORWARD: HOW PSYCHOLOGICAL AND DEMOGRAPHIC FACTORS AFFECT CONSUMER BEHAVIORS AMID THE COVID-19 PANDEMIC

Olhando para trás e avançando: Como os fatores psicológicos e demográficos afetam o comportamento do consumidor em meio à pandemia do COVID-19

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Abstract
By analyzing survey data collected from 857 U.S. adults, and applying the decision tree analysis, this study explores how psychological and demographic factors may affect consumer behaviors amid the COVID-19 pandemic. Protection motivation theory (PMT) and consumer demographics theory provide the theoretical foundation for this study. Decision tree is used for data analysis because it is a powerful predictive analytics method. There are a number of important findings. First, the result of decision tree analysis suggests that perceived threat/concern is the most important demographic factor that predicts consumers' overall online shopping behavior.

Resumo
Ao analisar os dados da pesquisa coletados de 857 adultos dos EUA e aplicar a análise da árvore de decisão, este estudo explora como os fatores psicológicos e demográficos podem afetar o comportamento do consumidor em meio à pandemia do COVID-19. A teoria da motivação da proteção (PMT) e a teoria da demografia do consumidor fornecem a base teórica para este estudo. A árvore de decisão é usada para análise de dados porque é um poderoso método de análise preditiva. Há uma série de descobertas importantes. Primeiro, o resultado da análise da árvore de decisão sugere que a ameaça/preocupação percebida é o fator demográfico mais

Second, education is the most important predictor for consumers' online grocery shopping behavior. Third, perceived threat/concern is the most important predictor for consumers' panic buying/hoarding behavior. Fourth, age is the most important predictor for consumers' work from home behavior. Finally, race is the most important predictor for consumers' spending more time watching TV behavior. The results support PMT and consumer demographics theory. This study brings additional insights into consumer behaviors amid the pandemic.
Keywords: COVID-19; Protection Motivation Theory; Consumer Demographics; Online Shopping; Decision Tree.

importante que prevê o comportamento geral de compras online dos consumidores. Em segundo lugar, a educação é o preditor mais importante para o comportamento de compras online dos consumidores. Terceiro, a ameaça/preocupação percebida é o preditor mais importante para o comportamento de compra/acumulação de pânico dos consumidores. Em quarto lugar, a idade é o preditor mais importante para o comportamento de trabalho dos consumidores em casa. Por fim, a raça é o preditor mais importante para os consumidores gastarem mais tempo assistindo TV. Os resultados apoiam a teoria da PMT e da demografia do consumidor. Este estudo traz *insights* adicionais sobre o comportamento do consumidor em meio à pandemia.
Palavras-chave: COVID-19; Teoria da Motivação da Proteção; Demografia do Consumidor; Compras online; Árvore de Decisão.

INTRODUCTION

From panic buying to online shopping, the pandemic can be regarded as the most disruptive event for consumer behaviors in decades. The World Health Organization (WHO) declared COVID-19 a pandemic on March 11, 2020. In an attempt to respond to this healthcare crisis and control the spread of the virus, the U.S. government imposed several public health policies since March, 2020. For example, there was an approximately three-month business shutdown period. Companies, retail stores, hair salons, gyms, and restaurants were not allowed to re-open without strict security measures, such as limited capacities, until the end of May or early June, 2020. Many U.S. consumers either chose to or are forced to shop online during this period. Thus, there has been a surge for e-commerce ever since the beginning of the pandemic.

Due to consumers' panic buying/hoarding behaviors and global supply chain issues, many products, such as toilet paper, food, and other staples, were out of stock for several months in the early stage of the pandemic. With the availability of the vaccine, the severity of the virus infection is not as bad as it was. However, the pandemic is not over yet. There are still different variants and sub-variants of the virus. Thus, we are still in the endemic stage. As public health experts argued, never let a crisis go to waste (Juliano, Castrucci, & Fraser, 2021).

Therefore, it's important to look back at this significant health and economic crisis, analyze it, and identify the factors that affected consumer behaviors during the pandemic. By doing so, we will know how to move forward in the post-pandemic era. Thus, this study aims to profile consumer behaviors amid the COVID-19 pandemic using psychological and demographic predictors by applying decision tree analysis.

PANDEMIC-INSPIRED CONSUMPTION TRENDS

Previous studies (e.g., Kohli et al., 2020; Sheth, 2020; Wu, 2020) have identified a number of pandemic-inspired consumer behaviors. For example, Wu (2020) identified four consumption trends that emerged in the early stage of the pandemic, including online shopping, panic buying, changing product categories, and consumers becoming more price sensitive. Kohli et al. (2020) also argued that COVID-19 has changed how consumers behave across all spheres of life, including work, learning, communications and information, travel and mobility, shopping and consumption, life at home, play and entertainment, and health and wellbeing. For example, consumers rely on more on TV and digital channels (e.g., social media) as opposed to public gatherings to get information.

There is a surge in e-commerce, preference for trusted brands, larger purchasing basket, reduced discretionary spending and shopping frequencies, and shift to stores closer to home. Because of the trend for remote working, “home is recast as the new coffee shop, restaurant, and entertainment center” (p. 2). Indeed, the pandemic has created a home economy. Kohli et al. further argued that some consumption trends, such as remote working, surge in e-commerce, rise of e-pharmacy and e-doctor, fitness on demand at scale, and entertainment-channel shift from physical to digital may endure. Even now, some pandemic inspired behaviors, such as surges in e-commerce and online grocery shopping, still persist and most likely will continue as we enter into the new normal (e.g., Atchley, 2021; Wu, 2022a). In summary, increases in overall online shopping, online grocery shopping, panic buying, home economy/work from home, and spending more time watching TV are the emerging consumption trends. The next sections of this paper provide a literature review for these consumption behaviors.

Increases in Online Shopping and Online Grocery Shopping. Because of the surge in e-commerce amid pandemic, researchers (e.g., Ecola, Lu, & Rohr, 2020; Wu, 2020) discussed how COVID-19 has changed consumers’ online shopping behaviors. Wu (2020) noted that consumers’ online shopping motivations have changed from convenience and economic motives before the pandemic to safety motives during the pandemic. Ecola, Lu, and Rohr (2020) noted that “With stay-at-home orders in place around the country, a huge increase in people ordering everything from groceries to clothing to household supplies online might be expected…the inability to shop in person and the high percentage of American households with access to the internet would suggest a major growth opportunity for online retailers” (p. 1). The authors analyzed Rand’s survey data (N = 2,000) to examine the relationship between demographic factors and online shopping behaviors in the U.S. They found that household income and age matter. For example, affluent households ($125,000 annual household income or higher) are more likely to increase their online shopping than those with lower household income ($ 40,000 or less). Younger consumers (under 35) were more likely to increase their online shopping than older consumers (over 55). However, some older consumers (60 and older) ordered groceries online for the first time.

Online grocery shopping, a specific form of e-Commerce, has attracted scholarly attention (e.g., Eriksson & Stenius, 2022; Jensen, Chen, & Yu, 2021; Van Droogenbroeck & Van Hove, 2017). Although a small number of consumers already had experience ordering groceries online before the pandemic, there is a surge of online grocery shopping amid the pandemic (e.g., Morgan, 2020). Morgan (2020) noted three online grocery shopping trends in the U.S, including surges in online ordering, larger basket for shelf-stable food, and focus on speed, convenience, and safety. As Morgan noted, “a year ago, 81% of consumers had never bought groceries online, but during the pandemic nearly 79% of shoppers have ordered online.

In August 2019, U.S. online grocery sales totaled $1.2 billion; in June 2020, that total was $7.2 billion” (p. 3) and concluded that the trend for online grocery shopping will continue. Research findings from several previous studies (e.g., Jensen, Chen, & Yu, 2021; Eriksson & Stenius, 2022; Van Droogenbroeck & Van Hove, 2017) suggested that demographic variables can be used as predictors for online grocery shopping. Eriksson and Stenius (2022) conducted a survey (N = 2,568) to examine how demographic and household characteristics affect consumers’ online grocery shopping behaviors amid the pandemic in Finland. They found that typical online grocery adopters due to COVID-19 are “less than 45 years old, and one with some concern over own health or that of a loved one” (p. 93). The more likely adopters also have a larger household size, higher household income, and live in the capital region.

Generally speaking, there is no sex/gender difference in online grocery shopping behaviors, expect for the older age group (45+), women and those with higher health concerns are more likely to be the adopters than the rest.

Panic Buying. Panic buying has attracted much scholarly attention. As Grohol (2020) noted, "panic buying is what people do when faced with an imminent disaster, whether it be natural — such as a hurricane or snowstorm — or something else, like the spread of a virus for which there is no effective treatment or vaccine. And while it seems irrational on the surface, it actually has a rational basis" (p. 2). Similar to Rogers' (1975) PMT, panic buying can be an emotional response driven by perceived threat or fear. It can also be a rational choice, because government officials and media advised consumers to prepare for the business lockdown period by purchasing more products than needed. A number of studies (e.g., Chua, Yuen, Wang, & Wong, 2021; Grohol, 2020; Kassas & Nayga, 2021; Ntontios et al., 2022) investigated the factors that affect consumers' panic buying behavior.

By surveying 1,200 US households in April 2020, Kassas and Nayga (2021) focused on perceived importance of panic buying (e.g., panic buying for control, to follow others, smart thing to do, product scarcity, to minimize trips) and timing. They found that the "general importance of panic buying is positively correlated with the need for control, the perception that it is a smart thing to do, and the desire to minimize the number of trips to the grocery store" (p. 7). As for demographic factors, they found that the importance of panic buying was lowest among White American households, followed by Asian households, then African and Hispanic American households. Ntontios et al. (2022) conducted a qualitative study by interviewing 23 consumers and found that "panic buying" is not merely caused by emotions, such as fear and worry. Other factors, such as observed product shortages, media influences, other people's stockpiling behavior, intention to reduce trips to supermarkets, and preparedness for product shortages and longer stay homes, can help explain consumers' motivations behind increased shopping amid the pandemic.

Home Economy/Work from Home. Because of the business lockdown and stay-at-home orders in the early stage of the pandemic in 2020, many American employees, except for front-line or essential workers, needed to work from home. The pandemic has created a home economy in the US and worldwide (e.g., Ingilizian, 2020; Kohli et al., 2020; Sheth, 2020,). As Ingilizian (2020) noted, "the coronavirus pandemic is fueling the growth of the stay-at-home economy. How consumers learn, work, shop and play is poised to change forever" (p. 1). The author also argued that the increases in e-commerce, online grocery shopping, video streaming, and online education, are associated with the home economy. Sheth (2020) noted that if consumers can't go to the stores due to lockdown and social distancing orders, the store comes to home. Similarly, work, education, and entertainment also happen at home. The trends for work from home or hybrid work mode are likely to continue. However, not everybody can work from home. Now, the question is: Who are the ones that can work from home? This study attempts to answer this question.

Spending More Time Watching TV. When there are crises (e.g., health crisis, natural disasters), many people would watch TV news to get updated information. Compared with other communication channels, such as radio, face-to-face communication, and social media, TV news is the primary information source during times of crises, because of perceived source credibility (Spence, Lachlan, Burke, & Seeger, 2007; Spence, Lachlan, & Burke, 2008). Recent studies (e.g., Hubbard, 2021) suggested that there is a surge in spending time watching TV amid the pandemic. As Hubbard (2021) noted, survey data collected from May to December 2020 suggested that Americans in average spent about 3.1 hours a day watching TV. However, consumers spent a lot of time watching TV not only for news, but also for leisure and entertainment at home.

TV news can have significant influence on people's protective heath behaviors. Thus, TV news can be used as an effective communication medium for disease prevention, especially in the initial stage of the pandemic. As Scopelliti et al. (2021) noted, "Mere exposure, positive attitudes toward social prevention promoted by TV content, and moderate levels of fear emerged as the variables most associated with positive behaviors in public spaces to prevent the risk of contagion. Calming information and indications for individual prevention also showed a significant association with healthy behaviors in correlation analysis, while alarming information was ineffective." (p. 11). As for entertainment purpose, survey results (N = 2,000) conducted by OnePoll revealed "Americans aged 25–

34 increased their streaming the most this summer — with the average respondent watching an additional four hours of content a day, on top of what they were watching at the start of quarantine in March or April" (Sadlier, 2020, p. 4). As Sadiler noted, there is a sharp increase of watching TV for entertainment purpose in summer 2020, compared to the early stage of the pandemic.

Summary. In summary, previous studies (e.g., Eriksson & Stenius, 2022; Jensen, Chen, & Yu, 2021; Grohol, 2020; Kassas & Nayga, 2021; Ntontios et al., 2022; Sheth, 2020; Wu, 2020, 2022) have identified several pandemic-inspired consumption trends and uncovered the underlying factors that may explain these behaviors. Nevertheless, most of the previous empirical studies mainly focus on one type of pandemic-inspired consumption behaviors, such as online grocery shopping (e.g., Jensen, Chen, & Yu, 2021; Eriksson & Stenius, 2022) and panic buying (e.g., Grohol, 2020; Kassas & Nayga, 2021; Ntontios et al., 2022), instead of a range of consumption behaviors (Wu, 2022a). To build on previous studies, this study aims to explore how psychological and demographic factors may affect five consumption behaviors amid the COVID-19 pandemic by analyzing survey data with decision tree analysis. By doing so, data-driven insights can be provided.

Both psychological and demographic factors can affect consumer behaviors amid pandemics (Bish & Michie, 2010; Wu, 2022a). Thus, protection motivation theory (PMT) (Rogers, 1975) and consumer demographic theory (e.g., Sheth, 1977; Martins & Brooks, 2010) provide the theoretical foundation for this study. The next section of this paper reviews these two guiding theories and relevant research findings.

PROTECTION MOTIVATION THEORY (PMT)

Protection motivation theory (PMT) (Rogers, 1975) has been used as a guiding theory that explains how psychological factors affect consumers' protective health Khosrai, 2020; Kowalski & Black, 2021; Okuhara et al., 2020) and consumption behaviors (Gordon-Wilson, 2021; Kim, Yang, Min, & White, 2021; Wu, 2022a) amid the COVID-19 pandemic. Rogers (1975) argued that "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 adopt protective health measures is significantly influenced by high levels of fear or perceived threat, and by perceptions of efficacy. Thus, the two major constructs in the original PMT/core PMT are perceived threat and efficacy (Aurigemma et al., 2019). Perceived threat means that if people perceive the disease is severe and the likelihood to be infected is high, they are more concerned about the impacts of disease infection and are more likely to adopt protective measures. The perceived threat construct is used in previous COVID-19 related studies (e.g., Khosravi, 2020; Wu, 2022a).

As Khosravi (2020) noted, people's risk perception of the pandemic is one of the factors that contribute to their participation in adopting protective health behaviors, based on PMT. Khosravi (2020) studied the role of perceived threat/public worry and trust amid the COVID-19 pandemic and noted that "one more factor that contributes to shaping an accurate risk perception is trust. According to the Trust and Confidence Model, trust plays an important part in managing a threat by affecting the public's judgements about the risks and the related benefits. It can also directly impact the adoption of the recommended measures" (p. 1). Thus, the author suggested government officials and healthcare workers to provide complete information about the COVID-19 pandemic to enhance public trust, instead of downplaying the realities of risk to reduce perceived threat/public worry. Wu (2022a) called the perceived threat construct as concern for the pandemic and examined the relationship between concern, perceived risks for consumption activities, and consumer demographics in the U.S. by analyzing IPSOS' COVID-19 survey panel data (N = 1,033) using cluster analysis. The author found the U.S. consumers can be categorized into two clusters: (1) high concern, high perceived risk, and (2) low concern, low perceived risk groups. Most importantly, cluster membership is associated with gender, race/ethnicity, and household income in the U.S.

Efficacy means the extent to which people believe they are able to perform a salient action (self-efficacy), and believe performing an action would be effective (response efficacy) (Aurigemma et al., 2019; Okuhara et al., 2020; Song & Yoo, 2020). Following Khosravi's (2020) and Wu's (2022a) approach, this study focuses on the perceived threat construct, instead of the efficacy construct of PMT, because people tend to have 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.

CONSUMER DEMOGRAPHICS THEORY

Consumer demographic theory (e.g., Martins & Brooks, 2010; Martins, Yusuf, & Swanson, 2012; Mothersbaugh et al., 2020, Pollard et al., 1991; Sheth, 1977) provides the second theoretical foundation for this study. The basic assumption of consumer demographic theory is that demographic variables, such as gender, age/generation, income, education, and race/ethnicity 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). Similarly, Martins et al. (2012) argued that consumers' sex/gender, age, and income are the three most important demographic variables that affect their actions, interests, and opinions (AIO). AIO can influence consumers' lifestyles and the nature of consumer markets.

Sex/gender is a basic demographic characteristic. Both biological and social factors can affect male and female consumers' preferences, decision making styles, and purchasing behaviors. In general, females have a greater home orientation. Thus, females tend to spend more on food for home, while males would spend more on food away from home. Because females are more concerned about their appearances, they would spend more on clothing, footwear, and personal care. Differently, males' outward orientation can make them spend more on alcoholic beverages and transport, such as motor vehicles (Martins et al., 2012). Martins and Brooks (2010) noted that 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 is an important demographic variable that affects consumer behaviors. As Martins et al. (2012) noted, major demographic and socioeconomic changes can take place over the life cycle. For example, household sizes, employment status, and household income. Thus, household expenditure on consumer goods and services can vary by age and age-related factors. Generally speaking, there is a peak in the average household consumer expenditure, if the household head is in the 45-54 age group. Due to retirement and other age-related factors, older adults who are 65 and over would increase the time spending at home. Thus, they may have greater consumption of home related products and services, such as food consumed at home, utilities, and products or services related to household operation. Because of aging, older adults also need more medical and health services.

Recent research findings (e.g., Schaeffer & Rainie, 2020; Wu, 2022b) suggested that age significantly affects consumers' perceptions about the COVID-19 pandemic and protective health behaviors. Specifically, elderly adults are regarded as high-risk population for COVID-19 infection. They are more likely to be inflected and develop severe symptoms. Thus, Centers for Disease Control and Prevention (CDC) recommends that older adults limit physical interactions with other people as much as possible (CDC, 2020). As Schaeffer and Rainie (2020) noted, experiences with the COVID-19 outbreak can vary for Americans of different ages. For example, older Americans who are 65 or older, are more likely to see the COVID-19 outbreak as a major threat to their personal health, instead of a threat to their financial situation. Because of health concerns, the safest way for older adults to shop or communicate with others is through computer-mediated communication. However, previous studies (e.g., Friemel, 2016; Hao, 2019, Wu, 2022b) suggested that there is grey divide. For example, Wu's (2022b) research findings suggested that there are age/generational differences in consumers' information and communication (ICT) and social media use behaviors in the U.S. and found that older generations (especially silent generation) are left behind younger generations in ICT and social media use in the pandemic era.

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 lower, household choices are driven by satisfying basic needs for food and shelter, instead of saving for the future. When 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), the ethnicity/race variable 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; Wu, 2021) 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; Martins et al., 2012; Sheth, 1977; Wu, 2022a) suggested that demographic factors have strong influences on consumer behaviors. Recent studies (e.g., Byrd et al., 2020; Papageorge, 2021; Shaffer & Rainie, 2020) 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 (e.g., Wu, 2022a) investigated how psychological (e.g., concern, perceived risk) and demographic factors (e.g., age, gender, race) affect consumer behaviors amid the pandemic by using predictive analytics. To bring additional insights into consumer behaviors amid the COVID-19 pandemic with empirical analyses, this study attempts to explore how psychological and demographic factors affect consumer behaviors, using decision tree analysis.

RESEARCH QUESTIONS

Five research questions guiding this study are proposed: What are the psychological and demographic factors that predict U.S. consumers'…
RQ1: spending more time online shopping behavior?
RQ2: online grocery shopping behavior?
RQ3: panic buying/hoarding behavior?
RQ4: work from home behavior?
RQ5: spending more time watching TV behavior?

METHODS

Procedure and Samples

The results of this study are based on Mammoth University's COVID-19 National Poll data (Monmouth University Polling Institute, 2020). The data of this study was collected from web-based surveys. This survey was conducted in April (April 3 – April 7), 2020 in the United States. The data collection point was chosen for analysis because consumer behaviors were significant disrupted during the early stage of the pandemic. It was also the business lockdown period in the U.S. Due to governmental regulations and public health concerns, almost all of the non-grocery retail stores and office buildings were closed nationwide in the U.S. Thus, consumers either chose to or were forced to shop online and worked from home during that period of time.

Participants were 857 U.S. adults, including 418 (48.8%) male and 438 (51.2%) female. Participants' ages ranged from 18 to 98 years old (M = 48.5). Participants' ethnicities include 574 (69.5%) white, 109 (13.2%) Black, 71 (8.6%) Hispanic, 53(6.4%) Asian, and 18(2.1%) other races. Respondents reported diverse educational levels: 46 (5.3%) have less than high school education, 263 (30.8%) were high school graduates, 26 (3.1%) have vocational/technical school education, 243(28.3%) have junior college or some college education, 161 (18.8%) have a Bachelor's degree, 110(12.8%) have graduate school degree. The data was weighted to reflect the demographic distribution in the United States.

Data Analysis

To answer the five research questions, decision tree analysis with the CHAID method was conducted in SPSS, version 28. As Srickland (2014) 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). Compared to traditional classification methods, such as logistic regression, the advantage of decision tree analysis is that the results are easier to interpret visually. In addition, the machine learning algorithm can clearly identify the most important predictor for the outcome variable in the model (IBM, 2010).

The independent variables/predictors for the decision tree analysis include perceived threat/concern, age, gender, race, education, and annual family income. Perceived threat/concern is a psychological variable which is widely used in previous studies (e.g., Khosravi, 2020; Rogers, 1975; Wu, 2022a). Following Wu's (2022a) approach, perceived threat is called concern in this study. The question which measures perceived threat/concern is: How concerned are you about someone in your family becoming seriously ill from the coronavirus break – very concerned, somewhat concerned, not too concerned, or not too concerned? The dependent variables for decision analyses were categorical variables which measure consumers' overall online shopping behavior, online grocery shopping behavior, panic buying behavior, work from home behavior, and spending more time watching TV behavior. The questions are phrased as: Have you personally done any of the following happen because of the coronavirus outbreak?...Spent more time shopping online, started your groceries delivered, bought more of certain groceries and supplies than you normally do, started to work from home for the first time, spent more time watching TV and movies (1 = Yes; 2 = No).

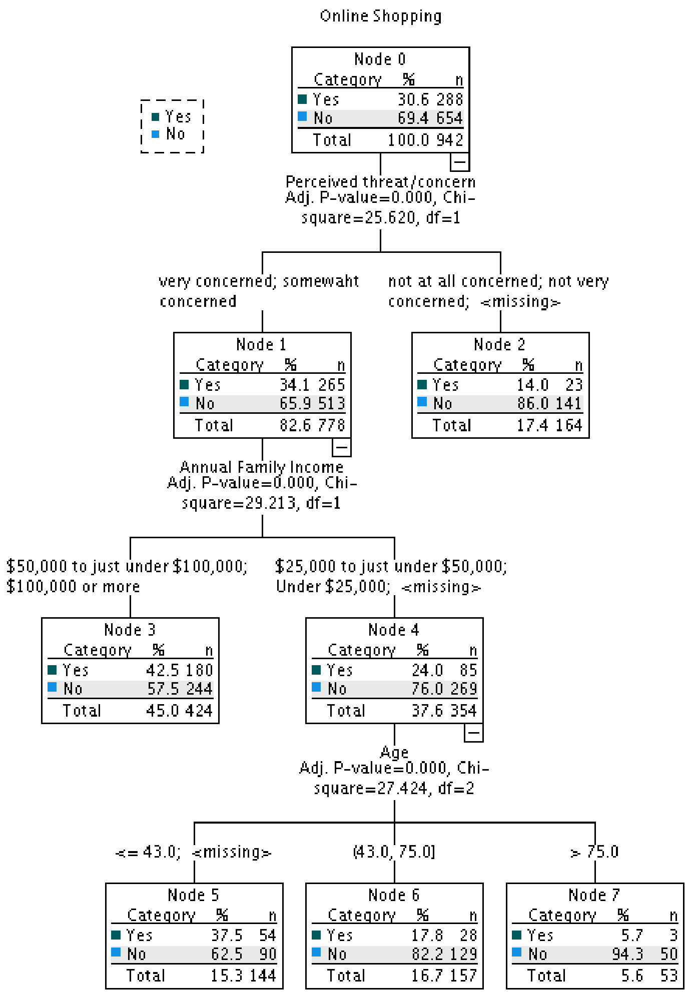
RESULTS AND DISCUSSION

RQ1: Predicting Consumers' Spending More Time Online Shopping Behavior

The result of decision tree analysis suggests that perceived threat/concern (χ^2 = 25.62, df = 1, p < .001) is the most influential variable for predicting consumers' overall online shopping behaviors, followed by annual family income (χ^2 = 29.21, df = 1, p < .001) and age (χ^2 = 27.42, df = 2, p < .001). The first split suggested that participants were categorized in to two Nodes, with Node 1 (very concerned, somewhat concerned) and Node 2 (not at all concerned, not too concerned) based on perceived threat/concern for the disease. Overall, consumers who have higher level of perceived threat/concern are more likely to shop online than those with lower level of perceived threat. Among the higher perceived threat/concern group, those with higher family income ($50,000 to just under $100,000 and $100,000 or more) are more likely to shop online than those with lower family income ($25,000 to just under 50,000 and under $25,000). Among the lower income group, age is the splitting variable suggesting that older consumers (> 75 years old) are less likely to shop online. The prediction accuracy rate is 69.4%. Figure 1 summarizes the decision analysis results.

The result that perceived threat/concern is the most influential factor that predicts consumers' online shopping behavior (similar to Wu, 2020) suggests that consumers' online shopping motives amid the pandemic is *different* from the pre-pandemic time. Wu's (2018) focus group interview results obtained before the pandemic suggested that consumers chose to shop online because of *convenience* and *economic* motives. However, consumers either chose to or are forced to shop online in the early stage of the pandemic because of *safety* motives (Wu, 2020).

The result that family income and age are the significant demographic predictors is consistent with Ecola et al. (2020). This finding is quiet striking because it indicates that older consumers (age > 75) with lower family income may have difficulties in purchasing the products they needed in the early stage of the pandemic during business shutdown period. Due to governmental regulations, most of the non-grocery retail stores and restaurants were closed during that period of time. Thus, consumers needed to order non-grocery products online. For those who didn't or couldn't shop online at that point of time, they may have had difficulties buying necessities.



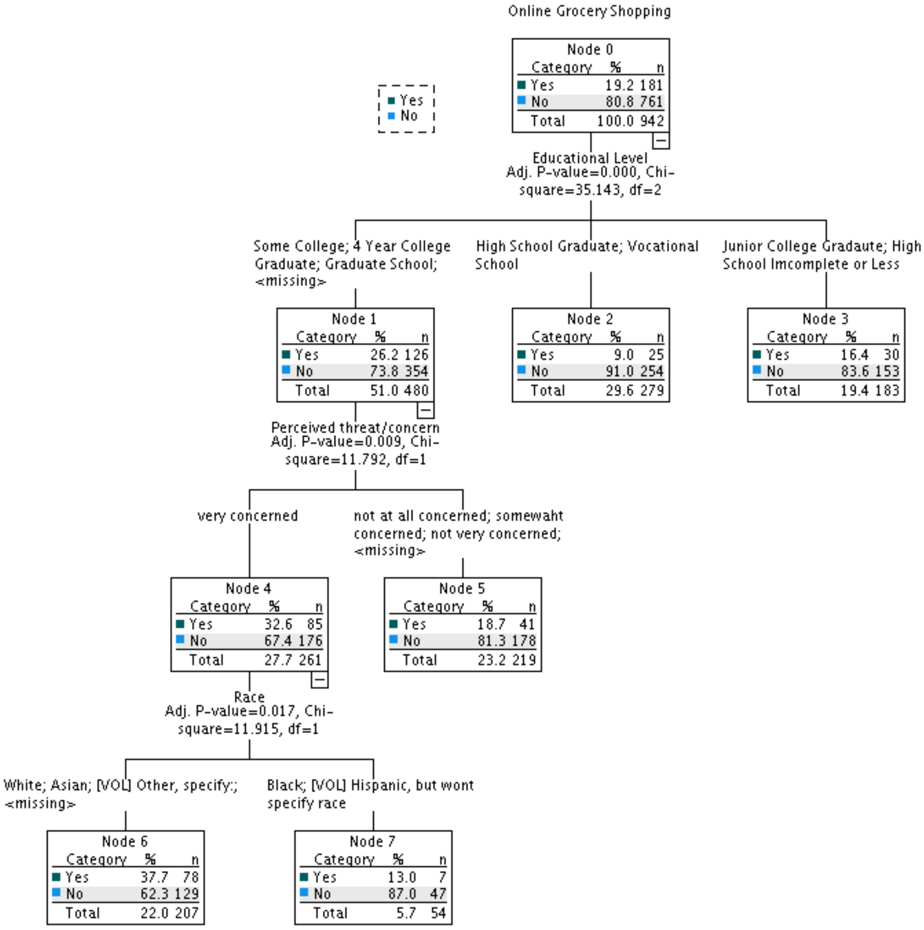
Source: Prepared by the author

Figure 1. Decision Tree Predicting Consumers' Overall Online Shopping Behavior

RQ2: Predicting Consumers' Online Grocery Shopping Behavior

The result suggests that education (χ^2 = 35.14, df = 2, p < .001) is the most influential variable for predicting consumers' online grocery shopping behaviors, followed by perceived threat/concern (χ^2 = 11.79, df = 1, p < .01) and race (χ^2 = 11.92, df = 1, p < .05). The first split by education categorized participants into three Nodes. Overall, consumers with higher educational level (Node 1: Some college, 4 year college graduate, graduate school) are more likely to order grocery online than those with lower educational levels. The second split by perceived threat/concern among the high education group suggested that those who are very concerned about the pandemic are more likely to order groceries online than other consumers. Among those who are very concerned, white and Asian Americans are more likely to order groceries online than Black and Hispanic Americans. The prediction accuracy rate is 80.8% (Figure 2).

The result suggests that both demographic and psychological factors can predict consumers' online grocery shopping behavior. The result that educational level is the most important predictor is in line with Brand et al.'s (2020) research finding that highly educated consumers are more likely to adopt online grocery shopping than others. The result that perceived threat/concern is a significant predictor is consistent with Eriksson and Stenius (2022) suggesting that consumers who care about the health of their loved ones are more likely to adopt online grocery shopping.



Source: Prepared by the author

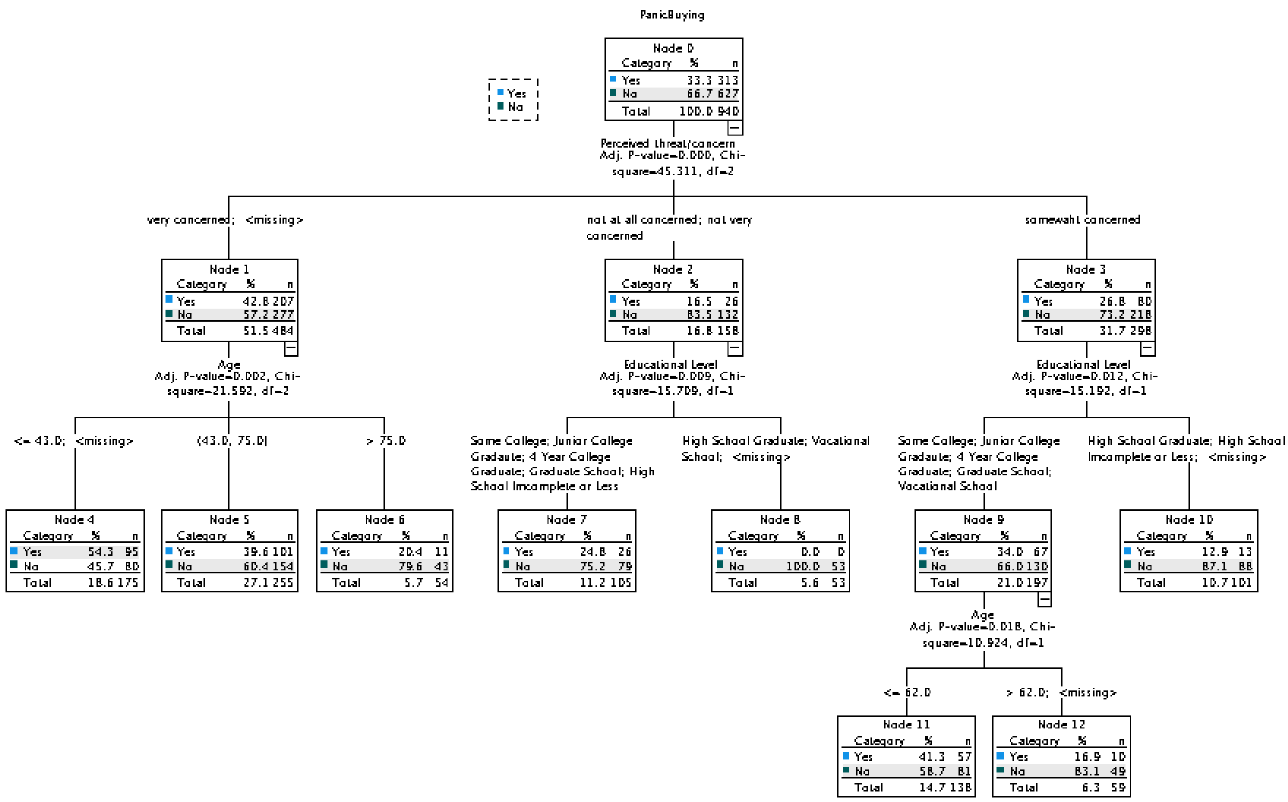
Figure 2. Decision Tree Predicting Consumers' Online Grocery Shopping Behavior

RQ3: Predicting Consumers' Panic Buying/Hoarding Behavior

The results of decision tree analysis suggested that perceived threat/concern (χ^2 = 45.31, df = 2, p < .001) is the most influential variable for predicting consumers' panic buying/hoarding behaviors. Other predictors are age and education. The first split by perceived threat categorizes participants into three Nodes. Overall, consumers who are very concerned about the disease infection are more likely to engage in panic buying/hoarding behaviors. Among those who are very concerned consumers, age serves as the split variable (χ^2 = 21.59, df = 2, p < .01) for Node 1. Younger consumers (< 43) are more likely to have panic buying behaviors. Education serves as the split variable (χ^2 = 15.71, df = 2, p < .01) for Node 2: not at all concerned, not too concerned consumers. Among those who are somewhat concerned, education serves as the split variable (χ^2 = 15.19, df = 1, p < .05) for Node 3. Consumers with higher educational level are more likely to have panic buying behaviors. Then, age serves as the split variable for Node 9 (χ^2 = 10.92, df = 1, p < .05). Consumers who are 62 years old or younger are more likely to have panic buying behaviors than those who are older. The prediction accuracy rate is 68.3% (Figure 3).

Previous literature (e.g., Gordon-Wilson, 2021; Grohol, 2020) suggested that consumers' hoarding behavior can be due to both emotional and rational responses. The result that perceived threat/concern is the most influential predictor for panic buying/hording behavior supports previous research findings (e.g., Gordon-Wilson, 2021; Rogers, 1975; Wu, 2020) suggesting that consumers' emotional response during crises can motivate them to purchase more products than needed. Thus, Rogers' (1975) PMT can be applied to not only consumers' protective health behaviors, but also consumption behaviors.

However, previous studies (e.g., Kassas & Nayga, 2021; Ntontis et al., 2021) suggested that panic buying can also be a rational choice. This may explain why the finding in this study suggests that educational level is a significant predictor for panic buying/hoarding behavior. Perhaps consumers with higher educational level take the pandemic more seriously in the very early stage of the pandemic, as the data of this study was collected from April 3 – April 7. Consumers with higher educational level could be more likely to follow government officials' public announcements to prepare for possible self-quarantine and the lockdown period. In this case, panic buying can be a rational choice, if consumers are advised to stock-up more products than needed.



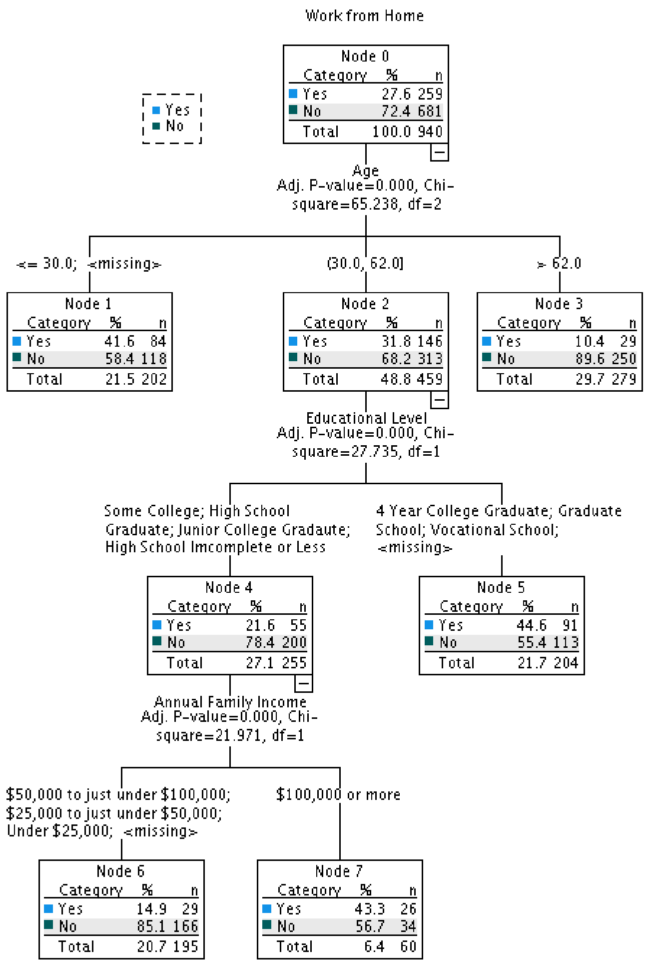
Source: Prepared by the author

Figure 3. Decision Tree Predicting Consumers' Panic Buying/Hoarding Behavior

The result suggests that older consumers are less likely to have panic buying behavior even they are somewhat concerned about the pandemic is surprising. Theoretically, older adults are more vulnerable amid the pandemic. Thus, older adults could be more likely to have panic buying behaviors. However, this is not the case here. This result may suggest that older adults may have difficulties purchasing products during the business lockdown period when the data was collected. The result of **RQ1** in this study suggests that older adults are less likely to engage in online shopping behaviors. Many products were out of stock in the grocery stores. Non-grocery retail stores were closed. Younger consumers who are tech savvy can easily order products online. However, previous studies (e.g., Hao, 2019; Friemel, 2016; Quan-Hasse et al., 2018; Wu, 2022b) suggested that there are generational differences in information and communication technology (ICT) use. In terms of ICT use, older generations are left behind younger generations. The *grey divide* still exists in the U.S. amid the pandemic. If older adults are not used to online shopping, they are less likely to purchase the products online for stockpiling. Regarding demographic factors, the result of this study is somewhat different from Kassas and Nayga (2021), because ethnicity is not a significant predictor for panic buying behavior. The differences in results may be explained by the fact that Kassas and Nayga (2021) measured US households' *perceived importance* of panic buying, whereas the present study investigated whether US consumers *purchased* more products than needed, instead of perceptions.

RQ4: Predicting Consumers' Work from Home Behavior

The results of decision tree analysis suggested that age (χ^2 = 65.24, df = 2, p < .001) is the most influential variable for predicting consumers' work from home behavior, followed by education (χ^2 = 27.74, df = 1, p < .001) and annual family income (χ^2 = 21.97, df = 1, p < .001). The first split by age categorizes participants into three Nodes. Overall, younger consumers who are less than 30 years old and mid-aged consumers (30 to 62 years old) are more likely to work from home than older consumers who are above 62 years old. The second split for mid-aged consumers by educational level suggested that consumers with higher educational level are more likely to work form home. The third split by annual family income suggests that consumers with higher annual family income ($100,000 or more) are more likely to work from home. The prediction accuracy rate is 72.4% (Figure 4).



Source: Prepared by the author

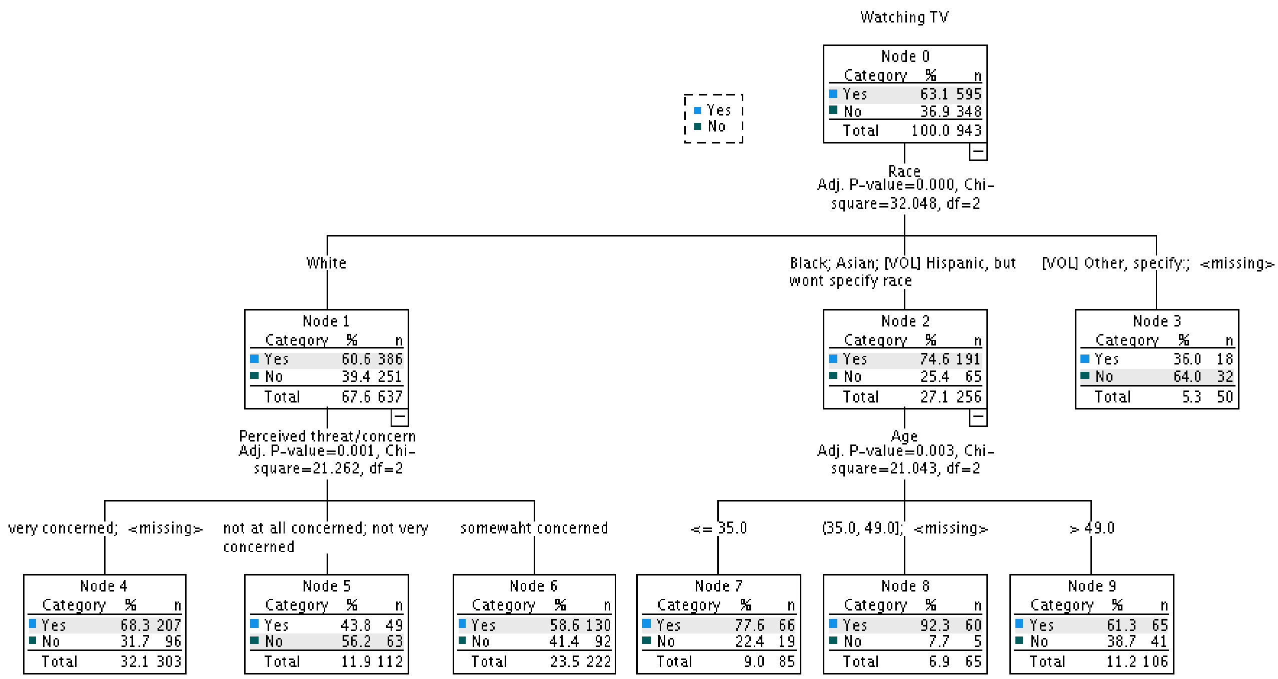
Figure 4. Decision Tree Predicting Work from Home Behavior

The result that age is the most significant predictor for work from home is consistent with previous studies (e.g., Brynjolfsson et al., 2020). Brynjolfsson et al. (2020) surveyed 25,000 U.S. adults in April (April 1 – April 5) and found that younger workers are more likely to be converted from commuting to work from home. Specifically, the differences between the 25-34 age group and the 65 and older group are statistically significant. The result that education and income are significant predictors for work from home is line with previous research findings (e.g., Mongey, 2020).

As Mongey (2020) argued, characteristics of workers who generally cannot work from home are nonwhite, lack a college degree, lack of health insurance, and making below medium income. The results suggest that consumers with higher educational level and income may have more advantage in working from home. Thus, there is inequality among different consumer segments, in terms of work from home. It also means that the home economy concept and related consumption activities, such as online grocery shopping and at-home entertainment, may apply to those who can work from home better.

RQ5: Predicting Consumers' Spending More Time Watching TV Behavior

The results suggested that that race (χ^2 = 32.05, df = 2, p < .001) is the most influential variable for predicting consumers' spending more time watching TV behavior. Other significant predictors are perceived threat/concern (χ^2 = 21.26, df = 1, p < .01) and age (χ^2 = 21.04, df =2, p < .01). The first split by race suggests that Black, Asian, and Hispanic Americans are more likely to spend more time watching TV than White Americans and other races. The split by perceived threat/concern for White Americans suggest that those who are very concerned about the disease are more likely to spend more time watching TV than those who are somewhat concerned, and not very concerned. The split for Black, Asian, and Hispanic Americans by age suggests that consumers in the 35-49 age group spend more time watching TV than consumers who are 35 or younger and those who are above 49. The prediction accuracy for this model is 66.1% (Figure 5).



Source: Prepared by the author

Figure 5. Decision Tree Predicting Spending More Time Watching TV Behavior

The result that race/ethnicity is the most important predictor for spending more time watching TV is quiet striking as more Black, Asian, and Hispanic Americans than White Americans did it in the early stage of the pandemic. This finding supports Lopez et al.'s (2020) argument that "the coronavirus outbreak has altered life in the United States in many ways, but in key respects it has affected black and Hispanic Americans more than others" (p. 1). As Lopez et al. argued, financial (e.g., job loss) and health impacts (e.g., hospitalization and death rate) of COVID-19 vary widely by race and ethnicity. Generally speaking, Black and Hispanic Americans were impacted more by the pandemic than White Americans.

There was also an Asian hate situation in the early stage of the pandemic (Barr, 2021). This may explain why consumers in minority groups would spend more time watching TV news to stay updated.

Among the White Americans, perceived threat/concern is the splitting variable in the decision tree model as those who are very concerned about the pandemic spent more time watching TV than others. As Spence at al. (2007) and Spence (2008) argued, TV news is the primary information source during times of crises. This is one of the possible explanations of the result. However, recent research findings (e.g., Hubbard, 2021; Scopelliti et al., 2021) suggested that audiences were spending more time watching TV not only for news, but also for entertainment at home amid the pandemic. Since the data of this study was collected in April, 2020 which is the very early stage of the outbreak of the disease in the U.S., it is more likely the respondents would mainly watch TV to get updated information about the health crisis, because there was high level of uncertainty at that point in time.

CONCLUSION

This study attempts to use a data mining approach to profile consumer behaviors by using psychological and demographic factors to predict a number of pandemic-inspired consumer behaviors. Because all of the major consumption trends are covered, the scope of this study is broad. There are a number of significant findings with theoretical, practical, and methodological implications.

Theoretical and Practical Implications

The results support PMT (Rogers, 1975), because perceived threat/concern is a significant predictor for most of the consumption behaviors (except for work from home) examined in this study. Specifically, perceived threat/concern is the most important predictor for online shopping behaviors and panic buying behaviors. This finding is important for retailers and marketers. As Wu (2022a) noted, what consumers need during crises is a low-risk shopping environment. Compared with in-store shopping, online shopping is considered to be safer, because it is low contact. Thus, retailers may sell products online or utilize multi-channel marketing during and after the business shut down period. The trends for e-commerce and online grocery shopping will continue in the post-pandemic era (e.g., Kohli et al., 2020).

The results also support consumer demographics theory (e.g., Sheth, 1977; Martins et al., 2012), because age, education, family income, and race/ethnicity serve as significant predictors for a variety of consumer behaviors. As Kotler (1977) noted, 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. There are a number of significant findings from this perspective. First, annual family income and age are significant predictors for overall online shopping behavior. If elder consumers with low family income had difficulties shopping online, grocery stores may give them the priority to purchase necessities in-store. That’s why many supermarkets and grocery stores would let senior citizens enter the stores first before other customers when they just opened in the morning during the business lockdown period. Second, education is the most important predictor for two consumption behaviors: online grocery shopping and panic buying/hoarding behaviors. This result may imply that consumers with higher educational levels (with college degree or graduate degree) may be more tech savvy. Thus, they can easily order products online by using digital devices and have the advantages in purchasing products online for stockpiling. In addition, they may want to be more prepared and to be more in control, in order to deal with the uncertainties.

To control excessive amount of panic buying, retailers may set the quantity limits that every consumer can purchase per order for some items (e.g., toilet paper, hand sanitizer) to help consumers in different demographic segments (not only the tech savvy, highly educated, and rich consumers) to get what they need. Third, age is the most important predictor for consumers’ work from home behavior. Fourth, race/ethnicity is the most important predictor for consumers’ spending more time watching TV behavior. This finding is important for public health officials and healthcare practitioners as more Black, Asian, and Hispanic Americans did it than White Americans. If government officials would like to communicate with minority groups, build trust with them, and promote protective health behaviors, they may use TV news as a crisis communication channel. Finally, sex/gender is *not* the most important predictor for any of the five behaviors which are investigated in this study.

This study has challenged some theoretical assumptions *pre-pandemic* time. No sex/gender difference is consumption behaviors is one of the examples. This finding is different from Martins et al.'s (2012) theoretical assumption about gender differences in male and female's home orientation. Because of the pandemic, both male and female may work from home during the business shutdown period. Both male and female may choose to shop online or are forced to shop online for all kinds of goods, including groceries.

Methodological Implications

With the increasing popularity of using predictive analytics, this study uses decision tree for data analysis. Until recently, very few academic studies (e.g., Wu, 2022a) used decision tree analysis, although decision tree is considered as a powerful data mining method (Rokach & Maimon, 2008). In this study, decision tree analysis was performed to identify the most influential psychological and demographic predictors for consumer behaviors during crisis. Future studies may continuously use predictive analytics to identify *other* important factors that affect consumer behaviors in the past and predict consumption trends for the future as we move forward into the *new normal*.

Limitations and Suggestions for Future Studies

This study has some limitations. First, this study is purely a quantitative study by using decision tree analysis as a data mining tool. The predictors for consumer behaviors amid the pandemic can be identified. However, the results can't fully explain "why" consumers in specific segments are more likely to engage in certain consumption behaviors from this dataset. Thus, future studies may use qualitative research methods, such as focus group interviews or in-depth interviews, to hear consumers' voices and better understand consumers' motivations and behavioral intentions during crises. Second, the decision tree analysis result can only tell us which demographic segments are more likely to spend more time watching TV and movies. However, the result can't tell us exactly whether consumers spent more time watching TV mainly for news or for entertainment (e.g., movies).

Since the data was collected in the very early stage of the pandemic, consumers are most likely to watch TV to get crisis related information. However, as time goes by, more consumers may spend more time watching TV for entertainment (Sadlier, 2020). Ideally, spending more time watching TV "for news" or "for entertainment" can be two separate survey items. Futures studies may analyze data collected from different point of time and compare research findings with this study and track how consumers' watching TV motives and behaviors (e.g., for news or for entertainment) change over time amid the pandemic.

Research ethic statement

This manuscript is original, and not submitted to any other journals. An earlier version of this paper was presented at 2022 International Association for Intercultural Communication Studies (IAICS) Annual Conference, Virtual. 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

I am the single author. Thus, there is no conflict of interests.

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