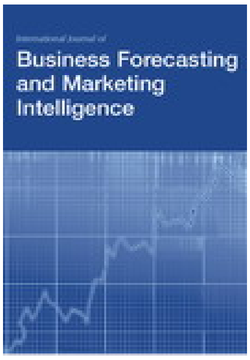

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COVID-19 and its perceived health belief impact on prepared food delivery services from a consumer behaviour perspective

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Abstract: COVID-19 has impacted the lives of billions of people around the globe. Industries are encountering challenges and adjusting to continue to survive the detrimental effects of the pandemic. Our group will focus on the restaurant (both fast-food and traditional sit downs) industry and further explore customer delivery services that has provided an opportunity for customers throughout the pandemic. DoorDash, Grubhub, and UberEats are leaders within the customer delivery industry and will be further analysed to see how impactful they have been throughout the pandemic. Four different categorical criteria were used to help empirically investigate the impact of prepared food services within the COVID-19 environment and afterwards. Questions will be developed within each of the categories to provide consumer insight. A sample of 3,240 respondents completed an online questionnaire. The results and conclusions projected potential continued and significant growth for customer delivery services DoorDash, Grubhub, and UberEats in a post-pandemic environment.

Keywords: consumer behaviour; COVID-19; DoorDash; empirical; Grubhub; health belief model; HBM; online food delivery services; pandemic; reasoned actions model; technical sophistication; UberEats.

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1 Introduction

1.1 COVID-19 impacts on consumer's eating preferences

The restaurant industry has taken a detrimental hit in the global economy since the start of the COVID-19 pandemic. A host of demographic factors associated with consumers of non-traditional food services, such as online food deliverers, in the midst of a global pandemic can be affected by age, gender, race, urban verses rural residency, and educational qualifications (Hervé and Mullet, 2009; Weitkunat et al., 2003), as well as exercise regime (Meshe et al., 2020). There are perceived food health risks by females that can be differentiated from their male counterparts (Tweneboah-Koduah, 2018) as well as generational differences (Ladhari et al., 2019). In general, consumers' perceptions of the desirability and affordability can be directly affected based on these demographic variables as well as intrinsic and extrinsic factors (Bish and Michie, 2010; Prendergast et al., 2010). Fear about food consumption, especially during a global pandemic, may drive many irrational decisions. Such irrational decision-making during a public food scare/health crisis are common (ddo et al., 2020; Manika and Golden, 2011; Rhodes, 2017), such as mad cow disease (Setbon et al., 2005) and SARs epidemics (Lau et al., 2004). Age can be a major factor as the COVID-19 has a greater impact as witness by the deaths occurred among adults aged ≥65 years (Mehrolia et al., 2021; Stieger, 2019). Many states have varying policies affecting the capacity and restrictions within operations. There have been a series of orders and public safety measures that have shaped how businesses can operate in Pennsylvania. The 15 April 2020 Order of the Secretary of the Pennsylvania Department of Health Directing Public Health Safety Measures for Business Permitted to Maintain In-person Operations and the 16 July 2020 Order of the Governor of the Commonwealth of Pennsylvania Directing Targeted Mitigation Measures have caused shifts in restaurant operation. Restaurants in Pennsylvania are limited to a maximum capacity of 50% of posted fire code within the restaurant (Commonwealth of Pennsylvania Health and Safety Requirements, 2020).

The increase in global restaurant capacity has created a higher demand for takeout and delivery options prior to the pandemic (Turnšek et al., 2020). In particular, prepared food ordering companies like DoorDash, Grubhub, and UberEats have provided an opportunity for customers to get their favourite meals from the comfort and safety of their own home. Customer delivery services vary in different locations and availability and, hence, may prohibit customers from using them. DoorDash, Grubhub, and UberEats all contract their drivers out, meaning almost anyone that have a valid motor operating license and access to a vehicle can apply to become a deliverer. Consumers pay delivery fees when purchasing through a delivery service. While it is a no-contact service, it can lead to higher expenses. DoorDash, Grubhub, and UberEats are very similar in the services they provide, but consumers differentiate between them based on their characteristics (Min et al., 2019; Newstex, 2019; Powe and Wagner, 2020).

DoorDash currently operates (at the time of the present study) in 80 cities around the world. Their service fees range from 7%–15% on orders (DoorDash, 2022). There are no delivery minimums within DoorDash and their rating leads to safe and reliable delivery of meals. Grubhub has a similar model to DoorDash, except service fees vary on individual restaurants' policy. UberEats tends to be better for larger orders in terms of absolute cost as the service fees are not calculated by order total. They are known to provide more promotions than DoorDash and Grubhub (Zhao and Bacao, 2020).

UberEats also will limit service fees for customers that share a route with another customer's order. This saves the driver time by delivering food to consumers near each other. Customer delivery services tend to be more popular in urban areas as there is a denser population and there are many options for restaurants to partner with the delivery services (Li et al., 2019). More rural cities are partnering with DoorDash too but, depending on the location, it may be more expensive for customers in these areas.

The primary focus of the present research effort is to investigate the various elements of these primarily online food delivery services, such as reliability and convenience, and their intrinsic and extrinsic motivations that may allow these services to continue to thrive in a relatively post-COVID-19 environment. To be included in the study, it was not required to use the apps for these various companies. Especially in times of uncertainty, these services have an opportunity to bloom and affect consumer behaviour within various groups of people. These services run off technology so technological skills may be a factor on the people who are using these services the most. Even if populations have not personally ordered food from these services, it would be interesting to discover if brand awareness has shifted since COVID-19. The attitude towards customer delivery services will indicate how the services may have changed since the progression of the pandemic. A conceptual model will further provide structure and organisation to our study. Our three hypotheses will shape our categories that will be analysed within our questionnaire.

1.2 Purpose of the present study

The COVID-19 pandemic has created new opportunities to shape consumer behaviour (Ivanov, 2020; Smith, 2022). The restaurant industry has taken a serious hit as indoor dining limitations have decreased revenue. However, the shift to mobile and virtual platforms has popularised delivery services. In this project, our group wants to identify if food delivery services, specifically DoorDash, Grubhub, and UberEats, have increased popularity since the pandemic and affected consumer behaviour. The results from this study should provide insights on how effective these services are from the perception of our sample and if these businesses will continue to be utilised in the post-pandemic era. The design of the study and types of variables measured were largely based on the particular impacts of COVID-19's impacts online food ordering and eating habits from recent research on such impacts on eating patterns (Aldaco et al., 2020; Belanche et al., 2017).

2 Background

2.1 Derivation of research hypotheses

The development of the hypotheses will allow our group to focus, breakdown, and concentrate on various aspects of our dataset. The four hypotheses were based on concepts of the theory of planned behaviour (French et al., 2005; Gabriel et al., 2019; Hardeman et al., 2002). These hypotheses concerning the pandemic and its impact of food delivery services have gained popularity (Belanche et al., 2017). Hence, a series of hypotheses from the increase in lockdowns across the country and the concern shared by many individuals of contracting COVID-19, especially in receiving prepared food that has been traditionally available through face-to-facing dining services. Due primarily to these reasons and the fear of food insecurity, many people have relied heavily on food online delivery services and, thus, these companies have noticed an increase in business (Aldaco et al., 2020; Berg and Lin, 2020).

In the derivation of research hypotheses, there are technological accessibility issues associated with ease-of-use associated with food online delivery services using mobile applications has resulted in increased sales due to the increased convenience of the mobile applications. Marketing of prepared food services can have a significant impact on its perceived health risks (Belanche et al., 2017). As a basic guide through the derivation of the hypotheses, the health belief model (HBM), combined with the reasoned Actions model, can help explain the self-protective behaviour that customers may display in certain online and tradition prepared food ordering process. With the current uncertainty of COVID-19, its variants, and the rapid growth in certain countries, like China, there has been much interests in the in the field of customer food safety. The application of HBM, according to Jones et al. (2014), is one of the most accepted models for understanding health behaviours. Its application as been useful in understand intrinsic and extrinsic motivations predicting individual changes in health behaviours. A number of the factors in the model include demographic (Bish and Michie, 2010), beliefs, and technological sophistication as some of the key factors that influence health behaviours/risks (Brug et al., 2009; Buhalis et al., 2019; Barrows and Vieira, 2013; Canziani et al., 2016; Commonwealth of Pennsylvania, 2020). It is anticipated that many consumers, regardless of healthcare risks, look for increased convenience through technological innovation not only due to the COVID-19 pandemic, but well beyond the post-COVID-19 impacts (Aucote et al., 2010; Belanche et al., 2017; Berg and Lin, 2020). Undoubtedly, it is not meant that current society will be free of the long-terms effects of this pandemic, merely the large-scale hospitalisations and deaths from the disease, especially since there is widespread availability of vaccines. These mobile applications allow for the consumer to order food from anywhere at any time and dismiss the need for human interaction or large computers. The familiarisation and accessibility of both the internet and technological applications may contribute to the success of customer delivery services.

The third hypothesis relates to the fact that the new food delivery service companies have shifted consumer behaviour and will continue to hold popularity after the pandemic is over. Many consumers have switched from wanting to go out to wanting to stay in. This switch was prevalent even before the pandemic and has recently sped up the process. Perceptions of diseases, product knowledge, country-of-origin, nutrition requirement, public fears and apprehension of contagious diseases, to mention a few, are extremely important to determine the motivations and perception of risk factors associated with such preferences for food delivery services (Shirin and Kambiz, 2011; Soliha and Widyasari, 2018; Valeeva et al., 2011).

After formulating the hypotheses based on the conceptual model found in Figure 1, emphasising intrinsic and extrinsic motivational factors of convenience, technological sophistication and accessibility, with the need for sanitary services, these factors will be crosstabulated with employment status, age, and gender. A total of four specific research hypotheses were created to empirically test for the changing in food-order and delivery services and its associated health belief behaviours within the context of the COVID-19 pandemic. They are as listed below.

H1 Knowledge and perceived intrinsic/extrinsic motivational factors (i.e., accessibility of mobile food apps and the impact of widespread vaccination and its impact on face-to-face restaurants will continue to take cleanliness seriously) based on gender differences should be statistically significant and insightful.

H2 Knowledge and perceived intrinsic/extrinsic motivational factors (i.e., accessibility of mobile food apps coupled with employment status) are significantly related to age differences. Employment status is used as a measure of financial resources and time restrictions making the use of mobile apps for food order more appealing.

H3 The relatively complex interactions among app preference versus employment status and accessibility to mobile applications have a significant impact on the type of food-order app/customer service choices. Less than full-time employment may impact food-ordering delivery usage in different than full-time employment as a function of accessibility to such mobile apps.

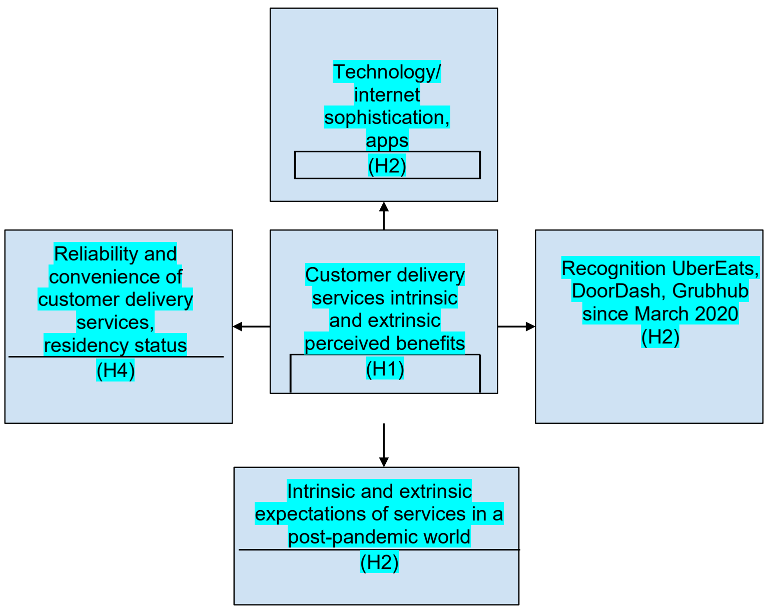
H4 The relatively complex interactions among respondents based on residency (location) and accessibility to mobile applications have a significant impact on the type of food-order app/customer service choices. Potential customers in more rural environments may typically have less experience and technical sophistication with such delivery services than their more urban and suburban counterparts.

The visualisation of this conceptual model helped create the survey outlined in Figure 1. It is based on the reasoned actions model as applied to healthy behaviours (Fishbein, 2008; Geshnizjani et al., 2013) in selecting healthy behaviours. The reasoned actions model is a popular theoretical approach that can be used to identify underlying intrinsic and extrinsic factors that may influence the intention to positively engage in positive health behaviours (e.g., getting vaccinated and seeking clean alternatives for food preparations). As suggested by Fishbein and Ajzen (2010), it is a relatively recent development in the evolution of the theory of reasoned action, the theory of planned behaviour, and the integrated behavioural model.

The survey was developed with primary categorical variables for each of use and interpretation with chi-square analyses techniques. Beside socioeconomic variables, respondents were asked about their reasons and/or confront level when they used these food delivery systems. Based on their experiences with these services, they were asked if they have increased their use of such services over the course of the pandemic. A number of questions were formulated regarding their demographics to properly categorise individuals and see if there was any direct correlation between their demographics and their answer to the following questions. Questions regarding their use of these food delivery apps regarding the frequency before, during, and what their expected use after the pandemic will be. These questions should allow if predictive relationships with the perceived horrors and/or inconveniences associated with the pandemic and their use of these apps as a way to mediate the pandemic. Google Forms within the author's LinkedIn account should allow easy distribution and data collection for the survey results. Please refer to Figure 1 for more information on the layout and the derivations of which the questions were created and asked. A sample size of at least 3,000 was the initial target to be surveyed in order to ensure a substantial sample.

Specific tests will be made to determine if respondents' residency status, degree of ease-of-use with apps, fears on the vaccination programs, age, and long-term lookout of the resumes that restaurants have made on food safety will be permanent. These statistical tests will help shape the future growth of the prepared food industry and the strategic viability of such apps in a post-COVID environment, assuming there is one. These tests should provide light if there is a significant relationship the respondents' technology use and their willingness to return to in-person dining once the pandemic is over. The results of this research effort should provide useful information to forecast if these apparent trends of food delivery applications could be due to the increased use of technology around the world or merely a method of accessing food safety due to the current global pandemic.

Figure 1 Conceptual model (see online version for colours)



2.2 *Impacts of reliance on internet and technology usage*

The unfolding of COVID-19 highlights the significant role of technology in delivery services. Internet and technological innovations facilitate automation. The internet has been a crucial tool to keep users connected with the external environment and provide a sense of normalcy in times of isolation. The use of the internet and technology should boost the capability of these organisations, such as UberEats, DoorDash, and Grubhub, to offer services at an affordable cost (Heinonen and Strandvik, 2021). Essentially, the use of the internet, in particular the almost universal availability apps on smart phones) helps to avail information to the market (Zhao and Bacao, 2020). Undoubtedly, the sophistication associated with using internet and smart phone-based apps to order food may be an impediment for the older generation not traditionally or routinely acquainted in such technology on a daily basis as their younger generational counterparts in terms of affordability and availability concerns (Bresman and Rao, 2017; Myers et al., 2020; Nam et al., 2019).

Therefore, questions concerning overall household wealth and internet-related technologies, mobile technology usage rates were included in the survey instrument to measure these potential economic and connection inequalities. By incorporating technology and internet usage and its related skills, some measure of such abilities to use and recognise customer delivery services can be determined to be either being a catalyst or a barrier to such food delivery services. There are well-research differences among generational charts in a variety of intrinsic and extrinsic motivational factors and preferences (Lissitsa and Kol, 2019) than may impact technical sophistication and, thus, acceptance of online food ordering and delivery services.

Specifically, Lissitsa and Kol (2019) found that baby boomers and Gen X, they were positively correlated with openness to experience and mobile-shopping intention (m-commerce). For them, using apps probably is just part of their everyday routine. Hence, the two spectrums of age (older and younger) were found to have personality traits that were more predictive associated m-shopping intention, as compared to younger generations. They also found that Gen Y's extraversion was positively related to m-shopping intention. However, an inverse Gen Z, correlation between agreeableness and m-shopping intention was found. It was decided that a simple linear or multi-linear modelling approach would not be a good research strategy to analyse these complex relationships. Therefore, chi-square statistical techniques were selected to be the primary method to isolate these differences and test the specific research hypotheses. As most of variables were categorical in nature, it was decided to be the best statistical technique available. A generational approach to understand these marketing trends are reflected in the specific research hypotheses. Technological advancements enable delivery firms to empower clients. That is, customers can take control and ownership of services and integrate them into their lives before, during, and after the pandemic.

2.3 Reliability and convenience of customer delivery service

To develop an excellent customer delivery service, management needs to incorporate convenience, accessibility, and reliability (Zhao and Bacao, 2020). These elements are essential, as they create a competitive advantage and foster sustainability for DoorDash, Grubhub, and UberEats. Essentially, the performance of these three companies during the pandemic strongly suggests that reliability and convenience boost customer relations (Heinonen and Strandvik, 2021). In particular, reliability and convenience are factors that will cause customers to use the app and become frequent customers. In this present research effort, it is hoped that studying and testing to gauge these elements as they will should allow the ability to correlate how easily these services can be integrated by various demographically classified groups of people. Trends show that reliability and convenience factors enable service firms to comply with the agreed delivery time (Hobbs, 2020).

2.4 UberEats, DoorDash, and Grubhub recognition since March 2020

It can be stated that March 2020 marked the beginning of lockdown protocols to prevent the spread of COVID-19, especially for fruit, vegetables, and other perishable food items (Richards and Richards, 2020; Zhao and Bacao, 2020). The pandemic theoretically started in January 2020, but there were essentially no procedures set in place to limit the spread until March of 2020 (Bialek et al., 2020). By gauging the recognition before the pandemic started, it can be seen how consumer behaviour transitioned after the pandemic started becoming more serious and affecting daily life. The in-person gathering restrictions meant that customer delivery services were in high demand (Nguyen and Vu, 2020). The three firms were recognised globally for excellent online prepared food services and reliability were DoorDash, GrubHub, and UberEats (Heinonen and Strandvik, 2021), the companies that are the focus for the present research effort.

2.5 Expectations of online food service in the post-pandemic marketplace

As operations resume back to normal, predicted demand for such online customer delivery services is likely to reduce (Heinonen and Strandvik, 2021). There needs more research on the market-driving forces that propel these services during the pandemic period and beyond to determine the sustainable and strategic practices that made these services such a success. Such research efforts should be able to document and provide more insight into the various important demographic and motivational factors associated with these phenomena. If there has been significant consumer behaviour shift towards such customer delivery services has occurred, as demonstrated by the recent popularity of remote working and online education, it is important to determine if the effects moving in a post-pandemic environment will be permanent or temporary. There has been a noticeable downtrend in such services that probably stems from the relaxation of COVID-19 mitigations. There is the possibility of customers wanting to utilise in-person services once again as isolation causes social deprivation (Nguyen and Vu, 2020). The other possibility is the customer delivery services such as DoorDash, Grubhub, and UberEats have become integrated within daily life and will continue to be heavily utilised as customers' concern for health safety moves into the future (Jeong and Ham, 2018; Keelery, 2020). Time will tell whether these trends in online food services are sustainable, but it is a rich and interesting area to research in terms of both public health and marketing services.

3 Method

Survey instrument was created and pre-tested mostly using constructs of the theory of planned behaviour (French et al., 2005; Gabriel et al., 2019; Hardeman et al., 2002; Povey et al., 2000). The Likert scales and types of questions in this instrument (available upon request) were patterned from work on crating as scale to measure the perceived benefits and risks of online shopping by Forsythe et al. (2006) and Ha (2012). The data collected were then categorised according to the various controlling variables. The case study procedures followed in this present study were designed classic work by Yin (2003). Male answers were separated from the females' answers to determine if any statistically significant gender biases were present in the present study. The set of 19 independent quality-related and socioeconomic variables and one dependent variable can be found in the descriptive statistics illustrated in Table 1. Although the dependent variables may change as a function of gender and age, such selections are based due to typical intrinsic and motivation factors in food service options (Hanks, et al., 2017; Kumar and Chandra, 2010; Lawton et al., 2009, 2007; Vermeir and Verbeke, 2006) and current environment of food supply chain disruptions during pandemics (Hobbs, 2020), geopolitical unrest, and high inflationary pressures on the global economy. A total of 3,240 participants sufficiently answered the survey sent via the message function on Facebook/LinkedIn and collected through Google Forms.

4 Results

4.1 Descriptive statistics

In the sample of 3,240, there were significantly more female respondents (n = 2,520, 77.8% female; n = 720 males, 22.2%) and rather young [18–30 years (n = 1,480, 45.7%), 31–40 years (n = 360, 11.1%), 41–50 (n = 400, 12.3%), 51–60 years (n = 560, 17.3%), 60+ years (n = 440, 13.6%)]. Table 1 illustrated the basic frequencies of the remaining demographic and intrinsic/extrinsic motivational variables collected in the study. As an inspection of Table reveals, only a minority of the respondents lived the rural areas (n = 600, 18.5%), most had disposable income of $100,000 or less (n = 2,400, 74.1%), worked at least part-time (n = 2,845, 87.8%, extensive internet users (7–14 times per week or more than once a day, n = 2,840, 87.7%), and were not frequent users of food apps, but most used them (1–5 times per week or not every day, n = 2,040, 63%). The vast majority felt that importance of technology was significant during the pandemic (n = 3,160, 97.6% were somewhat to very familiar with food-related technologies) and were almost evenly split on the favourability of experience with UberEats, Grubhub, and/or DoorDash. Relatively few rated the food delivery apps as not reliable (n = 320, 9.9%) and most are both familiar with these food-delivery apps and have purchased from them (n = 2,890, 58.1%). The sample was split evenly of whether these apps will continue to grow in popularity or not (some growth, n = 1,600, 49.4%) with only a tiny fraction expecting a large decline (n = 80, 2.5%) and a slightly larger portion expecting a large growth (n = 480, 14.8%). Most respondents felt that once a vaccine is widely available, infection rates decrease and in-store dining resumes, they were fairly confident that restaurants will continue to take cleanliness seriously, including heavy sanitation, extra space between tables, etc. (somewhat confident, n = 1,000, 30.9%; confident, n = 960, 29.6%, and very confident, n = 640, 19.8%).

Table 1 Frequencies of categorical variables used in the present study

1.1 General location				
Current residency	*Frequency*	*Percent*	*Valid percent*	*Cumulative percent*
Rural area (more than 30 miles from a city ex. Pittsburgh)	600	18.5	18.5	18.5
Suburban area (within a 30-mile radius from a city ex. Pittsburgh)	1,760	54.3	54.3	72.8
Urban area (within a 5-mile radius from a city ex. Pittsburgh)	880	27.2	27.2	100.0
Total	3,240	100.0	100.0	

Table 1 Frequencies of categorical variables used in the present study (continued)

1.2 Household income				
Disposable income	*Frequency*	*Percent*	*Valid percent*	*Cumulative percent*
<$50,000	1,280	39.5	39.5	39.5
$100,001–$150,000	240	7.4	7.4	46.9
$150,001–$200,000	440	13.6	13.6	60.5
$200,001+	160	4.9	4.9	65.4
$50,001–$100,000	1,120	34.6	34.6	100.0
Total	3,240	100.0	100.0	
1.3 Employment status				
Degree of employment	*Frequency*	*Percent*	*Valid percent*	*Cumulative percent*
Full-time employment	1,440	44.4	44.4	44.4
Part-time employment	1,405	43.4	43.4	87.8
Unemployed	395	12.2	12.2	100.0
Total	3,240	100.0	100.0	
1.4 Internet usage per week				
Weekly internet usage	*Frequency*	*Percent*	*Valid percent*	*Cumulative percent*
1–5 times per week (not every day)	160	4.9	4.9	4.9
6–7 times per week (usually once a day)	240	7.4	7.4	12.3
7–14 times per week (more than once a day)	2,840	87.7	87.7	100.0
Total	3,240	100.0	100.0	
1.5 Access mobile applications (ordering food) per week				
Weekly food ordering app	*Frequency*	*Percent*	*Valid percent*	*Cumulative percent*
1–5 times per week (not every day)	2,040	63.0	63.0	63.0
6–7 times per week (usually once a day)	160	4.9	4.9	67.9
7–14 times per week (more than once a day)	120	3.7	3.7	71.6
I do not order food off of mobile applications	920	28.4	28.4	100.0
Total	3,240	100.0	100.0	
1.6 Degree of importance technology throughout the pandemic				
Degree of importance	*Frequency*	*Percent*	*Valid percent*	*Cumulative percent*
Unknown	40	1.2	1.2	1.2
Not very familiar	40	1.2	1.2	2.5
Somewhat familiar	240	7.4	7.4	9.9
Familiar	440	13.6	13.6	23.5
Very familiar	2,480	76.5	76.5	100.0
Total	3,240	100.0	100.0	

Table 1 Frequencies of categorical variables used in the present study (continued)

1.7 Familiar with customer delivery services DoorDash, Grubhub, and/or UberEats				
Degree of familiarity	*Frequency*	*Percent*	*Valid percent*	*Cumulative percent*
I am familiar and use one or more of the services and have purchased from them	2,890	58.1	58.1	58.1
I have heard of more than of the services, but have never purchased anything from them	960	29.6	29.6	87.7
I have heard of one of the services, but have never purchased anything from them	360	11.1	11.1	98.8
I have never heard of these services	40	1.2	1.2	100.0
Total	3,240	100.0	100.0	
1.8 Delivery preference				
Preference	*Frequency*	*Percent*	*Valid percent*	*Cumulative percent*
DoorDash	1,360	42.0	42.0	42.0
Grubhub	240	7.4	7.4	49.4
None	1,320	40.7	40.7	90.1
UberEats	320	9.9	9.9	100.0
Total	3,240	100.0	100.0	
1.9 Rate your experience with UberEats, Grubhub, and/or DoorDash				
Rating	*Frequency*	*Percent*	*Valid percent*	*Cumulative percent*
Not good	560	17.3	17.3	17.3
Little favourability	80	2.5	2.5	19.8
Somewhat favourable	720	22.2	22.2	42.0
Good	1,080	33.3	33.3	75.3
Very good	800	24.7	24.7	100.0
Total	3,240	100.0	100.0	
1.10 Number of times used delivery services before March 2020				
Number	*Frequency*	*Percent*	*Valid percent*	*Cumulative percent*
0 times	1,240	38.3	38.3	38.3
1–5 times	880	27.2	27.2	65.4
10+ times	400	12.3	12.3	77.8
5–10 times	720	22.2	22.2	100.0
Total	3,240	100.0	100.0	

Table 1 Frequencies of categorical variables used in the present study (continued)

1.11 Number of times used delivery services since March 2020				
Number	*Frequency*	*Percent*	*Valid percent*	*Cumulative percent*
0 times	920	28.4	28.4	28.4
1–5 times	720	22.2	22.2	50.6
10+ times	1,120	34.6	34.6	85.2
5–10 times	480	14.8	14.8	100.0
Total	3,240	100.0	100.0	
1.12 Average spend per order				
Dollars spent	*Frequency*	*Percent*	*Valid percent*	*Cumulative percent*
<$10	640	19.8	19.8	19.8
$0–10	120	3.7	3.7	23.5
$10–15	440	13.6	13.6	37.0
$15–20	1,040	32.1	32.1	69.1
$20–30	600	18.5	18.5	87.7
$30+	400	12.3	12.3	100.0
Total	3,240	100.0	100.0	
1.13 Importance delivery services during the pandemic environment				
Degree of importance	*Frequency*	*Percent*	*Valid percent*	*Cumulative percent*
Not very important	800	24.7	24.7	24.7
Little importance	160	4.9	4.9	29.6
Somewhat important	440	13.6	13.6	43.2
Important	400	12.3	12.3	55.6
Very important	1,440	44.4	44.4	100.0
Total	3,240	100.0	100.0	
1.14 Degree of reliable do you believe customer delivery services				
	Frequency	*Percent*	*Valid percent*	*Cumulative percent*
Not reliable	320	9.9	9.9	9.9
Reliable	2,240	69.1	69.1	79.0
Very reliable	680	21.0	21.0	100.0
Total	3,240	100.0	100.0	
1.15 Degree of convenience do you experience with customer delivery service in comparison to dining out/cooking				
Coding scheme	*Frequency*	*Percent*	*Valid percent*	*Cumulative percent*
Not convenient than dining out/cooking	120	3.7	3.7	3.7
Less convenient than dining out/cooking	400	12.3	12.3	16.0
More convenient than dining out/cooking	1,560	48.1	48.1	64.2
Same level of convenience	1,160	35.8	35.8	100.0
Total	3,240	100.0	100.0	

Table 1 Frequencies of categorical variables used in the present study (continued)

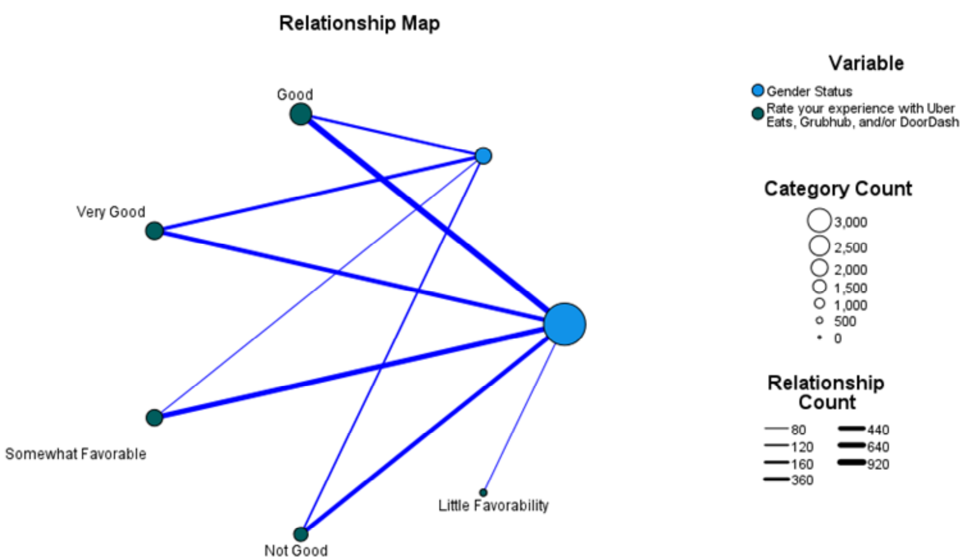
1.16 Previous issues with customer delivery services				
Coding scheme	*Frequency*	*Percent*	*Valid percent*	*Cumulative percent*
No	1,760	54.3	54.3	54.3
Yes	1,480	45.7	45.7	100.0
Total	3,240	100.0	100.0	
1.17 Delivery issues with food app				
Type of issue	*Frequency*	*Percent*	*Valid percent*	*Cumulative percent*
Food not arrive	160	4.9	4.9	4.9
Late arrival	680	21.0	21.0	25.9
Order incorrect	800	24.7	24.7	50.6
Other issue	1,600	49.4	49.4	100.0
Total	3,240	100.0	100.0	
1.18 Once in-store dining resumes, how often do you expect you will use food delivery services?				
	Frequency	*Percent*	*Valid percent*	*Cumulative percent*
Never	760	23.5	23.5	23.5
Not often	840	25.9	25.9	49.4
Somewhat often	920	28.4	28.4	77.8
Often	240	7.4	7.4	85.2
Very often	480	14.8	14.8	100.0
Total	3,240	100.0	100.0	
1.19 Once a vaccine is widely available, infection rates decrease and in-store dining resumes, how confident are you that restaurants will continue to take cleanliness seriously including heavy sanitation, extra space between tables, etc.				
Degree of confidence	*Frequency*	*Percent*	*Valid percent*	*Cumulative percent*
Not very confident	80	2.5	2.5	2.5
Little confidence	560	17.3	17.3	19.8
Somewhat confident	1,000	30.9	30.9	50.6
Confident	960	29.6	29.6	80.2
Very confident	640	19.8	19.8	100.0
Total	3,240	100.0	100.0	
1.20 Expect food delivery apps/companies to grow post-pandemic				
Coding scheme	*Frequency*	*Percent*	*Valid percent*	*Cumulative percent*
Large decline	80	2.5	2.5	2.5
Large growth	480	14.8	14.8	17.3
Some decline	440	13.6	13.6	30.9
Some growth	1,600	49.4	49.4	80.2
Stagnate/no growth or decline	640	19.8	19.8	100.0
Total	3,240	100.0	100.0	

4.2 Specific-hypothesis testing results

H1 Knowledge and perceived intrinsic/extrinsic motivational factors (i.e., accessibility of mobile food apps and the impact of widespread vaccination and its impact on face-to-face restaurants will continue to take cleanliness seriously) based on gender differences should be statistically significant and insightful.

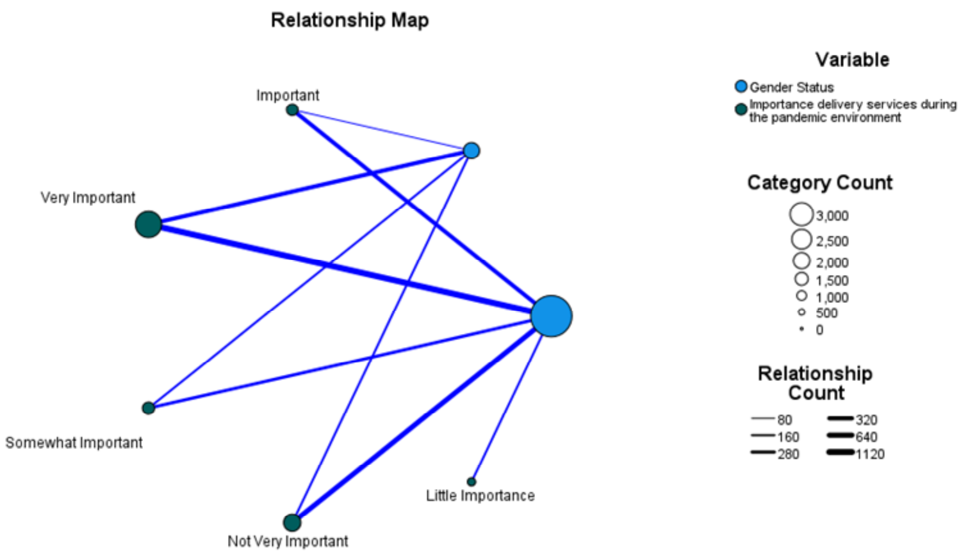
As displayed in Table 2 and Figures 2–5, respectively, are the statistical and graphical results of crosstabulating gender status with access mobile applications (ordering food) per week with restaurants will continue to take cleanliness seriously including heavy sanitation, extra space between tables, etc. once the pandemic is over. Table 2 is the chi-square results of testing H1, with Figures 2–5 graphically illustrating these complex relationships. Figure 2 displays the relationship between gender (females denoted by larger circle) and rating your experience with UberEats, Grubhub, and/or DoorDash; Figure 3 illustrates gender with degree of importance delivery services during the pandemic; Figure 4 presents gender with once in-store dining resumes, how often do you expect you will use food delivery services; and Figure 5 visualises the relationship between gender and once a vaccine is widely available, infection rates decrease and in-store dining resumes, how confident are you that restaurants will continue to take cleanliness seriously including heavy sanitation, extra space between tables, etc. respectively.

Figure 2 Relationship map between gender (females denoted by larger circle) and rating your experience with UberEats, Grubhub, and/or DoorDash (see online version for colours)



As demonstrated in Table 2, it found that there were highly significant relationships between the genders for the availability of mobile food-delivery apps, confidence that face-to-face restaurants will continue their heightened emphasis on provide a clean environment once the post-COVID period is in full swing (assuming widespread vaccine acceptance). In particular, males were significantly less optimistic about the continued cleanliness of in-store dining [somewhat confident (chi-square = 290.524, n = 1,000), confident (chi-square = 312.0, n = 960), and very confident (chi-square = 202.393, n = 640)]. Interesting, females, when using the food apps more frequently, had a seemingly better experience than their male counterparts and were statistically more included to be confident that the post-COVID world that restaurants will continue to be placing sanitary conditions as a high priority. Perhaps, males did not perceive use of these food-order apps as essential for good health as females. Logically, that conclusion would make sense if females are more involved in preparing meals for the family. Perhaps, to males, food apps are more of convenience and a requirement for their individual nutrition needs.

Figure 3 Relationship map between gender (females denoted by larger circle) and degree of importance delivery services during the pandemic (see online version for colours)



Upon an inspection of Figures 6–9, graphically inspects the crosstabulation level among gender, once vaccine widely available, with access mobile applications (ordering food) per week. In particular, the figures clearly illustrate these complex relationships little confidence with in-store dining (Figure 6), somewhat confident (Figure 7), confident (Figure 8), and very confident (Figure 9). It was not surprising that if there was no confidence concerning restaurants' sanitation practices (Figure 6), if was reflected more pronouncedly by the female sample. The vast majority of females chose not to use these mobile food-order apps as the perceived reputation of these restaurants, regardless of in-store dining or take-home delivery, the quality and/or safety of the food was in question. Hence, the vast majority preferred to take charge of sanitation of food preparation by cooking meals at home. On the extreme end of the continuum, very confident (Figure 9), no males refused to take part in these food-ordering apps. Although there was still some degree of hesitancy on the part of females' participation, most females did participate with these apps, but only at the 1–5 times per week, not everyday. As for the males, they appeared to be dividing their frequency of food-order apps between not everyday to 7–14 times per week or more than once a day). Hence, although the complexities associated with H1 are apparent, there appears to be statistically significant relations among gender, frequency/accessibility of food-order apps, with the degree of confidence with restaurants maintain sanitary conditions as a priority in the post-COVID period. Evidently, there is much distrust, especially with females, on the degree of safety and cleanliness on the part of prepared food providers that these apps source their food products. Hence, H1 was accepted at the 0.001 level.

Figure 4 Relationship map between gender (females denoted by larger circle) once in-store dining resumes, how often do you expect you will use food delivery services? (see online version for colours)

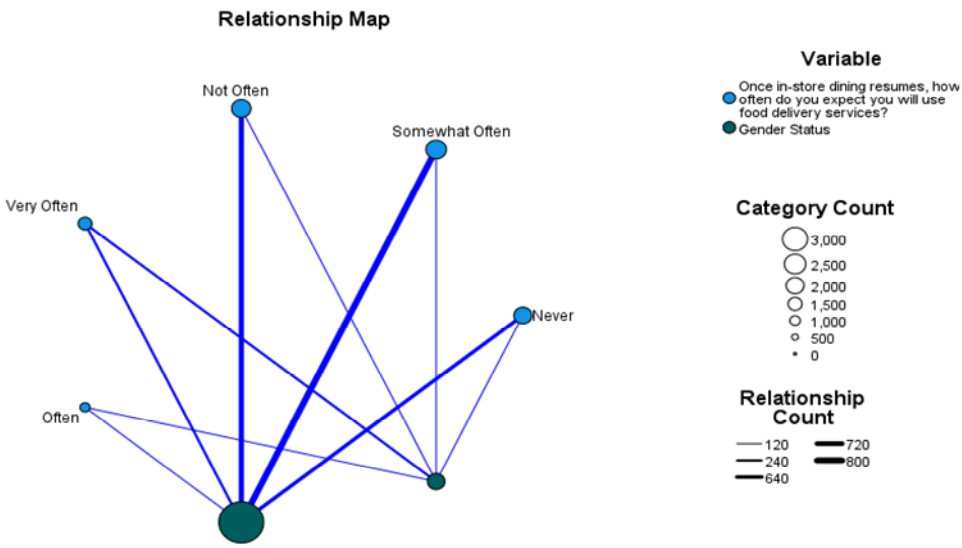


Figure 5 Relationship map between gender (females denoted by larger circle) once a vaccine is widely available, infection rates decrease and in-store dining resumes, how confident are you that restaurants will continue to take cleanliness seriously including heavy sanitation, extra space between tables, etc. (see online version for colours)

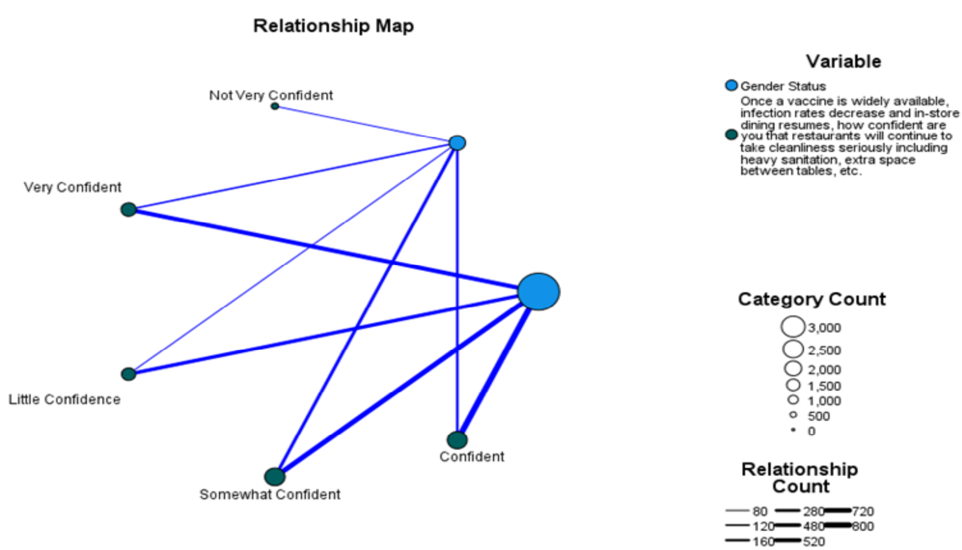


Table 2 Relevant statistics associated with the formal testing of H1 with of knowledge and perceived intrinsic/extrinsic motivational factors associated with food-ordering services as a function of gender

2.1 Crosstabulation counts

Once a vaccine is widely available, infection rates decrease and in-store dining resumes, how confident are you that restaurants will continue to take cleanliness seriously including heavy sanitation, extra space between tables, etc./gender status			*Access mobile applications (ordering food) per week*				*Total*
			1–5 times per week (not every day)	*6–7 times per week (usually once a day)*	*7–14 times per week (more than once a day)*	*I do not order food off of mobile applications*	
Not very confident	Gender status	Male	40			40	80
	Total		40			40	80
Little confidence	Gender status	Female	360		0	120	480
		Male	40		40	0	80
	Total		400		40	120	560
Somewhat confident	Gender status	Female	320	0		400	720
		Male	160	80		40	280
	Total		480	80		440	1,000
Confident	Gender status	Female	560	40	0	200	800
		Male	80	40	40	0	160
	Total		640	80	40	200	960
Very confident	Gender status	Female	400		0	120	520
		Male	80		40	0	120
	Total		480		40	120	640
Total	Gender status	Female	1,640	40	0	840	2,520
		Male	400	120	120	80	720
	Total		2,040	160	120	920	3,240

Notes: 2.1 – crosstabulation statistics of gender status with access mobile applications (ordering food) per week with once a vaccine is widely available, infection rates decrease and in-store dining resumes, how confident are you that restaurants will continue to take cleanliness seriously including heavy sanitation, extra space between tables, etc. followed by 2.2 – chi-square testing results.

[a]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 26.67.

[b]denotes no statistics are computed because Gender Status is a constant.

[c]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 5.71.

[d]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 22.40.

[e]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 6.67.

[f]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 7.50.

HS denotes highly significant at the 0.01 level for a two-tailed test.

Table 2 Relevant statistics associated with the formal testing of H1 with of knowledge and perceived intrinsic/extrinsic motivational factors associated with food-ordering services as a function of gender (continued)

2.2 Chi-square test results				
Once a vaccine is widely available, infection rates decrease and in-store dining resumes, how confident are you that restaurants will continue to take cleanliness seriously including heavy sanitation, extra space between tables, etc./statistics		*Value*	*df*	*Asymptotic significance (two-sided)*
Not very confident	Pearson chi-square	.[b]		
	N of valid cases	80		
Little confidence	Pearson chi-square	266.000[c]	2	<0.001 (HS)
	Likelihood ratio	199.264	2	<0.001 (HS)
	N of valid cases	560		
Somewhat confident	Pearson chi-square	290.524[d]	2	<0.001 (HS)
	Likelihood ratio	306.773	2	<0.001 (HS)
	N of valid cases	1,000		
Confident	Pearson chi-square	312.000[e]	3	<0.001 (HS)
	Likelihood ratio	271.908	3	<0.001 (HS)
	N of valid cases	960		
Very confident	Pearson chi-square	202.393[f]	2	<0.001 (HS)
	Likelihood ratio	185.161	2	<0.001 (HS)
	N of valid cases	640		
Total	Pearson chi-square	783.316[a]	3	<0.001 (HS)
	Likelihood ratio	689.677	3	<0.001 (HS)
	N of valid cases	3,240		

Notes: 2.1 – crosstabulation statistics of gender status with access mobile applications (ordering food) per week with once a vaccine is widely available, infection rates decrease and in-store dining resumes, how confident are you that restaurants will continue to take cleanliness seriously including heavy sanitation, extra space between tables, etc. followed by 2.2 – chi-square testing results.

[a]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 26.67.

[b]denotes no statistics are computed because Gender Status is a constant.

[c]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 5.71.

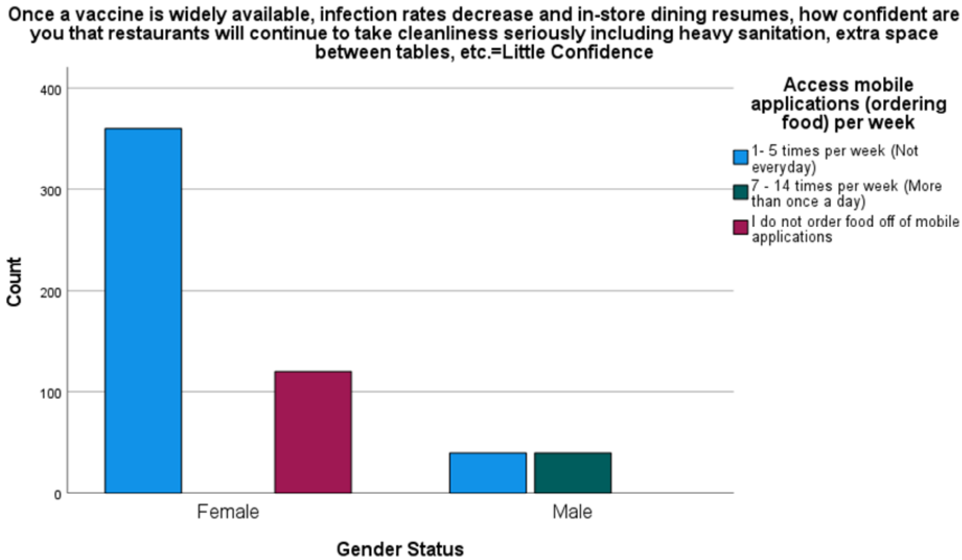
[d]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 22.40.

[e]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 6.67.

[f]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 7.50.

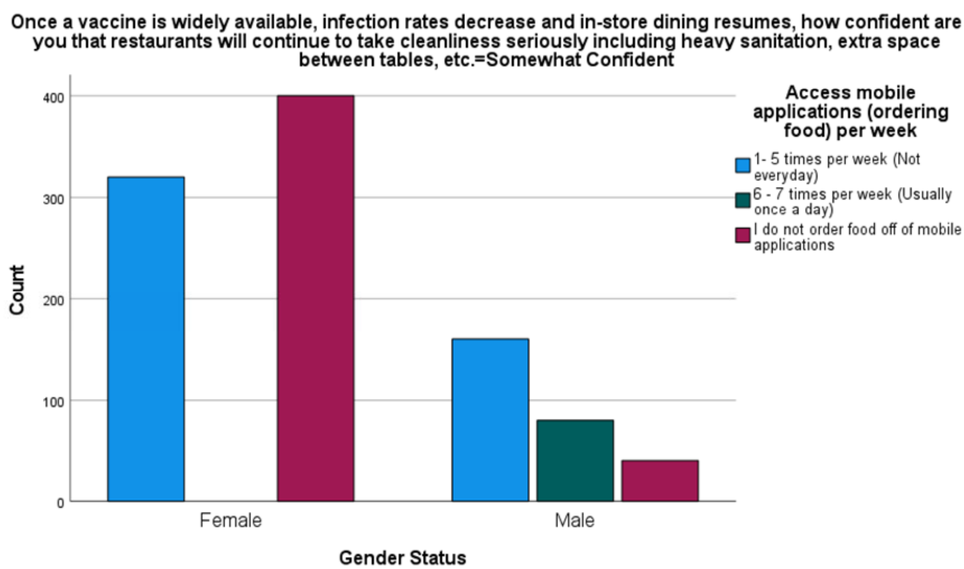
HS denotes highly significant at the 0.01 level for a two-tailed test.

Figure 6 Crosstabulation among gender, once vaccine widely available, with access mobile applications (ordering food) per week (see online version for colours)



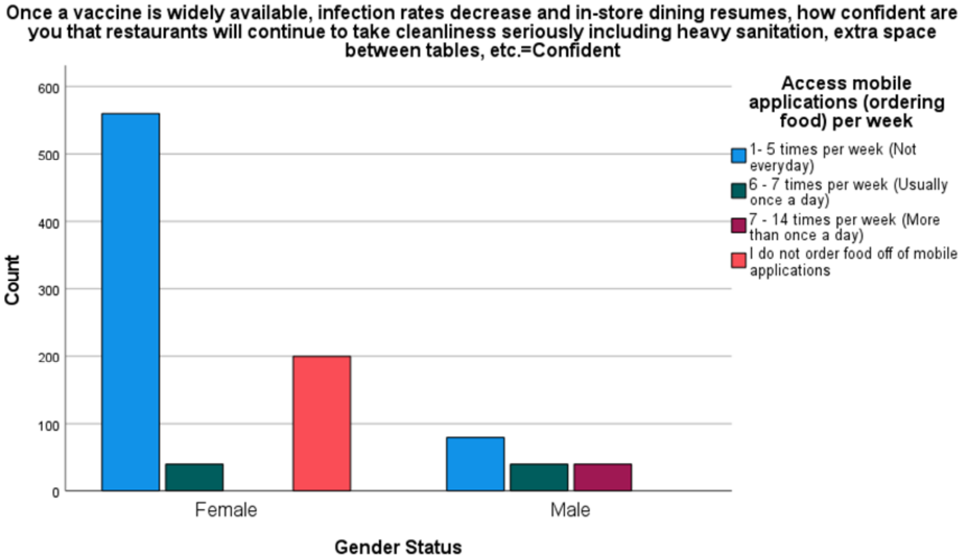
Note: Little confidence with in-store dining.

Figure 7 Crosstabulation among gender, once vaccine widely available, with access mobile applications (ordering food) per week (see online version for colours)



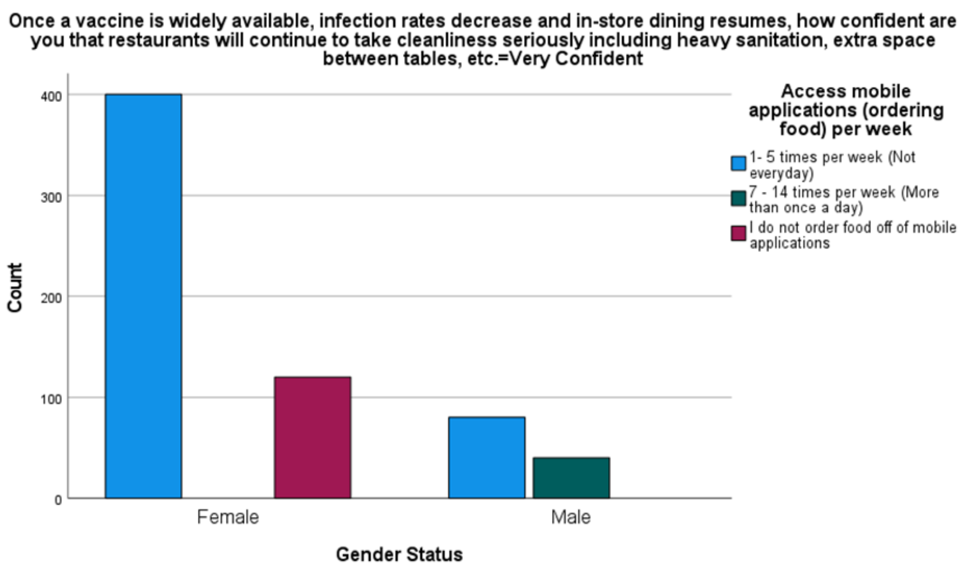
Note: Somewhat confidence with in-store dining.

Figure 8 Crosstabulation among gender, once vaccine widely available, with access mobile applications (ordering food) per week (see online version for colours)



Note: Confident with in-store dining.

Figure 9 Crosstabulation among gender, once vaccine widely available, with access mobile applications (ordering food) per week (see online version for colours)



Note: Very confident with in-store dining.

H2 Knowledge and perceived intrinsic/extrinsic motivational factors (i.e., accessibility of mobile food apps coupled with employment status) are significantly related to age differences. Employment status is used as a measure of financial resources and time restrictions making the use of mobile apps for food order more appealing.

Table 3 Relevant statistics associated with the formal testing of H2 with of knowledge and perceived intrinsic/extrinsic motivational factors associate with food-order services as a function of age

3.1 Crosstabulation counts

Access mobile applications (ordering food) per week/coding scheme			*Employment status*			*Total*
			Full-time employment	*Part-time employment*	*Unemployed*	
1–5 times per week (not every day)	Age range	18–30	160	840	0	1,000
		31–40	160	40	0	200
		41–50	240	0	0	240
		51–60	280	80	80	440
		61+	80	5	75	160
	Total	920	965	155	2,040	
6–7 times per week (usually once a day)	Age range	18–30	0	40		40
		31–40	80	40		120
	Total	80	80		160	
7–14 times per week (more than once a day)	Age range	18–30	40	40		80
		41–50	40	0		40
	Total	80	40		120	
I do not order food off of mobile applications	Age range	18–30	40	320	0	360
		31–40	40	0	0	40
		41–50	120	0	0	120
		51–60	120	0	0	120
		61+	40	0	240	280
	Total	360	320	240	920	
Total	Age range	18–30	240	1,240	0	1,480
		31–40	280	80	0	360
		41–50	400	0	0	400
		51–60	400	80	80	560
		61+	120	5	315	440
	Total	1,440	1,405	395	3,240	

Notes: 3.1 – crosstabulation statistics of age range by employment status by access mobile applications (ordering food) per week followed by 3.2 – chi-square testing results.
[a]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 43.89.
[b]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 12.16.
[c]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 20.00.
[d]denotes computed only for a 2 × 2 contingency table.
[e]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 13.33.
[f]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 10.43.
HS denotes highly significant at the 0.01 level for a two-tailed test.

Table 3 Relevant statistics associated with the formal testing of H2 with of knowledge and perceived intrinsic/extrinsic motivational factors associate with food-order services as a function of age (continued)

3.2 Chi-square test results

Access mobile applications (ordering food) per week/statistics		*Value*	*df*	*Asymptotic significance (two-sided)*	*Exact sig. (two-sided)*	*Exact sig. (one-sided)*
1–5 times per week (not every day)	Pearson chi-square	1,510.321[b]	8	<0.001 (HS)		
	Likelihood ratio	1,571.615	8	<0.001 (HS)		
	N of valid cases	2,040				
6–7 times per week (usually once a day)	Pearson chi-square	53.333[c]	1	<0.001 (HS)		
	Continuity correction[d]	50.700	1	<0.001 (HS)		
	Likelihood ratio	69.044	1	<0.001 (HS)		
	Fisher's exact test				<0.001 (HS)	<0.001 (HS)
	N of valid cases	160				
7–14 times per week (more than once a day)	Pearson chi-square	30.000[e]	1	<0.001 (HS)		
	Continuity correction[d]	27.792	1	<0.001 (HS)		
	Likelihood ratio	41.860	1	<0.001 (HS)		
	Fisher's exact test				<0.001 (HS)	<0.001 (HS)
	N of valid cases	120				

Notes: 3.1 – crosstabulation statistics of age range by employment status by access mobile applications (ordering food) per week followed by 3.2 – chi-square testing results.

[a]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 43.89.

[b]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 12.16.

[c]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 20.00.

[d]denotes computed only for a 2 × 2 contingency table.

[e]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 13.33.

[f]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 10.43.

HS denotes highly significant at the 0.01 level for a two-tailed test.

Table 3 Relevant statistics associated with the formal testing of H2 with of knowledge and perceived intrinsic/extrinsic motivational factors associate with food-order services as a function of age (continued)

3.2 Chi-square test results

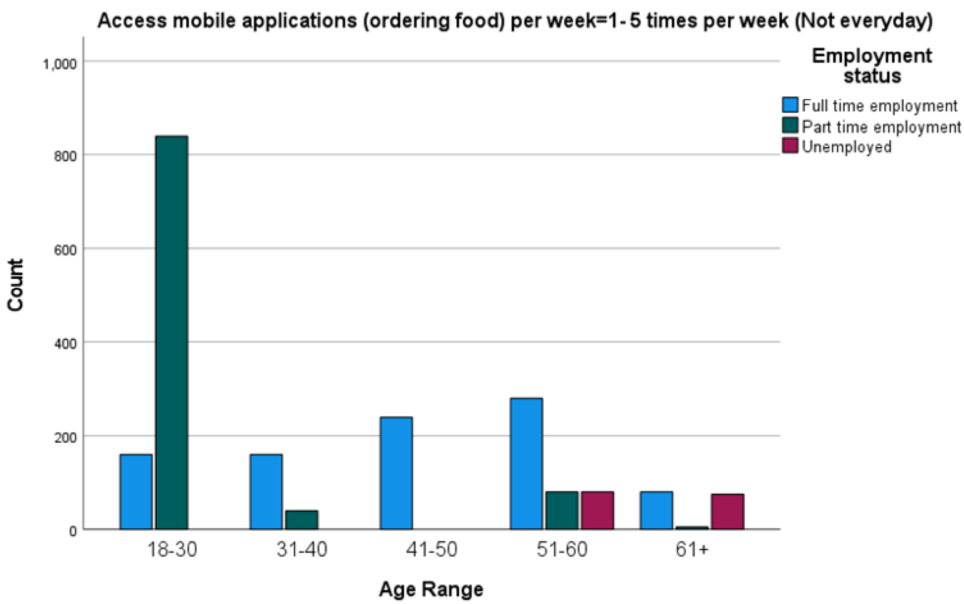
Access mobile applications (ordering food) per week/statistics		*Value*	*df*	*Asymptotic significance (two-sided)*	*Exact sig. (two-sided)*	*Exact sig. (one-sided)*
I do not order food off of mobile applications	Pearson chi-square	1,427.866[f]	8	<0.001 (HS)		
	Likelihood ratio	1,515.596	8	<0.001 (HS)		
	N of valid cases	920				
Total	Pearson chi-square	3,360.849[a]	8	<0.001 (HS)		
	Likelihood ratio	3,193.455	8	<0.001 (HS)		
	N of valid cases	3,240				

Notes: 3.1 – crosstabulation statistics of age range by employment status by access mobile applications (ordering food) per week followed by 3.2 – chi-square testing results.
[a]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 43.89.
[b]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 12.16.
[c]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 20.00.
[d]denotes computed only for a 2 × 2 contingency table.
[e]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 13.33.
[f]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 10.43.
HS denotes highly significant at the 0.01 level for a two-tailed test.

Employment status is certainly an indicator of the ability to afford such food-order apps and need for food preparation when work pressures reduce the time allocated for such activities. Technological sophistication and comfort level to take advantage of such mobile apps should vary as a function of age. As displayed in Table 3 and Figure 10, respectively, are the statistical and graphical results of crosstabulating education, age, and frequency of payment in order to formally test H2. Figure 10 dramatically illustrates the crosstabulation among employment status, age range, with access mobile applications (ordering food) per week for 1–5 times per week or not every day. As evident from Table 3, the largest proportion of respondents were in the 18–30 age range with 240 employed full-time, 1,240 employed part-time, and with no unemployment. The other age groups were well represented with the second largest group between 51–60 years old with 400 employed full-time, 80 employed part-time, and 80 unemployed.

The relevant statistics indicated that there was a highly significant relation among these interacting variables. For example, at the different levels of mobile app use for food-ordering, all levels of app usage and/or non-usage were found to be significant at the 0.001 level (1–5 times per week, not every day, chi-square = 1,510.321, n = 2,040; 6–7 times per week, usually once a day, chi-square = 53.333, n = 160; 7–14 times per week or more than once a day, chi-square = 30.000, n = 120; having a total relationship with chi-square = 3,360.848, n = 3,240). As evident by the graphical crosstabulation for the most common mobile app usage of 1–5 times per week, it was clearly higher for the younger 18–30 age group, with greater proportion of respondents employed full-time in the older age groups and still relative active with using the mobile food-order app. In short, younger adults are very active with mobile apps as expected and using such apps were dominated by part-time employment (note none of the youngest age group were unemployed, but the last two older groups, as expected, had significantly higher proportional levels of unemployment). Overall, H2 was accepted at the 0.001 level.

Figure 10 Crosstabulation among employment status, age range, with access mobile applications (ordering food) per week (see online version for colours)



Note: 1–5 times per week.

H3 The relatively complex interactions among app preference versus employment status and accessibility to mobile applications have a significant impact on the type of food-order app/customer service choices. Less than full-time employment may impact food-ordering delivery usage in different than full-time employment as a function of accessibility to such mobile apps.

As displayed in Table 4 and Figures 11–14, respectively, are the statistical and graphical results of crosstabulating app preference versus employment status and accessibility to mobile applications in order to formally test H3. To illustrate the conceptual complexity of app preference versus employment status and accessibility to mobile applications, Figure 11 displays app preference (DoorDash), Figure 12 app preference (Grubhub), Figure 13 app preference (no preference), and Figure 14 app preference (UberEats). As illustrated in table, the total relationship was found to be highly significant (chi-square

= 262.972, $p < 0.001$). The same result was found to be true for the various options of food-ordering app usage options [(DoorDash, chi-square = 263.148, $p < 0.001$), (Grubhub, chi-square = 80.00, $p < 0.001$), (UberEats, chi-square = 1,320.0, $p < 0.001$), and (none, chi-square = 31.748, $p < 0.001$)]. To better visualise the complexity of the crosstabulations, Figures 11–14 are good reference guides. As displayed in Figure 11, full-time employment status was associated with DoorDash for the two groups of accessibility of mobile apps for order of not everyday (1–5 times per week) and not ordering any food per week via a mobile app. Part-time employment status was found to be for produced with more frequent use of the DoorDash app for the usually once per day (6–7 times per week) and more than once a day (7–14 times per week) groups. By far the most popular option was working part-time, followed by full-time employment status for the not everyday users (1–5 times per week).

As for the other options of food-ordering apps, interesting relationships appear in the reaming graphs displayed in Figures 12–14. True, as demonstrated in Figure 12 (Grubhub preference), the not everyday option was the most popular (as with the preference for DoorDash), but for this group, employment status was not a factor (both part-time and full-time groups were essentially equal in frequency). When comparing this trend with UberEats (Figure 14), the overall counts of preference for this option were greatly lower than DoorDash and/or Grubhub, the most popular option was the not everyday user (1–5 times per week). Although there were a greater portion of full-timers in terms of employment option within not everyday group, there were a significant presence of part-timers. The everyday users were only part-timers, but still a fairly unpopular food-order option.

Lastly, the not to use online food-order option, the next most popular option, second only to DoorDash, is illustrated in Figure 13. Interestingly, the only two groups present were the not everyday (1–5 times per week) and the do not order food off of mobile apps (probably those that prefer to the various delivery options to directly call in their orders). In both groups, a dominate presence of full-time employment status in the not everyday group and, although the most in the do not use mobile apps for ordering food, the three groups of employment status (i.e., full-time, part-time and not employed respondents) were presented in this group. In fact, essentially the entire unemployed sample was also found in this option and no use of mobile apps group.

Evidently, DoorDash was the commonly preferred options, especially by the not everyday and do not typically use mobile apps groups, followed by Grubhub, and UberEats. It is unmistakable that such food order delivery options are popular, and are probably here to stay, long after the initial fears of the COVID-19 pandemic. Mobile apps are the most popular to accessing these food-order and delivery service, but it is not the only way. Employment status definitely has an impact of the use of these services, regardless of using certain mobile apps or not. It would be truly just speculation of why DoorDash is some popular as choice among the various mobile apps' options. Perhaps, its presence was initially well-established, had better name/brand recognition, advertised more, or because the company had developed initial agreements with restaurant earlier in the pandemic. That would be an interesting research questions for future directions of research. As with the previous two specific research hypotheses, H3 is accepted at the $p < 0.001$ level. However, the relationships are apparently fairly complex. It is a mixed set of demographic trends that lead to that decision. The exploratory factor analysis found in the testing of H3 should shed some light on these complexities.

Table 4 Relevant statistics associated with the formal testing of H3 with of knowledge and perceived intrinsic/extrinsic motivational factors as a function of gender

4.1 Crosstabulation counts

App preferences/coding scheme			*Employment status*			*Total*
			Full-time employment	*Part-time employment*	*Unemployed*	
DoorDash	Access mobile applications (ordering food) per week	1–5 times per week (not every day)	360	640	40	1,040
		6–7 times per week (usually once a day)	80	0	0	80
		7–14 times per week (more than once a day)	80	40	0	120
		I do not order food off of mobile applications	0	120	0	120
	Total		520	800	40	1,360
Grubhub	Access mobile applications (ordering food) per week	1–5 times per week (not every day)	80	80		160
		6–7 times per week (usually once a day)	0	40		40
		I do not order food off of mobile applications	40	0		40
	Total		120	120		240

Notes: 4.1 – crosstabulation statistics of access mobile applications (ordering food) per week by app preference by employment status by app preferences followed by 4.2 – chi-square testing results.
[a]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 14.63.
[b]denotes 3 cells (25.0%) have expected count less than 5. The minimum expected count is 2.35.
[c]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 20.00.
[d]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 137.88.
HS denotes highly significant at the 0.01 level for a two-tailed test.

Table 4 Relevant statistics associated with the formal testing of H3 with of knowledge and perceived intrinsic/extrinsic motivational factors as a function of gender (continued)

4.1 Crosstabulation counts

App preferences/coding scheme			*Employment status*			*Total*
			Full-time employment	*Part-time employment*	*Unemployed*	
None	Access mobile applications (ordering food) per week	1–5 times per week (not every day)	320	125	115	560
		I do not order food off of mobile applications	320	200	240	760
	Total		640	325	355	1,320
UberEats	Access mobile applications (ordering food) per week	1–5 times per week (not every day)	160	120		280
		6–7 times per week (usually once a day)	0	40		40
	Total		160	160		320
Total	Access mobile applications (ordering food) per week	1–5 times per week (not every day)	920	965	155	2,040
		6–7 times per week (usually once a day)	80	80	0	160
		7–14 times per week (more than once a day)	80	40	0	120
		I do not order food off of mobile applications	360	320	240	920
	Total		1,440	1,405	395	3,240

Notes: 4.1 – crosstabulation statistics of access mobile applications (ordering food) per week by app preference by employment status by app preferences followed by 4.2 – chi-square testing results.
[a]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 14.63.
[b]denotes 3 cells (25.0%) have expected count less than 5. The minimum expected count is 2.35.
[c]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 20.00.
[d]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 137.88.
HS denotes highly significant at the 0.01 level for a two-tailed test.

Table 4 Relevant statistics associated with the formal testing of H3 with of knowledge and perceived intrinsic/extrinsic motivational factors as a function of gender (continued)

4.2 Chi-square test results						
App preferences/statistics		*Value*	*df*	*Asymptotic significance (two-sided)*	*Exact sig. (two-sided)*	*Exact sig. (one-sided)*
DoorDash	Pearson chi-square	263.148[b]	6	<0.001 (HS)		
	Likelihood ratio	332.293	6	<0.001 (HS)		
	N of valid cases	1,360				
Grubhub	Pearson chi-square	80.000[c]	2	<0.001 (HS)		
	Likelihood ratio	110.904	2	<0.001 (HS)		
	N of valid cases	240				
None	Pearson chi-square	31.748[d]	2	<0.001 (HS)		
	Likelihood ratio	32.017	2	<0.001 (HS)		
	N of valid cases	1,320				
UberEats	Pearson chi-square	45.714[c]	1	<0.001 (HS)		
	Continuity correction[e]	43.457	1	<0.001 (HS)		
	Likelihood ratio	61.186	1	<0.001 (HS)		
	Fisher's exact test				<0.001 (HS)	<0.001 (HS)
	N of valid cases	320				
Total	Pearson chi-square	262.972[a]	6	<0.001 (HS)		
	Likelihood ratio	265.894	6	<0.001 (HS)		
	N of valid cases	3,240				

Notes: 4.1 – crosstabulation statistics of access mobile applications (ordering food) per week by app preference by employment status by app preferences followed by 4.2 – chi-square testing results.
[a]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 14.63.
[b]denotes 3 cells (25.0%) have expected count less than 5. The minimum expected count is 2.35.
[c]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 20.00.
[d]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 137.88.
HS denotes highly significant at the 0.01 level for a two-tailed test.

H4 The relatively complex interactions among respondents based on residency (location) and accessibility to mobile applications have a significant impact on the type of food-order app/customer service choices. Potential customers in more rural environments may typically have less experience and technical sophistication with such delivery services than their more urban and suburban counterparts.

Figure 11 Crosstabulation among employment status, access mobile applications (ordering food) per week with app preference (DoorDash) (see online version for colours)

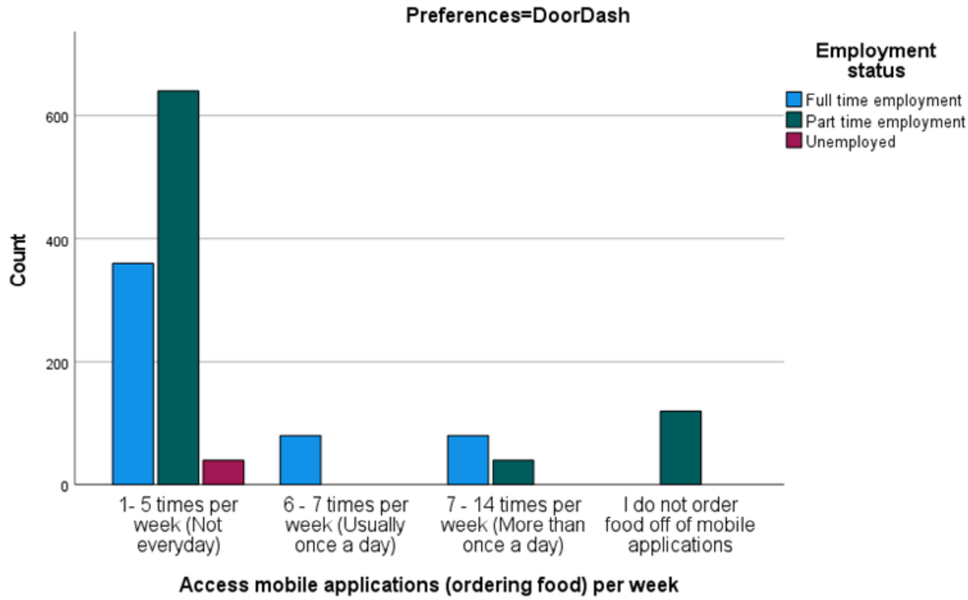


Figure 12 Crosstabulation among employment status, access mobile applications (ordering food) per week with app preference (Grubhub) (see online version for colours)

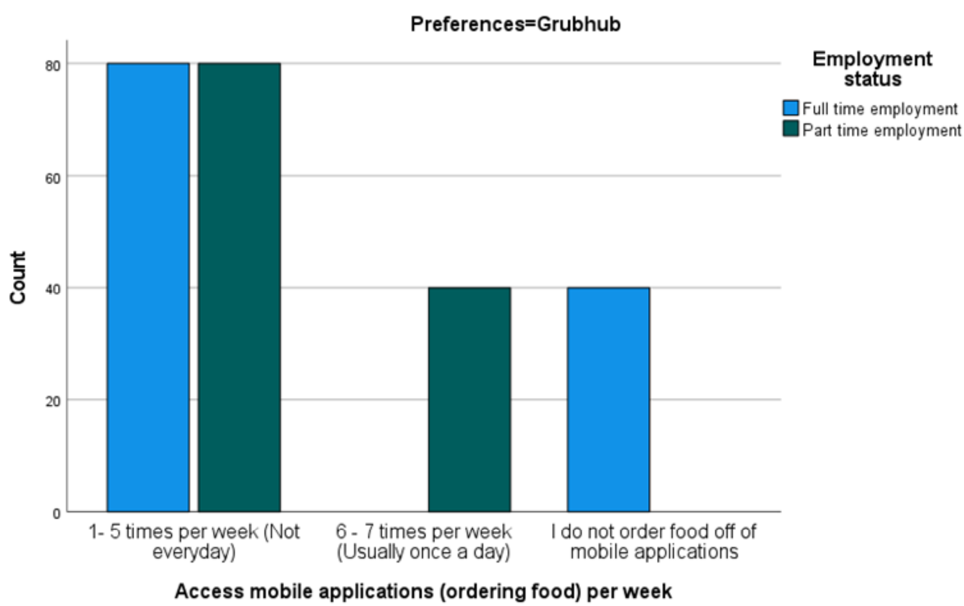


Figure 13 Crosstabulation among employment status, access mobile applications (ordering food) per week with app preference (no app preferences) (see online version for colours)

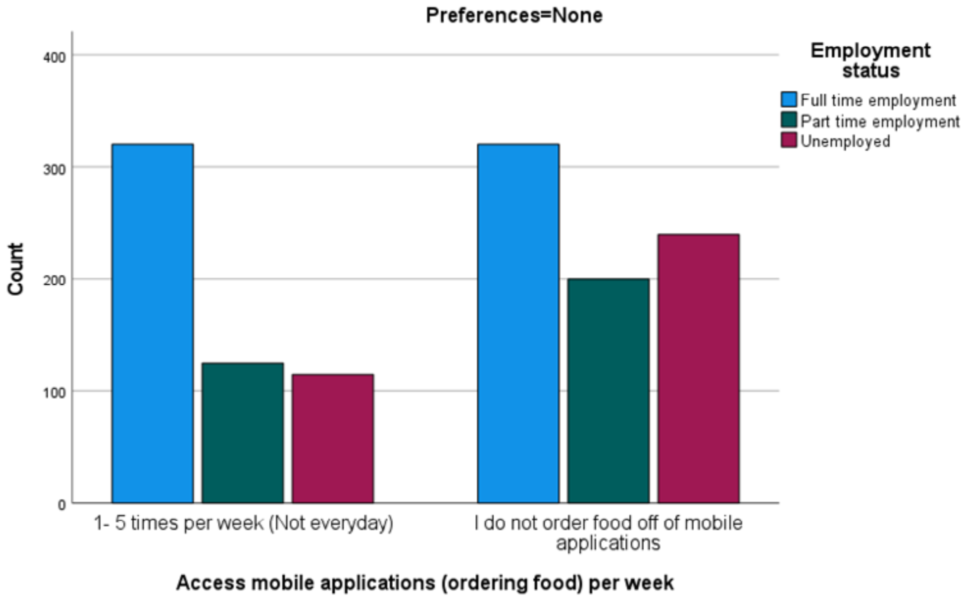
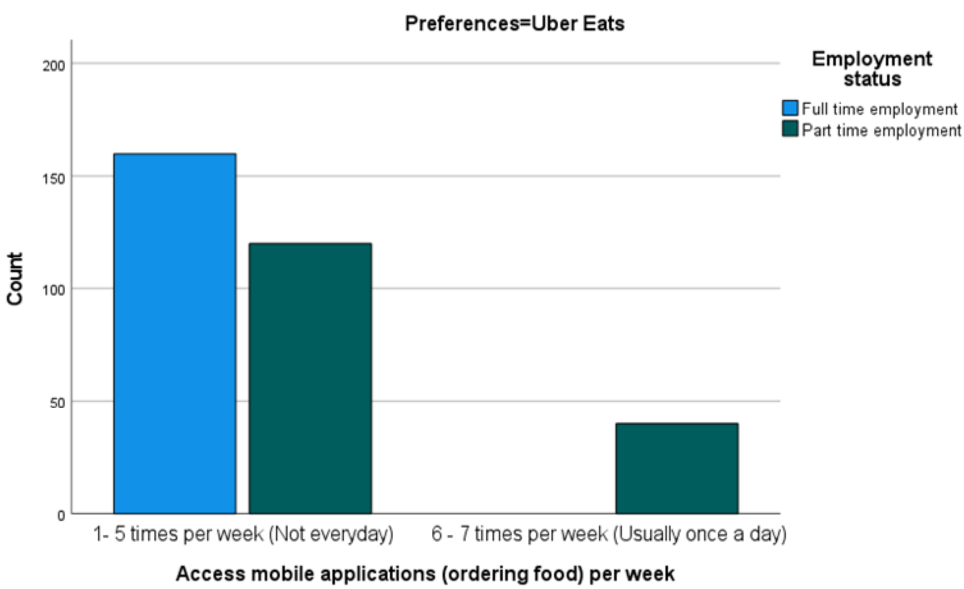


Figure 14 Crosstabulation among employment status, access mobile applications (ordering food) per week with app preference (UberEats) (see online version for colours)



To adequate test H4, a number or related statistical methods that were established in testing H1–H3 were brought to bear on testing H4, namely chi-square and graphical cross-tabulations. As illustrated in Table 5 and Figures 15–17, respectively, are the statistical and graphical results of crosstabulating of these variables [i.e., access mobile applications (ordering food) per week by employment status by general location] selected to test H4. It is hypothesised that accessibility to such food-order services are significantly impacted by employment status and residency. Urban and suburban environments have characteristically different internet connectivity and familiarity to mobile apps and customer deliveries than compared to their more rural counterparts. Since chi-square is essentially a non-directional test with less statistical power, the sample size is large enough that even greatly reduced effect sizes should pick up these relatively subtle differences. As clearly displayed in Figures 14–17, are the crosstabulations of employment status, access mobile applications (ordering food) per week with residency/location for rural area residents (Figure 15), for suburban area residents (Figure 16), and urban area residents (Figure 17). As with the other specific research hypotheses, the total relation was found (Table 5) to be highly significant as well (chi-square = 262.972, $p < 0.001$). The various levels of residency were also found to be equally significant [rural area (more than 30-miles from a city), chi-square = 54.545, $p < 0.001$, n = 600; suburban area (within a 30-mile radius from a city), chi-square = 604.621, $p < 0.001$, n = 1.760; urban area (within a 5-mile radius from a city), chi-square = 297.257, $p < 0.001$, n = 880].

As shown in Figure 15, when dealing with rural areas (more than 30 miles from a city) the two basic groups that dominated as in H1-H3 were the not everyday (1–5 times a week) and not order food via a mobile app, these residents where dominated by full-time employment status, followed by significantly less with part-time employment. Only the first group (not everyday) had a significant number of unemployed respondents. It seems, as expected, that rural areas are more isolated from traditional sources of prepared food and depend on mobile apps for food-ordering services (not everyday) to drastically more for the sample that typically do not use mobile apps for such food-ordering and delivery services.

As the data in Figure 16 present for the suburban area residents, the trends do significantly change as compared to their rural counterparts. The strong showing of full employment is the major characteristic for the not everyday (1–5 times a week) for using food-ordering delivery services, the part-time employment for this group was nearly the same in terms of numbers of respondents. The opposite was true for suburbanites as compared to the rural areas in the only showing of the unemployed was in the typically do not use food-ordering mobile apps to take advantage of such prepared food ordering services. As for residents in urban areas, full-time employed workers were represented in all four of the food-ordering delivery services, with part-time workers being the dominate category for the not using mobile apps to order prepared food. This trend is not found in the other residency options. Perhaps urban workers have easier or less technically sophisticated methods of calling in food orders. Overall, food ordering and delivery services. Hence, the complexity of employment and accessibility factors, combined with residency, offer insights to the acceptance of food-ordering and delivery industry among consumers. The results of formally testing H4 leads to the acceptance of this specific research hypothesis at $p < 0.001$.

Table 5 Relevant statistics associated with the formal testing of H4 with of knowledge and perceived intrinsic/extrinsic motivational factors associated with food-order services as a function of employment and residency

5.1 Crosstabulation counts

General location (residency)/coding scheme			*Employment status*			*Total*
			Full-time employment	*Part-time employment*	*Unemployed*	
Rural area (more than 30 miles from a city ex. Pittsburgh)	Access mobile applications (ordering food) per week	1–5 times per week (not every day)	200	80	40	320
		I do not order food off of mobile applications	240	40	0	280
	Total		440	120	40	600
Suburban area (within a 30-mile radius from a city ex. Pittsburgh)	Access mobile applications (ordering food) per week	1–5 times per week (not every day)	560	520	80	1,160
		6–7 times per week (usually once a day)	0	80	0	80
		7–14 times per week (more than once a day)	0	40	0	40
		I do not order food off of mobile applications	80	160	240	480
	Total		640	800	320	1,760
Urban area (within a 5-mile radius from a city ex. Pittsburgh)	Access mobile applications (ordering food) per week	1–5 times per week (not every day)	160	365	35	560
		6–7 times per week (usually once a day)	80	0	0	80
		7–14 times per week (more than once a day)	80	0	0	80

Notes: 5.1 – access mobile applications (ordering food) per week by employment status by general residency or location crosstabulation, followed by 5.2 – chi-square testing results.
[a]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 14.63.
[b]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 18.67.
[c]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 7.27.
[d]denotes 2 cells (16.7%) have expected count less than 5. The minimum expected count is 3.18.
HS denotes highly significant at the 0.01 level for a two-tailed test.

Table 5 Relevant statistics associated with the formal testing of H4 with of knowledge and perceived intrinsic/extrinsic motivational factors associated with food-order services as a function of employment and residency (continued)

5.1 Crosstabulation counts

General location (residency)/coding scheme			*Employment status*			*Total*
			Full-time employment	*Part-time employment*	*Unemployed*	
Urban area (within a 5-mile radius from a city ex. Pittsburgh)	Access mobile applications (ordering food) per week	I do not order food off of mobile applications	40	120	0	160
	Total	360	485	35	880	
Total	Access mobile applications (ordering food) per week	1–5 times per week (not every day)	920	965	155	2,040
		6–7 times per week (usually once a day)	80	80	0	160
		7–14 times per week (more than once a day)	80	40	0	120
		I do not order food off of mobile applications	360	320	240	920
	Total		1,440	1,405	395	3,240

5.2 Chi-square test results

General (residency) location/statistics		*Value*	*df*	*Asymptotic significance (two-sided)*
Rural area (more than 30-miles from a city ex. Pittsburgh)	Pearson chi-square	54.545[b]	2	<0.001 (HS)
	Likelihood ratio	70.016	2	<0.001 (HS)
	N of valid cases	600		
Suburban area (within a 30-mile radius from a city ex. Pittsburgh)	Pearson chi-square	604.621[c]	6	<0.001 (HS)
	Likelihood ratio	598.540	6	<0.001 (HS)
	N of valid cases	1,760		

Notes: 5.1 – access mobile applications (ordering food) per week by employment status by general residency or location crosstabulation, followed by 5.2 – chi-square testing results.

[a]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 14.63.

[b]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 18.67.

[c]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 7.27.

[d]denotes 2 cells (16.7%) have expected count less than 5. The minimum expected count is 3.18.

HS denotes highly significant at the 0.01 level for a two-tailed test.

Table 5 Relevant statistics associated with the formal testing of H4 with of knowledge and perceived intrinsic/extrinsic motivational factors associated with food-order services as a function of employment and residency (continued)

5.2 Chi-square test results				
General (residency) location/statistics		*Value*	*df*	*Asymptotic significance (two-sided)*
Urban area (within a 5-mile radius from a city ex. Pittsburgh)	Pearson chi-square	297.257[d]	6	<0.001 (HS)
	Likelihood ratio	359.787	6	<0.001 (HS)
	N of valid cases	880		
Total	Pearson chi-square	262.972[a]	6	<0.001 (HS)
	Likelihood ratio	265.894	6	<0.001 (HS)
	N of valid cases	3,240		

Notes: 5.1 – access mobile applications (ordering food) per week by employment status by general residency or location crosstabulation, followed by 5.2 – chi-square testing results.
[a]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 14.63.
[b]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 18.67.
[c]denotes 0 cells (0.0%) have expected count less than 5. The minimum expected count is 7.27.
[d]denotes 2 cells (16.7%) have expected count less than 5. The minimum expected count is 3.18.
HS denotes highly significant at the 0.01 level for a two-tailed test.

Figure 15 Crosstabulation among employment status, access mobile applications (ordering food) per week with residency/location (rural area) (see online version for colours)

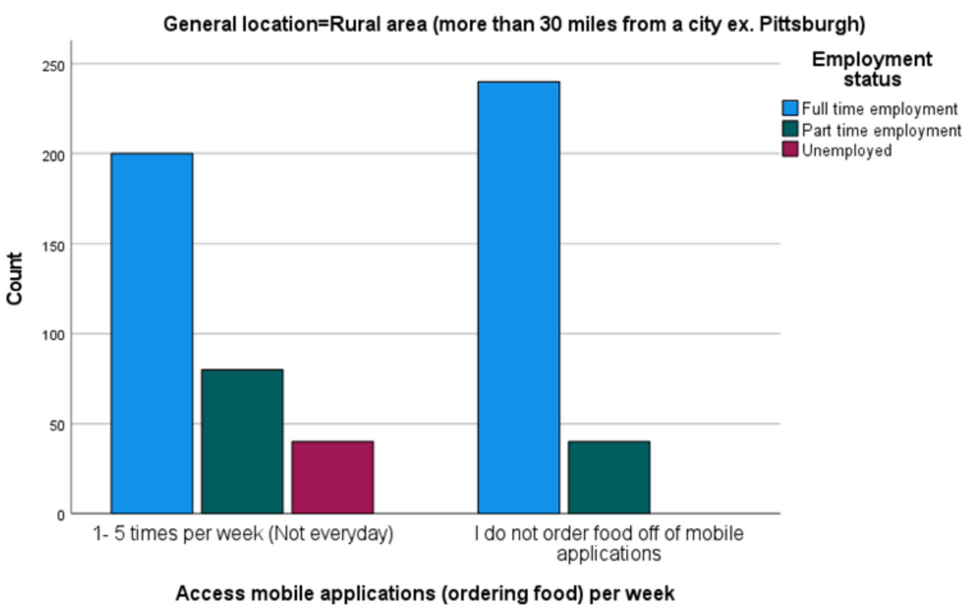


Figure 16 Crosstabulation among employment status, access mobile applications (ordering food) per week with residency/location (suburban area) (see online version for colours)

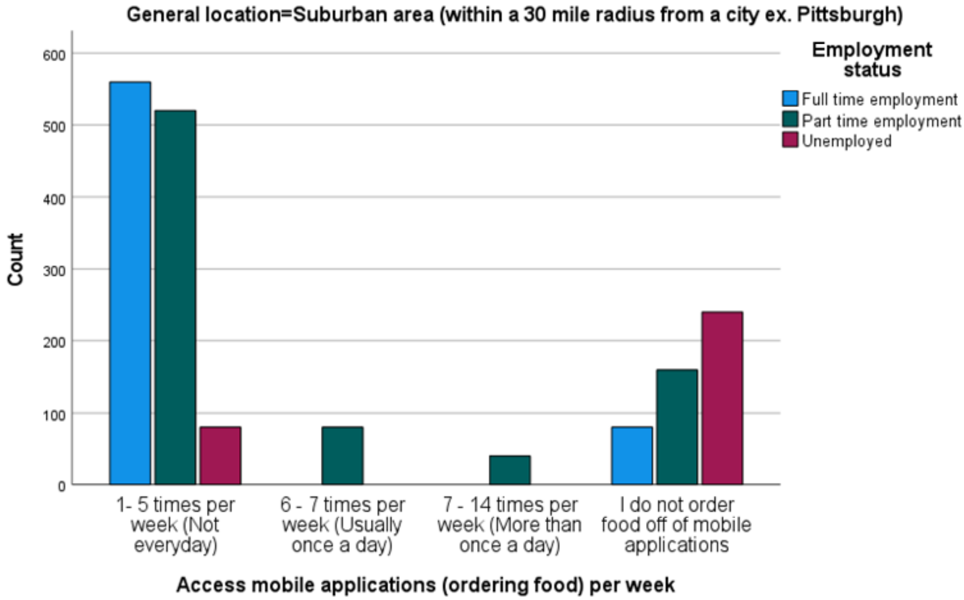
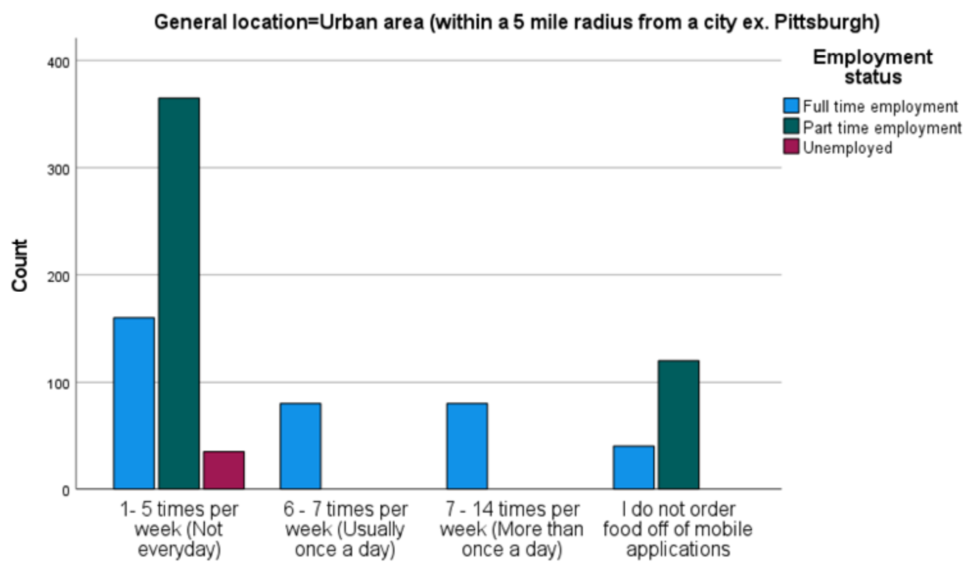


Figure 17 Crosstabulation among employment status, access mobile applications (ordering food) per week with residency/location (urban area) (see online version for colours)



5 Managerial implications

The initial survey (available upon request) started with demographic questions to get an understanding of the general characteristics of the potential respondents. The roles of gender, age, and residency status were compared with access ability to the internet, and type of mobile app options. The four specific research hypotheses provided a glimpse into the complexities of how these variables interacted with each other. It was obvious from the descriptive statistics that the pandemic greatly accelerated the use of food-order and delivery services, both for basic groceries and prepared food items. The presently primarily concentrated on prepared food items, but some respondents may have included groceries as well, but to a very slight degree.

As the various specific research hypotheses were found to be all highly significant, there are a number of profound and important demographic questions when understanding consumer behaviour and its preference for online delivery means. These included residency or location (specifically distance from a city) and respondents' age, gender, and degrees of sophistication with and accessibility with mobile apps. Even with age ranges, as older groups are less comfortable with mobile apps with ordering prepared food from the major vendors, they found a way to order the food items they desired (typically through the internet and/or more commonly using the phone). Although income level was not directly tested, part-time (or unemployed – very small portion of the sample) or full-time employment certainly could serve as a proxy for income, interesting relationships were found. The complexities of food-order services were becoming popular before the global pandemic occurred, but the pandemic and related conditions about the clean and sterile environment that food is prepared and the viability associated with sit-down restaurants opened the door for the various services of DoorDash, UberEats, and Grubhub.

After basic demographics, technological usage and ease of use among consumers were important factors to consider. Again, the pandemic forced many consumers to find alternatives for order prepared food outside traditional restaurants. This research effort questioned many preconceived concepts of consumer usage of online food delivery services. The results derived from the formal testing the 4 specific research hypotheses and the descriptive statistics suggested that these food-ordering services will undoubtedly remain popular long after the global pandemic begins to significant subside. As dramatically illustrated in Table 1 (1.20), most respondents expected that food delivery apps/companies to grow post-pandemic period. Only 2.5% (n = 80) expected a large decline. Interestingly, only 14.8% (n = 440) expected some decline that vast majority expected some growth (49.4%, n = 1,600) or large growth in the industry (14.8%, n = 480). Hence, customer food delivery services (i.e., Grubhub, DoorDash, UberEats) have gained mush in popularity since March 2020. The vast majority of respondents felt that this trend will continue into 2022 and beyond. Nearly 65% of respondents thought that online food delivery services will continue to somewhat grow post-pandemic. Another 15%, believed that the industry will largely grow post pandemic.

As before the pandemic, during, and probably for a significant time after the pandemic, DoorDash will continue its dominance of the food-order industry. As the detailed analysis of the survey results indicated the importance of online customer delivery services throughout the pandemic and what people think post-pandemic life will look like in traditional restaurants – it tends to be positive. Although many respondents think that restaurants will not continue to keep superior levels of cleanliness post-pandemic/vaccine periods, they expected to see improvements in hygienic factors to support returning to traditional restaurants. However, certain face-to-face restaurants' traffic will probably never be the same as before the pandemic. Of course, only time will tell. Probably, customers will still use online delivery services post-pandemic period and the trend will likely grow in popularity. The convenience and trust that the online food ordering industry has built up a strong and loyal following. Based on results of the present study, online customer delivery services will be an acting part of our society post-pandemic for the foreseeable future. The ease-of-usage through technology (apps), convenience of delivery, limited error in the order process, and restaurants' cleanliness post-pandemic are focal points to the success of this industry in the future.

6 Conclusions

A detailed inspection and summary of the various descriptive and specific-hypotheses testing results have indicated that online ordering and delivery services will probably be here to stay during the post-pandemic period. It is recommended that mid-level managers should plan on keeping/making online delivery as a prominent option in the future. People of all ages and incomes are now aware of the ease-of-access to such delivery services and will, undoubtedly, continue to use them. There are complexities in the use of these technologies and it is not linear in decision-making thinking as demonstrated in part-time/full-time employment, residency status. Accessibility of technology, and age relationships associated with food-ordering options. As demonstrated in the hypotheses, although all were found to be highly significant and relevant, they are complex and not as simple as they may, at first, appear. Restaurant cleanliness will also be an important factor with strategies with mid-level managers in order to return to their business as usual. It will be important to incorporate companies like Grubhub, DoorDash, and UberEats into their business model. However, post-pandemic restaurants' cleanliness will be looked at with a keen eye by consumers so it will be important for businesses to continue, regardless of their customers' acceptance of food-order apps.

What happens as the post-pandemic period unfolds will be vital when companies such as Grubhub, DoorDash, and UberEats continue to push marketing and promotion campaigns that keep them present in the mind of the consumer. People will still be interested in the post-pandemic period in these services, but they will have more options to choose from. Hence, staying relevant to their potential customers will be very important for these companies. It would be wise for mid-level and upper managers of online delivery service companies to be thinking of campaigns that will outdo their delivery service counterparts in the future. The post-pandemic period, whether the market of online delivery grows or shrinks, the competition will be significantly higher for these customers. After recent successes of these companies, others will be looking to join the marketplace. There appears to be an ample opportunity for all newcomers. However, the reputation and market share currently held by the dominate DoorDash will be hard to beat.

COVID-19 has been a detriment to the entire world in providing healthy choices for people and has negatively impacted billions of people and the businesses that they depend upon. The pandemic has exposed underlying failures in health systems, supply chains' disruptions, geopolitical instability, and the role of business and government in the daily lives of its citizens. Life of everyday citizens will never be the same. However, it has afforded many opportunities as well. During the pandemic, it is hoped that whole societies have come together as a people with a common cause and have found new ways to remain safe and continue to live their lives to some form of normalcy. Part of this normalcy involves the emergence of online delivery services, QR codes to access a variety of services, and the need to take some degree of control for personal service quality. These services have exploded during the pandemic and many people have begun to learn and like the world of mobile/app/online delivery services. According to the statistical results and its interpretations within the present study, the online food ordering/delivery market will be taking up a significant part of the restaurant/food industry's marketplace for time to come.

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