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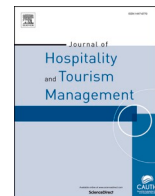
Factors affecting customer intention to use online food delivery services before and during the COVID-19 pandemic

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ABSTRACT

With the emerging popularity of online food delivery (OFD) services, this research examined predictors affecting customer intention to use OFD services amid the Coronavirus disease (COVID-19) pandemic. Specifically, Study 1 examined the moderating effect of the pandemic on the relationship between six predictors (perceived useful-ness, perceived ease of use, price saving benefit, time saving benefit, food safety risk perception, and trust) and OFD usage intention, and Study 2 extended the model by adding customer perceptions of COVID-19 (perceived severity and vulnerability) during the pandemic. Study 1 showed that all of the predictors except food safety risk perception significantly affected OFD usage intention, but no moderation effect of COVID-19 was found. In Study 2, while perceived severity and vulnerability had no significant impact on OFD usage intention, the altered ef-fects of socio-demographic variables during the COVID-19 pandemic were found. Theoretical and managerial implications are provided.

1. Introduction

The World Health Organization (WHO) declared the Coronavirus disease (COVID-19) a pandemic due to the high risk of fatality and human-to-human transmission on March 11, 2020 (World Health Or-ganization, 2020). Accordingly, the majority of U.S. states and their local ordinances issued stay-at-home or shelter-in-place orders and forced foodservice operations to be closed or restricted (Restaurant Law Center, 2020). The official orders have had harsh effects on the restau-rant industry, such as job losses and worst sales than other sectors (National Restaurant Association [NRA], 2020a). For example, by April 2020, more than 8 million employees working in the restaurant industry were furloughed, and consumption at restaurants/bars in April 2020 plummeted to the lowest level after October 1984 (NRA, 2020b).

As restaurants struggle to find ways to survive, online food delivery (OFD) services have recently gained high demands by delivering food and drinks to customers' doorstep (NPD, 2020). OFD services refer to internet-based food ordering and delivery systems that connect cus-tomers with partner restaurants via their websites or mobile applications (Ray, Dhir, Bala, & Kaur, 2019). Although the OFD market had signifi-cantly grown before the pandemic, more customers have utilized OFD services during the COVID-19 pandemic, as evidenced by a report by the

NPD Group, which revealed that the number of the OFD orders surged 67% in March 2020 compared to March 2019 (NPD, 2020).

To date, several researchers have provided a fundamental under-standing of OFD customers' decision-making process and their behav-ioral intentions including motivations to use OFD services (Yeo, Goh, & Rezaei, 2017) and factors affecting OFD usages (Ray, Dhir, Bala, & Kaur, 2019). However, it remains unclear whether the pandemic influences customers' substantial OFD purchasing behavior and decision-making process regarding OFD services. As the COVID-19 pandemic has had the most impact on recent human behavior changes (Laato, Islam, Far-ooq, & Dhir, 2020), it is salient to consider the COVID-19 pandemic as a contextual factor affecting customers' OFD usages (Kim, Kim, & Hwang, 2021). Furthermore, with several findings demonstrating that people who perceived health risks altered their actions in preventive ways (Ali, Harris, & Ryu, 2019; Cahyanto et al., 2016), more customers might utilize OFD services to avoid human contact with restaurant employees and other customers during and even post COVID-19 pandemic. How-ever, no research has considered the impact of customers' perceptions about the health risk on customer intention to use OFD during the COVID-19 pandemic.

In light of this, this study explores factors affecting customer inten-tion to use OFD services across two-time frames (before and during the

COVID-19 pandemic) and investigates how customer perceptions on the COVID-19 pandemic alter their relationships through two studies. Specifically, Study 1 investigates the prominent predictors affecting customer intention to use OFD before and during the COVID-19 pandemic and examines the moderating effect of the COVID-19 outbreak between the relationships. To better understand the high demand for OFD services during the pandemic, Study 2 incorporates customers' perceptions about the COVID-19 pandemic—perceived severity and perceived vulnerability—into the relationship between the predictors and customer intention to use OFD.

2. Literature review

2.1. Study 1

2.1.1. Online food delivery services

Online food delivery (OFD) refers to "the process whereby food that was ordered online is prepared and delivered to the consumer" (Li et al., 2020, p. 3). The proliferation of OFD services was supported by the development of integrated OFD platforms, such as Uber Eats, DoorDash, and Grubhub. When a customer places an order from various restaurant options through an OFD service platform on its mobile application or website and pays for the order, the restaurant receives the order and prepares the food. Then, a delivery driver delivers the order to the customer. Customers can track the status of their orders and contact their drivers via the app. OFD services offer various benefits to their customers including no waiting in line, no traveling for pick-up, no misunderstanding of the order which happen frequently in restaurants or phone call orders, and discounts from daily offers (The Other Stream, n.d.).

The customer demand of OFD services has increased tremendously over the last few years and is expected to grow steadily. The total revenue of the global OFD service market was estimated at approximately $107.4 billion in 2019 and is expected to exceed $182.3 billion by 2024 (Statista, 2020). Moreover, since the COVID-19 outbreak, the OFD market has gained even more attention globally due to its contactless ordering and delivery system and is expected to continue attracting new customers (Maida, 2020).

Researchers have explored various factors affecting customer intention to use OFD (CIU) (Cho, Bonn, & Li, 2019; Gunden et al., 2020; Suhartanto, Helmi Ali, Tan, Sjahroeddin, & Kusdibyo, 2019; Yeo, Goh, & Rezaei, 2017). For example, Gunden et al. (2020) found that performance expectancy and congruity with a self-image significantly affect customers' adoption intention of OFD. Additionally, Cho, Bonn, & Li, 2019 identified system trust, convenience, design, and various food choices as significant predictors of customer intention to continuously use food delivery apps. Roh and Park (2019) also revealed that compatibility, ease of use, and usefulness were significant predictors of CIU, but Ray & Bala, 2021 presented price benefits, trust, and app-interaction enhanced CIU. Considering the inconsistent findings, the significant predictors affecting CIU are not clearly outlined. Given the peculiarities of ordering food and beverage online rather than going to restaurants and based on existing literature related to technology acceptance (i.e., Technology Acceptance Model) and OFD-related literature (Cho, Bonn, & Li, 2019; Gunden et al., 2020; Ray & Bala, 2021; Ray, Dhir, Bala, & Kaur, 2019; Roh & Park, 2019; Suhartanto, Helmi Ali, Tan, Sjahroeddin, & Kusdibyo, 2019; Won et al., 2017; Yeo, Goh, & Rezaei, 2017; Zhao & Bacao, 2020), Study 1 employs the six variables to predict customer intention to use OFD services. Moreover, two factors adopted from the Health Belief Model — perceived severity and perceived vulnerability—were included in Study 2 to reflect the COVID-19 pandemic context. In the following section, these factors are explained in detail.

2.2. Predictors of online food delivery usage intention

2.2.1. Service attributes

The Technology Acceptance Model (TAM) originally proposed by Davis (1989) states that perceived usefulness and perceived ease of use of a new technology play significant roles in the adoption of the technology (Davis, Bagozzi, & Warshaw, 1989). In the TAM model, perceived usefulness (PU) was defined as "the prospective user's subjective probability that using a specific application system will increase his or her job performance within an organizational context" (Davis, Bagozzi, & Warshaw, 1989, p. 985). When customers consider that new technology will improve their productivity, PU arises (Gentry & Calantone, 2002). Previous studies revealed that PU positively affected technology adoption in a variety of fields, such as mobile phone adoption for shopping (Hung et al., 2012), hotel self-service kiosks (Kim & Qu, 2014), and healthcare wearable technology (Zhang et al., 2017).

In this study, to apply PU to the OFD service setting, PU refers to the degree to which people believe that using an OFD service would be a useful way to order meals. Similar to other technology-related studies, OFD research has demonstrated a significant impact of PU on OFD usage intention. For example, Yeo, Goh, & Rezaei, 2017 demonstrated that PU positively influenced continuance intention toward OFD services. Similarly, Roh and Park (2019) revealed PU to be the strongest factor affecting OFD usage intention.

Perceived ease of use (PEOU) is defined as the degree to which a person expects mental or physical challenges in adopting new technology (Pinho & Soares, 2011). Numerous studies have confirmed that PEOU has a significant effect on customers' usage intentions toward a wide variety of technologies. For instance, Ramayah and Ignatius (2005) proposed that if mobile devices and web interfaces are easy to access and require little effort, customers are willing to accept online shopping. They reported that PEOU is a critical factor affecting online shopping intention. The same positive association between PEOU and CIU has been reported in the OFD context (Ray, Dhir, Bala, & Kaur, 2019; Roh & Park, 2019; Won et al., 2017). Roh and Park (2019) found that the higher the customer's PEOU, the greater the willingness to use OFD services, and ultimately the higher the chance of OFD service success. Ray, Dhir, Bala, & Kaur, 2019 also emphasized the importance of PEOU of OFD services by demonstrating the important roles of the order process, order tracking, and filtering options of the interface in determining CIU.

Besides PEOU and PU, this study employs trust (TR) as a technology-oriented service attribute because TR in the system has been validated as a key driver in adopting new technology in various disciplines, from self-service kiosks during check-in/out in hotels (Kaushik, Agrawal, & Rahman, 2015) to electronic payments (Mendoza-Tello, Mora, Pujol-López, & Lytras, 2018). TR refers to an index of a positive belief regarding the perceived reliability, dependence, and assurance in an individual, object, or procedure (Fogg & Tseng, 1999). TR produces positive feelings toward the technology-based service (Liu, 2012), and customers with low TR about the service tend to be skeptical and reluctant to adopt it (Grabner-Kraeuter, 2002). In the OFD setting, while Jeon et al. (2016) revealed that TR does not affect intention to reuse OFD, several studies have agreed that TR is one of the most critical factors positively affecting CIU (Cho, Bonn, & Li, 2019; Ray & Bala, 2021; Zhao & Bacao, 2020). Thus, this study generated the following hypotheses:

H1. PU positively influences CIU.

H2. PEOU positively influences CIU.

H3. TR positively influences CIU.

2.2.2. Perceived benefits

Some OFD services charge customers extra fees, such as delivery charges and service fees (Lichtenstein, 2020). However, as OFD

companies compete to gain market shares, they frequently offer promotions that cover the fees or discount the total charges to attract new customers and accelerate orders from new and old customers. For example, Grubhub offers a $10-off promotion to new customers and a student discount (Groupon, 2021). In OFD service setting, price saving promotions often serve as effective marketing tools as demonstrated by Kaur et al. (2021) as well as Ray & Bala, 2021 who revealed that free delivery, lower delivery fees, or promotional incentives enhance CIU. Kaur et al. (2021) further noted that customers using OFD services search for a price advantage. Thus, this study examines price saving benefits (PSB) as a critical predictor of CIU. PSB is defined as money-saving benefits (e.g., 10-off promotion, lower delivery/service fee) as well as not charging any additional costs for purchasing products/services (e.g., free delivery) (Yeo, Goh, & Rezaei, 2017). Considering the significant role of PSB in customer OFD usage from existing literature, it is hypothesized that PSB would increase CIU.

Online shopping also saves time traveling to and from a retail store in a time-sensitive modern society (Morganosky & Cude, 2000). Similarly, OFD services could save customers time by avoiding the time spent traveling to a restaurant and waiting in line. Moreover, many web browsers and OFD apps allow customers to store payment and previous order details for efficient checkout, enabling customers to save time (Statista, 2020; Bansal, 2019). While Ray, Dhir, Bala, & Kaur, 2019 found no significant association between time saving benefits (TSB) and customer usage intention, much of the existing literature has indicated that TSB of OFD services positively influence CIU (Correa et al., 2018; He, Han, Cheng, Fan, & Dong, 2019; Yeo, Goh, & Rezaei, 2017). In other words, when customers believe they can avoid traffic and save time by using OFD services, they are more likely to use OFD services. Hence, this study proposed the following hypotheses:

H4. PSB positively influences CIU.

H5. TSB positively influences CIU.

2.2.3. Perceived risk

When dining out, customers oftentimes do not possess tools or skills to measure actual food safety. Instead, customers evaluate the cleanliness and food safety of the restaurant based on various aspects of the restaurant, including restaurant hygiene and employees' safety practices of wearing clean uniforms and sanitary gloves while touching food (Liu & Lee, 2018). The perceived risk associated with food consumption is called food safety risk perception (FSRP) (Nardi, Teixeira, Ladeira, & de Oliveira Santini, 2020).

FSRP plays a crucial role in the decision-making process of customers buying food (Frewer et al., 2009). For example, customers who have higher FSRP have a higher willingness to buy and pay a premium for safer products or services (Sharma et al., 2012). Customers might possess different FSRP depending on the selling site. A study by Kitsikoglou et al. (2014) demonstrated that consumers have higher FSRP when buying groceries or food online as compared to offline because they cannot see the freshness of products online.

OFD services are challenged to sustain food safety and hygiene because food delivered through OFD services can also be exposed to contamination due to the addition of delivery processes to the traditional restaurant business model. Specifically, controlling temperature, packaging, and using appropriate food containers during the delivery process are additional concerns with OFD services (Maimaiti et al., 2018). Therefore, customers may have higher FSRP when using OFD because they cannot observe the restaurants and employees' hygiene in person, which may play a negative role in CIU. Based on the previous research related to FSRP and characteristics of OFD services, the following hypothesis was formulated:

H6. FSRP negatively influences CIU.

2.3. The moderating effect of COVID-19

The hospitality and tourism industry is subject to being immediately influenced by the external environment, such as natural disasters, pandemics, and terrorist incidents (Jin, Qu, & Bao, 2019). One of the noticeable events that affected the hospitality and tourism industry was the September 11 attacks in 2001, which harmed travel demand dramatically with a 30% decline until two years after the attack (Ito & Lee, 2005). A crisis event also can change human behavior positively or negatively.

As the coronavirus has dramatically spread, administrative governments or local ordinances have mandated staying-at-home or shelter-in-place orders in March 2020 onward to help prevent person-to-person transmission and shut down businesses (Sibley et al., 2020). The lockdown has promoted sweeping changes to people's lifestyles and psychological aspects (Laato, Islam, Farooq, & Dhir, 2020). Notably, customers showed unusual buying behavior after the COVID-19 outbreak, such as panic buying, which caused a shortage of toilet paper, hand sanitizer, and canned food products in every store (Laato, Islam, Farooq, & Dhir, 2020). Consequently, this study anticipated that the coronavirus alters customer behavior to use OFD amid the pandemic and devises the following hypothesis:

H7a-f. The COVID-19 outbreak moderates the relationships between the predictors and CIU.

2.4. Study 2

Regardless of the actual risk or contagion of the disease, consumers' perception of the COVID-19 pandemic plays a critical role in their purchase decision-making (Ali, Harris, & Ryu, 2019). Among various measurements used to determine people's perceptions of a disease, researchers have widely used perceived severity (PS) and perceived vulnerability (PV), which have their roots in the Health Belief Model (HBM) proposed by Hochbaum (1958). PS is defined as a personal concern with the seriousness of a situation, and PV refers to personal belief(s) regarding the risk of getting a disease (Cahyanto et al., 2016). The HBM explains that when people have higher PS and PV to an adverse health condition and such outcomes, individuals are more likely to take actions that reduce the threat (Carpenter, 2010).

In the hospitality literature, researchers have widely utilized PS and PV to predict customer behaviors that might be affected by an event or disease such as foodborne illness (Ali, Harris, & Ryu, 2019), Ebola (Cahyanto et al., 2016), norovirus (Fisher, Almanza, Behnke, Nelson, & Neal, 2018), or H1N1 (swine flu) pandemic (Scherr, Jensen, & Christy, 2017). According to Ali, Harris, & Ryu, 2019, PS and PV negatively affect customer intention to patronize restaurants, as diners hesitated to revisit restaurants after an outbreak of foodborne illness, mostly when they recognized their high vulnerability and the severity of foodborne illness. In a similar vein, travelers who reported higher PS and PV were more likely to avoid domestic travel after the outbreak of Ebola than those who showed low PS and PV (Cahyanto et al., 2016). Accordingly, this study assumes that customers who have high PS and PV may utilize OFD services to minimize the possibility of exposure to the COVID-19 from dining out at restaurants. Thus, the following two hypotheses were developed:

H8. PS positively influences CIU.

H9. PV positively influences CIU.

Fig. 1 depicts the proposed hypotheses in this study.

3. Methodology

3.1. Sampling and data collection

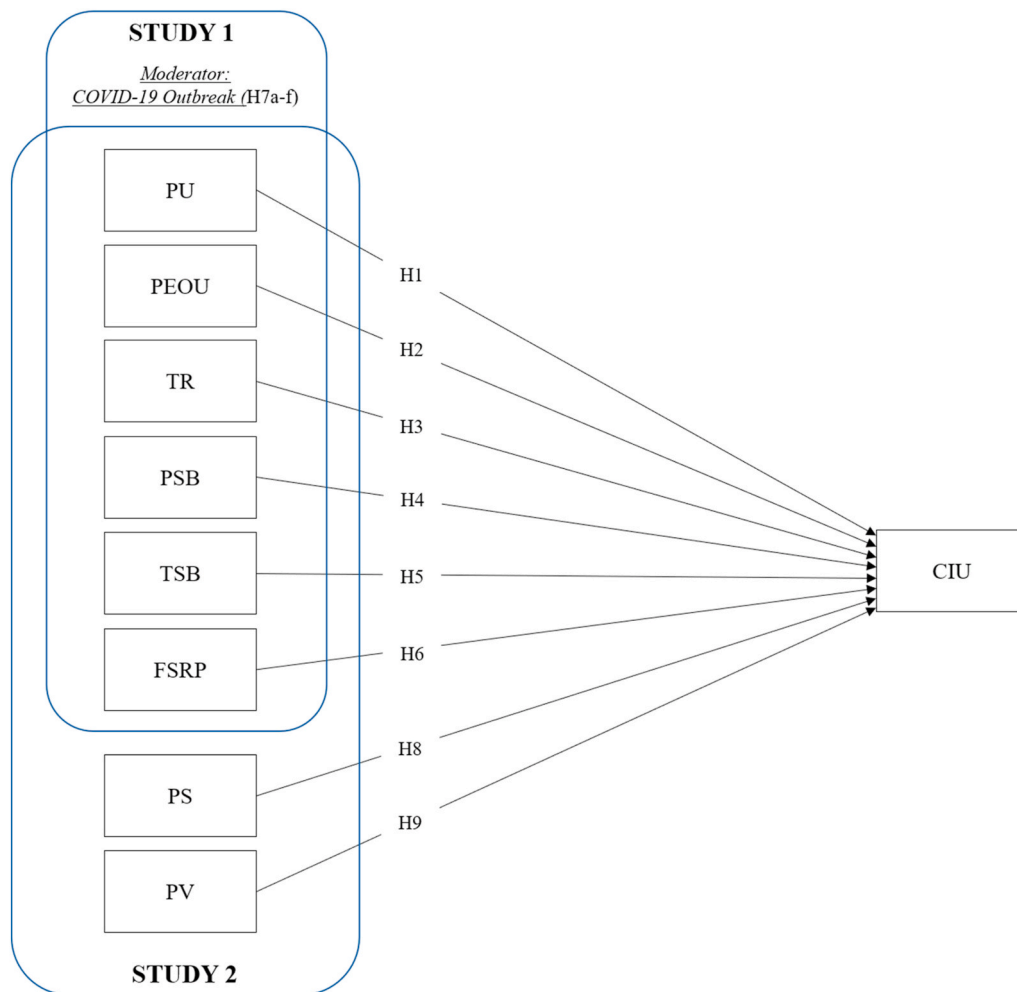The target population of this study was U.S. consumers over 18 years

Fig. 1. The proposed conceptual framework.
Note. PU = Perceived Usefulness, PEOU = Perceived Ease of Use, TR = Trust, PSB = Price Saving Benefits, TSB = Time Saving Benefits, FSRP = Food Safety Risk Perception, PS = Perceived Severity, PV = Perceived Vulnerability, CIU = Customer Intention to Use OFD.

old. The data were collected through Amazon's Mechanical Turk (MTurk) over two time periods: the third week of June 2019 and the fifth week of July 2020, representing before and during the COVID-19 pandemic, respectively.

A total of 1045 responses (571 for the before-COVID-19 group and 474 for the during-COVID-19 group) were collected. In the data screening process, 90 incomplete questionnaires and 46 respondents who incorrectly answered attention check questions were omitted. Additionally, three participants who provided straight-lining answers were dropped. Also, 150 responses that took less than 150 s of response time were removed following the cutoff norms of response time suggested by DeSimone & Harms, 2018 and Huang, Curran, Keeney, Poposki, & DeShon, 2012. Lastly, 56 responses with the same internet protocol and location were removed to prevent duplicate participants. After scrutinizing the data, a total of 700 responses were retained with 333 respondents in the before-COVID-19 group and 367 respondents in the during-COVID-19 group.

The chi-square (χ^2) test of homogeneity was conducted to determine whether frequency counts in the socio-demographic variables were distributed identically between the before-COVID-19 and during-COVID-19 group. The results showed that the majority of demographic variables had no significant differences between before-and during-COVID-19 respondents ($p > .05$), except for education level ($p < .001$) (see Table 1).

3.2. Measurements

A self-administered questionnaire was developed based on a comprehensive review of previous literature (Castañeda, Muñoz-Leiva, & Luque, 2007; Hung et al., 2006; Lando et al., 2016; Xie et al., 2017; Yeo, Goh, & Rezaei, 2017). At the beginning of the questionnaire, a definition of OFD was presented. The first section of the questionnaire was comprised of items measuring study constructs, including PU, PEOU, TR, PSB, TSB, FSRP, PS (*Study 2 only*), PV (*Study 2 only*), and CIU using a 7-point Likert scale (1 being "strongly disagree"; 7 being "strongly agree"). The second section included questions asking the socio-demographic information of the respondents. The measurement items and their references are listed in Appendix A.

3.3. Data analysis

The collected data were analyzed using IBM SPSS v26 and AMOS v25. In Study 1, descriptive statistics including frequencies, means, and standard deviations were conducted to summarize the data, and a hierarchical multiple regression analysis was conducted to test the proposed hypotheses (H1−7). Before the hierarchical multiple regression analysis, confirmatory factor analysis was performed to check the validity and reliability of the measurement items. Additionally, in Study 2, multiple regression analysis was conducted to test hypotheses 8 and 9, and an independent samples *t*-test was used to examine the differences

Table 1
Profiles of respondents ($N = 700$).

Characteristics	Category	Total ($n = 700$)		Before COVID-19 ($n = 333$)		During COVID-19 ($n = 367$)		χ^2
		n	%	n	%	n	%	
Gender	Male	365	52.1	163	48.9	202	55.0	2.60
	Female	335	47.9	170	51.1	165	45.0	
Age	Less than 30 years	148	21.1	78	23.4	70	19.0	5.56
	30–39 years	266	38.1	128	38.5	138	37.6	
	40–49 years	130	18.6	50	15.0	80	21.8	
	50–59 years	94	13.4	45	13.5	49	13.4	
	Over 59 years	62	8.8	32	9.6	30	8.2	
Ethnic	Caucasian	511	73.0	244	73.3	267	72.7	4.04
	African American	59	8.4	26	7.8	33	9.0	
	Hispanic	44	6.3	25	7.5	19	5.2	
	Native American	7	1.0	4	1.2	3	0.8	
	Asian	67	9.6	27	8.1	40	10.9	
	Other	12	1.7	7	2.1	5	1.4	
Education level	Less than high school	5	0.7	2	0.6	3	0.8	27.40***
	High school graduate	59	8.4	31	9.3	28	7.6	
	Some college	191	27.3	116	34.9	75	20.5	
	College graduate	285	40.7	105	31.5	180	49.1	
	Some graduate school	35	5.0	18	5.4	17	4.6	
	Completed graduate	125	17.9	61	18.3	64	17.4	
Marital status	Married	336	48.0	147	44.1	189	51.5	4.09
	Widowed	7	1.0	4	1.2	3	0.8	
	Divorced	58	8.3	28	8.4	30	8.2	
	Never married	299	42.7	154	46.3	145	39.5	
Annual income	Under $10,000	24	3.4	14	4.2	10	2.7	6.21
	$10,000-$29,999	136	19.4	69	20.7	67	18.3	
	$30,000-$49,999	170	24.3	87	26.2	83	22.6	
	$50,000-$69,999	148	21.2	64	19.2	84	22.9	
	$70,000-$89,999	88	12.6	35	10.5	53	14.4	
	$90,000-$109,999	54	7.7	24	7.2	30	8.2	
	Over $110,000	80	11.4	40	12.0	40	10.9	
Employment status	Employed, full-time	420	60.0	195	58.6	225	61.3	7.76
	Employed, part-time	155	22.1	70	21.0	85	23.1	
	Not employed	74	10.6	39	11.7	35	9.6	
	Retired	32	4.6	17	5.1	15	4.1	
	Student	19	2.7	12	3.6	7	1.9	
Residence	Urban	257	36.7	110	33.0	147	40.1	4.03
	Suburban	369	52.7	188	56.5	181	49.3	
	Rural	74	10.6	35	10.5	39	10.6	

Note. ***$p < .001$.

between frequencies to use OFD services both before and during the COVID-19 pandemic.

As previous studies discovered the significant effect of demographic factors on consumers' online shopping behavior (Chiang & Dholakia, 2003; Hernández, Jiménez, & Martín, 2011), four demographic factors—age, gender, household income, and residency—were controlled to determine the pure relationships between the predictors and CIU. Before conducting the hierarchical multiple regression analysis, respondents' age and income were regrouped. Based on the studies by Dhanapal et al. (2015) and Priporas, Stylos, & Fotiadis, 2017, age was categorized into two groups comprising of Generation Y/Z and Generation X/Baby Boomers. Furthermore, respondents' household income was grouped into low (less than $69,999) and high (above $70,000) income categories based on the median household income ($68,703) in the United States (Ahn & Back, 2018; U.S. Census Bureau, 2020). All categorical control variables were dummy coded, and all continuous predictor variables were mean-centered to clarify regression coefficients and reduced multicollinearity.

4. Results

4.1. Study 1

4.1.1. Profile of the sample

Table 1 presents a breakdown of the socio-demographics of both samples. In terms of gender, 365 respondents (52.1%) were male, and 335 respondents (47.9%) were female. The respondents' average age was 39.92 years. The majority of the respondents were Caucasian (73%), and about half of the respondents were married (48.1%). More than half of the respondents (60%) worked full-time, and the largest respondent group reported an annual household income between $30,000 and $49,999 (24.3%). Regarding respondents' residency, over half of the respondents (52.7%) reported living in suburban.

4.1.2. Validity and reliability of constructs

Confirmatory factor analysis was conducted to evaluate the reliability and convergent and discriminant validity of the measurement model which was comprised of seven factors: PU, PEOU, TR, PSB, TSB, FSRP, and CIU. Each of the overall goodness-of-fit indices suggested that the seven-factor model fit the data well, $\chi^2_{(168)} = 403.90$, $p < .001$, χ^2/df

= 2.404, CFI = 0.978, TLI = 0.972, RMSEA = 0.045 (90% CI: 0.039-0.050), SRMR = 0.035. The constructs' internal consistency was acceptable with composite reliability coefficients ranging from 0.758 to 0.931 (Fornell & Larcker, 1981). Construct validity was examined by assessing convergent and discriminant validity. For convergent validity, both factor loadings and average variance extracted (AVE) were satisfied with the acceptable ranges (Anderson & Gerbing, 1988). Discriminant validity was determined by comparing AVEs with the squared multiple correlations between constructs, but the results indicated that distinctions between PU and PEOU and between PU and TSB were not established. Therefore, chi-square difference tests were conducted and found that six-factor models—PU-PEOU combined and PU-TSB combined—statistically degraded the original measurement model, PU-PEOU combined: $\Delta\chi^2_{(6)} = 174.47$, $p < .001$ and PU-TSB combined: $\Delta\chi^2_{(6)} = 175.99$, $p < .001$, suggesting that the seven-factor model showed a significant improvement in chi-squares over both six-factor models. Thus, discriminant validity was ensured.

4.1.3. Hypotheses testing

A three-step hierarchical multiple regression was conducted to test the hypotheses. First, the control variables of gender, age, income, and residency were entered. Second, predictor variables (PU, PEOU, TR, PSB, TSB, and FSRP) and a moderator variable (COVID-19) were entered. In the third step, interaction terms were entered into the model.

Table 2 presents the results of the hierarchical multiple regression analysis. As for the control variables, the results indicated that female ($\beta = -0.08, p < .05$), Gen Y/Z ($\beta = 0.11, p < .01$; comparing to Gen X/Baby Boomer), urban ($\beta = 0.17, p < .01$; comparing to rural resident), and suburban residents ($\beta = 0.15, p < .05$; comparing to rural resident) showed significantly higher CIU. However, there was an insignificant

Table 2
Results of hierarchical regression analysis predicting customer intention to use OFD.

Variables	Model 1 β	Model 1 t	Model 2 β	Model 2 t	Model 3 β	Model 3 t
Control variables						
Male (*ref*: female)	-.08	−2.08*	-.06	−2.39*	-.06	−2.34*
Gen Y and Z (*ref*: Gen X and Baby Boomers)	.11	2.96**	.03	1.13	.03	1.15
High income (*ref*: low income)	-.03	−0.66	-.01	−0.33	-.01	−0.33
Residence (*ref*: rural)						
Urban	.17	2.61**	.10	2.43*	.09	2.31*
Suburban	.15	2.37*	.10	2.41*	.10	2.37*
Independent variables						
PU			.45	11.75***	.43	6.95***
PEOU			.08	2.35*	.09	1.73
TR			.19	5.70***	.24	4.52***
PSB			.11	3.85***	.08	1.85
TSB			.11	3.21**	.11	2.02*
FSRP			-.02	−0.55	-.02	−0.56
Moderator						
COVID-19 (*ref*: Before-COVID-19)			.05	2.06*	.05	2.02*
Interactions						
COVID-19 × PU					.02	0.39
COVID-19 × PEOU					-.01	−0.10
COVID-19 × TR					-.06	−1.15
COVID-19 × PSB					.04	0.86
COVID-19 × TSB					-.00	−0.04
COVID-19 × FSRP					.01	0.21
R^2	.03		.62		.62	
ΔR^2	.03**		.59***		.00	
F	3.87**		93.13***		61.93***	
ΔF	3.87**		152.65***		0.44	

Note. Ref: Reference group; Durbin-Watson statistic = 2.07.
*$p < .05$.
**$p < .01$.
***$p < .001$.

difference in CIU between high-income and low-income groups ($\beta = -0.03, n.s.$). Hypotheses 1–6 predicted that six predictors regarding OFD services influence CIU. As proposed, PU (H_1: $\beta = 0.45, p < .001$), PEOU (H_2: $\beta = 0.08, p < .05$), TR (H_6: $\beta = 0.19, p < .001$), PSB (H_3: $\beta = 0.11, p < .001$), and TSB (H_4: $\beta = 0.11, p < .01$) were positively associated with CIU, supporting H1, H2, H3, H4, and H5, respectively, controlling for participants' gender, age, income, and residency (see Model 2). However, FSRP showed an insignificant, negative relationship with CIU ($\beta = -0.02, n.s.$), failing to support H6. Additionally, COVID-19—as an independent variable—showed a positive, significant impact on CIU, controlling for other variables. This finding implies that customers tend to show more positive CIU during the COVID-19 pandemic than the before-COVID-19 pandemic.

Lastly, H7a-f proposed that the COVID-19 pandemic moderates the relationships between the predictors and OFD usage intention. However, as Model 3 shows, none of the interaction terms were statistically significant, and the addition of interactions to the model did not improve the model's predictability ($\Delta R^2 = 0.00, n.s.$), meaning that H7a-f were not supported. The findings indicate that the pandemic event was significantly associated with CIU but did not affect the relationships between the OFD predictors and CIU.

4.2. Study 2

In response to the impact of the COVID-19 pandemic on the restaurant industry, Study 2 further incorporated PS and PV to the COVID-19 into the OFD usage intention prediction model by conducting a multiple regression.

The results indicated that there were no significant impacts of PS ($\beta = 0.03, n.s.$) and PV ($\beta = 0.03, n.s.$) on CIU, failing to support H8 and H9 (see Table 3). Although PS and PV were not significantly associated with CIU, the degrees of the effects of the other independent variables—including socio-demographic variables—have changed significantly. Considering these variables in the model, more situation-appropriate findings were proposed, i.e., during the COVID-19 pandemic situation. That is, female customers ($\beta = -0.05, n.s.$) and urban residents ($\beta = 0.08, n.s.$) are no longer more favorable to CIU compared to their counterparts. On the other hand, the results indicated that Gen Y/Z customers are more willing to use OFD compared to older generations ($\beta = 0.07, p < .05$). Besides, PU ($\beta = 0.43, p < .001$), TR ($\beta = 0.17, p < .001$), PSB ($\beta = 0.14, p < .01$), and TSB ($\beta = 0.13, p < .01$) were

Table 3
The results of multiple regression analysis predicting customer intention to use OFD during the COVID-19 pandemic.

Variables	B	SEB	β	t
Constant	−1.06	0.40		−2.66**
Control variables				
Male (*ref*: female)	−0.12	0.09	-.05	−1.34
Gen Y and Z (*ref*: Gen X and Baby Boomers)	0.19	0.09	.07	1.97*
High income (*ref*: low income)	−0.04	0.10	-.01	−0.39
Residence (*ref*: rural)				
Urban	0.21	0.16	.08	1.32
Suburban	0.36	0.16	.14	2.32*
Independent variables				
PU	0.54	0.07	.43	7.84***
PEOU	0.09	0.08	.06	1.26
TR	0.21	0.06	.17	3.37***
PSB	0.12	0.04	.14	3.21**
TSB	0.16	0.06	.13	2.64**
FSRP	−0.00	0.04	-.00	−0.07
PS	0.03	0.05	.03	0.73
PV	0.03	0.04	.03	0.69

Note. Ref: Reference group.
R^2(adj. R^2) = 0.59 (0.57), $F_{(13, 353)} = 38.64***$, Durbin-Watson statistic = 2.07.
*$p < .05$.
**$p < .01$.
***$p < .001$.

still significantly associated with CIU; however, PEOU was no longer significant ($\beta = 0.06$, *n.s.*).

Lastly, the respondents' actual usage (frequency) of OFD was compared before and during the COVID-19 pandemic. An independent samples *t*-test was conducted to compare the frequencies of OFD usage. The results indicated that respondents tended to use OFD more frequently during the COVID-19 pandemic than before the COVID-19 pandemic ($t = 5.14$, $p < .001$). Specifically, the number of respondents who used OFD services 2–3 times a month, 1–2 times, or 3–5 times a week has increased during the COVID-19 pandemic, while those who used OFD services once a month or less has decreased. Fig. 2 shows more detailed frequencies between the two conditions.

5. Discussion and conclusion

5.1. Discussion

The results of both Study 1 and Study 2 showed that PU was the most influential factor in increasing CIU. Similar to previous studies (Lee, Lee, & Jeon, 2017; Yeo, Goh, & Rezaei, 2017), this study confirmed that customers are more likely to adopt OFD if they perceive it as useful. The second most significant factor was TR. This finding is paralleled with Flavián et al. (2006) and Wang, Lin, & Luarn, 2006 who found that TR has a significant effect on customer technology adoption intention in the online shopping context. Considering the nature of OFD services that customers place an order via OFD platforms, customers might doubt whether the restaurant accurately receives orders or the quality of food delivered is as good as the quality of food served at the restaurant which explains the importance of TR in the OFD setting.

Surprisingly, Study 1 found that the COVID-19 pandemic did not moderate the relationships between the predictors and CIU. This finding differs from earlier studies, which claimed that a crisis event brings significant behavioral changes to people (Jin, Qu, & Bao, 2019; Laato, Islam, Farooq, & Dhir, 2020). The insignificant moderating effect can be interpreted as the factors that significantly influenced CIU before the pandemic still play decisive roles to customers.

Study 2 revealed that PS and PV did not significantly affect OFD usage intention during the pandemic, contradicting the findings of Ali, Harris, & Ryu, 2019 and Cahyanto et al. (2016). The insignificant effects of PS and PV might be attributable to OFD usage itself not being considered *health-related behavior* because the Health Belief Model indicated that PS and PV affect consumer's health-promoting behavior.

Additionally, Study 2 uncovered situation-appropriate results under the COVID-19 pandemic situation precisely, showing that younger customers (Generation Y/Z) are more willing to use OFD than older customers (Generation X/Baby Boomers). This finding is consistent with other research that revealed Generation Y/Z's online purchasing frequency was higher than Generation X/Baby Boomers, possibly because Generation Y/Z use the internet more frequently than older generations (Dhanapal et al., 2015; Priporas, Stylos, & Fotiadis, 2017).

Another notable finding of Study 2 is that FSRP did not significantly affect CIU during the pandemic even though customers are generally more concerned about their safety and health during the pandemic (Shin & Kang, 2020). This could be because customers are aware of the low risk of getting sick with COVID-19 from food as the Center for Disease Control and Prevention (CDC) and other media have reported (Centers for Disease Control and Prevention, 2020). Moreover, considering that both PSB and TSB significantly increased CIU, customers might also perceive benefits received from food products/services obtained through OFD as outweighing the risks associated with using OFD which is in line with the findings of Nardi, Teixeira, Ladeira, & de Oliveira Santini, 2020.

5.2. Theoretical implications

This study contributes to the current literature with various theoretical implications. Most importantly, as the OFD market share has grown, researchers have devoted increased attention to OFD customers and their decision-making process. The present research extended the existing literature related to OFD by incorporating various predictors and perceptions of OFD driven from the TAM with additional constructs of TR, PSB, TSB, and FSRP (Study 1). Additionally, under the pandemic situation, Study 2 integrated customers' PS and PV adopted from the Health Belief Model to the COVID-19 pandemic to better predict CIU. Even though PS and PV were not significant predictors of OFD usage intention, the findings showed the altered effects of different socio-demographic variables and OFD perceptions by controlling severity and vulnerability factors. In this respect, this study fills a significant gap in the extant literature on OFD attributes and CIU.

The current study is arguably among the first to identify relationships between various predictors and CIU across different time frames (before and during the COVID-19 pandemic) to evaluate the effect of a crisis on OFD usage intention. While the results do not indicate that COVID-19 served as a moderator between the predictors and CIU, this
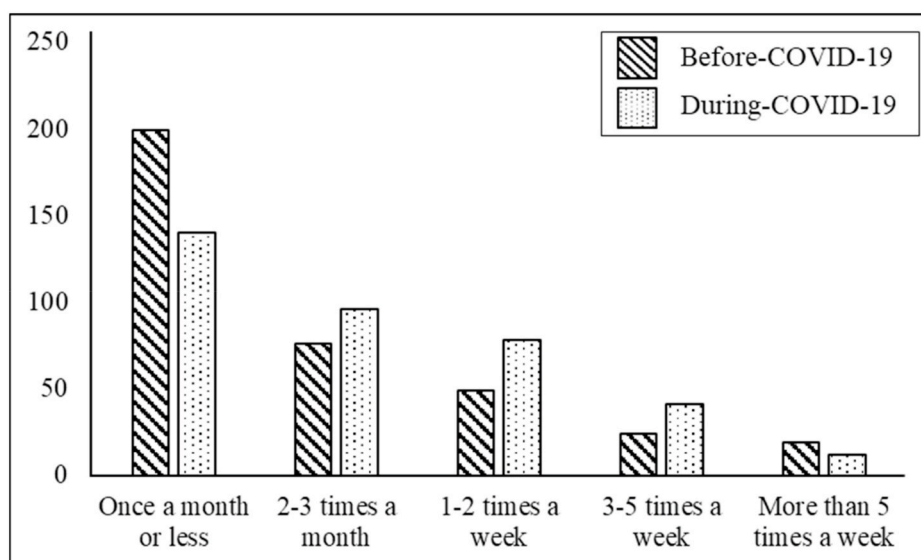

Fig. 2. Comparison of the OFD usage between before and during the COVID-19 pandemic.

study still enriches the literature on consumer behavior toward OFD and OFD usage intention.

5.3. Practical implications

This research provides several unique practical implications for OFD stakeholders. First, considering that PU was the most significant predictor of CIU in both studies, OFD marketers should focus on increasing current and/or potential customers' awareness of the business and advertising service efficiency to their customers. Specifically, marketing materials should highlight the usefulness of OFD services by emphasizing that customers can stay where they are, enjoy their food anywhere they want and avoid ordering by phone, traveling to pick up meals, and waiting for pick-up. Moreover, OFD services can be useful during a pandemic like COVID-19 because the service minimizes contact between customers and restaurant employees and allows customers to enjoy their favorite restaurant food at home. For example, Uber Eats and Deliveroo, among others, launched contactless "leave at your door service" to help drivers and customers adhere to social distancing guidelines. This gives the restaurant industry, which has been severely damaged, another opportunity to thrive and evolve by meeting the changing demand in the foodservice market.

Second, the results demonstrate that TR is the second most significant factor of CIU, which means that the more customers trust OFD services, the more willing they are to use them. From the business's perspective, gaining trust from their customers is building relationships with their customers. Therefore, OFD businesses should invest in customer relationship management (CRM) through various communication channels such as social media and newsletters by being transparent, authentic, and willing to listen to their customers. Furthermore, like major online retailers, OFD providers could present tangible evidence to reduce customer uncertainty on the quality of OFD service by showing 100% customer satisfaction guaranteed and statistics on customer satisfaction scores or number of users. Additionally, customers who have not used OFD might consider it a new technology, which might cause them to doubt how OFD operates or how personal information will be protected. Thus, OFD companies need to explain how they work and how personal and payment information collected through the company will be restored and protected.

Third, because this study confirmed that PSB and TSB positively affect CIU, companies should understand that customers expect benefits from using OFD services. Therefore, using promotional materials such as ads and social networking site (SNS) postings, OFD companies should accentuate potential benefits—time and cost— that the customers can receive as compared to cooking over a hot stove all day or waiting in a long line at a restaurant. Additionally, OFD marketers can provide regular discount promotions, such as free delivery, to attract new customers and launch reward programs. For instance, Uber Eats regularly offers a "$0 delivery fee" promotion and advertises this on their website.

Furthermore, they recently teamed up with American Express to provide a Free Eats Pass membership, which provides free delivery and 5% off restaurant orders. By providing information on the estimated delivery time on the OFD platform, customers can visualize the time saving benefits they would gain from using the service.

Fourth, the change in frequency of customer usage of OFD between time periods before and during the pandemic indicates that social distancing measures associated with the pandemic led customers to use OFD services more frequently. Thus, as restaurant business models are shifting in keeping with changing consumer preferences, restaurants can benefit from the popularity of OFD services by partnering with them. Many restaurants transformed their service methods during the pandemic, offering curbside pickup and OFD service, to adapt to the new normal and survive in the competitive market. As an extreme case, DoorDash recently launched a "Reopen for Delivery" program, which gives bankrupted restaurants a fighting chance by matching them with ghost kitchen facilities. Thus, for restaurants, a new business model or re-shaping operation could be a plausible strategy to survive in this era.

Lastly, the findings of Study 2 highlight that during the COVID-19 pandemic, generations Y and Z were more willing to use OFD compared to older generations. OFD businesses should target younger generations to maximize business growth. For instance, OFD service marketers can use SNSs to hold competitions and/or distribute discount codes because the younger generations actively use SNSs to communicate with others (Williams & Page, 2011). Utilizing social media influencers to promote OFD would also appeal to the younger generations.

5.4. Limitations and future studies

As with any research, this study is not free from limitations. This study focused on the general perception of OFD rather than focusing on a specific OFD platform. As customers might perceive each OFD service platform differently, future studies can examine whether significant predictors affecting CIU differ depending on the different OFD services. In addition, this study only considered the platform-to-consumer delivery type of OFD services (e.g., DoorDash, Uber Eats) and did not assess restaurant-to-consumer OFD (e.g., Domino's Pizza, Pizza Hut) (Poluliakh, 2020). Factors affecting CIU might change depending on the type of OFD which is worth investigating for future research. Also, this study focused on CIU to use OFD regardless of their previous experience with OFD. Future studies may consider adding more attitudinal and behavioral intention constructs—customer satisfaction, positive word-of-mouth, willingness to pay a premium, and revisit intention—to provide more fruitful explanations of the linkages between them. Lastly, this study collected the during-pandemic data in July 2020, but CIU may change in the early or late stage of the COVID-19 pandemic. Future research can analyze what factors have a significant impact on the CIU in the later period of COVID-19.

Appendix A. Measurement items

Items	References	Cronbach's α
Perceived usefulness	Castañeda, Muñoz-Leiva, & Luque, 2007	.885
Using an OFD service is an efficient way to ordering my meals.		
Using an OFD service makes my life easier.		
Overall, using an OFD service is a useful way to order meals		
Perceived ease of use	Castañeda, Muñoz-Leiva, & Luque, 2007; Xie et al. (2017)	.797
It is easy to find what I want through an OFD service.		
My interaction(s) with an OFD service is clear and understandable.		
It is easy to become skillful at navigating through an OFD service.		
Trust	Hung et al. (2006)	.931
I trust an OFD service.		
I believe that an OFD service is trustworthy.		
I trust an OFD service to do the job right.		

(*continued*)

Items	References	Cronbach's α
Price saving benefit	Yeo, Goh, & Rezaei, 2017	.897
Using an OFD service saves money.		
An OFD service offers cheap deals.		
An OFD service offers better value for my money.		
Time saving benefit	Yeo, Goh, & Rezaei, 2017	.758
Using an OFD service is time-saving.		
Using an OFD service helps me accomplish things more quickly in the meal purchasing process.		
It is important for me that the purchase of meals is done as quickly as possible using an OFD service.		
Food safety risk perception	Lando et al. (2016)	.889
It is likely for OFD customers to get food poisoning because of the way food is delivered through an OFD service.		
Contamination of food by being delivered by an OFD service is a serious food safety problem.		
Food delivered by an OFD service is likely to have germs or other microorganisms that could make customers sick.		
Customer intention to use OFD	Yeo, Goh, & Rezaei, 2017	.895
I plan to use an OFD service in the future.		
If possible, I will try to use an OFD service.		
I will try to use an OFD service if necessary.		
Perceived severity	Ali, Harris, & Ryu, 2019; Cahyanto et al. (2016); Cui et al. (2017); Yazdanpanah et al. (2015)	.864
COVID-19 could cause me to be ill for a long time.		
If I get the COVID-19, it would have a severe, negative influence on my quality of life.		
I am afraid that I may die if I am infected with the COVID-19.		
Humans infected with COVID-19 will be more serious than being infected with other diseases.		
It is hard to cure if a human is infected with COVID-19.		
Perceived vulnerability	Ali, Harris, & Ryu, 2019	.892
Even though there have been COVID-19 outbreaks in my area, I don't believe the threat is an issue.		
Just because someone becomes infected with COVID-19, doesn't mean I will.		
I view COVID-19 outbreaks in the media to be a contained threat and not really a threat to me.		
I am healthy and do not believe that I am susceptible to COVID-19.		

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