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THE IMPACT OF COVID-19 PANDEMIC ON THE USE OF FOOD DELIVERY APPLICATIONS

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INTRODUCTION

The so-called Covid-19 “new normal” arises from the perspective that we will be living with the coronavirus pandemic into 2021, behavior change will be more permanent and measures such as physical distancing will need to stay in place even after lockdowns are lifted (Ghosh, 2020; Lacina, 2020).

The disruption of social activity and the threat to livelihood and life in pandemics differ from adaption and resilience to other disruptors such as economic downturns and natural disasters. Besides, to help health responses across pandemic phases, information systems (IS) could perform to mitigate non-pharmaceutical interventions (NPIs) economic and social costs in a digital resilience approach (Karahanna, 2020). Thus, understanding individual behavior and its relationship with technology in a pandemic context becomes pressing.

There is an immense variety of economic, behavioral, technological, and organizational phenomena under the expansive and ever-growing banner of IS research. Within the study of IS, the basis for why and how users accept technology is an extensively studied concept, with the evolution of various models and theories being developed and expanded over the years. Profiles of IS research reported in major journals show a pronounced pattern around technology acceptance and adoption research (Soper & Turel, 2016; Stein et al., 2016).

RESEARCH PROBLEM AND OBJECTIVE

One of the emerging global challenges in combating infectious diseases is to deal with the new coronavirus (Covid-19), that is a highly contagious disease firstly identified in Wuhan, Central China in December 2019 (Ahorsu et al. 2020; Mahato et al. 2020). Up to July 24, 2020, 2.289.951 people in Brazil have been infected with Covid-19. From these, 1.570.237 were recovered and 84.207 accumulated deaths, indicating a lethality rate of 3.68% (Ministry of Health, 2020).

The government has been taking actions to control the dissimination of Covid-19 in accordance with the recommendations from World Health Organization (WHO, 2020) such as social distancing, testing for detection, building hospitals and lockdown. Only markets and others of extreme need are allowed to remain open. Given this lockdown conjecture, with the closure of bars and restaurants, it is possible to notice an increase in the use of food delivery applications. In times of uncertainty, consumer behavior changes significantly (Kumar et al., 2020).

As a research problem we have: Has the Covid-19 pandemic impacted on consumer behavior in the use of food delivery applications? To answer this question, this research aims to analyze the effect of perceived infectability and the fear of Covid-19 on the acceptance and use of delivery applications during the Covid-19 pandemic. To achieve this goal, we used the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model with the addition of two new constructs: Perceived Infectability and Fear of Covid-19.

THEORETICAL BACKGROUND

Delivery Applications

The context of food delivery and consumer behavior were considered suited to this research because of the enforced substitution of personal relationship among consumers and restaurants due to the social distancing.

Online food delivery (OFD) services stand for ordering and delivering food from various restaurants through website or app and this trend has fuelled the growth of various food delivery apps (FDA) (Ray et al., 2019). The emergence of specialized companies in providing online delivery services enabled the consumer to choose products quickly, easily, and compare between the options available with an easy interaction platform is a worldwide trend and a growing sector in Brazil. The main companies operating in such a Brazilian market started their operations after 2010 (Pigatto et al., 2017).

Preliminary studies point to some negative results on the health of individuals who are in lockdown, especially in school age children and adolescents. The increased consumption of unhealthy foods and the lack of physical exercise are described (Pietrobelli et al., 2020). One of the possible reasons for this is that because they are in social isolation in their homes, an alternative is to use applications to order food. Otherwise, Food delivery applications are a solution for vulnerable populations, as users have access to same-day delivery services, allowing them to stay in their homes and maintain social distance (Banskota et al., 2020).

A survey from April 2020 reveals that 76% of the interviewees used food delivery services within 30 days and the major Brazilian delivery apps accounted for 61% of the orders. However, 32% of the orders were placed directly using WhatsApp, and 4% used social media such as Facebook or Instagram (Madureira, 2020).

UTAUT2

Various authors have dedicated significant efforts to helping understand how individuals behave when it comes to accepting to use technology and UTAUT and its extensions become an amalgam concept and have been applied to the study of technologies in both organizational and non-organizational settings (Venkatesh et al., 2003, 2012, 2016). Recently, blockchain adoption was studied with this theoretical lens (Queiroz & Fosso Wamba, 2019).

The theory of reasoned action proposes that a person's behavior, referred to as actual behavior, is largely determined by a construct referred to as behavioral intent (BI) and could be defined as the measure of one's intention to perform a specified behavior (Fishbein & Ajzen, 2011). The foundational concepts regarding user acceptance of technology are largely based on a theory from the social psychology discipline called the theory of reasoned action (TRA) which was developed by Ajzen and Fishbein.

The UTAUT (Venkatesh et al., 2003) model is composed of the following constructs: Performance Expectancy is defined as the degree of benefits to users that a technology can bring (Venkatesh et al., 2003, 2012); Effort Expectancy is the degree of ease associated with the use of the technology (Venkatesh et al., 2003, 2012); Social Influence is the extent to which users of a given technology perceive that other important people believe they should use it (Venkatesh et al., 2003, 2012); Facilitating Conditions refer to users' perceptions of resources and the support available to perform a behavior (Brown and Venkatesh 2005; Venkatesh et al., 2003, 2012).

From the model extension, now UTAUT2 (Venkatesh et al., 2012) we have Hedonic Motivation, that is defined as the fun or pleasure derived from using a technology (Brown and Venkatesh 2005; Venkatesh et al., 2003, 2012). Price Value is a cognitive tradeoff between the perceived benefits of applications and the monetary cost to use them (Dodds et al. 1991; Venkatesh et al. 2012). Habit is defined as the extent to which people tend to perform behaviors automatically due to learning (Limayem et al. 2007; Venkatesh et al. 2012). Behavioral Intention measures the individual's intention and acceptance to use a particular technology (Davis et al. 1989; Venkatesh et al. 2003; 2012). Use Behavior is a formative construct that evaluates the use frequency of certain technology (Venkatesh et al. 2012; 2016).

In a consumer context, UTAUT2 explained 74% of the variance in consumers' behavioral intention to use technology and 52% of the variance in consumers' technology use (Venkatesh et al. 2012; 2016). Therefore, this research proposes to verify the impact of COVID-19 pandemics in the use behavior of food delivery applications., under the lens of UTAUT2 model, a well-tested and prevalent model within the IS field.

Fear of COVID-19 And Perceived Infectability

The Fear of COVID-19 Scale (FCV-19S, Ahorsu et al. 2020), has been recently developed with the objective of providing a scale that can support the actions of government on treat the growing public fear caused by COVID-19. FCV-19S is a seven-item unidimensional scale with robust psychometric properties (Ahorsu et al., 2020).

The correlation between FCV-19S, the government treat to public fear and FDA goes further considering, the existence of this fear, the government should assume some actions to facilitate this type of activities in the cities with target to having totally free society of COVID-19. Countries worldwide should also work on individual fears to archive the holistic goal of having a society free of COVID-19 (Ahorsu et al., 2020).

For Ducan et al. (2009), infectious diseases have imposed a threat to human well-being for a long time. Objective vulnerability to disease has implications for a wide range of outcomes. They have developed a tool that can specifically and reliably assess individual differences in perceived vulnerability to infectious diseases. In this research, we used the scale that measures Perceived Infectability, which is composed of 7 items, which evaluate beliefs about immune function and personal susceptibility to infectious diseases (Ducan et al., 2009).

Theoretical Model and Hypotheses

According to UTAUT2, performance expectancy, effort expectancy, social influence, hedonic motivation, price value are theorized to influence the behavioral intention to use a technology, behavioral intention determines the use of the technology, and facilitating conditions and habit determine both behavioral intention and use (Venkatesh et al., 2003, 2012). To expand the original UTAUT2 model, the constructs Perceived Infectability (Ducan et al. 2009) and Fear of Covid-19 (Ahorsu et al. 2020) are added to the UTAUT2 model. Figure 1 demonstrates the proposed theoretical model in this research.

Figure 1. **Proposed Theoretical Model**

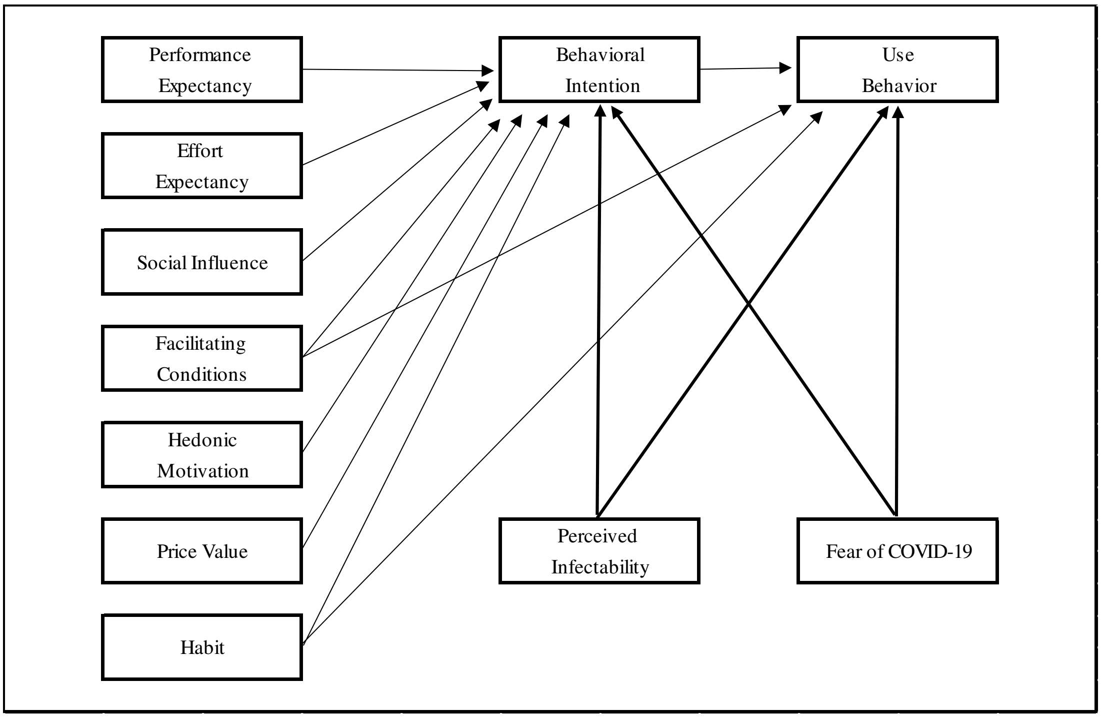


Table 1 lists the hypotheses that have been tested in this article.

Table 1. **Hypotheses**

Latent Variable	Hypotheses
Performance Expectancy	H1: There is a causal relationship between Performance Expectancy and Behavioral Intention.
Effort Expectancy	H2: There is a causal relationship between Effort Expectancy and Behavioral Intention.
Social Influence	H3: There is a causal relationship between Social Influence and Behavioral Intention.
Facilitating Conditions	H4: There is a causal relationship between Facilitating Conditions and Behavioral Intention. H5: There is a causal relationship between Facilitating Conditions and Use Behavior.
Hedonic Motivation	H6: There is a causal relationship between Hedonic Motivation and Behavioral Intention.
Price Value	H7: There is a causal relationship between Price Value and Behavioral Intention.
Habit	H8: There is a causal relationship between Habit and Behavioral Intention. H9: There is a causal relationship between Habit and Use Behavior.
Behavioral Intention	H10: There is a causal relationship between Behavioral Intention and Use Behavior.
Perceived Infectability	H11: There is a causal relationship between Perceived Infectability and Behavioral Intention. H12: There is a causal relationship between Perceived Infectability and Use Behavior.
Fear of COVID-19	H13: There is a causal relationship between Fear of COVID-19 and Behavioral Intention. H14: There is a causal relationship between Fear of COVID-19 and Use Behavior.

METHOD

The research philosophy is post-positivist, with a deductive approach and exploratory. The method is the quantitative one, through the survey strategy. As for the time horizon of the research, a cross-section was chosen. The technique adopted is the partial least squares structural equations modeling (PLS-SEM) carried out in the SmartPLS 3.3.2 software. Adequacy and validity of the model were verified according to Ringle et al. (2011) and Hair et al.'s (2017) steps. The sample size was estimated as described by Ringle et al. (2014) using the G*Power 3.1 software (Faul; Erdfelder; Buchner; Lang, 2009). The minimum sample calculated was 74 cases. Following Ringle's suggestion (2014), a sample was collected at least 3 times larger than indicated in the sample calculation. The final sample consisted of 230 respondents.

A questionnaire consisted of the (a) UTAUT2 questions (Venkatesh et al. 2012), (b) Perceived Infectability scale (PINS, Duncan et al. 2009), (c) The FCV-19S (Ahorsu et al. 2020), and (d) a question asking which food delivery application one uses (if any) was sent to a convenience sample in theree different Brazilian regions: southeastern, northern and southern, with different patterns of pandemics development, and consequently different recommendations to social distancing. PINS and FCV-19S were the constructs added to the UTAUT2 model and the delivery application question was the dependent variable. Before sending the questionnaire, all questions were translated into Portuguese and all authors checked and critically discussed them to assure that they kept the original meaning. The questionnaire was answered voluntarily.

Table 2 shows the coded items of the scales that were used and their respective sentences in the questionnaire.

Table 2. **Questionnaire Items**

Constructs	Items	Survey Items
Performance Expectancy	PE1	I find the food delivery application useful in my daily life.
	PE2	Using the food delivery application increases my chances of achieving the things that are important to me.
	PE3	Using the food delivery application helps me accomplish things more quickly.
	PE4	Using the food delivery application increases my productivity.
Effort Expectancy	EE1	Learning to use the food delivery app is easy for me.
	EE2	My interaction with the food delivery application is clear and understandable.
	EE3	The food delivery application is easy to use.
	EE4	It is easy for me to be skilled in using the food delivery application.
Social Influence	SI1	People who are important to me think that I should use the food delivery application.
	SI2	People who influence my behavior think I should use the food delivery app.
	SI3	People whose opinions I value prefer to use the food delivery app.
Facilitating Conditions	FC1	I have the resources to use the food delivery app.
	FC2	I have the knowledge to use the food delivery application.
	FC3	The food delivery application is compatible with other technologies that I use.
	FC4	I can get help from others when I have difficulties using the food delivery application.
Hedonic Motivation	HM1	Using the food delivery application is fun.
	HM2	Using the food delivery application is nice.
	HM3	Using the food delivery application is very interesting.
Price Value	PV1	The food delivery application gives me cheaper products.
	PV2	The food delivery application is cost effective.
	PV3	At the current price, the food delivery application offers a good return.
Habit	HT1	Using the food delivery application has become a habit for me.

	HT2	I am addicted to using the food delivery application.
	HT3	I should use the food delivery app.
	HT4	Using the food delivery app has become a natural for me.
Behavioral Intention	BI1	I intend to continue using the food delivery app in the future.
	BI2	I will always try to use the food delivery app in my daily life.
	BI3	I plan to continue using the food delivery application frequently.
Use Behavior	USE1	a) Search for prices.
	USE2	b) Compare prices.
	USE3	c) Order meals.
	USE4	d) Order drinks.
	USE5	e) Use discount coupons.
	USE6	f) Search for promotions.
Perceived Infectability	PIN1	In general, I am very susceptible to colds, flu and other infectious diseases.
	PIN2	I am unlikely to catch a cold, flu or other illness, even if it is ‘going around’. (reverse-scored)
	PIN3	If an illness is ‘going around’, I will get it.
	PIN4	My immune system protects me from most illnesses that other people get. (reverse-scored)
	PIN5	I am more likely than the people around me to catch an infectious disease.
	PIN6	My past experiences make me believe I am not likely to get sick even when my friends are sick. (reverse-scored)
	PIN7	I have a history of susceptibility to infectious disease.
Fear of COVID-19	FCO1	I am most afraid of coronavirus-19.
	FCO2	It makes me uncomfortable to think about coronavirus-19.
	FCO3	My hands become clammy when I think about coronavirus-19.
	FCO4	I am afraid of losing my life because of coronavirus-19.
	FCO5	When watching news and stories about coronavirus-19 on social media, I become nervous or anxious.
	FCO6	I cannot sleep because I’m worrying about getting coronavirus-19.
	FCO7	My heart races or palpitates when I think about getting coronavirus-19.

RESULTS ANALYSIS

Sample characteristics

The information described on Table 3 aims to characterize the profile of respondents to this survey, demonstrating the descriptive statistics of frequency and relative frequency. The statistical software Statistical Package for the Social Science (SPSS), version 24.0, was used to make the calculations operational, and in a systematized way the frequencies of responses were calculated on gender, age, monthly income, civil status, education, and experience in using delivery applications.

All 230 respondents agreed to participate in the survey on a voluntary, non-compulsory basis, and with full autonomy to decide whether or not to participate, as well as to withdraw participation at any time. By agreeing to participate in the survey, confidentiality and privacy of the information provided were guaranteed.

The sample consisted of 230 components, 41.7% male and 58.3% female. Regarding age, 60.87% are between 18 and 30 years old, 30% between 31 and 40 years old, and 9.13% are over 40 years old. For education, 0.43% have completed elementary school, 16.09% have completed high school, 36.09% have completed graduation and 47.39% have completed post-graduation. For the delivery apps cited by the respondents, ifood represented 36.53%, whatsapp 21.47%, uber eats 19.96%, rappi 6.41% and other 15.63%.

The responses on monthly income, 6.50% of respondents earn less than 1 minimum wage, 26.10% earn between 1 and 2 minimum wages, 10.90% earn between 2 and 3 minimum wages, 10% earn between 3 and 4 minimum wages, 9.60% earn between 4 and 5 minimum wages and 37% earn more than 5 minimum wages. Regarding the respondents civil status, 44.80% are single, 39.60% are married, 9.60% are in stable union and 6.10% are divorced. About the experience in using delivery applications, 37.00% respondents use at least 1 year, 23.40% between 1 and 2 years, 19.20% between 2 and 3 years and 20.40% respondents over 3 years.

Table 3. **Demographics**

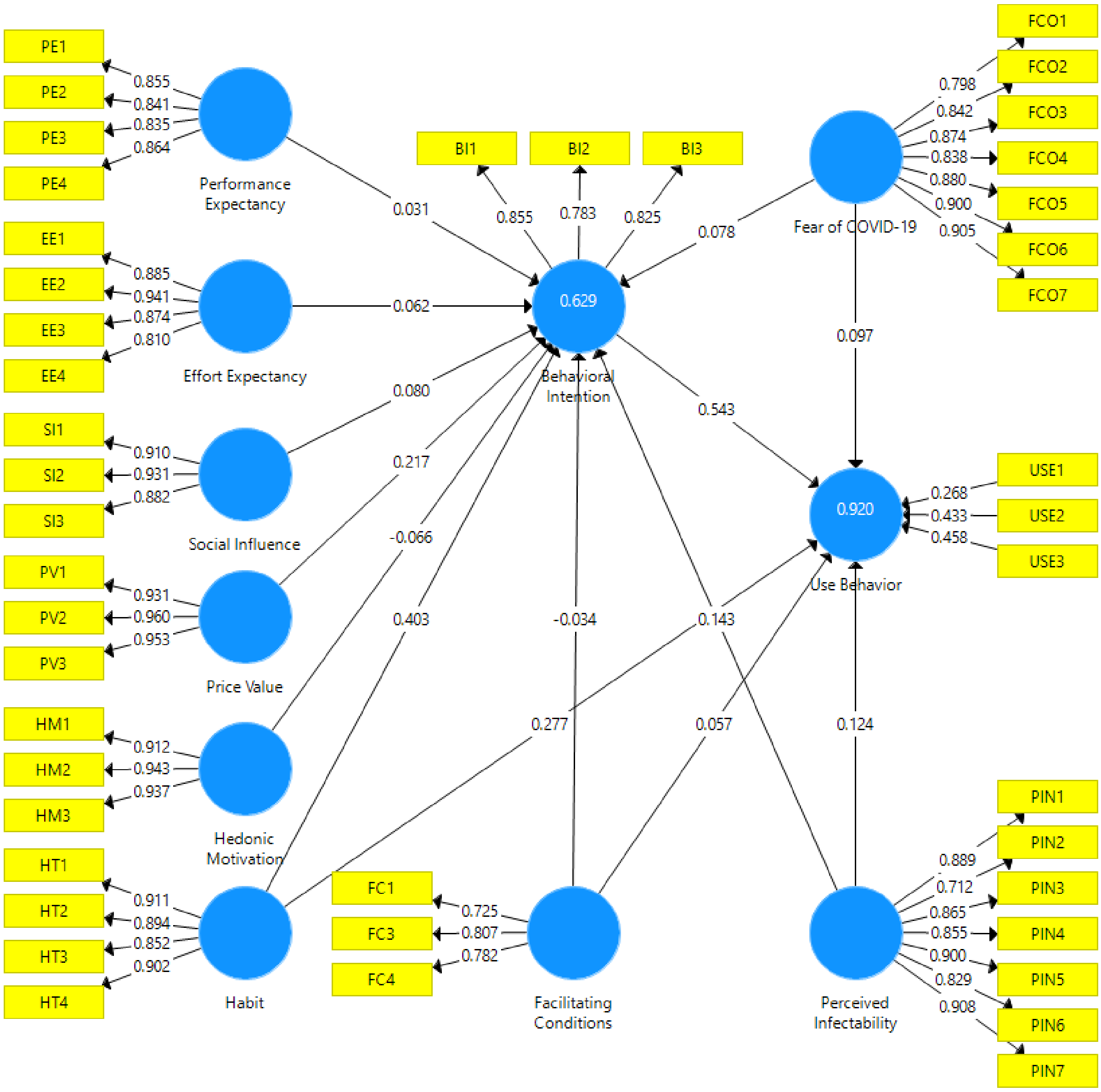
	Demographics	**Freq.**	**%**	**Cumulative %**
Gender	Male	96	41.70%	41,70%
	Female	134	58.30%	100,00%
Age	Between 18 and 30 years old	140	60.87%	60,87%
	Between 31 and 40 years old	69	30.00%	90,87%
	Over 40 years old.	21	9.13%	100,00%
School Level	Elementary school	1	0.43%	0,43%
	High school	37	16.09%	16,52%
	Graduation	83	36.09%	52,61%
	Post-graduation	109	47.39%	100,00%
Delivery Apps	Ifood	84	36.53%	36,53%
	WhatsApp	49	21.47%	58,00%
	Uber Eats	46	19.96%	77,96%
	Rappi	15	6.40%	84,37%
	Others	36	15.63%	100,00%
Income (monthly)	Less than 1 Minimum Wage	15	6,50%	6,50%
	Between 1 and 2 Minimum Wages	60	26,10%	32,60%
	Between 2 and 3 Minimum Wages	25	10,90%	43,50%
	Between 3 and 4 Minimum Wages	23	10%	53,50%
	Between 4 and 5 Minimum Wages	22	9,60%	63%
	Over 5 Minimum Wages	85	37%	100%
Civil Status	Single	103	44,80%	44,80%
	Married	91	39,60%	84,30%
	Stable Union	22	9,60%	93,90%
	Divorced	14	6,10%	100%
Experience	At least 1 year	85	37.00%	37.00%
	Between 1 e 2 years	54	23.40%	60.40%
	Between 2 e 3 years	44	19.20%	79.60%
	Over 3 years	47	20.40%	100.00%

Measurement Model Analysis

To investigate causal relations between COVID-19 pandemic aspects and use of food delivery applications, we incorporated the PINS and FCV-19S into the UTAUT2 model.

Figure 2 depicts the estimated measurement model. In the validity and reliability analysis of the structural model, it was generated the factor loadings, Cronbach´s α coefficients, Average Variances Extracted (AVE), Composite Reliability (CR) and R^2 for the reflective variables (Table 4), and the validation of the formative variable Use Behavior with the variance inflation factor (VIF), p-values and R^2 (Table 5).

Figure 2. **UTAUT2 structural model with Perceived Infectability and Fear of COVID-19**



In the model, only the items with loadings greater than 0.700 (Hair, Hult, Ringle & Sarstedt, 2009) were used. Therefore, the item FC2 was excluded from the Facilitating Conditions construct. In the evaluation of the structural model, the Pearson coefficient of determination (R^2) for the latent variable Behavioral Intention was 0.629, and for the variable Use Behavior was 0.920, both considered a large effect (Cohen, 1988). The values of the AVE were higher than 0.500, confirming the convergent validity (Fornell & Larcker, 1981; Henseler, Ringle & Sarstedt, 2015).

For the reliability analysis, the Cronbach's α coefficients, whose values should be greater than 0.700, and the CR, with values greater than 0.500 (Hair et al., 2009; 2017) were calculated. Only the variable Facilitating Conditions obtained a value below the recommended one (0.670), but with CR optimal (0.816), being the latter an upper reliability parameter, confirming the reliability of the model.

Table 4. **Adjustment quality values of the SEM model**

Latent Variable	Items	Loadings	Cronbach's α	AVE	CR	R^2
Behavioral Intention	BI1	0.855	0.761	0.675	0.862	0.629
	BI2	0.783				
	BI3	0.825				
Effort Expectancy	EE1	0.885	0.901	0.772	0.931	-
	EE2	0.941				
	EE3	0.874				
	EE4	0.810				
Facilitating Conditions	FC1	0.725	0.670	0.597	0.816	-
	FC3	0.807				
	FC4	0.782				
Fear of COVID-19	FCO1	0.798	0.943	0.745	0.953	-
	FCO2	0.842				
	FCO3	0.874				
	FCO4	0.838				
	FCO5	0.880				
	FCO6	0.900				
	FCO7	0.905				
Hedonic Motivation	HM1	0.912	0.923	0.867	0.951	-
	HM2	0.943				
	HM3	0.937				
Habit	HT1	0.911	0.912	0.792	0.938	-
	HT2	0.894				
	HT3	0.852				
	HT4	0.902				
Performance Expectancy	PE1	0.855	0.871	0.721	0.912	-
	PE2	0.841				
	PE3	0.835				
	PE4	0.864				
Perceived Infectability	PIN1	0.889	0.937	0.728	0.949	-
	PIN2	0.712				
	PIN3	0.865				
	PIN4	0.855				
	PIN5	0.900				
	PIN6	0.829				
	PIN7	0.908				
Price Value	PV1	0.931	0.944	0.899	0.964	-
	PV2	0.960				
	PV3	0.953				
Social Influence	SI1	0.910	0.893	0.824	0.934	-
	SI2	0.931				
	SI3	0.882				

The items from formative variable Use Behavior are observed in Table 5. All of them have low levels of multicollinearity (VIF<4). All the items also have statistical significance and are statistically different from zero ($p<0.05$), providing convergent validity in the formative construct of Use Behavior (Fornell & Larcker, 1981; Henseler, Ringle & Sinkovics, 2009). Items USE4, USE5 AND USE6 were excluded as they did not reach the required values.

Table 5. **Analysis of the latent formative variable**

Formative Items	Weights	VIF	T Statistics	P Values	R^2
USE1	0.268	2.742	4.829	0.000	0.920
USE2	0.433	1.733	8.881	0.000	-
USE3	0.458	2.148	10.199	0.000	-

For the analysis of Cross Loadings values, all calculated loadings were higher in their respective latent variables, when compared to the others, as shown in Table 6, which indicates the discriminant validity of the model (Chin, 1998; Ringle et al, 2014).

Table 6. **Values of Cross Loadings**

LV	BI	EE	FC	FCO	HT	HM	PIN	PE	PV	SI
BI1	**0.855**	0.324	0.324	0.489	0.532	0.434	0.474	0.472	0.520	0.517
BI2	**0.783**	0.532	0.417	0.528	0.787	0.527	0.530	0.631	0.597	0.567
BI3	**0.825**	0.288	0.295	0.439	0.472	0.419	0.493	0.458	0.520	0.465
EE1	0.401	**0.885**	0.436	0.302	0.565	0.587	0.282	0.419	0.388	0.362
EE2	0.462	**0.941**	0.461	0.257	0.620	0.545	0.278	0.446	0.464	0.431
EE3	0.451	**0.874**	0.460	0.241	0.519	0.545	0.320	0.393	0.367	0.388
EE4	0.360	**0.810**	0.411	0.326	0.518	0.589	0.334	0.397	0.370	0.371
FC1	0.266	0.459	**0.725**	0.239	0.408	0.378	0.264	0.379	0.361	0.381
FC3	0.281	0.468	**0.807**	0.251	0.362	0.359	0.273	0.377	0.218	0.402
FC4	0.415	0.284	**0.782**	0.443	0.456	0.490	0.420	0.535	0.372	0.607
FCO1	0.391	0.053	0.253	**0.798**	0.364	0.306	0.530	0.435	0.338	0.401
FCO2	0.448	0.257	0.237	**0.842**	0.464	0.364	0.591	0.540	0.404	0.463
FCO3	0.595	0.323	0.387	**0.874**	0.650	0.534	0.794	0.613	0.555	0.596
FCO4	0.439	0.297	0.348	**0.838**	0.457	0.459	0.584	0.489	0.351	0.377
FCO5	0.464	0.244	0.389	**0.880**	0.500	0.461	0.618	0.522	0.414	0.485
FCO6	0.626	0.337	0.424	**0.900**	0.657	0.548	0.830	0.576	0.576	0.646
FCO7	0.569	0.326	0.450	**0.905**	0.590	0.553	0.797	0.560	0.508	0.594
HT1	0.669	0.584	0.501	0.498	**0.911**	0.627	0.521	0.715	0.635	0.624
HT2	0.678	0.489	0.433	0.640	**0.894**	0.662	0.653	0.671	0.616	0.644
HT3	0.625	0.501	0.509	0.646	**0.852**	0.694	0.584	0.754	0.637	0.696
HT4	0.688	0.677	0.465	0.451	**0.902**	0.619	0.463	0.633	0.611	0.605
HM1	0.540	0.595	0.489	0.524	0.675	**0.912**	0.490	0.583	0.564	0.605
HM2	0.533	0.616	0.529	0.469	0.700	**0.943**	0.523	0.593	0.513	0.574
HM3	0.512	0.578	0.491	0.533	0.661	**0.937**	0.549	0.570	0.540	0.610
PIN1	0.578	0.301	0.345	0.746	0.578	0.480	**0.889**	0.540	0.585	0.573
PIN2	0.408	0.206	0.277	0.514	0.413	0.408	**0.712**	0.341	0.252	0.337
PIN3	0.544	0.341	0.418	0.760	0.562	0.504	**0.865**	0.557	0.471	0.526
PIN4	0.477	0.320	0.365	0.578	0.515	0.480	**0.855**	0.428	0.423	0.421
PIN5	0.545	0.303	0.426	0.760	0.571	0.508	**0.900**	0.580	0.569	0.565
PIN6	0.403	0.251	0.280	0.590	0.412	0.422	**0.829**	0.373	0.352	0.356
PIN7	0.640	0.310	0.406	0.782	0.618	0.522	**0.908**	0.564	0.587	0.629
PE1	0.574	0.398	0.484	0.475	0.650	0.506	0.433	**0.855**	0.563	0.590
PE2	0.559	0.363	0.430	0.554	0.649	0.530	0.529	**0.841**	0.603	0.697
PE3	0.496	0.414	0.511	0.457	0.628	0.516	0.435	**0.835**	0.495	0.596
PE4	0.558	0.426	0.521	0.630	0.709	0.572	0.562	**0.864**	0.542	0.713
PV1	0.603	0.432	0.330	0.486	0.651	0.607	0.524	0.600	**0.931**	0.618
PV2	0.646	0.440	0.412	0.543	0.688	0.547	0.521	0.638	**0.960**	0.678
PV3	0.658	0.417	0.438	0.492	0.656	0.499	0.543	0.612	**0.953**	0.633
SI1	0.622	0.339	0.558	0.569	0.627	0.541	0.539	0.701	0.698	**0.910**
SI2	0.566	0.445	0.548	0.544	0.698	0.582	0.506	0.736	0.587	**0.931**
SI3	0.538	0.429	0.585	0.531	0.639	0.629	0.549	0.646	0.552	**0.882**

The square roots of the Average Variances Extracted (AVE) values of each construct were compared with Pearson's correlations between the latent variables. The square roots of the AVEs showed values greater than the correlations, indicated in Table 7, in this case the discriminant validity was confirmed by Fornell and Larcker (1981) criterion.

Table 7. **Discriminant Validity (Fornell & Larcker Criterion)**

Latente Variable	BI	EE	FC	FCO	HT	HM	PIN	PE	PV	SI
Behavioral Intention	**0.822**									
Effort Expectancy	0.479	**0.878**								
Facilitating Conditions	0.429	0.504	**0.772**							
Fear of COVID-19	0.598	0.316	0.422	**0.863**						
Habit	0.747	0.633	0.535	0.626	**0.890**					
Hedonic Motivation	0.568	0.641	0.541	0.546	0.730	**0.931**				
Perceived Infectability	0.612	0.343	0.427	0.803	0.623	0.559	**0.853**			
Performance Expectancy	0.646	0.471	0.572	0.625	0.777	0.625	0.578	**0.849**		
Price Value	0.671	0.453	0.416	0.535	0.701	0.579	0.558	0.651	**0.948**	
Social Influence	0.636	0.442	0.620	0.605	0.720	0.641	0.585	0.766	0.678	**0.908**

To analyze the direct effects of the latent variables of the model, the Blindfolding technique was used, which allowed the calculation of Stone-Geisser's Q^2 value (Stone, 1974; Geisser, 1974) for the evaluation criterion for the predictive relevance of the model. The Q^2 calculated for the latent variable Behavioral Intention and Use Behavior were greater than zero and indicates that the PLS path model has predictive relevance for this construct (Hair et al., 2009; 2017).

To assess how representative each construct is for the model (Table 8), we calculated the Effect Size (f^2), the values 0.02, 0.15 and 0.35, considered small, medium and large, respectively (Cohen, 1988; Hair et al, 2009; 2017).

Table 8. **Predictive Validity (Q^2) or Stone-Geisser Indicator, and Effect Size (f^2) or Cohen Indicator**

Latent Variable	CV RED (Q^2)	CV COM (f^2)
Behavioral Intention	0.390	0.343
Use Behavior	0.683	0.481
Effort Expectancy		0.611
Facilitating Conditions		0.208
Fear of COVID-19		0.658
Habit		0.637
Hedonic Motivation		0.685
Perceived Infectability		0.639
Performance Expectancy		0.522
Price Value		0.744
Social Influence		0.612

To check if the causal relations are significant, the student T-values were calculated through Bootstrapping with resampling of 5000 times. The path coefficients in Table 9 indicate how much one construct relates to another and should be greater than 1.96 and P-values less than 0.05 (Hair et al, 2017).

Table 9. **Decisions on the hypotheses**

H	Relationship	β	T Statistics	P Values	Decision
H1	Performance Expectancy → Behavioral Intention	0.031	0.331	0.741	Rejected
H2	Effort Expectancy → Behavioral Intention	0.062	0.833	0.405	Rejected
H3	Social Influence → Behavioral Intention	0.080	0.968	0.333	Rejected
H4	Facilitating Conditions → Behavioral Intention	-0.034	0.548	0.584	Rejected
H5	Facilitating Conditions → Use Behavior	0.057	2.105	0.035	**Supported**
H6	Hedonic Motivation → Behavioral Intention	-0.066	0.896	0.370	Rejected
H7	Price Value → Behavioral Intention	0.217	3.122	0.002	**Supported**
H8	Habit → Behavioral Intention	0.403	4.218	0.000	**Supported**
H9	Habit → Use Behavior	0.277	5.840	0.000	**Supported**
H10	Behavioral Intention → Use Behavior	0.543	8.581	0.000	**Supported**
H11	Perceived Infectability → Behavioral Intention	0.143	1.870	0.062	Rejected
H12	Perceived Infectability → Use Behavior	0.124	2.914	0.004	**Supported**
H13	Fear of COVID-19 → Behavioral Intention	0.078	0.981	0.327	Rejected
H14	Fear of COVID-19 → Use Behavior	0.097	2.931	0.003	**Supported**

This study sought to investigate the impacts of COVID-19 pandemic on customer behavior toward using delivery applications to order food. By adding the PINS and FCV-19S to the UTAUT2 model as latent variables, we have found that Perceived Infectability and the Fear of COVID-19 have direct causal relationships with Use Behavior. Besides, the results add to previous studies (Pigatto et al. 2017) by reinforcing the evidence that online delivery services in Brazil have been expanding over the past two decades and constitute convenient options for consumers.

For the original variables of the UTAUT2 model (Venkatesh et al. 2012), Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation did not obtain a significant causal relationship in Behavioral Intention. It is believed that due to the current context of the pandemic, sudden changes may affect this relationship in Behavioral Intention. The variable Behavioral Intention is one that measures the intention to use a certain technology. Sudden changes such as the Covid-19 pandemic have directly affected the Use Havior, without the need of a Behavioral Intention as a predictor.

Previously, studies have investigated the adoption and use of online shopping (Lian & Yen, 2014) and the continuous intention on food delivery applications (Lee, Sung & Jeon, 2019), but no studies have yet investigated causal relationships between PINS, FCV-19S and the use of food delivery technology. For those who work with food delivery by selling food in applications during this pandemic, these findings can be a positive guide to consumer behavior by proving that fear of the new disease and perceived likelihood of catching the infection are drivers of application use. These findings can be used by restaurants, markets and delivery applications to increase revenues by providing a safe environment for citizens in social isolation. It also provides social welfare and helps prevent the spread of covid-19 or any other contact transmissible infectious disease that may appear.

Altogether, our findings suggest that personal perceptions of the risks that diseases pose, combined with easy-to-use technologies and availability, lead one to decide to use FDA in epidemic and pandemic contexts. In other words, a subjective perspective of health crises causes consumers to use FDA, provided the latter is available straightforwardly. Regarding contention and distancing measures, our findings show some evidence that people have gone out less to eat and have opted to order food via applications instead.

The FCV-19S has been proved to be a comprehensive and useful tool to indicate the society fear and can be used to support the government actions with the objectives of holistically having a free COVID-19 society. The social (FCV-19S) and economic (FDA) correlation between FDA and fear of COVID-19 is a great indicative to the government that, with a better support to FDA workers, fear can be reduced in society and help control this new infectious disease.

CONCLUSION

The main objective of this article was to analyze the impact of perceived infectability and fear of Covid-19 on the acceptance and use of delivery applications during the Covid-19 pandemic. For this, we used the UTAUT2 model and added the scales for measuring the perceived infectability and fear of Covid-19. The results point to evidence of the impact of the Covid-19 pandemic on the use behavior of the delivery application. In conclusion, this study has demonstrated that there has been a change in consumer behavior regarding the use of food delivery applications, as both constructs added to the model had a direct causal relationship in the use behavior.

This research has a practice contribution by clarifying the dimension of the impact on user behavior. The pandemic also affects people's mental health. When we verify the relationship of perceived infectability and fear of covid-19 with the behavior of use, this indicates a need for safety by users, maintaining social distance. Delivery companies can take actions to promote this sense of well-being and safety to users.

This research has a theoretical contribution by proving the use of the UTAUT2 as a consistent model to verify the acceptance and use of a certain technology, which can be used in other researches.

We highlight, however, its limitations such as we use only one of the behavioral models for the acceptance and use of technology, there are others that can be used. Another limitation is that we add only two new constructs (perceived infectability and fear of Covid-19), where there is the possibility that other variables may be part of the model. There is also the limitation of the sample, collected by convincing, which may also not represent the universe of delivery applications users.

Finally, as future research we suggest that new variables should be added to the model to analyze the causal relationships and motivations behind changing consumer behavior. New items that were excluded from the structural model in this research should also be remodeled, since the meanings that constructs have at certain times can change as time goes by due to the breakdown of paradigms and behavioral changes in societies.

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