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COVID-19 and Hospitality Services: The Role of Information Sources, Believability, Fear, and Behavioral Intentions

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Abstract

Based on the Social Amplification of Risk Framework (SARF) and crisis decision theory, this study examined the influence of trust in different types of information sources on the believability of COVID-19 information (BCI). Furthermore, the influence of BCI on fearfulness and the corresponding influence of fearfulness on the intention to use hospitality services and stay at home are analyzed. Structural equations modeling, using data from 1,017 American consumers, successfully confirmed the significant influences of trust in media and government on BCI and the corresponding positive effect of BCI on fearfulness. Additionally, the negative effects of fearfulness on intentions to visit hotels and restaurants (general and Chinese) and the positive effects of fearfulness on intentions to stay at home and use third-part food delivery services are validated. Trust in social media was not found to influence BCI and the negative effect of fearfulness on Chinese restaurants was weaker than that of general restaurants. Numerous implications are offered for practitioners.

Keywords: Coronavirus, Chinese restaurants, food delivery, social amplification of risk framework, crisis decision theory

Introduction

As reported by the World Health Organization (2020), the Covid-19 epidemic is showing the critical role of information diffusion in a disintermediated news cycle. Due to the strict physical distancing policies, people rely on maintaining connections through global digital networks such as mass and social media (for example, Facebook, Twitter, and other national news broadcasting agencies) to facilitate human interaction and information sharing about the virus (Limaye et al., 2020). As a result, an unusual pattern is uncovered, highlighting a parallel is not only the rapid spread of the virus itself but also information and misinformation pertaining to the management of the virus outbreak.

Supplement to this, the delayed federal response to the severity of the virus has fostered confusion about the nature of the virus and the necessary steps to address it (Haffajee & Mello, 2020). With the increased popularity of social media platforms being used to spread COVID-19 information, the notion of legitimacy has changed. For instance, social media users increasingly view peers within their networks who exchange valued information as authoritative sources of information; regardless of the information source, its perceived legitimacy increases as information is further disseminated (Limaye et al., 2020). Notably, the methods used to share and validate information on social media platforms are contrary to methods used by traditional media who have specialized knowledge and responsibilities pertaining to information sharing and verification (Eysenbach, 2007). Nevertheless, misinformation or delayed information on the coronavirus could further extenuate damages to the tourism and hospitality industry by fragmenting social response.

The Lombardy case study highlights the influence of media on people/tourist behavior and the need to streamline information on COVID-19 so that various information centers can join forces to control the spread of the virus. For example, without fact-checking a rumor about the possible lock-down of Lombardy (a territory in northern Italy) to contain coronavirus, CNN published the story hours before the official communication from the Italian Prime Minister (John & Wedeman, 2020). Because of this, people crammed trains and airports to flee Lombardy before the lock-down was enforced, thereby disrupting the government's initiative to contain the virus before it spread to other regions (Cinelli et al., 2020). Consequently, the perceived legitimacy of digital social networks, the divergent views of traditional news agencies, and delayed government response to COVID-19 have facilitated the spread of a different viral entity – misinformation, which could heavily influence tourist behavior.

Although an increasing number of studies are assessing the post-pandemic impacts on tourist flows and economic revenue (Gössling et al., 2020; Ranasinghe et al., 2020), only a few studies have focused on the interrelationships between media coverage and epidemics (Ritchie & Jiang, 2019) or the influence of social media communication overall during a pandemic (Luo & Zhai, 2017). Previous research on events such as SARS (2002-2003), swine flu (2009-2010), and Ebola (2014-2016) indicate that trust is of vital importance during infectious disease outbreaks (Cairns et al., 2013; Fischhoff et al., 2018; National Academy of Sciences, 2016; Smith, 2006). Also, theories on risk perception draw attention to psychological barriers or the mental state (e.g., belief and fear) that may further impede behavior intentions during a crisis (Edwards, 1961; Kasperson et al., 1988). Therefore, to fulfill these gaps, this study will extend the Social Amplification of Risk Theory (SARF) and crisis decision theory to a hospitality context to examine the interplay of trust in various sources of information about a viral disease, BCI and fearfulness on intention to use various hospitality services. The findings can provide significant insights into hospitality consumers' psychological responses to various information sources and how this in turn influences behavior intention. This study will enable hospitality managers to gauge consumer confidence to use various hospitality services in the midst of a catastrophic event and provide an overview of how consumer behavior changes from sources of information context.

Literature Review

The Influence of Media

According to Depoux et al. (2020), public sentiments, as shared on social media platforms and media reporting, may significantly influence people's decision to discontinue hospitality and tourism services due to specified travel restrictions. As evidenced in the Lombardy case study, media reports can influence people's behavior and even reverse the effectiveness of policies implemented by the government to protect its citizens. In this regard, social media platforms such as Twitter, Facebook, and YouTube give consumers direct access to a large amount of data that could be used to amplify rumors and dubious information. Moreover, built-in algorithms facilitate content promotion based on users' attitudes and preferences to further spread information (Kulshrestha et al., 2017).

As stated by Schmidt et al. (2017), social media influence develops peoples' social perceptions over time and frames their narratives, thereby influencing political communication, policymaking and public debate (Zarocostas, 2020). It is also customary for people to endorse information that is aligned with their worldviews and ignore opposing information to form polarized groups (Bail et al., 2018; Baronchelli, 2018; Zollo et al., 2017). Furthermore, misinformation might quickly spread when polarization is high (Vicario et al., 2019; Wardle & Derakhshan, 2017). In fact, Vosoughi et al. (2018) report showed that inaccurate information (fake news) might spread more speedily than fact-based news, although this effect might be platform-specific (Collins et al., 2020). While previous studies assess the effects of COVID-19 related information diffusion from a single platform (Bovet & Makse, 2019; Ruth, 2019), the study extends this framework to capture consumers' trust in multiple platforms of information sources including government, mainstream media, and social media.

Theoretical Framework: SARF, Crisis Decision Theory

Larson (2018) argued that the biggest pandemic risk is misinformation. However, the current risk-averse strategies of social distancing and stay-at-home orders have not completely eliminated the extraordinary spreading properties of COVID-19 that are causing high rates of morbidity and mortality (Lipsitch et al., 2020). The coronavirus pandemic can be viewed as a risk event that includes several factors that may influence people's perceptions. Through the SARF, a major assumption is that while news media are critical in amplifying risks, other 'amplification stations' such as organizations or social institutions are also important (Kasperson et al., 1988). According to DeFleur (1966), amplification in communication is the process of transmitting information from source to receiver through one or multiple transmitters, whereby the message or signal can be changed by mitigating or intensifying the encoding/decoding process. Consequently, amplification also involves people's social experiences of risk that could further alter their risk perception from its original level to shape their risk consequences (Kasperson et al., 1988).

Kasperson et al. (1988) propose that once a risk event begins, it is pertinent to identify the sources of amplification through personal experience, direct and indirect communication. Placing the coronavirus as an event shaping risk perception, people practicing social distance depend on professional information brokers (e.g., media news), social media, and their individual experiences to respond to the coronavirus. This informal social network is further processed by social stations of amplification, such as opinion leaders (social media influencers), news media representatives, and government agents as it is shared through multiple communication channels, including media press, telephones, and direct conversation. It is during this phase that individual stations of amplifications are formed, thereby enabling people to decode or evaluate the message differently such that unique behavioral responses are formed. The individual response represents the impact of the risk event (coronavirus), which further informs how people will interact socially (for example, staying at home or overcoming fear to stay at a hotel, traveling, dining in restaurants, or ordering via third party delivery services). These individual responses can further spread to various groups to create a ripple effect of how consumers respond to the coronavirus information as shared through various information sources in a hospitality context.

COVID-19 could also be framed as a crisis event of extreme significance. According to the crisis decision theory, consumers' response to crisis events depends on the level of severity (Sweeny, 2008). This theory addresses questions pertaining to decision processes that occur when people respond to a negative event as well as the factors that influence response choices. Sweeny (2008) identified three stages (in no particular order) people undergo when experiencing a negative life event; they evaluate the severity of the negative event using various types of information, determine their response options, and evaluate their response options. Similarly, the coronavirus can be perceived as an extreme crisis event due to death reports and lived experiences of persons who survived the crisis as shared through various information platforms. These incidents may influence psychological and physical responses to the virus. Sweeny (2008, p.61) also noted that "people may re-evaluate the severity of their situation throughout the process of evaluating and choosing a response". To that end, behavioral responses can fluctuate depending on the severity of the crisis and the information source platform.

Trust in Various Platforms and Believability of COVID-19 Information

Given the absence of consistent scientific and government agreement on how to control the spread of the coronavirus (Chinazzi et al., 2020), people rely on informal information platforms to share opinions, experiences and discuss possible responses (Shahsavari et al., 2020). Expectedly, communication media has been found to influence people's perceptions and behaviors, especially in risk and crisis situations (Paek et al., 2016; Tyler & Cook, 1984). These findings suggest that trust could play a critical role in the extent to which people are influenced by various media sources. For example, trust can influence transmissibility, perceived severity, and willingness to adapt to interventions such as information-seeking behavior and physical distancing (Blair et al., 2017; Vinck et al., 2019). Trust is defined as an individual's confidence in the trustworthy characteristics of members or platforms (Wang et al., 2016). As such, its effect may differ depending on the platform information is shared.

According to Haffajee and Mello (2020), early misleading statements from government officials pertaining to the gravity of the coronavirus swayed public sentiments against taking steps to curb the spread of the virus. The authors contrasted the approach of the U.S. government to those of South Korea and Taiwan, which rapidly implemented a centralized national strategy to prevent widespread community transmission. Nevertheless, people's sentiment toward government response can change during a crisis; for example, previous research by Bults et al. (2011) found that trust in government information sources changes as a pandemic progress. Therefore, it is predicted that people will trust information from government officials now that they have

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implemented social distancing procedures and broadcast frequent coronavirus briefings with representatives from the WHO. Comparatively, many stories from traditional media news sources are often perceived as the product of fact-based reporting, while information from social media is perceived as anecdotal, the product of speculation, wishful thinking, or conspiratorial fantasy (Shahsavari et al., 2020). This implies that information shared from media news could be perceived as more trustworthy than those retrieved via social media platforms.

As stated by Pilditch et al. (2020) credibility from trust is not the only way to evaluate reports; an individual's previous belief regarding the hypothesis (e.g., the coronavirus risk event), the context, available evidence, as well as the information sequence may contribute to belief uptake. To understand the trust-belief link, Pilditch and Custers (2018) proposed a theoretical paradigm that argues that the first evidence people encounter in the environment is often used to verify the truth-value of a communicated belief. In other words, believability of the coronavirus depends on the initial evidence provided by the information source. For example, although both a random Facebook user and Anderson Cooper from CNN may provide the same information about the coronavirus, the persuasiveness of the message differs based on the source. Anderson Cooper is more likely to have relevant knowledge (expertise) and a motive to convey it honestly due to his job affiliation compared to an ordinary Facebook user who does not have the same credentials. Consequently, believability is an extension of trust in the information source that further provides directional predictions to maintain or dismiss the message received (Pilditch & Custers, 2018; Staudinger & Buchel, 2013).

To assess the impact of source credibility, Pilditch et al. (2020) found that beliefs are processed in the context of source cues, and that perceived trustworthiness predicts the direction of first choices to show varying effects of high vs. low trust groups. Thus, a similar pattern is predicted for the influence of trust on believability of information pertaining to the coronavirus; people are more likely to believe the information if they trust the source and are less likely to believe the information if there is a lack of trust in the source the information was disseminated from in the first place. Furthermore, consumers are more likely to trust information shared by news media and the government compared to social media platforms. Therefore, the following hypotheses were proposed:

- **H1:** Trust in media has a significant and positive effect on BCI.
- **H2:** Trust in government has a significant and positive effect on BCI.
- **H3:** Trust in social media has a significant and negative effect on BCI.

The Influence of Believability of COVID-19 Information on Fearfulness

So far, the literature reviewed two psychological factors that play a vital role in consumers' response to COVID-19; however, a critical component of the coronavirus is fear. DeHoog et al. (2007) define fear as an unpleasant emotional state that is triggered by the perception of threatening stimuli. Fear is manifested when people believe and expect a threatening and unfortunate event to take place (Stankovska et al., 2020). Unprecedented events such as the coronavirus can induce fear among people. In some cases, fear has even led people to commit suicide because they thought they had contracted the virus, although the autopsies proved they did not (Goyal et al., 2020). According to the crisis decision theory, the way an anticipated event is perceived will significantly influence the intensity of fear experienced (Stankovska et al., 2020).

Previous studies found that fear-arousing communication is often used in health education campaigns to increase people's concern about the consequences of their health-impairing behavior (DeHoog et al., 2007); presumably, these campaigns increase the likelihood that people will accept the recommended treatments (DeHoog et al., 2007). In one study, Hong and You (2016) found a positive relationship between fatalistic beliefs and experience of uncertainty, especially among less-educated people. In the same way, when people believe the information shared about COVID-19, they are more likely to experience fear due to visible severe effects on other people's health, often leading to death. Therefore, the more people believe the information shared about the coronavirus, the more likely they will become fearful, thus predicting a positive effect of believability of information on fear. According to Stankovska et al. (2020), the fight or flight response to anxiety or fear-induced situations is a useful strategy that can influence people to take extra precautions. In this context, fear responses will be aligned to the belief that the threat of the coronavirus is real. This admission could be used as a psychological threat-management resource to reduce actions that increase exposure to the virus, since people will rely on COVID-19 information to protect themselves throughout the pandemic. Therefore, the following hypothesis was proposed:

- **H4:** BCI has a significant and positive effect on fearfulness.

The Effect of Fearfulness on Tourist Behavior

As confirmed in several Meta-analyses on fear appeals, high fear messages are proposed to influence attitude, intention, and behavior change compared to low fear messages (DeHoog et al., 2007; Witte & Allen, 2000). Similarly, when consumers perceive the threat of the coronavirus to be severe, this will negatively influence their behavior. In other words, fear will undermine people’s intention to use hospitality services if perceptions of the environment increase the likelihood to contract the virus. Previous studies on the effect of the crisis on tourism flow indicate that aftershocks can induce fear and put stress on tourist decisions to travel in and around destinations (Senbeto & Hon, 2020). As a result, tourist consumption may change depending on the magnitude or type of crisis.

Comparably, the novel coronavirus compounds these issues with health and safety precautions that increase anxiety and may influence tourist behavior in several ways. For instance, in a financial crisis, tourists prefer to choose budget hotels and inexpensive rooms (Song et al., 2011). Also, in subsequent years after the outbreak of SARS in 2003, the pandemic resulted in unemployment, a reduction in tourism receipts and reduced airline seats and hotel occupancy rates in Southeast Asian countries (Chen, 2011; Pine & McKercher, 2004).

Since China was central to the virus outbreak, it is projected that its inbound tourism will be affected. Considering the metonymic principle, prospective users [of hospitality services] are likely to remember the images directly associated with the physical epicenter of crisis (Depoux et al., 2020). The viral spread of misinformation on several media platforms in the past led to widespread outbursts of racism towards Chinese restaurants, Chinese tourists, and goods from Asia (King, 2015). Also, several nations, including the U.S. and the U.K. have suspended their trade and travel relationship with China due to the panic of spreading the virus (Aljazeera, 2020). In the same way, the spillover effects are in motion where several Asian-owned restaurants in the U.S. also saw a reduction in business sales (Urenda, 2020). This suggests that hospitality services

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affiliated with Asian service providers are more likely to be discriminated against compared to non-Asian affiliated hospitality services. Likewise, Bodosca et al. (2014) found that consumer confidence changes during a crisis to reflect shorter vacation periods, more frequently entertaining at Home, and a reduced the rate of eating out. Overall, it is predicted that contactless hospitality services or those that can be offered with minimal interaction between the service provider and customer will have greater success. Therefore, the following hypotheses were proposed:

- **H5:** Fearfulness has a significant and negative effect on intention to visit hotels.
- **H6:** Fearfulness has a significant and negative effect on intention to visit restaurants.
- **H7:** Fearfulness has a significant and negative effect on intention to visit Chinese restaurants.
- **H8:** Fearfulness has a significant and positive effect on intention to stay at home.
- **H9:** Fearfulness has a significant and positive effect on intention to use third party food delivery service.

Methods

A self-reported survey was prepared using Qualtrics. We targeted American consumers above the age of nineteen. The survey was distributed through Amazon Mechanical Turk (MTurk) - a crowd-sourcing platform in which tasks, known as hits, are allocated to a population of unidentified workers for completion in exchange for compensation (Buhrmester et al., 2016). Studies have shown that the quality of data obtained through MTurk is comparable to that gathered through other sources (Buhrmester et al., 2016; Casler et al., 2013; Kees et al., 2017). Buhrmester et al. (2016) also found that compensation rates for the samples do not significantly impact the quality of the data, but rather only the speed of the collection process. Each participant was paid $1 for filling out the survey in Amazon MTurk. Of the 1100 participants recruited, 1017 were usable after removing items that failed the attention checking questions as well as participants who completed the survey in less than 3 minutes. Reliability analysis, descriptive analysis, correlation analysis, and structural equation modeling were undertaken via MPLUS version 8.

The survey instrument included questions that were adapted from previous studies with high internal validity and demographics such as gender, age, ethnicity, etc). Trust in media and social media were adapted from Fletcher et al. (2000), trust in government was adapted from Bansal et al. (2004), believability was adapted from Gürhan-Canli and Maheswaran (2000), fearfulness was adapted from Andrews et al. (2014), and the behavioral intention scales were adapted from Rahman and Reynolds (2016). All items were measured on a seven-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree).

Findings

Table 1 presents the demographic information of the respondents. A unique inclusion was the top ten locations of travel respondents, along with their work and living arrangements during the coronavirus. Most participants were from California (N=104) Florida (N=87), Texas (N=80), New York (N=71), and Pennsylvania (N=60). More than half of the respondents had children (N=529), work from home (N=681), and currently lives with family (N=739).

Table 1. Demographic Profile of the Respondents

Demographic Characteristic	Number	%
Gender		
Female	434	42.7
Male	578	56.8
Other	5	0.5
Age		
18-25	124	12.2
26-35	404	39.7
36-45	222	21.8
46-55	154	15.1
56-65	84	8.3
>65	29	2.9
Ethnicity		
Asian	67	6.6
American Indian or other Native American	10	1.0
Hispanic, Latino, or Spanish origin	53	5.2
Black/African American	141	13.9
White	721	70.9
Mixed	22	2.2
Other	2	0.2
Prefer not to answer	1	0.1
Top 10 states		
California	104	10.2
Florida	87	8.6
Texas	80	7.9
New York	71	7.0
Pennsylvania	62	6.1
North Carolina	42	4.2
Ohio	39	3.8
Georgia	39	3.8
Illinois	32	3.1
Michigan	30	2.9
Living arrangements		
I live alone	154	15.1
Family	739	72.7
Roommate/s	57	5.6
Other	67	6.6

Demographic Characteristic	Number	%
Education		
Less than High school	2	0.2
High school or equivalent	101	9.9
Associate degree	92	9.0
Some college	131	12.9
Bachelor’s degree	495	48.7
Master’s degree	174	17.1
Doctorate degree	22	2.2
Household income		
<$10,000	34	3.3
$10,000-$19,999	50	4.9
$20,000-$29,999	87	8.6
$30,000-$39,999	115	11.3
$40,000-$49,9999	111	10.9
$50,000-$59,999	139	13.7
$60,000-$69,999	98	9.6
$70,000-$79,999	97	9.5
$80,000-$89,999	57	5.6
$90,000-$99,999	45	4.4
$100,000-$109,999	38	3.7
$110,000-$119,999	21	2.1
$120,000-$129,999	25	2.5
$130,000-$139,999	17	1.7
$140,000-$149,999	32	3.1
$150,000-$159,999	17	1.7
$159,999<	34	3.4
Work status		
Yes, I work from home	681	67.0
Yes, I work outside the Home	160	15.7
I am unemployed	123	12.1
Other	53	5.2
Do you have children?		
Yes	529	52.0
No	488	48.0

Measurement Model

The adequacy of the measurement model was examined using confirmatory factor analysis (CFA) in MPLUS. The standardized maximum likelihood loadings and fit statistics are provided

Table 2. Confirmatory Factor Analysis Results Including Standardized Factor Loading Estimates

Measure	TM	TSM	TG	BCI	FRN	IVH	IVR	IVCR	ISH	ITPD
TM_1_How much can you count on media news about coronavirus (COVID-19)?	.94									
TM_2_ How much can you trust media news on coronavirus (COVID-19)?	.92									
TSM_1_ How much can you count on social media information about coronavirus (COVID-19)?		.94								
TSM_2_ How dependable is social media information on coronavirus (COVID-19)?		.94								
TSM_3_ How much can you trust social media information on coronavirus (COVID-19)?		.91								
TG_1_ My government is truly sincere in its promises.			.94							
TG_2_ My government is honest and truthful with me.			.94							
TG_3_ My government treats me fairly and justly.			.88							
TG_4_ I feel that government can be counted on to help me when I need it.			.91							
TG_5_ I feel that government can be counted on to help me when I need it.			.90							
BCI_1_ Highly believable				.86						
BCI_2_ Absolutely true				.89						
BCI_3_ Totally acceptable				.86						
BCI_4_ Very credible				.90						
BCI_5_ Completely trustworthy				.91						
FRN_1_ Very fearful					.94					
FRN_2_ Very anxious					.89					
FRN_3_ Very nervous					.91					
FRN_4_ Very afraid					.94					
IVH_1_I intend to stay at a hotel in the near future.						.85				
IVH_2_ I am willing to visit a hotel in the near future.						.89				
IVR_1_ I intend to dine in at a restaurant in the near future.							.91			
IVR_1_ I am willing to visit a restaurant in the near future.							.88			
IVCR_1_ I am willing to visit a Chinese restaurant in the near future.								.83		
IVCR_2_ I intend to go to a Chinese restaurant in the near future.								.90		
ISH_1_ I intend to stay at home as much as possible in the near future.									.91	
ISH_2_I plan on staying at home as much as possible in the near future.									.96	
ITPD_1_ I intend to use a third-party food delivery service in the near future (e.g., DoorDash, UberEats, GrubHub).										.87
ITPD_2_ I am willing to use a third-party food delivery service in the near future (e.g., DoorDash, UberEats, GrubHub).										.84

Note: χ^2 (344) = 1501.85, $p < 0.001$; CFI: 0.960, *TLI:* 0.953, *RMSEA*: 0.058; *SRMR*: 0.067; TM = Trust in Media, TSM = Trust in Social Media, TG = Trust in Government, BCI = Believability of COVID-19 Information, FRN = Fearfulness, IVH = Intention to Visit Hotel, IVR = Intention to Visit Restaurant, IVCR = Intention to Visit Chinese Restaurant, ISH = Intention to Stay at Home, ITPD = Intention to use Third-Party Food Delivery.
****=p<.001, **=p<.01, *=p<.05.*

in Table 2. The $\chi 2$ value of the measurement model was significant ($\chi 2$(344) = 1501.85, p<.001), suggesting that the theoretical model and data did not fit well. However, given the likely effect of sample size on the chi-square values, depending on the $\chi 2$ value alone can be erroneous. Therefore, other model fit indices were evaluated. The comparative fit index (CFI) and Tucker-Lewis Index (TLI) ranges from zero to 1.00 with values above .90 indicating a good fit (Byrne, 2010); the results from this study were .96 and .95 respectively. The root means a square error of approximation (RMSEA) was .05[90% CI =.05, .06]; values under .05 are indicative of excellent model fit, and CI range between .05 and .08 suggests reasonable error and acceptable fit (Browne & Cudeck, 1992; Hu & Bentler, 1998; Costa et al., 2014). The standardized root means square residual (SRMR) was .67, with values less than .08 are deemed acceptable (Hu & Bentler, 1998). Therefore, given the sample size and the number of measured items, the measurement model was adequate.

Reliability and Validity

Both Cronbach's alpha and composite reliability (CR) of the constructs were used to measure the latent variable's internal consistency in this study. The results indicated that Cronbach's Alphas for all the constructs ranged from .84 to .96, exceeding the minimum cutoff value of .70 (Hair et al., 1998). CR is computed from the squared sum of factor loadings for each construct and the sum of the error variance terms for the construct (Hair et al., 2010). Prior research indicates that CR values should be greater than .60; the higher the CR value, the more precise the measures can predict construct reliability (Fornell & Larcker, 1981). The CR values for all the constructs used in this study ranged from .85 to .96. Table 3 shows the Cronbach alphas and CR values of all the latent constructs, with results demonstrating adequate internal consistency.

Convergent validity suggests that items representing a latent factor should share a high proportion of variance (Hair et al., 2010). Convergent validity was tested by evaluating the factor loadings and t values of each construct to see whether the measured items toward the construct displayed standardized estimates of at least .50 and ideally .70 to meet convergent validity standards and whether it is statistically significant (Hair et al., 2010). Table 2 shows that all the item-factor loadings were greater than the .50 cut-off point. Another way to evaluate convergent validity is by calculating the average variance extracted (AVE) by extracting the mean-variance for the items loading on a construct (Hair et al., 2010). An AVE of .5 or above is considered to represent adequate convergent validity. The AVE scores for the study ranged from .61 to .87. Therefore, it was concluded that adequate convergent validity was achieved (see Table 3).

Discriminant validity is the “extent to which a construct is truly distinct from other constructs" (Hair et al., 2010, p. 687). This means that individual variables should only represent one construct. Fornell and Larcker (1981) suggested that discriminant validity is determined by comparing the squared pairwise correlations between constructs and the AVE for each construct. As shown in Table 3, each construct’s square root of AVE ranged from .78 to .92 and was greater than their correlations with the other constructs. As such, discriminant validity is achieved, showing that each construct was statistically different from the other.

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Table 3. Correlations Among Latent Constructs

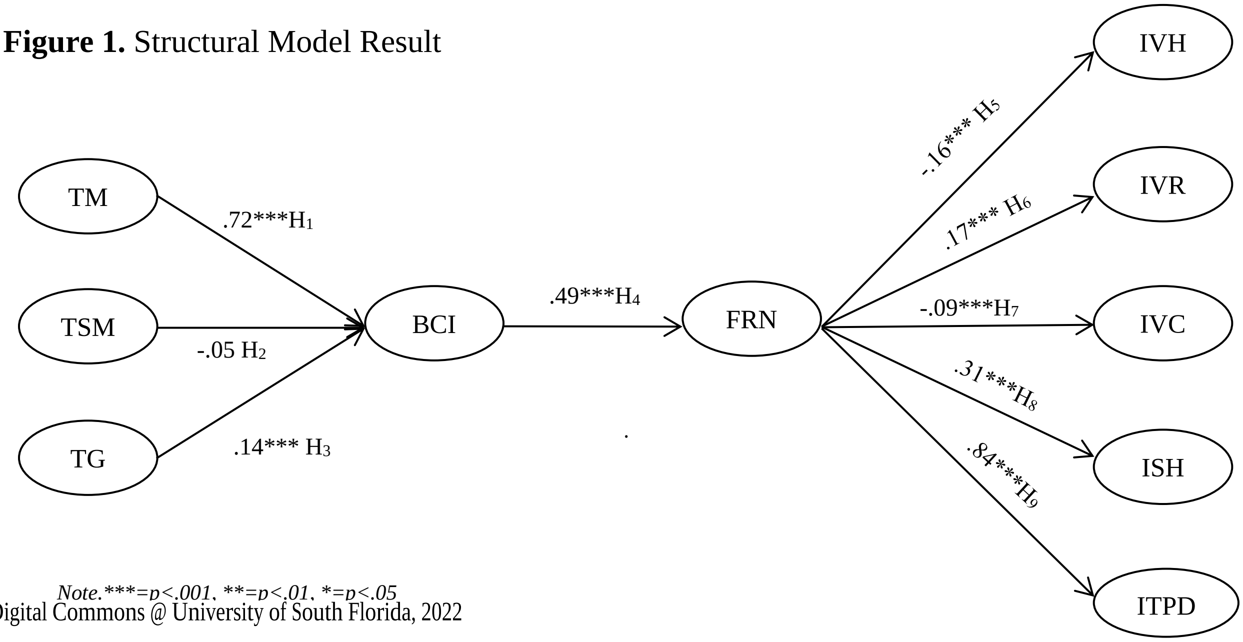
Measure	TM	TSM	TG	BCI	FRN	IVH	IVR	IVCR	ISH	ITPD
TM	1									
TSM	.52**	1								
TG	.36**	.58**	1							
BCI	.70**	.41**	.37**	1						
FRN	.34*	.27**	.12**	.31**	1					
IVH	.03	.28**	.32**	.01	-.14**	1				
IVR	.00	.08*	.10**	.04	-.10**	.58**	1			
IVCR	-.03	.24**	.36**	-.02	-.15**	.73**	.58**	1		
ISH	.27**	.00	-.04	.25**	.27**	-.24**	-.08*	-.30**	1	
ITPD	.23**	.78**	.18**	.24**	.17**	.17**	.21**	.22**	.12**	1
Mean	4.47	3.59	3.83	5.11	4.39	4.18	4.64	4.49	5.24	4.64
SD	1.57	1.73	1.71	1.29	1.76	1.81	1.77	1.82	1.60	1.73
Cronbach's α	.93	.95	.96	.95	.96	.86	.90	.85	.93	.85
CR	.92	.94	.96	.94	.95	.85	.89	.85	.93	.84
AVE	.86	.86	.66	.61	.84	.75	.80	.74	.87	.72
SQRT AVE	.92	.92	.81	.78	.91	.86	.89	.86	.93	.85

TM = Trust in Media, TSM = Trust in Social Media, TG = Trust in Government, BCI = Believability of COVID-19 Information, FRN = Fearfulness, IVH = Intention to Visit Hotel, IVR = Intention to Visit Restaurant, IVCR = Intention to Visit Chinese Restaurant, ISH = Intention to Stay at Home, ITPD = Intention to use Third-Party Food Delivery.*$***=p<.001$, $**=p<.01$, $*=p<.05$.*

Hypothesis Testing

A structural model with ten constructs was estimated using Maximum Likelihood (ML) through MPLUS version 8.4. Figure 1 displays the standardized, theoretical paths linking the trust in media, trust in social media, and trust in government, BCI, fearfulness, and intention to use various hospitality services. The results show a significant and positive influence of trust in media on BCI (.72, p <.001) and trust in government on BCI (.14, p <.001), thus H_1 and H_3; however, trust in society did not influence BCI (-.05, p =.17), thus rejecting H_2. The analysis further suggests significant direct effects of BCI on fearfulness (.49, p<.001), thus supporting H_4. Furthermore, the negative and significant effects of fearfulness on intention to visit hotels (-.16, p <.001), intention to visit restaurants (-.17, p <.001) and intention to visit Chinese restaurants (-.09, p <.01) as hypothesized by H_5, H_6, and H_7 were supported. In addition, the positive and significant effects of fearfulness on stay-at-home intention (.31, p <.001) and intention to use third party delivery service (.84, p <.001) as hypothesized by H_8 and H_9 were supported.

Figure 1. Structural Model Result



Note.$***=p<.001$, $**=p<.01$, $*=p<.05$

Conclusions

The findings highlight the disproportionate influence of trust in media, social media, and government on BCI and the influence of fearfulness on the intention to use various hospitality services. The perceived legitimacy and popularity of social media usage can create the perception that people trust information shared on these platforms. Although it was hypothesized that trust in social media would have a negative effect on BCI (H2), this effect was not significant. This finding can be explained by Shahsavari et al. (2020), who proposed that information from social media is often perceived as anecdotal and the product of speculation, wishful thinking, or conspiratorial fantasy. Therefore, people who generally trust information available on social media are prone to believe incorrect, speculated, and conspiracy-induced information instead of factual information.

Alternately, trust in media had a stronger positive and direct effect on BCI compared to trust in government. This is because the information from traditional media news is often perceived as the product of fact-based reporting (Shahsavari et al., 2020). Although the government's ongoing press briefings and precautionary policies may affirm people's trust, their delayed response to the initial threats of the novel coronavirus could have weakened the effect it had on people's psychological perceptions (BCI and fearfulness) and behavioral intentions.

As argued from a crisis decision theory perspective, people often choose the best option to evaluate the severity of a crisis event (Sweeny, 2008). In the same way, despite the trauma from fear arousing communication, people cope better with their fears by accepting the information shared to make decisions that will protect against the anticipated event (Stankovska et al., 2020). Expectedly, the more people believed COVID-19 information, the more fearful they were about the event; this effect was found in this study where BCI positively influenced fearfulness. This finding is similar to Hong and You's (2016) study, where they found a positive relationship between fatalistic beliefs and experience of uncertainty. The BCI in this context can be used as a psychological threat-management resource to monitor people's actions to protect against contracting the virus.

As guided by previous studies on the effect of the crisis on tourism flow (Song et al., 2011), it was proposed that fearfulness would weaken people’s intention to use hospitality services, especially if the service environment is perceived to increase the likelihood to contract the coronavirus. Expectedly, the study found that fearfulness reduced intention to visit hotels and restaurants (general and Chinese) in the near future. Although not explicitly mentioned, it was expected that the negative spillover effect would be stronger for intention to visit Chinese restaurants than general restaurants since China was central to the virus outbreak (Depoux et al., 2020); however, this was not the case. The negative effect of fearfulness was more enhanced for intention to visit a general restaurant (-.17, $p<.001$) compared to a Chinese restaurant (-.09, $p<.001$). This suggests that people might not be affected by the viral spread of misinformation that has been found in previous studies to affect patronage of Chinese business services (King, 2015). However, a closer look at the findings showed that mean ratings to visit Chinese restaurants ($M=4.49$) were lower than that of regular restaurants ($M=4.64$). Although the effect of fearfulness on intention to visit Chinese restaurants is a little weaker than the effect of fearfulness on intention to visit restaurants in general, the lower mean ratings for intention to visit Chinese restaurants show that some consumers might be less inclined to visit such restaurants for emotions other than fear.

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As Wuhan, China is widely believed to be the epicenter of the novel coronavirus, some consumers might be boycotting Chinese restaurants based on anger, disappointment, and frustration. Nevertheless, China has been praised for its efforts in controlling the virus situation in recent months. As a result, people have developed a more favorable reputation of Chinese restaurants lately with regard to maintaining high safety standards. In retrospect, Chinese restaurants have suffered heavy losses in the initial two months of the pandemic when the virus was starting to spread beyond China. With the pandemic spreading all over the world and China successfully controlling the spread of the virus within its borders, China now is not at a bigger risk of spreading the virus than many other countries in the world.

Among other findings, fearfulness increased the intention to stay at home (.31, $p<.001$) and even greater the intention to use third-party delivery services (.84, $p<.001$). Of all the direct effects analyzed in this study, intention to use third-party delivery service was the highest. This suggests that participants would be more willing to use this hospitality service above the others. Perhaps this is because of the contactless nature of food delivery compared to visiting a hotel or a restaurant.

Theoretical Implications

This study extends previous research on the effects of COVID-19 relation information from a single platform (Bovet & Makse, 2019; Ruth, 2019), to capture consumers' trust in multiple platforms of information sources such as government, mainstream media, and social media. Of the three platforms, trust in media was the most influential, thus highlighting the incongruent effect of sources of information on perception and behavior.

This study also successfully applied the SARF (Kasperson et al., 1988) to highlight how to trust in various sources of information can be used as 'amplification stations' to shape risk perception and intention to use various hospitality services. Focusing on three psychological variables that are known to influence behavior in crisis events, this study presented the coronavirus as a risk event as filtered through multiple channels of communication to influence hospitality behavior. The finding suggests that trust in government and traditional media platforms are the strongest amplification stations that induce peoples’ psychological response (believability of COVID info, fear) to a crisis event compared to social media information stations. Results further demonstrate through the crisis decision theory (Sweeney, 2008) that although social media platforms allow people to discuss their experience with COVID-19 openly, participants perceive the severity of the crisis event more than earlier mentioned platforms. Therefore, it is more effective to communicate crisis events (e.g., COVID-19) through traditional media or government-related platforms since these evoke psychological reactions that further influence intention to use various hospitality services. Also, the theoretical paths linking trust in sources of information, BCI, fearfulness, and intention to use hospitality services highlight the ongoing changes to consumer behavior during a crisis. It is possible that consumer intention to use hospitality services may revert to pre-COVID-19 levels as the severity of the crisis subsides. Overall, the distinction of contact vs. contactless hospitality service environment can further inform innovative ideas that service providers can use to fulfill fluctuating customer demands.

Practical Implications

Our findings offer numerous implications for the hospitality industry and beyond. First, trust regarding COVID-19 related information disseminated through traditional media and government platforms seems to positively affect peoples' believability of COVID-19 related information. However, no significant effect was observed in the case of social media. This suggests that information shared through social media is not perceived as credible (Llewellyn, 2020). Therefore, it is advised that hospitality professionals consider these platforms when searching for information to guide their decision-making process during a crisis event.

Second, BCI shared through platforms that are perceived to be trustworthy (e.g., traditional media and government) increase fearfulness among participants. This psychological reaction further affects people's intention to use various hospitality services. This implies that fearfulness is a critical factor that hospitality service providers should consider regulating in patronage to their businesses. They can lower fear perceptions by responding to government mandates as shared through traditional media and government sites and making this information known to consumers via their website or on-premises location. As the economy is reopening, it is important for hotels and restaurants to reduce fear among consumers. Therefore, they need to emphasize heavily on the precautions they are taking to reduce or eliminate risks of spreading the virus. Restaurants can supplement some of their lost revenue through food delivery and curbside pickup. However, it will be more challenging for hotels since people would be less comfortable traveling or taking vacations. It is therefore recommended that hotels and restaurants go above and beyond in developing policies such as more frequent cleaning, offering hand sanitizers at multiple locations, and offering masks and gloves for employees and customers. It is recommended that service providers go above and beyond Center and Disease Control's recommended minimum guidelines to reduce fear among consumers.

Some strategies that can be effectively used to curtail fear among consumers are deep cleaning rooms after checkout, cleaning and disinfecting stations, tables, elevators, door handles, equipment, and furniture in public areas after each use by a customer, using glass barriers at front desk and counters, limiting the number of people allowed on elevators, dining rooms, guestrooms, and public areas, mandating the use of masks in public areas within a property, screening customers at entry points by asking questions and checking body temperature via infrared thermometers, leveraging technology for contactless check-ins, check-outs, and orders, and last but not least improving HVAC (Heating, Ventilation, and Air Conditioning) controls and air quality for more outside air circulation. In addition to these aforementioned strategies, practitioners need to advertise heavily emphasizing on these key points so that fear is reduced enabling more people to use these hospitality services. Given the financial losses that hospitality businesses have suffered during this pandemic, practitioners are naturally tempted to cut down costs such as training and development, supplies, and the number of employees. However, in order to reduce fear and increase patronage, it is essential for these businesses to recruit additional staff for cleaning purposes, invest further in training, and procure more cleaning supplies. Eventually, these additional expenses will pay off as more consumers will start visiting and re-visiting once their fear is reduced and safety is ensured.

Lastly, our findings suggest that Chinese restaurants are not at a bigger disadvantage than other restaurants as opposed to what was speculated in the initial days of the pandemic. With the epicenter of the pandemic switching from China to Europe to USA and now to South America, Russia, and Southeast Asia, consumers are no longer apprehensive about Chinese restaurants specifically. In fact, China has been praised for its efforts in controlling the virus situation in recent months. As a result, people have developed a more favorable reputation for Chinese restaurants lately with regard to employing high safety standards and preventive care. The unprecedented pandemic has resulted in insurmountable losses for hospitality businesses worldwide, but with careful planning and proper safety standards in place we are optimistic that hospitality businesses will be able to reduce fear among consumers and steadily bounce back in business.

Limitations and Future Research

The limitations of this study pertain to recruiting the sample of participants through popular crowdsourcing platform Amazon Mturk. These include lack of control, deceptive responses, and rushed responses, which might have affected data quality to some extent. However, precautions such as using filter questions at specific intervals to screen negligent answers and keeping track of the time participants take to fill out the items to capture hurried responses diminished those limitations. Future studies should replicate this model post-pandemic to determine if the strength and direction of the relationship still hold up. Future studies could also evaluate the effect of other psychological variables such as perceived stress, happiness, safety, and perceived control on intention to use various hospitality services to determine if these variables have any significant effect on behavior. The authors suggest collecting longitudinal data to track how consumer behavior changes over time prior to, during and post a crisis event.

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