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Leveraging data analytics to understand the relationship between restaurants' safety violations and COVID-19 transmission

Arthur Huang^{a,*}, Efrén de la Mora Velasco^a, Ashkan Farhangi^b, Anil Bilgihan^c,
Melissa Farboudi Jahromi^a^a Rosen College of Hospitality Management, University of Central Florida, Orlando, FL 32819, USA^b Department of Electrical and Computer Engineering, University of Central Florida, Orlando, FL 32816, USA^c College of Business, Florida Atlantic University, Boca Raton, FL 33431, USA

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ABSTRACT

This paper leverages natural language processing, spatial analysis, and statistical analysis to examine the relationship between restaurants' safety violations and COVID-19 cases. We used location-based consumers' complaints data during the early stage of business reopening in Florida, USA. First, statistical analysis was conducted to examine the correlation between restaurants' safety violations and COVID-19 transmission. Second, a neural network-based deep learning model was developed to perform topic modeling based on consumers' complaints. Third, spatial modeling of the complaints' geographic distributions was performed to identify the hotspots of consumers' complaints and COVID-19 cases. The results reveal a positive relationship between consumers' complaints about restaurants' safety violations and COVID-19 cases. In particular, consumers' complaints about personal protection measures had the highest correlation with COVID-19 cases, followed by environmental safety measures. Our analytical methods and findings shed light on customers' behavioral shifts and hospitality businesses' adaptive practices during a pandemic.

1. Introduction

The outbreak of COVID-19 has significantly impacted the hospitality industry. Business closures, lockdowns, businesses' capacity control, and travel restrictions have caused an immediate downturn in the hospitality market with potential long-term consequences (Baum & Hai, 2020; Huang et al., 2020). In the United States, most states mandated stay-at-home orders during the first week of April 2020 and allowed businesses to reopen in late April or early May 2020. Immediately after reopening, May and June of 2020 witnessed an upsurge in COVID-19 cases (New York Times, 2020). It was found that 25% of the COVID-19 cases were linked to visits to bars and restaurants (Foster & Mundell, 2020). The ongoing outbreaks have pressured many states such as Florida to reclose bars and restaurants for another short period to curb the fast transition of the disease (Siemaszko, 2020).

The restaurant industry is one of the most affected industries amid a the COVID-19 pandemic (Huang et al., 2021; Gössling et al., 2020). Fears and worries about catching the COVID-19 disease were

amplified in food and beverage establishments due to the high-contact nature (Chen & Eyoun, 2021). As the economy reopened, restaurants needed to redesign their business operations to offer consumers higher safety and security standards using flexible service and payment mechanisms. For example, contactless menus, mobile payment systems, on-site sanitizers, routine sanitization practices, and screening diners were implemented by food and beverage establishments to encourage customers to dine out (Dube et al., 2020). Despite growing research on restaurants' adaptive strategies in such swiftly changing environments, a general halo of uncertainty still lingers about how to enhance restaurants' quality of service and consumers' satisfaction while reducing COVID-19 transmission.

To bridge this gap, this research leverages interdisciplinary approaches and multiple data sources to link restaurants' safety violations to COVID-19 cases. Big data analytics and machine learning methods facilitate the discovery of patterns and insights that traditional approaches (e.g., surveys and interviews) may not recognize in large volumes of data (Alaei et al., 2019). There is significant value in

* Corresponding author.

E-mail addresses: arthur.huang@ucf.edu (A. Huang), efren@ucf.edu (E. de la Mora Velasco), ash@Knights.ucf.edu (A. Farhangi), abilgihan@fau.edu (A. Bilgihan), Melissa_Farboudi@Knights.ucf.edu (M.F. Jahromi).<https://doi.org/10.1016/j.ijhm.2022.103241>

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investigating customers' opinions and sentiments towards safety concerns at restaurants during the COVID-19 pandemic (Luo & Xu, 2021). Thus, the present pre research aims to understand whether diners complaints about restaurants safety violations are correlated with COVID-19 cases using models and methods from multiple disciplines (e.g., computer science, statistics, geography). This study first discusses individuals' behaviors during health threats using the stimulus-organism-response (S-O-R) paradigm, the protection motivation theory, the behavioral immune system concept, and the health belief model. Then, we review the literature on the correlation between diners' complaints and illnesses. We further demonstrate how to combine state-of-art neural network modeling, regression modeling, and spatial analysis to classify complaints data and identify their correlation with the COVID-19 cases. The results serve to shed light on new restaurant management practices and economic policies to support restaurants' safe and successful reopening and operation.

The remainder of this paper is organized as follows. Section 2 reviews the literature and develops hypotheses. Section 3 introduces the coding schemes and the classification model. Section 4 describes the results and analysis. The theoretical and practical implications are presented in Section 5.

2. Literature review and hypothesis development

2.1. The importance of safety measures in restaurants during the COVID-19 pandemic

The outbreak of COVID-19 has significantly impacted the hospitality industry and consumers' expectations of how services should be altered in the current situation. For example, diners' main concern before the COVID-19 pandemic was food safety violations that could lead to foodborne illnesses (Harris et al., 2020). However, with the beginning of the pandemic, customers started to fear for contracting the coronavirus when interacting with service providers (Bove & Benoit, 2020). Thus, there has been increasing attention to customers' reactions to safety policies and regulations in restaurants and their adaptive behaviors to prevent the COVID-19 infection (Gkoumas, 2021). Previous studies showed that if diners perceive a safety threat, they will try to eliminate it (Harris et al., 2020; Leighton & Sperber, 2015). During the pandemic, diners may perceive stimuli that pose risk to their health (e.g., a coughing server or a big crowd) and want to eliminate them by showing negative responses. Thus, it is critical for dining services to better understand these stimuli and customers' responses so that they can address consumers' concerns accordingly.

This study adopts multiple theories and paradigms to explain the rationale behind diners' behaviors during the pandemic and why their complaints are valid reactions to threats. First, the stimulus-organism-response (S-O-R) paradigm and the concept of behavioral immune system are discussed to show how psychological mechanisms enable diners to recognize the potential presence of infectious pathogens in the dining environment and engage in behaviors that inhibit contact with sources of infection (Ackerman et al., 2018; Schaller & Park, 2011). Next, the health belief model (HBM) is discussed to understand diners' strategies to prevent infection (Rosenstock, 1966). Finally, the protection motivation theory is adopted to show that diners protect themselves based on factors such as the perceived severity of the pandemic, probability of contracting the coronavirus, vulnerability to the infection, the effectiveness of their preventive behavior, and self-efficacy. This research builds upon the aforementioned theories and concepts to better understand the diners' complaining behavior during the pandemic and use this behavior as an alternative research variable to the number of safety violations. More specifically, these theories support that diners' complaints are not hyperbolized reactions to threatening situations. These theories posit that diners' complaints can be seen as reliable proxy indicators of safety violations. It is worth mentioning that personal observation of safety violations in restaurants was not possible due to

the constraints of the pandemic. Also, violations identified through inspections by health authorities were limited in number since most restaurants were inspected only twice a year.

2.2. Diners' behaviors during the COVID-19 pandemic

The following subsections review the literature that explains diners' behavioral responses to risks and safety violations.

2.2.1. The stimulus-organism-response (S-O-R) paradigm

According to the stimulus-organism-response (S-O-R) model, environmental stimuli cues (S) arouse specific emotional states in individuals (O), which in turn trigger behavioral responses (R) (Mehrabian & Russel, 1974). The S-O-R paradigm posits that when individuals perceive appetitive (e.g., rewarding) stimuli, they experience pleasantness/excitement/a sense of control and show approach behaviors; However, after perceiving aversive (e.g., punishing) stimuli, individuals would experience unpleasantness, boredom, or a lack of control, and thus show avoidance behaviors.

In the food and beverage services, studies have examined several environmental stimuli cues that may activate the positive/negative emotions and behavioral responses among customers. Social clues such as positive interactions between guests and employees may directly affect pleasant arousal (i.e., positive emotional states towards an establishment) and lead to positive post-visit evaluations of hotels and restaurants (Sun et al., 2021). Ambient aspects of the retail environment (e.g., cleanliness and layout) may also lead to consumers' positive experiences (e.g., relaxation and tranquility) which in turn, could influence consumers' impulsive purchases (Chang et al., 2011). Similarly, restaurant layouts which aesthetics (e.g., color and decoration) are perceived positively may elicit positive affective states (e.g., happiness, joyfulness, satisfaction) which ultimately affect customers revisiting intentions (Nusairat et al., 2020).

Studies have also examined how food characteristics as stimuli affect customers' internal evaluations and behavioral intentions. For instance, food aromas (e.g., bacon and hickory smoke) were found to largely contribute to feelings of pleasure, perceptions of food quality, and positive ratings of the food (Ouyang et al., 2018). In the context of organic food restaurants, it was found that food tastiness, healthiness, visual appealing, and freshness were positively correlated with perceptions of food quality, which in turn influence customers' revisit intention and word-of-mouth (Konuk, 2019). Similarly, consumers' perception of food-related attributes such as nutritional content, ecological welfare, sensory appeal, and price was associated with utilitarian (i.e., instrumental) and hedonic (sensorial) attitudes towards purchasing green food (Qi & Ploeger, 2021).

Customers' perceived importance of each of the above-mentioned stimuli (i.e., environmental, food attributes) may vary by the type and location of food and beverage enterprises as well as customers' demographics, lifestyle, preferences, and dining occasion (Hanks et al., 2017; Kim & Moon, 2009; Voon, 2017). However, natural or manmade incidents may also moderate the relationship between stimuli, organisms, and behavioral responses and can affect food and beverage enterprises (Kim & Lee, 2020). During a pandemic, customers' attention and reaction to ambient and social stimuli can be altered since there is a possibility of infection. The increase in customers' attention and possible aversive reactions is the result of the activation of their behavioral immune system during the spread of pathogenic diseases.

2.2.2. The behavioral immune system

The behavioral immune system is a motivational system that activates affective, cognitive, and behavioral responses when individuals are exposed to pathogenic diseases (Ackerman et al., 2018; Schaller & Park, 2011). More specifically, the behavioral immune system motivates individuals to evaluate their environment and detect pathogen cues. If they perceive any pathogen cues, they experience aversive emotional

and cognitive responses, which result in avoidance behaviors (Culpeper et al., 2018; Scaller, 2006). During the COVID-19 pandemic, people's behavioral immune system is constantly active since they are exposed to pathogen cues anytime anywhere. In food and beverage enterprises, diners are more likely to carefully evaluate the above-discussed stimuli. If they find any pathogen cues, such as violation of safety protocols, they may experience disgust, a feeling of strong dislike (Schaller & Park, 2011). They may also develop aversive cognitive responses, such as negative person-perceptions and judgments. For example, individuals who perceive pathogen cues in a restaurant, such as seeing/hearing an employee coughing, may suppose that the employee is infected with a pathogenic disease and judge the employee and the restaurant negatively (Ackerman et al., 2018; Scaller, 2011). With the emergence of emotional and cognitive responses, individuals may show avoidance behaviors such as leaving the restaurant before finishing their meals, on-site and post-consumption complaining behaviors, spreading/posting negative word of mouth, and not returning to the restaurant. In summary, diners' behavioral immune system becomes activated when exposed to pathogenic cues (stimuli), they experience disgust (organism), and subsequently show complaints/lack of patronage (response). In this process, customers' perceptions and motivations play a significant role, which can be explained by the health belief model and the protection motivation theory.

2.2.3. The health belief model

The health belief model (HBM) aims to explain or predict individuals' health-related actions including preventive measures (Rosenstock, 1966). The major components of the HBM are perceived susceptibility, perceived severity of a disease, and perceived benefits and barriers of health-related actions. Perceived susceptibility is the individuals' perception of their vulnerability to contracting a disease. Perceived severity is the perception of the seriousness of the disease if being contracted. Perceived benefits refer to the perception of the benefits that can be acquired by health-related actions to prevent or cure the disease, while perceived barriers refer to the perception of the impediments to undertaking health-related actions (Janz & Becker, 1984). The HBM is based on the expectancy-value theory, which postulates that individuals' behavior depends on the extent to which they value a specific goal and the extent to which they believe a specific action helps them to achieve that goal (i.e., expectancy) (Atkinson, 1957). In the health context, the goal is to prevent or cure a disease and the expectation is that a health-related action prevents or cures the disease.

According to the HBM, in the dining context during the COVID-19 pandemic, customers with high levels of perceived susceptibility to COVID-19 may choose restaurants that follow safety protocols, such as proper sanitation and social distancing. After the selection of the restaurant, during the consumption stage, customers may pay close attention to safety details and if restaurants do not follow the protocols, they may complain or show a lack of patronage. According to the HBM, a lack of patronage is a cautionary measure to prevent contracting the coronavirus. Customers who perceive that safety protocols are highly beneficial may react to safety violations more strongly. However, in addition to perception, customers' motivational state also defines their intentions and behaviors during the pandemic, which can be explained by the protection motivation theory.

2.2.4. The protection motivation theory

The protection motivation theory (PMT) is similar to the HBM; however, it includes individuals' self-efficacy as an additional factor that influences preventive health behaviors. According to the protection motivation theory (PMT) (Rogers, 1975), the major factors that affect individuals' behaviors towards the COVID-19 pandemic are their perceived severity of the pandemic, probability of contracting the coronavirus, vulnerability to the infection, the effectiveness of their preventive behavior, and self-efficacy. In the foodservice literature, previous studies showed the effect of the PMT factors on diners'

behavioral intentions. For example, Lee, Mustapha, and Hwang (2019) applied the PMT to explain customers' behaviors towards ethnic restaurants. They showed that when ethnic restaurants provide food safety information in their menus, they reduce customers' perceived risk and increase their intention to revisit. Ali et al. (2019) conducted a study on customers' intention to revisit restaurants known for causing foodborne illnesses. They found that customers' perceived vulnerability to and perceived severity of the illnesses had a negative effect on their intentions to patronize the restaurants. Thus, restaurant customers tend to dine at facilities with food safety practices and avoid the ones that violate safety regulations and put their health at risk (Choi et al., 2019). Regarding the role of self-efficacy, if customers perceive any safety violations and believe that they are capable of demonstrating an effective reaction, they may show complaining behavior. Thus, during the pandemic, since the perceived risk of the infection is high, customers may be more vigilant about safety violations and may complain about them if they have high self-efficacy (Harris et al., 2020). In short, the above-discussed theories show that there is a rationale behind diners' complaining behavior during the pandemic and their concerns are valid. Thus, this study includes the number of complaints to restaurants' safety violations as a proxy indicator of the actual safety violations.

2.3. Hypothesis development

The foremost reason why restaurant customers are hesitant to go to restaurants during the COVID-19 pandemic is arguably the perceived risk of catching the disease (Wang et al., 2021). Consequently, restaurateurs are trying to find ways to keep guests and staff safe (Taylor, 2020). However, violations of safety control measures have been a persistent problem in the restaurant industry even before the pandemic (Yeager et al., 2013). Before the pandemic, empirical research supported the positive correlation between restaurants' safety violations and foodborne illnesses. For example, Harrison et al. (2014) analyzed Yelp.com online reviews posted by diners who experienced and complained about symptoms of foodborne illnesses and identified the restaurants that had food-handling violations. In another study, Quinlan (2013) discussed that ethnic groups experience higher rates of foodborne illnesses, which is partially due to safety violations in independent ethnic foodservice facilities. Li et al., (2011, 2020) also showed that the correlation between number of diners' complaints, and foodborne outbreak rates in the U.S. was positive.

During the pandemic, indoor dining restaurants were found to be associated with COVID-19 cases. For example, a study by the CDC (2020) revealed that reopening restaurants in the U.S. for on-premises dining was associated with an increase of daily infections about six weeks later and COVID-19 death rates about two months later (Guy Jr et al., 2021). Chang et al. (2021) also found that restaurants produced the most significant predicted increases in COVID-19 infections; their study findings showed that a 20% of maximum occupancy can decrease infections by more than 80%. Another study correlated restaurant spending to the evolution of the pandemic using 30 million customers' credit card spending data; the result indicated that the more spending on restaurants, the greater the number of infections (Lucas, 2020). Furthermore, according to a study on Swiss restaurants, restaurants that did not follow the safety guidelines during the pandemic significantly contributed to the reproduction ratios of COVID-19 (Sruthi et al., 2020). Based on these studies, the following hypotheses are proposed using customers' complaints as a proxy indicator of restaurants' safety violations:

- H1.** Diners' complaints about safety violations during the pandemic are positively correlated with COVID-19 cases.
- H2.** Diners' complaints about safety violations during the pandemic are positively correlated with COVID-19 positivity rates.
- H3.** Diners' complaints about safety violations during the pandemic

are positively correlated with COVID-19 hospitalizations.

In addition to testing the above hypotheses, this study employs spatial analysis to affirm the correlation between diners' complaints and COVID-19 cases. Spatial analysis models have been increasingly adopted in hospitality and tourism research for different purposes. In the food and beverage context, Lee et al. (2019) explored the spatial patterns of food safety violations in the Miami Metropolitan Area and indicated that the vicinity to places of interest (e.g., beaches, business districts, airport) is strongly correlated with food safety violations in hotel restaurants. Using spatial analysis, Harris et al. (2015) indicated that dissimilarity in food sanitation inspections at the county, city, and state levels in the U.S. would justify disparities in the number of restaurants' violations. During the COVID-19 pandemic, COVID-19 rates may differ at county, city, and state levels due to the regional differences in policies and human behavior. Some cities are densely populated and attract many tourists, which may impact the number of restaurants, visits to restaurants, and safety violations. There are also geographical variations when it comes to consumers' restaurant patronage behaviors, such as the tendency to dine out (Smith, 1983). Therefore, this study investigates the hotspots of diners' complaints and COVID-19 cases at the county level to further shed light on the correlation between restaurants' safety violations and COVID-19 transmission.

3. Research methods

This section introduces models and approaches from different disciplines to gain insight into the research question, including coding scheme development, neural network-based content classification, regression modeling, and spatial analysis.

3.1. Data

This study examined the State of Florida, a well-known tourist destination as the case study. Restaurant guests' complaints data were obtained from the Florida Department of Business and Professional Regulation (DBPR) complaint portal from May 1st to June 30th, 2020 (Staletovich, 2020). A government-operated database was used for three reasons: (a) the researchers wanted to ascertain that the complaints constituted violations of Florida COVID-19 guidelines; (b) the data from the governmental portal provided more detailed notes about the nature of the violation (e.g., actions and behaviors) on the complaints' form than the general reviews on social media sites; and (c) the researchers

wanted to consistently track the changes in the number of complaints over time, especially in regions with a high level of complaints and strengthened policy enforcement and investigation. In addition, the official DBPR data were chosen over the general online review websites because they were validated and verified in partnership with local law enforcement (Federal Department of Law Enforcement, 2020), thus reducing the likelihood of review manipulation and increasing its reliability (Kumar et al., 2018).

The dataset included 2,297 complaints; the variables included in the dataset were date, restaurant address, city, county, and allegation notes. The data were linked to the daily COVID-19 cases in Florida during the same period for both statistical and content analyses. Fig. 1 shows the seven-day moving average of consumers' complaints and COVID-19 cases in Florida from May to June of 2020. The data trend seems to suggest a close relationship between the number of daily complaints about restaurants' violations and COVID-19 cases.

3.2. Development of coding themes

The development of coding themes relies upon a thorough analysis of the complaints data. Such analysis typically requires a group of experts' efforts in developing the coding themes. However, this approach is not feasible for such a large data set. To this end, we adopted the K-means++ clustering method to detect the potential coding themes (Kapoor & Singhal, 2017). This method is advantageous in showing the correlation of complaints to support the authors' judgement on topic categorization.

First, we transformed the textual data to the vector representation of discrete variables known as embeddings. Because each word's meaning is dependent on the context of the sentence or paragraphs, static embeddings are not efficient in providing high-quality embeddings. Therefore, we developed the contextual embeddings of the complaints based on a pretrained deep neural network (i.e., BERT) which was trained on over 10 million restaurant reviews (Devlin et al., 2018). Contextual embeddings allowed us to capture the appropriate meaning of words based on their context in complaints. For example, the word "clean" differs significantly in "clean my plate" from "plates are not clean." Hence, the contextualized embeddings generate different embeddings for the same word under different contexts and are favorable compared to static embeddings. The result of the contextual embedding clustering is shown in Fig. 2, where the clusters are labeled with initial data categorizations.

We then conducted a thematic analysis to derive the coding themes

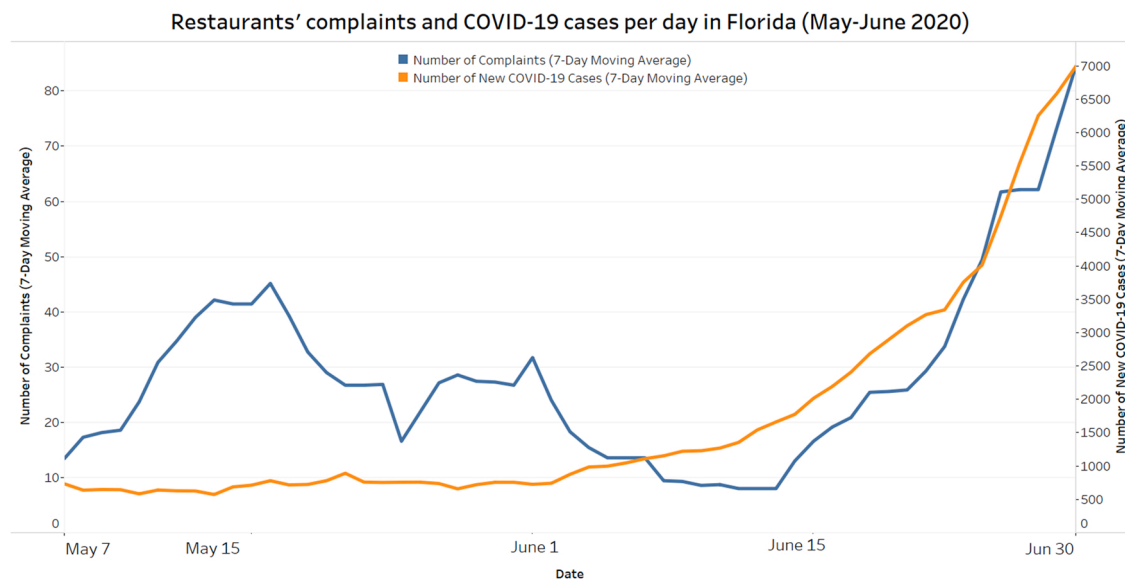


Fig. 1. Consumers' complaints about restaurants' safety violations and COVID-19 cases per day in Florida from May to June of 2020 (seven-day moving average).

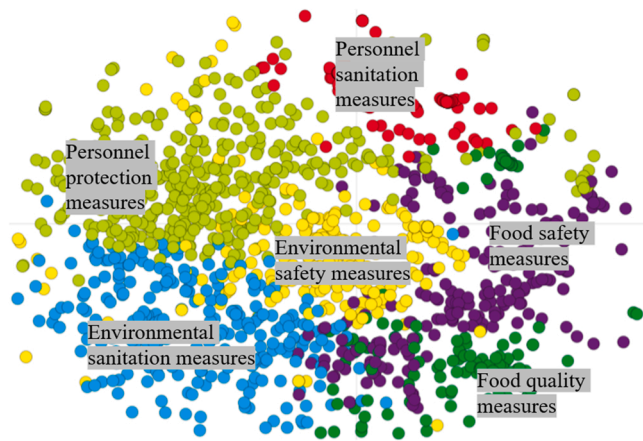


Fig. 2. The clustering method detects the theme-based categories. A pretrained network is used to transform the raw complaint texts to a vector of discrete values. The embeddings represent the relationships of complaints in the dataset.

from the initial clusters. Thematic analysis is a method of six phases that allows researchers to identify and analyze themes within data (Braun & Clarke, 2006). In the first phase, the authors familiarized themselves with the complaints. In the second phase, they randomly selected 200 samples of the data and individually generated the initial codes and classified the data based on the codes. In the third phase, codes were categorized into themes based on keywords. In the fourth phase, the authors reviewed and discussed the generated themes collectively to see if they were related to the extracted codes and the entire dataset and created a thematic map of the analysis. In the fifth phase, the definition and name of each theme were developed. Finally, the analysis was reviewed and revised based on the research objectives. Table 1 shows the developed coding scheme (labels) and examples from the first 200 samples. Since the number of complaints was fairly large, a neural network-based natural language processing model was used to label the remaining complaints.

3.3. Neural network-based model for classification of complaints data

Complaints are expressions of dissatisfaction or annoyance about a situation or experience. In the context of food and beverage service, customers' complaints are often related to the quality of service and have deep ramifications for service providers' business operations (Kecinski et al., 2020). However, the reasons behind these complaints are often unclear and depend on a great number of factors. With the recent advances in natural language processing (NLP) methods in sentiment analysis, deep learning models have been increasingly

Table 1
Coding schemes for customers' complaints about restaurants' violations.

Label code	Label name	Type	Example
1	Personnel protection measures	Service	"Not wearing masks; Allowing sick employees to be at work."
2	Personnel sanitation measures	Service	"No handwashing and using hand sanitizers."
3	Environmental sanitation measures	Environment	"No cleaning and sanitizing of dining areas, kitchen, and bathrooms."
4	Environmental safety measures	Environment	"No proper social distancing; operating at more than 50% capacity."
5	Food safety measures	Food	"No cooking foods properly; Not observing food safety regulations."
6	Food quality measures	Food	"No acquiring high-quality ingredients; low food quality."

utilized to classify different types of sentiments (Zimbra et al., 2018). This study focused on learning the representative features of a complaint (words and sentences) that caused such classification to occur in the first place. The classification model allowed the authors to classify the complaint data without the involvement of human experts.

In this study, attention-based neural networks were chosen to classify diners' complaints and understand the nature of restaurants' safety violations. The attention mechanism allows the neural networks to access long-term dependencies. Moreover, neural networks can provide a general language model that is bidirectionally trained on the text, which can then have a more profound sense of language context and flow (Hu, 2019). What is more, due to their self-attention mechanism, which can be evaluated in parallel for each token of the input sequence, they can eliminate the sequential dependency of single-direction language models (Makridakis et al., 2020). This allows the model to cover a wide variety of tasks from classification, translation, or even text generation. Specifically, the pretrained network weights can act as the parameters for a language model of restaurant complaints. Such a language model can then be used to classify some categories of the complaints.

We first provided the appropriate labels of each complaint based on the derived themes. To properly assign labels to the complaints, the sentences were reprocessed by removing stop words (e.g., "a", "the") since they did not hold significant information about the content of complaints (Dai et al., 2020). We then pretrained the proposed attention-based neural network on over 10 million restaurant reviews, which allowed the model to understand the key review words and phrases and their relationships (Joulin et al., 2016). The reviews were collected from Yelp.com, which is an online platform for customer reviews and complaints. It is worth mentioning that the review data contained the responses from both parties (customers and management). The restaurant teams typically respond to the customers' original complaints and provide comments on how they would like to address the complaints.

Next, we fine-tuned our pretrained model on the complaint dataset. To train the network on the complaint dataset, a typical 80–20 train-test split procedure was conducted. Specifically, about 80% of the dataset (150 complaints) were used in training while 20% of the complaints (50 complaints) were used in testing to evaluate the performance of the model on unseen data (Sun et al., 2017). Hence, the training phase started by feeding the pre-labeled data into the model. Then, the model was trained in multiple iterations to reduce its loss function. For a set of N complaints, this step helped to minimize the negative loglikelihood over the labels:

$$-\frac{1}{N} \sum_{n=1}^N y_n \log(f(BAx_n))$$

Where x_n is the trained data of the n -th complaint and y_n is the assigned label. A and B represent the neural weight matrices. The training was performed asynchronously using stochastic gradient descent and a linearly decaying learning rate (Wang et al., 2018). To find the most fit label for each complaint, this model used the hierarchical softmax mechanism, where the predicted labels were projected based on the estimated probability of the model (Peng et al., 2017). The outcome of the experiment was evaluated through the estimation of accuracy metric:

$$\text{Accuracy} = \frac{T_p + T_n}{T_p + T_n + F_p + F_n}$$

where T_p, T_n, F_p, F_n are true positive, true negative, false positive, and false negative, respectively. The precision metric of the model can be expressed as:

$$\text{Precision} = \frac{T_p}{T_p + F_p}$$

Where precision indicates the fraction of relevant instances among all retrieved instances. The recall metric can be written as:

$$\text{Recall} = \frac{T_p}{T_p + T_n}$$

Where recall indicates the fraction of retrieved instances among all relevant instances of the predicted labels (Joulin et al., 2016).

3.4. Mixed-effects regression models

A mixed-effect linear regression model was developed to understand the correlation between consumers' complaints about restaurants' safety violations and COVID-19 transmission:

$$y_{it} = \beta_0 + \beta_1 w_{it} + \alpha_i + \mu_t + \varepsilon_{it}$$

Where y_{it} indicates the dependent variable such as the number of new COVID-19 cases, hospitalizations, and positivity rate on the day of week t in week i of the study period. w_{it} refers to the number of complaints on the day of week t in week i . α_i and μ_t respectively represent the fixed effects for week i and for day of week t . ε_{it} denotes the random error term. β_1 is the estimated coefficient of w_{it} . We hypothesized that β_1 is positive and varies for different dependent variables as restaurants' violations likely cast different influences on COVID-19 cases, hospitalizations, and positivity rates.

3.5. Spatial modeling

To understand the county-level differences in restaurant violations and COVID-19 cases, hotspot analysis was performed by calculating the Getis Ord G_i^* statistics using the ArcGIS tool (Manepalli et al., 2011). According to Mollalo et al. (2020), this analysis can reveal geographic hotspot areas with a high concentration of the interested variable. Choudhary et al. (2015) believe that Getis-Ord G_i^* can reveal hot and cold spots where features with substantially high or low values are geographically enclosed by features with statistically high or low values. The Getis-Ord G_i^* statistics is a local spatial autocorrelation index, which can be written as:

$$G_i^* = \frac{\sum_{j=1}^n w_{ij}}{\sum_{j=1}^n x_j}$$

Where G_i^* is the spatial correlation of a case I over n cases. x_j indicates

the degree of the variable x at circumstances j the total samples of n . The positive or negative G_i^* statistic is correlated with high or low values of the interested variable. The Z score of G_i^* and p -value indicate where the features with either high or low values cluster spatially (Manepalli et al., 2011). The Z score of G_i^* can be calculated as:

$$Z(G_i^*) = \frac{\sum_{j=1}^n w_{ij} x_j - x \sum_{j=1}^n w_{ij}^2}{\sqrt{\frac{n \sum_{j=1}^n w_{ij}^2 - (\sum_{j=1}^n w_{ij})^2}{n-1}}}$$

To be a statistically significant hotspot, a feature needs to have a high Z score of G_i^* and be surrounded by other features with high Z scores of G_i^* .

4. Results and analysis

The attention-based neural networks model produced an 88.2% accuracy, 89.3% precision, and 84.3% recall for the 200 pre-labeled data, which have achieved our satisfactory level. The trained model was applied to the remaining complaint data set to label the types of complaints. Fig. 3 shows the frequency of the types of complaints over time. Over 80% of the complaints were about violations of personal protection measures and environmental safety measures, which spiked tremendously after early June. Food safety and food quality concerns remained stable; they accounted for less than 10% of the total complaints during the study period, though they would not necessarily be related with COVID-19 transmission.

Different types of restaurants received different proportions of consumers' complaints. The highest proportion of consumers' complaints was about fine-dining restaurants (75%), while 19% of the complaints were about casual dining restaurants. Complaints about fast-food restaurants only accounted for about 6% of the total complaints, possibly due to drive-through, delivery, and take-out options. Bars, cafés, and other restaurants with indoor seating have a higher risk when safety violations happen. Regarding content, complaints were mainly about the lack of the use of masks, either by restaurant staff, employees, or customers, and social distancing. These violations were cited in approximately 25% of all records. Other topics of complaints included violations in serving food (other than exceeding capacity) (10%), positive COVID-19 cases originating in the restaurant (4%), and exceeding capacity limits (4%).

The word cloud in Fig. 4(a) shows the high-frequency words from the complaints data. The top ten high-frequency words were: "mask", "employee", "social distancing", "complaint", "wearing", "food",

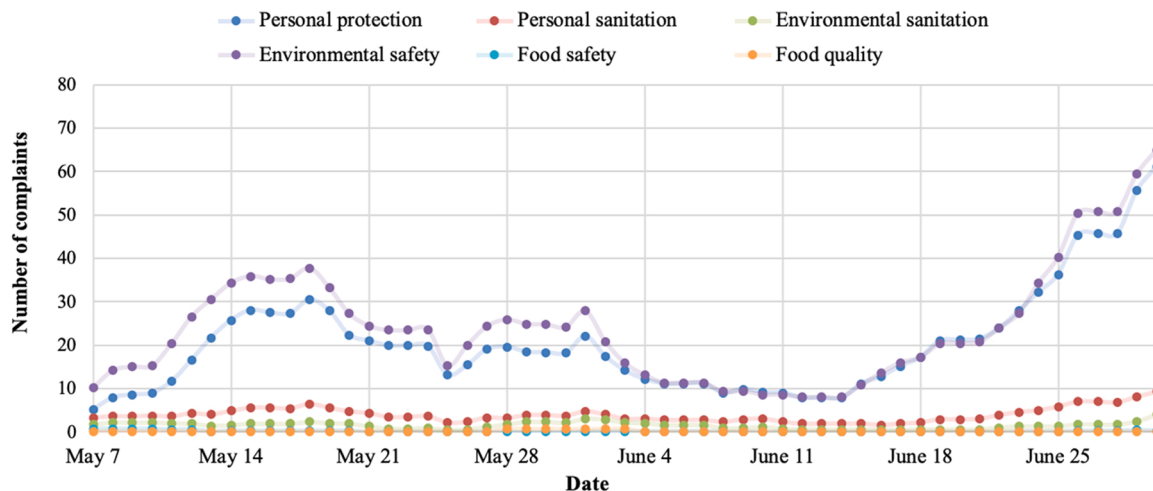


Fig. 3. Frequency of the types of consumers' complaints from May to June of 2020 (seven-day moving average). (a) High-frequency (b) Concept web showing the co-occurrence of keywords.

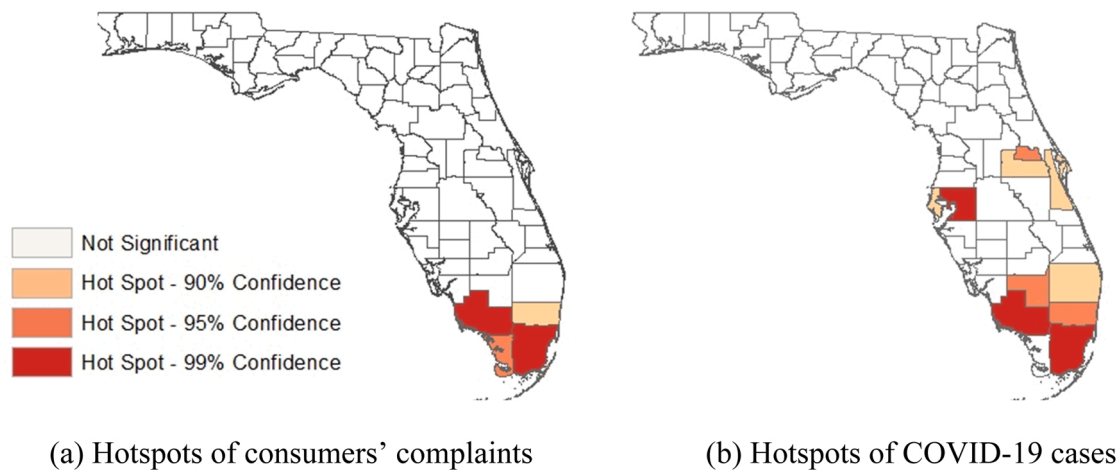


Fig. 5. Hotspots of consumers' complaints about restaurants' violations and COVID-19 cases (normalized by county population) in Florida during May and June of 2020.

Several other counties in the Miami metropolitan area were also hotspots of COVID-19 positive cases per thousand people.

5. Discussion and conclusion

This research utilized multiple models and approaches to investigate customers' complaints about restaurants' safety violations and their correlation with COVID-19 transmission during the pandemic. Thematic analysis and natural language processing modeling were adopted to assess the types of violations. Of the six types of complaints about restaurants, employees' personal protection (e.g., wearing masks and gloves) and restaurants' environmental safety (e.g., social distancing) were customers' major concerns. Statistical analysis confirmed the positive relationship between complaints about restaurants' violations and the COVID-19 cases. In addition, spatial analysis was performed to identify the hotspots of COVID-19 cases and restaurants' safety violations at the county level. The findings were consistent with [Lee et al.'s \(2019\)](#) study, suggesting that higher occurrences of food safety violations can be found at tourist destinations. The findings also confirmed the results from [Yang et al. \(2020\)](#), which showed that fast-food restaurants overall receive fewer complaints regarding safety violations than indoor dining services due to the flexibility of food delivery options.

5.1. Theoretical and methodological implications

This study enhances three key environmental psychology theories that explain consumers' behaviors during disease outbreaks. First, it expands the stimulus-organism-response (S-O-R) theory by [Mehrabian and Russell \(1974\)](#) by identifying new atmospheric subfactors in restaurants that can affect customers' negative/positive emotions and eventually lead to avoidance responses. The findings from topic modeling highlight the importance of ambient clues such as cleanliness, sanitation, and disinfection of dining areas, kitchen, and bathrooms, design factors (e.g., customers' social distancing arrangement, capacity control), and social clues (e.g., employees'/consumers' protection measures (use of masks), violations in serving food and employees' sanitation measures). During a pandemic, the aforementioned subfactors might better explain approach behaviors (e.g., revisiting intention) than other known factors about the physical environment (e.g., layout, aesthetics, and employee appearance). Empirical studies (e.g., surveys) can be further conducted to examine the levels of predictability about organism factors (e.g., emotions) and response factors (e.g., approach behaviors) in the S-O-R model. More research is needed to understand the above subfactors' level of impact on consumers'

behavior over time (e.g., maintained, increased, or decreased) as the pandemic situation continues to evolve across the world.

Second, our findings support that the COVID-19 pandemic may have influenced consumers' behavioral immune systems (BIS) ([Schaller & Park, 2011](#)). The findings revealed that some consumers' evaluation of pathogenic cues during their dining experiences was acute and proactive, indicating that greater attention was paid to cues associated with the disease. Our findings identified perceived pathogen cues within the BIS framework for further analysis, such as violation of safety protocols, a lack of personal protection measures, deficient sanitation measures, environmental safety measures, and food safety measures. For instance, overgeneralization of cues, aversion, and stigmatization towards certain social groups (e.g., employees, other customers) that do not conform to social norms (e.g., wearing masks) could have been exacerbated by COVID-19 and might influence consumers' future visiting intentions, place detachment, and brand loyalty.

Third, the health belief model (HBM) ([Rosenstock, 1966](#)) and the protection motivation theory (PMT) ([Rogers, 1975](#)) are enriched by the research findings. In addition to individuals' internal factors (e.g., perceived susceptibility, perceived severity), perceived environmental risks (PER) might also influence consumers' perceived threat, which in turn, might affect the likelihood of engaging in health-protective behaviors. As shown in [Table 1](#), customers' complaints include perceived risks associated with the dining place such as protection measures, sanitation, and safety protocols. Under the HBM perspective, the outcome (i.e., likelihood of engaging in health behavior) is beneficial for consumers as it involves reducing the exposure to the virus. However, such behaviors might affect restaurants' operations and profitability. Thus, empirical research could apply the HBM framework to explore the correlations between PER and perceived threat to determine if PER is a reliable predictor of customers' avoidance behaviors. Concerning the PMT, our findings suggest that food and beverage service providers that incur safety violations during COVID-19 might impact consumers' perceived vulnerability to diseases. Consumers who submitted complaints might have possessed high perceived response efficacy and high self-efficacy (i.e., confidence) in performing avoidance behaviors (e.g., negative word of mouth). Further studies can explore the relevance of the frequency and content of consumers' complaints on behavioral intentions and actual behaviors to inform the application of the PMT in food and beverage settings during and after disease outbreaks.

Methodologically, this research showcases how to employ models and methods from different disciplines to better understand consumer behavior and inform consumer-centered decision-making processes. The state-of-art neural networks-based natural language processing models and clustering methods were used to derive theme-based categories and

their relationships from consumers' comments, which were further verified by experts based on existing theories. The model structure and the procedure would bode well for other hospitality and tourism research topics which harness textual data. In addition, methods in GIS modeling such as hot spot analysis and spatial autocorrelation analysis are proven to be useful for verifying the correlation between consumers' complaints about restaurants' safety and COVID-19 cases from the spatial perspective. Identifying hotspots or creating location-based buffered zones would shed light on various geographic factors and characteristics. As more and more data in the hospitality industry have temporal and spatial dimensions, we encourage hospitality researchers to consider using spatial modeling to complement standard analytical approaches. This paper provides a case study to illustrate the adoption of different methods and models to gain insight into human-environment interactions in the hospitality industry.

5.2. Practical implications

This study sheds light on how restaurant management and public health policies should address public safety requirements. Most of the customers complaints about restaurants' violations during the pandemic are about environmental safety, such as wearing masks, indoor dining, and social distancing issues. Restaurants not only should follow COVID-19 safety guidelines but also should take additional measures to reduce their customers' perceived risks and increase their perceived cleanliness. For example, they should make all surfaces disinfected and shiny, provide proper ventilation, put hand sanitizers and napkins at dining tables, and use pleasant scents in the dining area (Magnini & Zehrer, 2021). In addition, restaurants can offer off-premise dining options and develop digitized customer engagement platforms with personalized offers to provide contact-free or reduced-contact services (McKinsey, 2020). Furthermore, restaurants may use social media tools to announce their safety regulations during pandemics. Transparent communication can help restaurants to build trust among their customers (Yost & Cheng, 2021). Also, restaurants should use cleaning safety messages to target customers who are skeptical to dine-in or order from them (Kim et al., 2021). Using safety messages can help restaurants to build trust with customers, particularly the ones with a high level of perceived risk and susceptibility to the coronavirus infection. The other safety measure is to collect feedback from customers about the applied safety policies and procedures to ensure that they are satisfied with the protocols.

This study also sheds light on various policy implications. The spatial analysis highlighted the geographic areas that need attention for interventions. It also indicated that there is probably no one-size-fits-all mode of enforcement or incentivization for COVID-19 guidelines. Different guidelines and levels of enforcement in Floridian counties might have affected different COVID-19 situations in the development of the pandemic. Simply enforcing these guidelines with fines and restrictions may lead to more negative outcomes. A greater level of communication and cooperation between local governments and restaurant owners may be more influential in balancing business development and curbing COVID-19 transmission. The forms of cooperation may include incentive programs to award the restaurant following safety guidelines, free training programs for staff, and more frequent on-site inspections. For example, the State Department of Health may use spatial analysis tools to locate restaurants with higher rates of safety violations and supply supportive resources and tools to educate their employees and managers regarding personal and environmental safety. The implementation of training programs may provide the knowledge, skills, and attitudes needed for restaurants' employees to remain competitive while creating a safe and trust-enhancing environment for customers and staff (Transact, 2018). Businesses and employees that adhere to such guidelines should also be rewarded periodically as positive reinforcement.

5.3. Limitations and future research

This paper has two limitations. First, the dataset is limited to the business reopening stage in 2020. Second, although the content analysis and spatial analysis suggest restaurants' safety violations as a possible contributor to COVID-19 transmission, this research does not directly reveal a causal relationship between restaurants' violations and COVID-19 cases. Future work should consider contact-tracing analysis while controlling for exogenous variables to further confirm the causality. In addition, future research should address how different types of consumers' complaints about restaurants' safety violations are related to the spread of COVID-19. Experimental research and comparative studies are needed to validate the health risks of different types of safety violations.

Declaration of Competing Interest

The authors declare no conflict of interest.

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