Spatial and experimental analysis of peer-to-peer accommodation consumption during COVID-19

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Abstract

The COVID-19 pandemic has disrupted peer-to-peer (P2P) accommodation markets. However, how the interplay between tourists and destination attributes has affected P2P accommodation consumption during the pandemic has not been investigated. To address this gap, this study first explored the spatially varying relationship between destination attributes and COVID-19-disrupted Airbnb performance change across Florida counties. Subsequently, we performed two experimental studies to examine whether trip purpose and the level of perceived threat affect Airbnb use intention. The results of the spatial analysis show that, depending on the type of destination attribute, Airbnb listings experienced different revenue losses across urban and rural areas. Additionally, results of experimental studies show that business tourists with a low perceived threat of COVID-19 are more willing to consume Airbnb listings than leisure tourists. This study contributes to ascertaining the destination and behavioral heterogeneity in pandemic-induced P2P accommodation consumption using spatial analytic and experimental studies.

Keywords

COVID-19; peer-to-peer accommodation; mixed-methods; geographically weighted regression; destination attribute; trip purpose

1. Introduction

The global tourism market has been severely affected by the novel coronavirus (COVID-19) pandemic. Peer-to-peer (P2P) accommodation businesses (e.g. Airbnb), the most disruptive hospitality provider, have seen demand decrease significantly due to travel restrictions and fear of potential virus infection while traveling, although hosts have opened their listings (DuBois, 2020). According to Statista (2020), short-term rental bookings on the Airbnb platform saw a continuous drop in the first quarter of 2020 compared to 2019 as a result of the COVID-19 pandemic, specifically -57% in week 10 and -95% in week 14 of 2020. In this pandemic period, tourist decision-making likely depends on complex, multiple interrelationships between tourists, destinations, and the environment (e.g. safety, attractions, transportation, activities, and landscape) (Karl, 2018; Olmedo & Mateos, 2015).

The extant literature has largely defined two types of perceived risks: destination-related risks (Otoo et al., 2019) and personal and behavior-borne risks (Chien et al., 2017). In the context of tourist decision-making during the pandemic, destination-related risks can be linked to the extent of the virus spread in a particular area. Due to the population density and the difficulty of social distancing, urban areas may have higher destination-specific risks than rural areas. These destination-related risks are difficult or impossible to proactively control, and their impacts differ with the nature of the risks and their intensity or severity levels (Walker & Page, 2003). In addition, personal and behavior-related risks can be linked to tourist-related factors such as physical conditions, and the purpose of the trip. Such perceptions of risk and safety are likely to influence tourists' preferences and destination choices (Kim et al., 2007; Lepp & Gibson, 2008). When two types of risks are combined, perceived risks may constrain people's intention to travel but may result in strategies to mitigate the risks (Reisinger & Mavondo, 2006).

Although P2P accommodation guests will make their own decisions during the pandemic, it is important for hosts and policymakers to employ a destination-based perspective for coping with the devastating impact of the pandemic on the accommodation-sharing economy. This is because COVID-19 has been spread through social interactions across communities (e.g. cities and countries). Each destination has a different situation with regards to the virus spread, and collective actions need to be taken to confront the virus. Furthermore, some tourists attempt to explore sensation-seeking despite the anxiety resulting from participating in perceived risky activities (Lepp & Gibson, 2008). For example, some people may decide to travel to a particular destination by taking precautionary measures (e.g. hygiene and social distancing) during their trip and further consume P2P accommodation in that destination. COVID-19 has disrupted the P2P accommodation market in a highly localized way, and some tourists may visit certain destinations by avoiding the potential risks of infection. However, many studies on risk and tourist decision-making have focused on either specific destinations or tourist characteristics separately, and thus lack the comprehensive understanding that can be obtained through the integration of both destination and tourist perspectives (Karl, 2018).

To fill these gaps, this study attempted to (1) understand the impact of COVID-19 and destination attributes on P2P accommodation consumption from the destination perspective and (2) investigate what behavioral characteristics affect P2P accommodation consumption during the pandemic from the tourist perspective. To address these objectives, we used a mixed-methods approach with spatial and experimental studies. First, we hypothesized spatially varying relationships between destination attributes—a set of local assets and resources, such as leisure/hospitality businesses, transportation, Airbnb supply, past Airbnb performance, and socioeconomic factors—and the pandemic-induced Airbnb performance (H1). For the spatial analytical approach, we collected secondary data in the form of COVID-

19 statistics and destination attributes across Florida counties and employed a geographically weighted regression (GWR) to examine the spatially varying effects of COVID-19 and destination attributes on Airbnb performance. Next, we hypothesized a tourist-related factor (i.e. the purpose of a trip), with a combination of destination-related factors (i.e. destination type), that may explain the different P2P accommodation consumption during the pandemic (H2 and H3). To test the two hypotheses, we conducted two experimental studies using a hypothesized setting of Airbnb listing consumption in Florida.

This research contributes to a comprehensive understanding of complex tourist decision-making during the pandemic by combining spatial (destination-level) and experimental (tourist-level) perspectives. First, this study examines the spatially heterogenous influence of COVID-19 on P2P accommodation performance across destination attributes. In doing so, this study extends existing research that focuses mainly on tourist-level decision-making processes during the pandemic, which lack a spatial behavioral assessment of P2P accommodation consumption across multiple destinations. Second, this research identifies that the trip purpose (business vs. leisure) plays a critical role in tourists' decision-making during the pandemic. This finding advances the literature on risk perception in decision-making based on the perspective of the tourist environmental bubble, which shields leisure tourists from the perceived risk at a planned destination. Finally, the mixed-methods approach of this study enables researchers and policymakers to capture the interplay among tourists, destinations, and the environment, when understanding the complexity of both tourist decision-making and P2P accommodation markets.

2. Literature review

2.1. The complexity of tourists' decision-making during COVID-19

Tourism is often considered as a complex adaptive system in which tourism actors improve their own behavior and the behavior of the whole system by dynamically interacting with each other and with the external environment (Stacey, 1995). This means that a tourism business can never be considered isolated, as there are numerous different types of relationships between it and other businesses, and between it and the environment. Because tourists tend to have specialized demands, emphasizing environmental issues and the culture of the destinations visited, and seeking adventure and independence (Aguiló et al., 2005), tourist behavior can be affected not only by endogenous and exogenous shocks to the destination system but also by other insignificant factors (Boukas & Ziakas, 2014).

Before the COVID-19 outbreak, research on P2P accommodation platforms found that the decision-making and overall experience of consumers who consume P2P accommodation are likely to be influenced by the price-quality nexus, the risk perspective, and social interaction, ultimately generating higher complexity (Pappas, 2017; 2019a). Among these factors, social interaction is fostered between hosts and guests and between local guests and local communities by sharing their personal experiences. For example, Airbnb consumers would like to get to know new people (e.g. the host and local people) and to receive travel recommendations (e.g. local attractions) from them (Poon & Huang, 2017). Such interactions can include giving guests information about local transportation and taking them to the beach (Camilleri & Neuhofer, 2017). As such, the nature of P2P accommodation's collaborative consumption provides guests, especially leisure tourists, with opportunities to socially interact with the host and with local people.

During the COVID-19 pandemic, P2P accommodation has been hit severely due to measures such as social distancing and quarantine requirements (Fong et al., 2020). Some previous research has shown the negative impact of the outbreak of a virus on travel decisions. For instance, if tourists who have planned international travel perceive health-related risks (e.g. 2009 H1N1), they may postpone or cancel their plans (Reisinger & Mavondo, 2005). People normally believe that avoiding travel, especially to places experiencing the spread of a viral infection, can help to minimize their risk of acquiring the disease (Lau et al., 2009). In addition, researchers have found that Americans are likely to avoid domestic travel due to confirmed cases of a virus (e.g. Ebola in late 2014; Cahyanto et al., 2016). Therefore, the perceived risk induced by COVID-19 is assumed to be a significant predictor of avoiding travel destinations and the consumption of P2P accommodation.

A second stream of studies indicates that when tourists perceive that potential benefits outweigh risks, their travel decisions may not be influenced because they take non-pharmaceutical intervention measures (e.g. personal hygiene and social distancing). For example, people who viewed themselves at increased risk from SARS tended to take precautionary actions to avoid contracting the disease (Brug et al., 2004), and people with feelings of perceived susceptibility tended to take preventive measures against the human avian influenza (de Zwart et al., 2010). As personal measures can be an adaptive behavior that lowers the infection threat and reinforces behavioral intention, the perception of an outbreak (e.g. 2009 H1N1) did not constrain potential tourists' desire to travel (Lee et al., 2012). Additionally, a past survey conducted by the Global Business Travel Association found that most respondents said the 2009 outbreak had a minimal effect on business travel (Martin, 2014). As such, during the pandemic, some domestic and/or business tourists who take personal measures might not change their travel plans and may continue to consume P2P accommodation.

Although tourist decision-making during the pandemic is complex, hospitality researchers have developed, mainly for the hotel industry, a COVID-19 management framework comprising anti-pandemic phases, principles, and strategies (Hao et al., 2020) and a research agenda including studies on artificial intelligence and robotics, hygiene and cleanliness, and health and health care (Jiang & Wen, 2020). In addition, Shin and Kang (2020) examined the impact of expected guest-employee interaction and expected cleanliness on perceived health risk and hotel booking intention. For the P2P accommodation market, researchers have primarily explored host perceptions of the short- and long-term impacts of the pandemic on their hosting practice (Farmaki et al., 2020) and the decision-making logic of different types of hosts (Zhang et al., 2021). These studies have provided limited empirical evidence on how tourists assess the pandemic risk in P2P accommodation consumption decision-making based on both destination- and tourist-level characteristics.

Given that the complexity of the sharing economy challenges the boundaries between production and consumption and across geographic markets (Mair & Reischauer, 2017), it is imperative to enhance our understanding of travel decision-making initiated by a specific event (e.g. COVID-19) in the accommodation-sharing economy (Pappas, 2019b). As discussed earlier, prior studies suggest two contrasting views on the impact of pandemics on tourist decision-making: a negative trigger and its minimal effect. A promising way to shed light on this debate is to empirically study how tourists' P2P accommodation consumption is determined by interrelated factors—destinations (e.g. urban and rural areas), their environment (e.g. safety, attractions, transportation, and landscape), and tourists' reasons for travel (e.g. trip purpose) (Karl, 2018; Olmedo & Mateos, 2015). Fig. 1 depicts the proposed research model and outlines the research hypotheses, which will be discussed in greater detail subsequently.

[Insert Fig. 1 about here]

2.2. The effect of destination type on P2P accommodation consumption during COVID-19

Location is one of the most critical factors affecting the operating performance of lodging providers such as hotels (Peiró-Signes et al., 2015) and Airbnb listings (Lee et al., 2020a). The locational advantage can support local P2P accommodation listings that often rely on other tourism services (e.g. food and touristic activities) (Gutiérrez et al., 2017). Researchers also suggest that tourism development may differ between urban and rural areas (Ashworth & Page, 2011). Rural tourism operators tend to be family-owned firms, often showcasing local agricultural products and cultural activities (Jaafar et al., 2015). For example, agritourism offers farming-related activities that are carried out in agricultural settings for multiple purposes (e.g. entertainment and education) (Arroyo et al., 2013). Urban areas, on the other hand, are multifunctional entities that comprise a complex social, economic, and environmental phenomenon; tourists can be drawn to cities with various types of attractions, such as festivals, historical areas, and cultural activities (Ashworth & Page, 2011). Hence, while tourists traveling to rural areas are likely to be interested in contacting with nature/natural heritage, visiting cultural facilities (e.g. monuments), and participating in leisure activities (Devesa et al., 2010), tourists visiting cities may have a variety of business and/or leisure reasons, and are often drawn to the multitude of urban facilities and functions provided by a city.

When pandemic crises occurred in the past, the tourism sector was affected differently across urban and rural areas. Zeng, Carter, and De Lacy (2005) examined how the SARS crisis had a significant negative effect on tourism development in China. They found that SARS had a severe impact on rural areas, especially where the local economy relied on tourism-related businesses or on physical labor efforts in urban areas. While cities suffered huge financial losses in absolute terms, rural communities were more significantly affected in relative terms. Furthermore, urban areas differ fundamentally in population size, spatial structure, and connectivity, in ways that may affect infectious contact patterns (Dalziel et al., 2013). However, rural populations in the US and many other countries are relatively older, making them more at risk for falling seriously ill from COVID-19 and having more limited access to health care (Bliss & Capps, 2020). Hence, although the type of destination can be divided broadly into urban and rural areas, the effect of COVID-19 on P2P accommodation can vary across destinations due to deliberate and organic tourism development based on specific destination attributes (Morrison, 2006).

Each destination, whether urban or rural, is a complex system that requires simultaneous management of destination attributes (i.e. local assets and resources) for destination development (Laing & Lewis, 2017). Destination attributes are often defined as the group of disparate elements that attract tourists to a destination (e.g. Kim, 2014). Prior studies have identified that tourists are motivated to travel to a particular destination by various factors such as safety and security, leisure entertainment options, accessibility and transportation systems, and the hygiene and cleanliness of the destination and its facilities (Goeldner & Ritchie, 2003; Wong & Wan, 2013). It follows that if a destination does not fulfill the aforementioned requirements, tourists are unlikely to travel to the destination or find their trips satisfactory. Additionally, when a special crisis or disaster occurs, tourists tend to evaluate destination attributes and the event as antecedents of perceived destination image, which further affects tourist satisfaction and intention to recommend (Eid et al., 2019). In the case of COVID-19, we also assume that destination attributes that heterogeneously configure each destination might influence overall consumption of P2P accommodation in a particular destination during the pandemic. Hence, we hypothesize the following:

H1. The effect of COVID-19 on P2P accommodation consumption varies (a) across destination locations and (b) depending on destination attributes in each destination.

2.3. The effect of trip purpose on P2P accommodation consumption during COVID-19

Many studies have compared tourist segments, in terms of trip purpose (i.e. business or leisure), hotel selection/revisit criteria and travel motivation. For example, while business tourists are more concerned with cleanliness and location (e.g. McCleary et al., 1993), leisure tourists tend to consider security, personal interactions, and room rates as important (e.g. Clow et al., 1994). Extant studies suggest that leisure tourists can be divided into multiple segments; for example, city sightseers, beach and sunshine lovers, those visiting friends/relatives, and culture and nature enthusiasts (e.g. Hsieh et al., 1992; Jang et al., 2004). In contrast with leisure tourists, business tourists, comprising 13% of the international tourism market (UNWTO, 2018), have been characterized as a heterogeneous or homogeneous group in terms of tourist motivation and forms of travel. For example, business tourists can be divided into two categories: those who travel together for meetings, incentive trips and/or corporate hospitality, conferences, and exhibitions; and individual business tourists whose work requires trips to various distant destinations (Davidson & Cope, 2003).

However, the dichotomy of business and leisure described above has been challenged by another stream of research that sheds light on situations in which business and touristic activities are combined. For instance, Uriely and Reichel (2000) coined the term “working tourist” with respect to all kinds of tourists who engage in situations that combine work with tourism or leisure pursuits (e.g. shopping and sightseeing). Recently, Lichy and McLeay (2018) delineated five types of “bleisure tourists” who combine tourism motivations (leisure) with work obligations (business): experimental learners, escapers, working vacationers, altruistic knowledge sharers, and research-active trailblazers. Some studies (e.g. Unger et al., 2016) identified that business tourists prefer familiar facilities or services rather than novel or unusual things. Hence, while leisure tourists are more concerned with leisure-oriented motivation and activities, business tourists are likely to engage with both work obligations and tourism motivations.

Compared with leisure tourists, business tourists are more likely to experience difficulties associated with the strangeness of a visited destination; however, they are also more likely to gain an authentic experience in the destination (Unger et al., 2020). In other words, business tourists who frequently visit a particular destination can obtain profound knowledge about local sites, which are less accessible to leisure tourists, by interacting with workplaces, industrial districts, bars and restaurants, and residential neighborhoods. Hence, during the COVID-19 pandemic, business tourists can still make their planned trips, reduce their exposure to local communities, and avoid leisure activities which may spread the virus to them. In contrast, the vast majority of leisure tourists are likely to experience the visited destination within a “tourist environmental bubble” (Cohen, 1972)—contacts with the locals are confined to professional hosts and tourist experiences being confined to familiar settings provided by the local tourism industry. Because leisure tourists are shielded from the risks and inconveniences associated with the strangeness of a particular destination (Cohen, 1972), the risk of COVID-19 infection may affect leisure tourists’ decisions and behaviors, and they tend to modify their travel plans (e.g. postponement or cancellation of an original plan).

Based on the above argument, we predict that the type of trip should significantly influence usage intention for P2P accommodation. Specifically, our prediction is that a tourist’s intention to use P2P accommodation during the pandemic will be lower when the trip purpose is leisure-oriented (vs. business-oriented). Hence, we hypothesize the following:

H2. The intention to use peer-to-peer accommodation during COVID-19 will be lower for leisure (vs. business) tourists.

With regard to the joint effect of trip purpose and destination type, we predict that a tourist's intention to use P2P accommodation during the pandemic will be influenced mainly by the purpose of a trip, irrespective of destination type (i.e. urban vs. rural). There are two reasons for this prediction. First, business tourists are likely to repeat their destination areas, either urban or rural, due to destination loyalty and work obligations in those destinations (Olmedo & Mateos, 2015). Second, the perceived threat of COVID-19 is not likely to constrain business tourists' desire to travel to a particular destination, either urban or rural, because they will take precautionary measures that lower the infection threat (Lee et al., 2012). Hence, we hypothesize the following:

H3. The intention to use peer-to-peer accommodation during COVID-19 will be lower for leisure (vs. business) tourists regardless of destination type.

3. Methodologies

3.1. Stage 1: spatial study

3.1.1. Data collection

To test H1 (i.e. the spatially varying effect of COVID-19 and destination attributes on P2P accommodation consumption), we conducted a spatial analysis of secondary data that included COVID-19 statistics, destination attributes, and Airbnb operating performance in the state of Florida. Specifically, we attempted to explore the existence of a spatially varying relationship between a set of destination attributes and the pandemic-induced change in Airbnb revenue performance across counties. As an empirical setting, we selected Florida as the study area because Florida is one of the most active Airbnb destinations, with 60,000

Airbnb listings and $1.2 billion in rent from 6.6 million guests in 2019. Airbnb in Florida has shown a high growth rate in rural counties, and Florida became the seventh state in the US with a documented COVID-19 case. Hence, researchers have selected Florida as the optimal case for studying P2P accommodation with special reference to Airbnb listings (Lee et al., 2020a; 2020b; Xu et al., 2019). Monthly data related to Airbnb revenue performance and COVID-19 were collected from AirDNA and the Florida Division of Emergency Management, respectively, across 67 Florida counties. According to the Florida Department of Health (2020), Florida consists of 34 urban counties (more than 100 persons per square mile), 30 rural counties (100 persons or less per square mile), and 3 mixed counties (changed from rural to urban counties).

3.1.2. Measurements

As the dependent variable, we used a metric for measuring the growth rate of revenue performance of Airbnb listings before and after the COVID-19 pandemic. Revenue-per-available-listing (RevPAL) measures the amount of revenue that one Airbnb listing generates for a month (Dogru et al., 2020). Because our focus was on measuring the COVID-19-induced performance change, we calculated the year-over-year growth rate (i.e. relative change) of RevPAL in April 2020 compared to April 2019. The relative change was obtained by dividing the change value (i.e. RevPAL in April 2020 minus RevPAL in April 2019) by past performance (i.e. RevPAL in April 2019). Finally, we measured the growth rates of average Airbnb RevPAL for each county as the final dependent variable.

For independent variables, a set of destination attributes, including COVID-19 statistics, were employed in the analysis. We based the choice of destination attribute variables on four factors suggested by prior studies: safety; leisure and hospitality; transportation convenience; and hygiene and cleanliness (Chou et al., 2008; Goeldner &

Ritchie, 2003; Yang et al., 2018). First, the number of confirmed COVID-19 cases and deaths in each county can be taken to represent the level of safety in the corresponding county due to the potential risk of virus infection during the trip. Second, Airbnb accommodation performance is likely to be affected by the agglomeration of tourism product and service suppliers (e.g. leisure, entertainment, and restaurants), which form tourism clusters (Gutiérrez et al., 2017; Lee et al., 2020a). Third, because transportation convenience influences accommodation prices (Kim, Jang, Kang, and Kim, 2020) and satisfaction (Yang et al. 2018), this study measured distance to the nearest airport from the county centroid as transportation convenience. Finally, the level of food safety violations, which may affect tourism demand (Cohen & Avieli, 2004) and Airbnb demand (Lee et al., 2020a), was used as a measure of the hygiene and cleanliness of a destination.

In addition, we controlled for Airbnb and socioeconomic characteristics in each destination (i.e. county). First, Airbnb supply was measured by the number of Airbnb listings for each county, which may affect Airbnb performance (Lee et al., 2020a; Xie et al., 2020). Second, two metrics of past Airbnb performance—average daily rate (ADR) and occupancy rate (OCR)—were controlled because Airbnb price not only reflects a variety of Airbnb physical and host characteristics (Gibbs et al., 2018) but also predicts Airbnb occupancy rate (Gunter et al., 2020). Finally, we included two socioeconomic factors that might affect Airbnb revenue. Specifically, median household income was controlled in the model because neighborhoods with higher household incomes are likely to affect the prices and revenues of Airbnb listings (Jiao & Bai, 2020). In addition, as White neighborhoods may benefit from more numerous leisure and recreation facilities than minority neighborhoods (Porter & Tarrant, 2001), ethnic diversity was controlled by using the ethnic fractionalization index (Eriksen, 1993). Table 1 reports operational definitions, data sources and years for the variables used in the analysis.

[Insert Table 1 about here]

3.1.3. Model specification

To identify the spatially varying effects of COVID-19, destination attributes, and socioeconomic factors on Airbnb performance, we used a geographically weighted regression (GWR) that captures the local variations among spatially referenced variables. As a spatial regression technique for exploring spatial heterogeneity, the GWR method has typically been used in the areas of marketing (Jang & Kim, 2018; Jang et al., 2017), hospitality (Kim, Jang, et al., 2020), tourism (Lee et al., 2019; Lee et al., 2020b) and P2P accommodation (Xu et al., 2019; Lee et al., 2020a). The proposed GWR model is as follows:

$$\begin{aligned} Y_i = {} & \beta_{i0}(u_I, v_i) + \beta_{i1}(u_I, v_i)\mathrm{COVID\ 19}_1 + \beta_{i2}(u_I, v_i)\mathrm{Tourism\ clusters}_2 \\ & + \beta_{i3}(u_I, v_i)\mathrm{Airport\ distance}_3 + \beta_{i4}(u_I, v_i)\mathrm{Food\ safety\ violation}_4 \\ & + \beta_{i5}(u_I, v_i)\mathrm{Airbnb\ supply}_5 + \beta_{i6}(u_I, v_i)\mathrm{Past\ Airbnb\ OCR}_6 \\ & + \beta_{i7}(u_I, v_i)\mathrm{Past\ Airbnb\ ADR}_7 + \beta_{i8}(u_I, v_i)\mathrm{Income}_8 \\ & + \beta_{i9}(u_i, v_i)\mathrm{Ethnic\ diversity}_9 + \varepsilon_i , \end{aligned}$$

where Y_i denotes the growth rate of Airbnb revenue performance, (u_i, v_i) is the coordinate of the centroid of county i, and $\beta_{ik}(u_i, v_i)$ is the local regression coefficient for the corresponding variable in county i. To improve the GWR model fit, we employed a bisquare kernel function that captured the differing sizes of each county (Fotheringham et al., 1998). The spatial variability in the local coefficient of each independent variable was tested using rho values generated by the Monte Carlo significance test (Lee et al. 2020a). In addition, iterative statistical optimization was used for minimizing the corrected Akaike Information Criterion (AIC_c). Finally, geographical information system (GIS)-based mapping was used to visualize the spatial distribution of local coefficients and local R^2 across Florida counties.

3.1.4. Results

Table 2 and Fig. 2 show the descriptive statistics and the spatial distribution of dependent and independent variables across counties in Florida, respectively. The average growth rate of Airbnb RevPAL per county in April 2020 compared to April 2019 was -0.254 (a decrease of 25.4%) with a minimum of -0.79 and a maximum of 4.30. This shows that Airbnb listings in Florida experienced revenue losses during the COVID-19 pandemic and the level of loss varied across counties. It can be seen from COVID-19 statistics that Floridian counties had different levels of virus spread, with an average of 109 cases and deaths ranging from 0 to 2251 in March 2020; urban counties had a wider (dark-colored) COVID-19 spread than rural areas. Furthermore, Floridian counties have different levels of destination attributes, Airbnb supply and performance, and socioeconomic factors (Fig. 2). Finally, correlation coefficients were relatively low with one exception (0.681), between tourism clusters and past Airbnb ADR. By applying the variance inflation factor (VIF) to detect the presence of collinearity, it was found that the highest VIF value was 2.301, meaning there was no serious multicollinearity issue.

[Insert Table 2 about here]

[Insert Fig. 2 about here]

Table 3 presents the results of both the OLS regression and the GWR models. Overall, tourism clusters were negatively related to the growth rate of Airbnb revenue during the pandemic, whereas past Airbnb ADR and ethnic diversity were positively related. As the OLS model results do not capture local dynamics, our main focus was on the results of the GWR model, which reveal the spatially varying relationships between destination attributes and Airbnb revenue performance. The local coefficients of the COVID-19 and destination attribute variables varied across 67 counties. Specifically, the number of COVID-19 cases and deaths, on average, negatively affected Airbnb RevPAL growth (β_{Mean} = -0.167), but, depending on the county, the effect was more negative (β_{Min} = -0.191) or less negative (β_{Max} = -0.131). In addition, past Airbnb ADR, on average, positively affected Airbnb RevPAL growth (β_{Mean} = 0.004), but, depending on the county, the effect was less positive (β_{Min} = 0.003) or more positive (β_{Max} = 0.005).

[Insert Table 3 about here]

According to Fig. 3, which illustrates the spatial distribution of local GWR coefficients, COVID-19 had more severe, negative effects on Airbnb revenue performance in the south Floridian (dark-colored) counties than in the northwest (light-colored) counties. Similar phenomena occurred in the destination attribute variables, such as tourism clusters, airport distance, Airbnb supply, and past Airbnb OCR. Conversely, the relationship between food safety violation and Airbnb revenue performance was more negative in the northern counties than in the southern counties. Interestingly, the effect of past Airbnb ADR on Airbnb performance was more positive in southern (urban and dark-colored) counties but less positive in northwestern (rural and light-colored) counties. The same phenomenon occurred in the ethnic diversity variable: the more ethnically diverse an area is, the better Airbnb revenue performance is. These results mean that southern areas (mainly urban) with more expensive Airbnb accommodations and a higher percentage of non-white Americans in the population were less damaged by the pandemic than northern areas (mainly rural) with cheaper accommodation and lower minority populations. In summary, our empirical findings show that the effect of the COVID-19 pandemic on Airbnb revenue performance varies across destinations (i.e. urban and rural counties) and destination attributes (i.e. tourism clusters, airport distance, and food safety violation), in support of H1.

[Insert Fig. 3 about here]

3.2. Stage 2: experimental study 1

To test the effect of trip purpose on P2P accommodation use intention under the pandemic (H2), we conducted the first experimental study. Specifically, we predicted that the trip intention of using Airbnb would interact with the perceived threat. When the threat from the pandemic was very high, people would not travel regardless of the purpose of their trip. However, when the perceived threat from the virus was not extremely high, we predicted that the trip intention of using P2P accommodation would be higher for a business (vs. leisure) trip. To test this additional prediction, we measured the perceived threat of COVID-19 in this study.

3.2.1. Participants, procedure, and measurement

The participants in this study were 175 U.S. adults (76 females, average age = 36.90, *SD* = 12.01) from an online panel (Amazon Mechanical Turk). They were randomly assigned to one of two experimental conditions (i.e. the purpose of a trip: business vs. leisure) in a between-subjects design.

First, participants were informed that this study consisted of multiple tasks. Participants were then offered basic information about COVID-19 obtained from the World Health Organization and were requested to rate their subjective threat regarding COVID-19 in two items (e.g. “In your opinion, how life-threatening is coronavirus?”) along an 8-point scale (1 = “not at all life-threatening” to 8 = “very life-threatening”, the same as in Kim, Giroux et al.’s (2020) study, Cronbach’s α = .800). Participants were then asked to imagine that they planned to travel to Florida and to use an Airbnb listing, as shown in Fig. 4. The price information was not presented because the maximum payment amount was to be measured. Based on two experimental conditions, participants in the business trip condition were informed that the purpose of their trip was business-related, such as attending a business meeting or conference. In contrast, participants in the leisure trip condition were informed that the purpose of their trip was leisure-related, such as visiting local attractions and parks. Participants were then asked to specify the maximum amount of money they would be ready to pay for this Airbnb option in dollars. However, since the findings were not significant for the dependent variable, this will not be discussed further. Finally, participants were asked to rate their intention to visit Florida with the Airbnb option provided, during the COVID-19 pandemic, using a 7 point-scale (1 = "not at all high" to 7 = "very high").

[Insert Fig. 4 about here]

3.2.2. Results of experimental study 1

We found that the overall perceived threat of COVID-19 was high (M = 6.27, SD = 1.55 vs. '4.5' [neutral point], t (174) = 15.03, p < .001). We tested the moderating role of the perceived threat on the impact of the experimental factor on the trip intention to Florida with Hayes' (2017) process analysis with model #1 (i.e. independent variable (IV): purpose of the trip; moderator: the perceived threat; and dependent variable (DV): trip intention). The number of bootstrapping samples was 5,000.

The results showed that the interaction effect between IV and moderator was significant (β = .45, t = 2.01, p = .047, 95% Confidence Interval [CI]: [.006, .886]). We further analyzed the difference between the two purposes of the trip for high (vs. low) perceived threat. For people with a relatively low perceived threat (for -1SD in threat perception measurement [M = 4.71 out of 8]), the trip intention was higher when the purpose of the trip was business (estimated M = 4.62) rather than leisure (M =3.64, p = .046). For people with relatively high perceived threat (for +1SD in threat perception measurement [M = 7.82 out of 8]), the trip intention was similar and low, irrespective of whether it was a business trip (M = 3.31) or a leisure trip (M = 3.72, p = .393), as shown in Fig. 5. This result is very pertinent: people would be very reluctant to travel and use an Airbnb listing especially under the condition of a high perceived threat.

[Insert Fig. 5 about here]

In summary, the results of this first experimental study supported H2 regarding the role of the trip purpose on P2P accommodation usage intention. However, insignificant results from the monetary judgment question could mean that there were individual differences in price. To reduce this heterogeneity of the internal difference, we provided an external reference price (Kim, Franklin, et al., 2020) in the second experimental study.

3.3. Stage 2: experimental study 2

To test H3 (i.e. the joint effect of trip purpose and destination type), we directly manipulated both the purpose of a trip and the destination type, as explained previously. If our theorizing is right, the effect of trip purpose should be significant and much more powerful than the effect of the destination type. However, if our theorizing regarding the purpose of travel is not valid, the effect of the destination type is still significant and the theoretical explanation of the purpose of a trip could be very weak.

3.3.1. Participants, procedure, and measurement

The participants in this study were 190 U.S. adults (98 females, average age = 37.78, *SD* = 12.62) from an online panel (Amazon Mechanical Turk). An additional 27 participants were excluded since they failed to pass an attention check (see below for details). Participants were randomly allocated to one of 2 (purpose of trip: business vs. leisure) x 2 (destination type: urban large city [Jacksonville] vs. rural small city [Titusville]) experimental conditions in a between-subjects design.

The procedure of this study was similar to that of the first experimental study, with a few modifications. First, participants were asked to imagine that they planned to travel to Florida and found an Airbnb listing, as presented in the first study. The manipulation of the purpose of a trip was the same as that in the first study. In addition, we also manipulated the destination type for large city (Jacksonville, the largest city in Florida; population: 926,000) or small city (Titusville, the 58th largest city in Florida; population: 46,000), as shown in Fig. 6. Participants were then asked to rate their intention to visit Florida with the Airbnb option as in the first experimental study. Participants were then instructed to specify the maximum amount of money they were ready to pay for the Airbnb option in dollars, compared with an external reference price ($100-$150 for a similar option). Finally, participants were asked to state the purpose of their trip (business or leisure) as an attention check (Oppenheimer et al., 2009).

3.3.2. Results of experimental study 2

We tested the moderating role of the destination type on the impact of the experimental factor on the trip intention to Florida with a 2 x 2 ANOVA model (IV: trip purpose; moderator: destination type; and DV: trip intention). The important findings are as follows. First, with regards to trip intention, only the main effect of the purpose of a trip was significant (F (1, 186) = 6.41, p = .012, η^2 = .033, 95% CI = [.155, 1.223]). Specifically, the trip intention was higher when the purpose of a trip was business (M = 4.79, SD = 1.74) versus leisure (M = 4.10, SD = 1.99), as shown in the upper panel of Fig. 6. The main effect of the destination type (F (1, 186) = 0.01, p = .984, η^2 < .001, 95% CI = [-.560, .507]) and the interaction effect (F (1, 186) = 2.17, p = .143, η^2 = .012, 95% CI = [-1.864, .271]) were not significant. Therefore, these results strongly supported H3, predicting that the intention to use Airbnb during the COVID-19 pandemic will be lower for leisure (vs. business) tourists regardless of destination type.

Second, for the monetary judgment, the two main effects were not significant (all ps > .291). However, the interaction effect was significant (F (1, 186) = 4.61, p = .033, η^2 = .024, 95% CI = [-35.487, -1.505]). Specifically, in the scenario of visiting a small city, the maximum monetary amount was higher when the purpose of a trip was business (M = \$123.69, SD = 33.33) versus leisure (M = \$109.88, SD = 24.96; F (1, 186) = 5.23, p = .023, η^2 = .027, 95% CI = [1.896, 25.729]). In contrast, when visiting a large city, the maximum monetary amount was similar when the purpose of a trip was business (M = \$113.27, SD = 19.92) versus leisure (M = \$117.95, SD = 38.62; F (1, 186) = .58, p = .447, η^2 = .003, 95% CI = [-16.795, 7.428]), as shown in the lower panel of Fig. 6. To summarize, the results of the second experimental study support both H2 and H3, meaning that the differential effect of COVID-19 on P2P accommodation performance across destinations can be explained by the purpose of the trip (business vs. leisure) irrespective of destination type (urban vs. rural).

[Insert Fig. 6 about here]

4. Conclusions

This study attempted to uncover the impact of COVID-19 on P2P accommodation consumption by investigating whether and how destination- and tourist-level characteristics affect P2P accommodation consumption during the pandemic. To address these objectives, spatial and experimental studies were performed in the setting of Airbnb consumption in Florida. First, using GWR and GIS-based visualization techniques, we identified spatially heterogeneous effects of COVID-19 and destination attributes (e.g. tourism clusters, airport distance, and food safety violation) on Airbnb revenue performance across 67 Floridian counties. Second, findings from two experimental studies showed that business tourists with a low perceived threat of COVID-19 were more willing to consume Airbnb accommodation than leisure tourists, and the effect of trip purpose (i.e. business vs. leisure) was still valid irrespective of destination type (i.e. urban or rural). These findings suggest that P2P accommodation consumption during COVID-19 can be explained by the complex interplay among destinations, tourists, and the environment. Thus, it is important for researchers and practitioners alike to use multiple research methods (including both spatial and experimental approaches) to better understand and cope with pandemic-induced P2P accommodation disruption.

4.1. Theoretical and methodological implications

Although recent studies have investigated tourists' decision-making processes during COVID-19 (e.g. Karl et al., 2020), this study was the first attempt to examine the effect of both destination- and tourist-level characteristics on P2P accommodation performance during the pandemic. First, the empirical study confirmed the spatial influence of destination attributes on P2P accommodation performance in the pandemic period. Specifically, the effect of COVID-19 on Airbnb revenue in Florida varied across destinations (e.g. urban and rural areas), depending on the levels of tourism clusters, transportation convenience, food safety violation, Airbnb supply, past Airbnb performance, and socioeconomic factors (i.e. income and ethnic diversity). The results of the spatial analysis implied that research on crisis management in the P2P accommodation sharing economy needs to pay attention to the configuration of each destination's attributes that are more or less crisis resistant. The results also underline the need for tourism research to concentrate on the complexity of tourism businesses across destinations, thereby contributing to the location-based tourism management literature (Lee et al., 2020a; Peiró-Signes et al., 2015).

Second, two experimental studies clearly showed that the perceived risk and consequent reduction in P2P accommodation consumption during the pandemic was stronger for leisure tourists than for business tourists, which contributes to the risk and destination experience literatures (e.g. Unger et al., 2020). Our findings indicated that the perceived risk of viral infection strengthens the tourist environmental bubble that might shield leisure tourists from the perceived threats and risks associated with a destination’s strangeness and COVID-19 spread, as compared with business tourists (Cohen, 1972; Unger et al., 2020). Conversely, the findings imply that business tourists wanting to travel to a particular destination, either urban or rural, possibly to meet work obligations, have profound knowledge about local sites, and take precautionary measures. In addition, although previous researchers have investigated the moderating role of perceived risk in various areas (e.g. Tavitiyaman & Qu, 2013), our research extends the literature to the perceived risk driven by COVID-19 in the context of trip purpose and P2P accommodation consumption (Yi et al., 2020).

Finally, from a methodological perspective, this paper contributes to the literature by combining multiple perspectives that reflect the destination (macro)-level and tourist (micro)-level characteristics of P2P accommodation consumption and decision-making patterns (Karl, 2018). The use of spatial analytic techniques highlights the need for tourism and hospitality researchers and practitioners to identify the spatial variations in the effect of determinants when measuring accommodation performance. However, spatial analysis tends to overemphasize the continuity of space, while failing to fully reflect the way tourists consume destinations (Beritelli et al., 2015). Hence, our mixed-methods approach combining spatial and experimental studies was able to identify a complex interplay of destination attributes, accommodation providers, and tourist decision-making process, which indicates this approach is an ideal method for destination management research. The key difference between this research and previous studies is the triangulation of empirical and experimental studies of tourist decision-making collected from behavioral, locational, and intentional data across destinations, and not simply from one particular source (e.g. Farmaki et al. 2020; Gössling et al., 2020).

4.2. Practical implications

Although questions have been raised over the future of the P2P accommodation sector as a result of the pandemic, P2P accommodation hosts and policymakers may exploit the underlying opportunities revealed by this study. For P2P accommodation businesses, this study suggests that accommodation hosts understand both the configuration of destination attributes in their destinations and their target tourist segments (business vs. leisure), and take full advantage of destination- and tourist-specific characteristics that are crisis-resilient. Specifically, urban Airbnb listings should keep in mind that urban areas are likely to be influenced negatively by rich tourism clusters and Airbnb supply, which may accelerate the virus spread and/or pandemic-induced lockdown. However, urban Airbnb hosts can maximize the benefit of high-quality amenities (i.e. expensive accommodation) while targeting business tourists who often combine work and leisure and take precautionary measures during their trip. In contrast, our findings reveal that rural Airbnb listings could take advantage of the low density of tourism facilities and businesses and the ease of social distancing in rural areas. As tourists' perceived risk of the virus infection may be reduced in rural destinations, rural listings can target and communicate with leisure-oriented tourists if their destinations are less preferred by business tourists before and during the pandemic.

From the tourism policy perspective, this study reveals how policymakers can plan and implement location-based destination management to build localized crisis-resilient environments for the sustainable accommodation sharing economy. As discussed above, the spatial behavior of tourists at a destination is complex and unique due to many destination attributes and localized factors. Depending on the geographical context of individual destinations, local governments should understand the spatially varying relationship between each destination attribute and P2P accommodation performance. For example, local government agents in Florida should acknowledge that COVID-19 disrupted Airbnb listings located in southern and northwestern Floridian counties—mostly urban and mostly rural areas respectively—where COVID-19 cases, tourism businesses, and Airbnb supply were highly or less concentrated, respectively. In addition, this study offers policymakers two strategic directions. One is that government agents can provide local P2P accommodation hosts with marketing support by selectively communicating with inbound tourists; they might emphasize the importance of self-precautionary measures for business tourists in urban destinations but encourage leisure tourists to travel to rural destinations. The other is that, from a long-term perspective, destination development in urban and rural communities needs to focus on developing localized assets and resources that are more resilient to future crises and disasters.

4.3. Limitations and future research

Despite the meaningful theoretical and practical implications of this research, several limitations should be acknowledged. First, the findings of this research are limited to one geographic area (i.e. Florida) and the early stages of the COVID-19 pandemic (i.e. April 2020). Because the spread of the pandemic varies across locations and time, future research should collect corresponding data (incidence of COVID-19 and Airbnb consumption) from other countries, during a more recent period, and resolve the generalizability issue (e.g. urban and rural differences). Second, this study used trip purpose as the primary tourist characteristic, without considering other characteristics influencing tourists' risk perceptions such as travel experience and psychographic factors (Karl et al., 2020). Further studies need to study the role of other tourist characteristics because they may influence destination choices and willingness to travel to a particular destination. Finally, this study focused on investigating the effects of COVID-19 statistical information and its perceived threat on tourists' actual consumption and P2P accommodation use intention, respectively. However, the pandemic may contribute to tourists' negative destination image of overall (e.g. Florida) and/or individual (e.g. specific counties) destinations, which can further affect tourist decisions. Consequently, studies examining the role of pandemic-induced destination image in P2P accommodation consumption are urgently needed for effective crisis management.

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Table 1
Operationalization of variables and data sources.

Variable	Operational definition	Source	Year (month)
Airbnb RevPAL growth	Year-over-year percentage change of average Airbnb revenue-per-available-listing for each county	AirDNA	2019 (April) and 2020 (April)
COVID-19	Number (in thousands) of COVID-19 cases and deaths for each county	Florida Division of Emergency Management	2020 (March)
Tourism clusters	Location quotient of tourism industries (North American Industry Classification System 71 and 72) for each county	U.S. Bureau of Labor Statistics	2019
Airport distance	Distance (in miles) to the nearest airport from the county centroid	Florida Geographic Data Library	2019
Food safety violation	Average number of critical food safety violations for each county	Florida Division of Hotels and Restaurants	2017
Airbnb supply	Number (in thousands) of Airbnb listings for each county	AirDNA	2020 (March)
Past Airbnb OCR	Aveage Airbnb occupancy rate in past month for each county		2020 (March)
Past Airbnb ADR	Average Airbnb average daily rate (in thousand dollars) in past month for each county		2020 (March)
Income	Median household income (in thousands) for each county	U.S. Department of Labor	2019
Ethnic diversity	Proportion of non-white American population for each county	American community survey	2015

Table 2
Descriptive statistics and correlation coefficients

	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Airbnb RevPAL growth	-0.254	0.669	1									
(2) COVID-19	0.109	0.324	-0.092	1								
(3) Tourism clusters	1.170	0.514	-0.122	0.054	1							
(4) Airport distance	30.632	16.729	-0.037	-0.221	-0.21	1						
(5) Food safety violation	5.876	1.620	-0.236	0.253*	0.174	-0.101	1					
(6) Airbnb supply	6.312	12.275	-0.114	0.496**	0.373**	-0.24	0.123	1				
(7) Past Airbnb OCR	0.288	0.073	-0.044	-0.049	0.116	-0.096	-0.008	0.107	1			
(8) Past Airbnb ADR	202.494	82.861	0.178	0.119	0.681**	-0.157	-0.111	0.386**	0.11	1		
(9) Income	4.885	0.975	-0.133	-0.058	-0.17	0.123	-0.172	-0.24	-0.103	-0.216	1	
(10) Ethnic diversity	0.451	0.126	0.236	0.085	-0.121	0.087	0.159	0.033	-0.041	-0.16	-0.08	1

* $p < 0.05$; ** $p < 0.01$.

Table 3
Results of OLS and GWR models

Variable	OLS Coefficient	GWR Coefficient		
		Min	Mean	Max
Constant	0.335	-0.092	0.453	0.800
COVID-19	-0.139	-0.191	-0.167	-0.131
Tourism clusters	-0.499*	-0.586	-0.534	-0.438
Airport distance	-0.005	-0.005	-0.005	-0.005
Food safety violation	-0.037	-0.069	-0.037	-0.006
Airbnb supply	-0.011	-0.013	-0.011	-0.008
Past Airbnb OCR	-0.943	-1.082	-0.985	-0.911
Past Airbnb ADR	0.004**	0.003	0.004	0.005
Income	-0.135	-0.151	-0.142	-0.124
Ethnic diversity	1.234†	0.821	1.191	1.639
R^2	0.276	0.281	0.309	0.323
Condition index		3.464	8.126	13.228
AIC_c	138.843		132.281	

†p < 0.10; * p < 0.05; ** p < 0.01.

Note: OLS: ordinary least sqaures; GWR: geographically weighted regression.

Fig. 1. Research model.

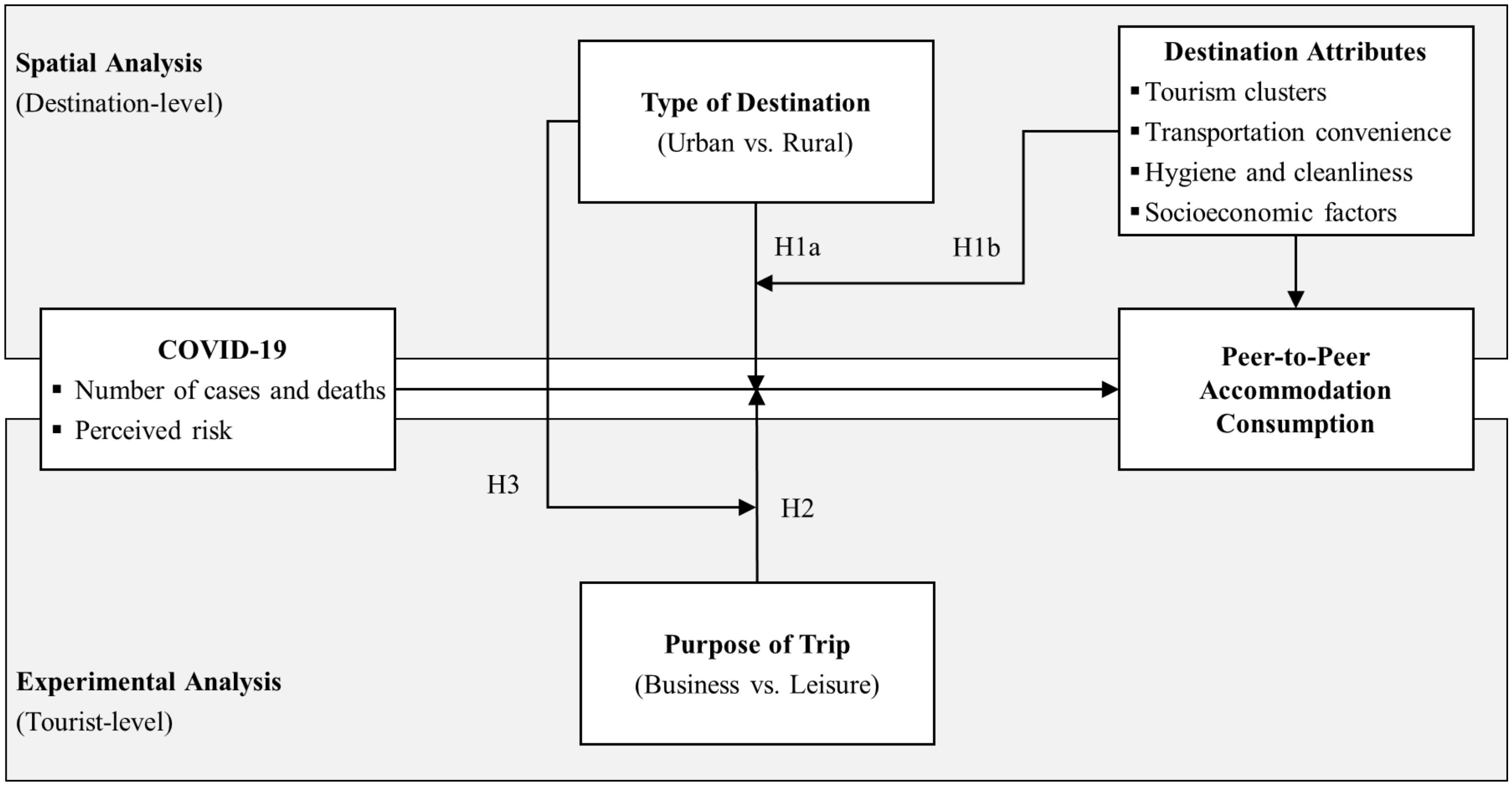
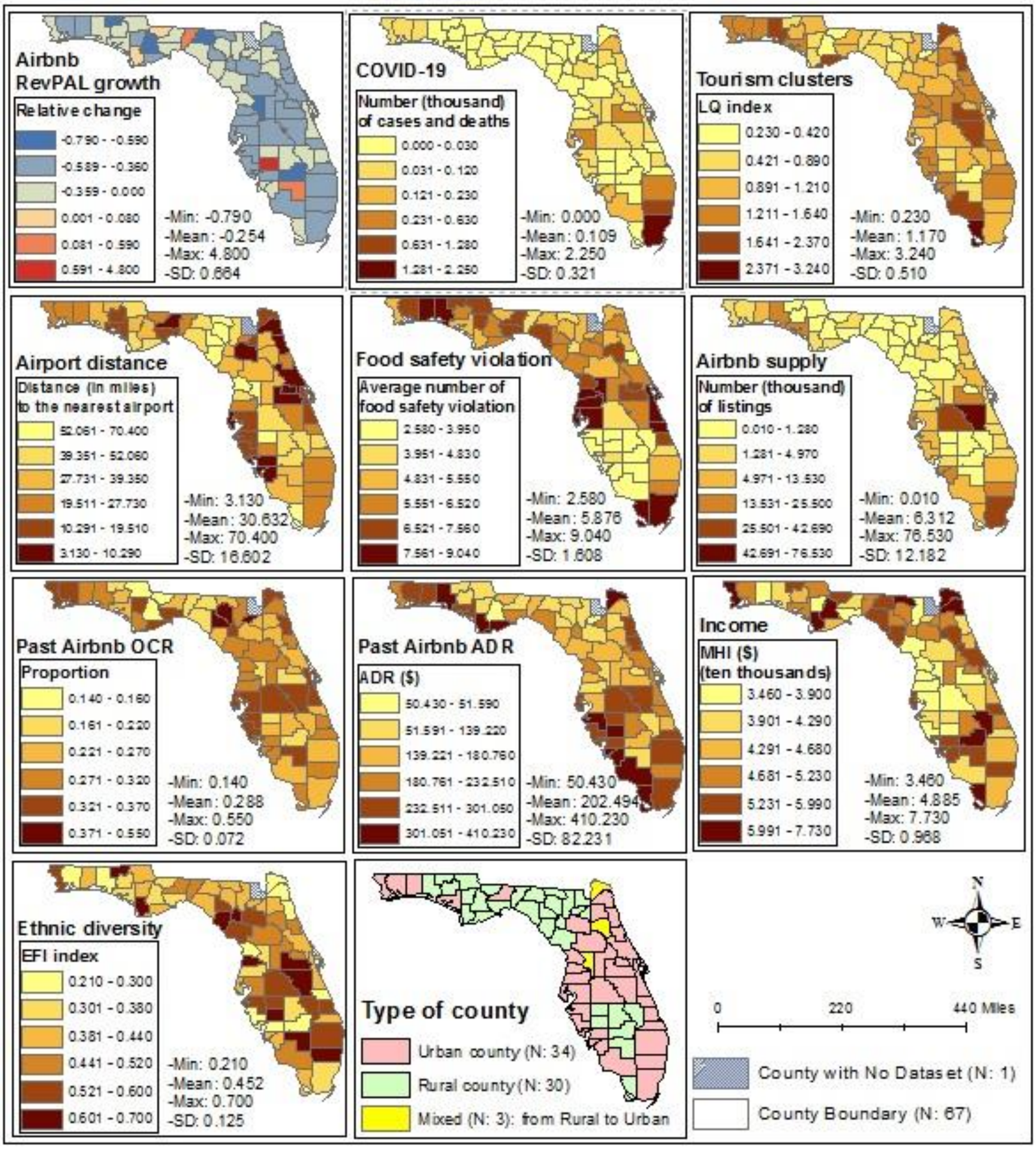
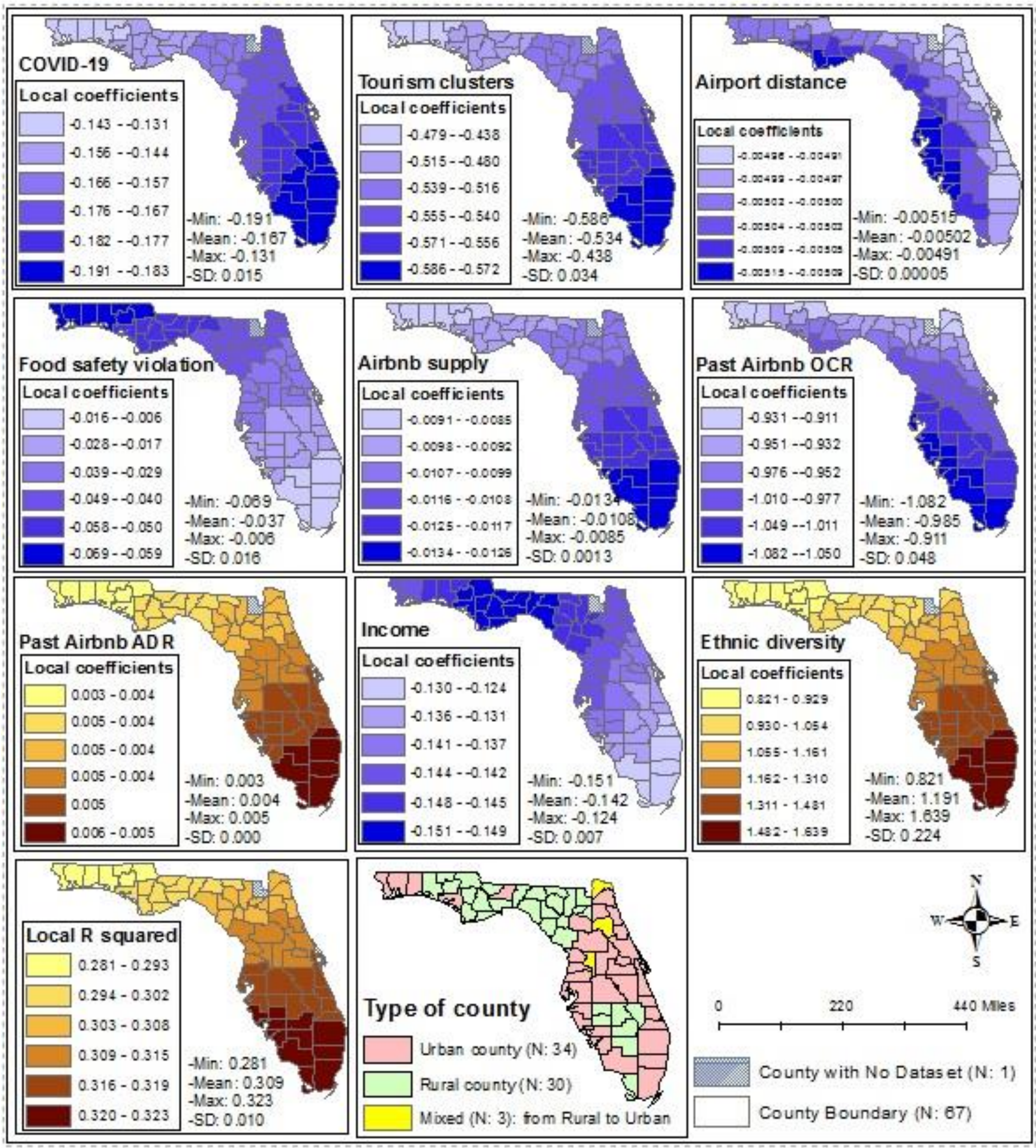


Fig. 2. Spatial distribution of dependent and independent variables.



Note: RevPAL: Revenue-per-available-listing.

Fig. 3. Spatial distribution of GWR-based local coefficients for COVID-19.



Note: RevPAL: Revenue-per-available-listing.

Fig. 4. Stimuli for experimental study 1.

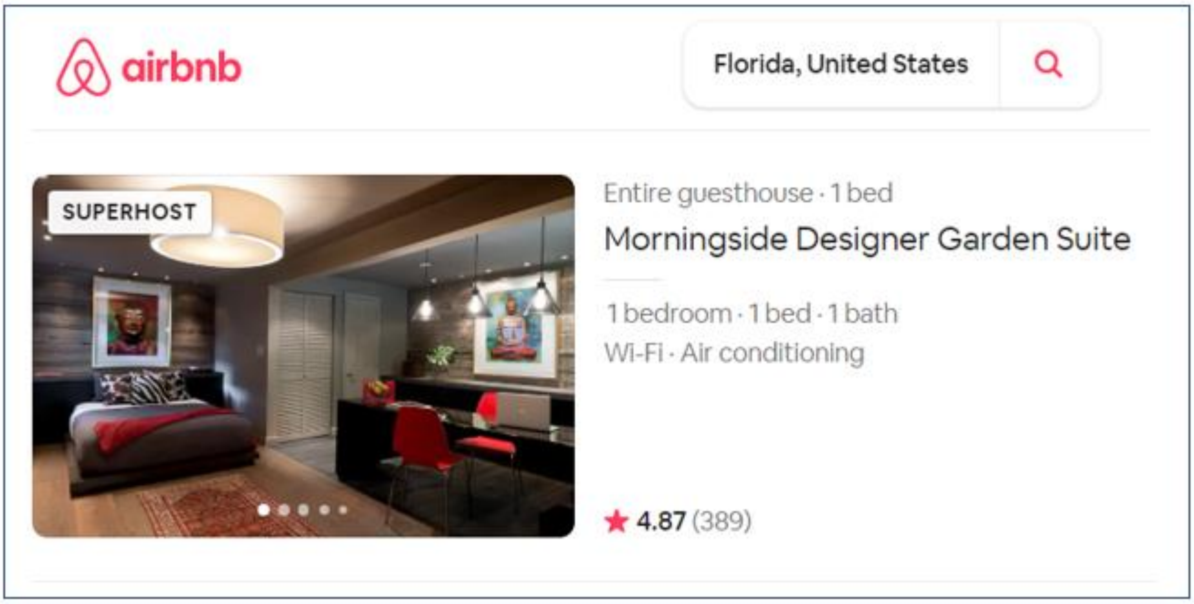


Fig. 5. Results of experimental study 1.

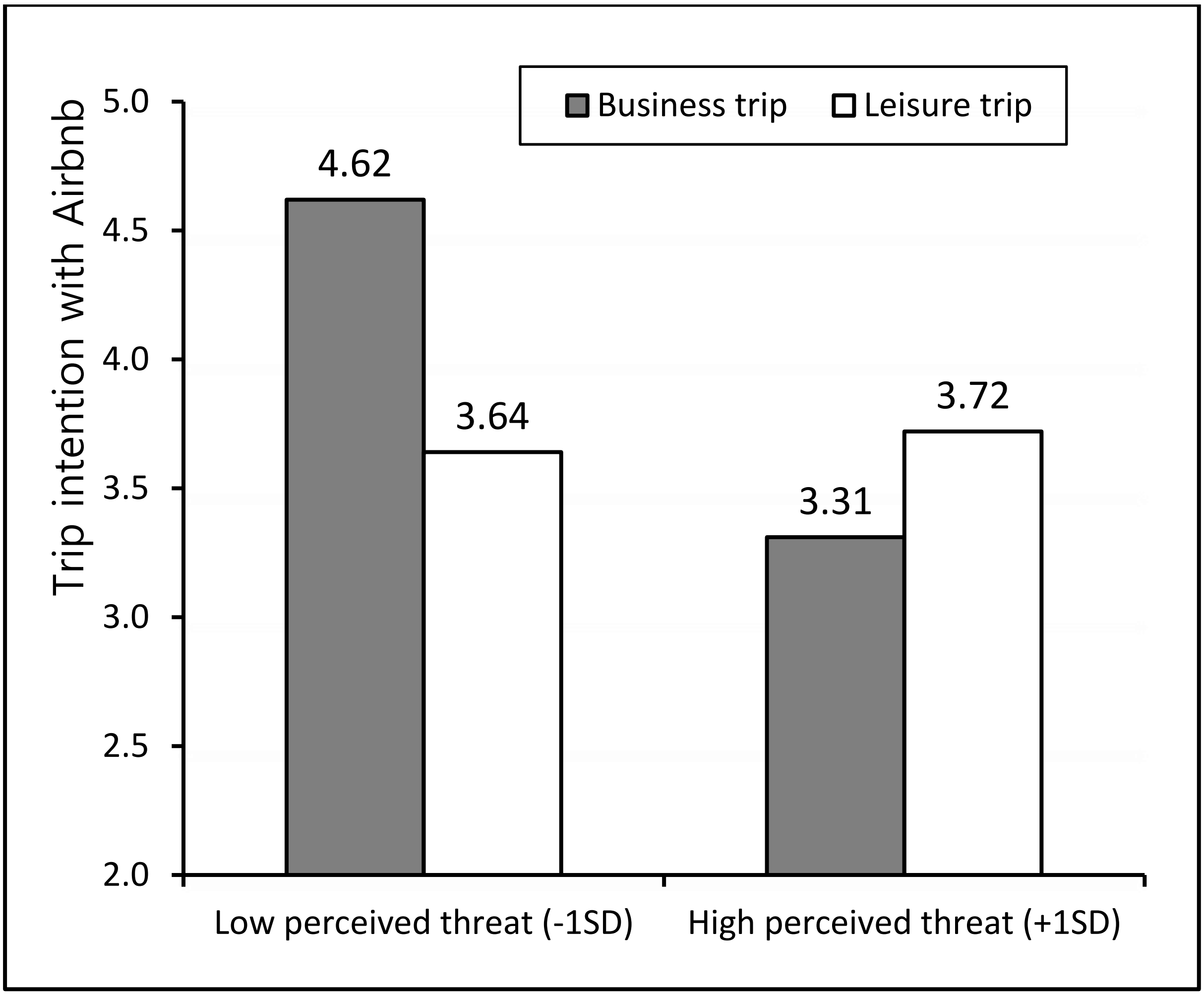


Fig. 6. Results of experimental study 2.