The following publication Shin, S., Lee, E., Yhee, Y., Kim, J. and Koo, C. (2023), "Mapping changes in human mobility for dining activities: a perceived risk theory perspective ", Tourism Review, Vol. 78 No. 4, pp. 1164-1181 is published by Emerald and is available at https://doi.org/10.1108/TR-08-2022-0392.

Mapping Changes in Human Mobility for Dining Activities: A Perceived Risk Theory Perspective

Structured Abstract

Purpose – This research aims to explain how the impact of COVID-19 on human mobility is affected by the perceived risk of the pandemic.

Design/methodology/approach – Using a statistical analysis and a geographic visualization technique, we investigate whether and how changes in people's restaurant visiting patterns during COVID-19 vary with their level of risk perception.

Findings – The changes in people's restaurant visiting patterns vary with their risk perception: the tendency to increase the number of visits to restaurants located in non-popular areas is related to the level of perceived risk.

Originality/value – This research confirms the importance of risk perception when examining the pandemic's multi-dimensional impacts.

Keywords: Mapping behaviour; human mobility; COVID-19 lockdown; perceived risk theory; dining activities

1. Introduction

COVID-19 has affected almost every destination around the world, mainly by influencing how people move within it. It has led people to avoid visiting popular travel sites (Falk et al., 2022) and avoid using public transport (Campisi et al., 2022). Considering that the pandemic reshaped people's behaviour in often hidden ways, destinations need to examine the changes in people's movement to understand the impact of COVID-19 on their region (Zenker and Kock, 2020). The examination of changes in movements within a destination can provide important insights for taking proper countermeasures to limit virus transmission; for example, by using different levels of social distancing measures (Chow et al., 2021).

The perceived risk theory argues that people make decisions based on the level of risk they perceive about the possible negative consequences associated with their decisions (Taylor, 1974). According to the theory, people react differently to similar potential negative consequences because risk perception is subjective (Chi et al., 2022). Once people's movement within a destination during the pandemic is considered, people are either more or less sensitive to potential infection risk depending on their perception (Abraham et al., 2020). Such subjective perception may lead them to make different spatial decisions (Zenker and Kock, 2020). The changes in people's movement within a destination during the pandemic should be explained based on consideration different levels of risk perception to further understand the impact of COVID-19 on a destination and, subsequently, develop granular countermeasures. However, the existing literature has scarcely examined the impact of risk perception on people's movement during COVID-19 because their behavioral intention has been primarily investigated (Neuburger and Egger, 2021, Zhan et al., 2022).

The aim of this study was to explain the effects of COVID-19 on people's mobility, taking into account risk perception in the response. While there are many factors affect people’s movement during COVID-19, we hypothesized that their risk perception is one of the factors based on the perceived risk theory (Taylor, 1974): the changes in people’s movements during COVID-19 would vary with their risk perception. Since risk perception is influenced by socio-demographic characteristics (Chi et al., 2022), we examined how the change in movement after the outbreak of COVID-19 differed with three characteristics that can affect risk perception: sex (Reisinger and Mavondo, 2006), age (Isaac and Van den Bedem, 2020), and status (Moreira, 2008). We targeted dining activities as the context of people’s movements, as these are among the most common aspects of our lives regardless of sex, age, and status. We adopted statistical analysis and geographic visualization techniques, using data from a smartphone driver navigation application. While some previous studies tracked people’s movements during COVID-19 with detail and precision by using mobile data (Chen et al., 2021), to our best knowledge, such movements have not been specified by socio-demographic characteristics. The mobile data used in this research, which were associated with users’ socio-demographic characteristics, allowed us to track the movement of people from different socio-demographic groups with detail and precision.

2. Literature Review

2.1. Determinants of human mobility

Human mobility is determined by interactions between and psychological factors (Grinberger and Shoval, 2019). The literature examined the effect of each factor on people's spatial behavior and identified different contingencies among the effects (McKercher and Lew, 2004). One stream of the literature investigated time and space constraints as the main determinants of people's spatial behavior. The literature developed a conceptual framework called time-geography to explain the effects of the time-space resources on an individual's movement (Ellegård and Svedin, 2012). A tourist's movement within a destination was found to be determined by the available time budget for travelling in the destination (Bauder and Freytag, 2015) and the distance between attractions (Wong et al., 2021). Another stream of the literature explained the effects of individuals' psychological factors on their representations of the physical world. The literature found that individuals' time and distance estimations are biased by cognitive (Kang et al., 2020), social (Zhao et al., 2018), and emotional factors (Han et al., 2018). The literature showed that individuals make different spatial decisions, determined by psychological factors, even when exposed to similar time-space constraints (Grinberger and Shoval, 2019). It is important to identify the psychological factors that affect their perception of the physical environment and to explain how these factors motivate specific spatial choices (Zheng et al., 2022). The impact of COVID-19 on people's movement during the pandemic can be explained based on the psychological factors that affect their perception of the surrounding environment.

2.2. Impact of COVID-19 on people's movement within a destination

Many studies investigated the multi-dimensional impact of COVID-19 on destinations, including political economy (Florido-Benítez, 2021), public health (Li et al., 2021), and social well-being (Wen et al., 2020). One stream of the literature attempted to explain the impact of COVID-19 on a destination based on the changes in people's movement within the area. Falk et al. (2022) found that people in four Europe countries were more likely to visit areas with a low population density than those with a high population density during their domestic travel in summer 2020. Li et al. (2022) verified that while tourism flow networks in large cities in Hubei Province damaged by the pandemic recovered slowly, rural and natural scenic spots showed rapid recovery. Although the existing literature described the change in people's movement during the COVID-19 pandemic, there has been little examination of what makes people display different spatial behaviour patterns during the pandemic. The impact of COVID-19 on people's movement can be further examined based on the psychological factors that affect their perception of the environment. This research aims to explain the impact of COVID-19 on people's movement based on the psychological factors that could affect their perception of the pandemic situation: the perceived risk (Abraham et al., 2020). This research targeted an essential activity for an individual when traveling, which is movement for dining activities.

3. Research Model and Hypotheses

This study anticipated that the change in people's movements for dining activities during COVID-19 would depend on their socio-characteristics affecting risk perception: sex (Reisinger and Mavondo, 2006), age (Isaac and Van den Bedem, 2020), and status (Moreira, 2008).

[Figure 1]

According to the perceived risk theory, when making decisions, people perceive a certain level of risk related to the possible negative consequences of those decisions and that perceived risk affects decision-making (Taylor, 1974). Individuals show a range of reactions to the same possible negative consequence because risk perception is subjective (Pope et al., 1999). The theory maintains that certain socio-demographic groups tend to perceive higher risk in general (Chi et al., 2022). Many studies used the perceived risk theory to explain how people react to COVID-19 pandemic situation differently based on their socio-demographic characteristics. Bae and Chang (2021) explored South Korean citizens' intention to conduct non-contact tourism during COVID-19 and found that males' preference for non-contact tourism is different from females' preference because of the difference between the groups in terms of the perceived risk of infection. The impact of risk perception of COVID-19 on people's travel intention was also examined as moderated by their age (Abraham et al., 2020). Joo et al. (2021) found that the residents of a destination perceived a higher level of risk than tourists and showed lower levels of support for tourism. We hypothesized that how people change their movements for dining activities within a destination during COVID-19 might be dependent on three socio-demographic characteristics that affect risk perception.

People's motivations for dining out at a restaurant are functional or hedonic (Park, 2004). Depending on the main motivation for dining out, people's choice of a restaurant to visit is determined by different aspects. If the functional motivation becomes pronounced because of the outbreak of the epidemic, the location of a restaurant can be a major determinant of people's choice (Radic et al., 2021). Thus, we expected that people in socio-demographic groups with high levels of perceived risk of COVID-19 would be more affected by functional motivation and, thus, be more active in avoiding visiting popular, crowded areas than their counterparts. The former group's active avoidance of crowded locations would lead them to diversify their choice of areas to visit and, thus, their visiting of places within a destination would become more evenly distributed after the outbreak of COVID-19 (Park et al., 2021).

We hypothesise that the extent to which people move to dine within a destination following an outbreak of COVID-19 varies by sex, age, and status. Males tend to perceive a higher risk of infection than females (Malik et al., 2020). Therefore, we postulate that males will have a stronger diversification pattern than females in selecting an area for eating activities during COVID-19.

H1a. Males perceive a higher risk of infection and they are more active in in diversifying their choice of areas to visit a restaurant than females after the COVID-19 outbreak.

H1b. The restaurants visited by males during COVID-19 are more evenly distributed than those visited by females.

A previous study showed that older generations had higher levels of fear of contracting COVID-19 (Shahid et al., 2020). We hypothesise that older generations would show more diversification in selecting dining activities during COVID-19 than younger generations.

H2a. Older generations perceive a higher risk of infection and they are more active in in diversifying their choice of areas to visit a restaurant than younger generations after the COVID-19 outbreak.

H2b. The restaurants visited by older generations during COVID-19 are more evenly distributed than those visited by younger generations.

The residents of a destination were found to feel a higher infection risk than tourists (Zenker and Kock, 2020). We hypothesise that residents would show more diversification in selecting an area for dining activities during COVID-19 than tourists.

H3a. Residents perceive a higher risk of infection and they are more active in in diversifying their choice of areas to visit a restaurant than tourists after the COVID-19 outbreak.

H3b. The restaurants visited by residents during COVID-19 are more evenly distributed than those visited by tourists.

If the changes in people's movement patterns during COVID-19 are due to their risk perception, people might return to their normal pattern if their perceived risk relating to the pandemic situation decreases (Gogoi et al., 2022). As the pandemic duration increases, people may become accustomed to the situation and less sensitive to the potential infection risk (Wang and Xia, 2021). We hypothesise that the diversified patterns in selecting an area for dining activities during COVID-19 will disappear as the pandemic situation becomes prolonged.

H4a. Both males' and females' movements for dining activities long after the COVID-19 outbreak will be similar to each group's movements before the outbreak.

H4b. Both older and younger generations' movements for dining activities long after the COVID-19 outbreak will be similar to each group's movement before the outbreak.

H4c. Both residents' and tourists' movements for dining activities long after the COVID-19 outbreak will be similar to each group's movements before the outbreak.

[Figure 2]

4. Methodology

We selected Jeju Island in South Korea as our study site. We used the usage data from a driver navigation application. We collected the usage data from Tmap, the country's most popular navigation application in terms of market share over almost a decade (Lee, 2022). We were able to access the usage data associated with sex, age, and status (i.e., whether the usage occurred within the person's area of residence or not) over a specific period (from June 2019 to June 2020). Since the number of navigation application users has already exceeded that of built-in car navigation users across sexes and age groups from 2014 in South Korea (Kim, 2022), we expected our data to be useful in showing the movement of the majority of Korean people. The dataset included the following information (see Appendix for the dataset preview):

- Trip: Date of the trip.
- User: Sex, age, and status.
- Destination: Location (latitude and longitude), category (e.g., restaurants, accommodation, and public services).

For each destination categorized as a restaurant (point of interest; POI, hereafter), we computed the number of visits made by different groups of people (i.e., visits by males or females; visits by people in their 20s, 30s, 40s, 50s, or 60s; visits by residents or tourists) for the months we targeted. All the computed values were normalized for the relative comparison of visit density for each POI. We used the computed values as an outcome variable: the normalized value of the number of visits to a restaurant over a month.

We targeted June 2019, April 2020, and June 2020 as the months before, right after, and long after the COVID-19 outbreak (hereafter referred to as before, right after, and long after COVID-19), respectively. While restaurant visits were possible in all the target months, people needed to wear a mask to visit a restaurant and were recommended to limit their gathering in April and June 2020. Although both April and June 2020 were within the pandemic period, the latter was about three months after the outbreak of COVID-19 and the situation was somewhat improved at that time: people might have been reverting to their normal patterns due to the prolonged pandemic situation (Gogoi et al., 2022). We used April 2020 to assess how people's movements for restaurant visits changed after the outbreak of COVID-19 (H1, H2, and H3) and June 2020 to estimate whether the change in the movement was maintained when the pandemic situation was prolonged (H4).

We conducted several analyses using the normalized value of the number of visits to a restaurant for a month as an outcome variable (normalized restaurant visits, hereafter). First, a regression analysis was performed. We used the Poisson regression model because the outcome variable represents the occurrence of a specific event (i.e., a visit to a restaurant). Each restaurant was treated as a unit of analysis and the normalized restaurant visits made by a certain socio-demographic was used as the outcome variable. The month was used as the independent variable (1: before, 2: right after, 3: long after COVID-19) and the socio-demographic characteristic was used as the moderating variable. The following elements relating to a restaurant's location were used as control variables (Table 1).

- Number of nearby restaurants (number of restaurants located within a 100-meter radius from a focal restaurant): A restaurant in an area where many alternatives are concentrated tends to be more visited by people compared to its counterparts (Ryu and Han, 2010).
- Proximity to nearby beach (Straight-line distance from a focal restaurant to the closest beach): The major tourist areas on Jeju Island are close to beach areas. A

restaurant near a beach area is considered as being located in a popular area (Jang and Jeong, 2011).

- Proximity to the airport (Straight-line distance from a focal restaurant to Jeju International Airport): A restaurant near Jeju International airport tends to be frequently visited by tourists right after arriving or right before leaving the island. Also, a restaurant close to the airport might be easily visited by residents because the airport is near to the major residential areas of the island (Cantallops and Salvi, 2014).

[Table 1]

A regression model was developed to examine the difference between 1) males' and females'; 2) age groups'; 3) residents' and tourists' restaurant visit patterns before, right after, and long after COVID-19, respectively.

- Model 1. $Visits_i = \alpha_i + \beta_i{\cdot}month + \gamma_i{\cdot}sex + \delta_i{\cdot}month{\cdot}sex + \zeta_i{\cdot}number\ of\ nearby\ restaurants + \eta_i{\cdot}proximity\ to\ nearby\ beach + \theta_i{\cdot}proximity\ to\ the\ airport + \varepsilon_i$
- Model 2. $Visits_i = \alpha_i + \beta_i{\cdot}month + \gamma_i{\cdot}age + \delta_i{\cdot}month{\cdot}age + \zeta_i{\cdot}number\ of\ nearby\ restaurants + \eta_i{\cdot}proximity\ to\ nearby\ beach + \theta_i{\cdot}proximity\ to\ the\ airport + \varepsilon_i\ t$
- Model 3. $Visits_i = \alpha_i + \beta_i{\cdot}month + \gamma_i{\cdot}status + \delta_i{\cdot}month{\cdot}status + \zeta_i{\cdot}number\ of\ nearby\ restaurants + \eta_i{\cdot}proximity\ to\ nearby\ beach + \theta_i{\cdot}proximity\ to\ the\ airport + \varepsilon_i$

where $Visits_i$ represents the normalized number of visits to a restaurant i, indicating how many visits were made to a certain restaurant (restaurant i in this case) for a month. The parameter δ_i represents the interaction effect between the month and a given socio-demographic factor on the dependent variable, which is the main focus of the current research. The parameters β_i and γ_i represent the impact of the month and a certain socio-demographic factor, and the other parameters (ζ_i, η_i, θ_i) represent the effects of three control variables on the dependent variable. Finally, the parameters α_i and ε_i represent the constant and error terms, respectively.

After statistically examining the change in people's movements, we conducted a geographic visualization using software called ArcGIS to visually describe the heterogeneous restaurant visit patterns. Based on the outcome variable, we mapped the restaurants hierarchically, where a restaurant of a higher value is represented by a bigger symbol on the map.

5. Results and Discussions

5.1. Sex

The first interaction variable (Males*Right after COVID-19) had a significant impact on the dependent variable (b = 0.541, p < 0.05) (Table 2). The extent to which males increased restaurant visits right after COVID-19 was 54.1% higher than the extent to which females did. However, the impact of the second interaction variable (Males*Long after COVID-19) was not significant (b = -0.147, p = 0.580). Both graphs increased right after COVID-19, but the line for males showed a stronger increase compared to the line for females (Figure 3). During the period of long after COVID-19, both lines decreased to levels similar to those recorded before COVID-19.

[Table 2]

[Figure 3]

The blue circles represent restaurant visits by males (top of Figure 4), and the red circles reflect those by females (bottom of Figure 4). As indicated in Figures 4b and 4e, both blue and red circles became more evenly distributed across Jeju Island right after COVID-19. More 2nd, 3rd, and 4th level circles (i.e., restaurants whose computed value was between 0.2 and 0.8) appeared right after COVID-19. These tendencies seem more evident for males than females. However, as shown in Figure 4c and 4f, both males' and females' restaurant visit patterns long after COVID-19 were similar to those before COVID-19.

While both males and females diversified their spatial choice for dining activities right after COVID-19, males were likely to be more active in diversifying their spatial choice for dining activities during the pandemic compared to females. However, the diversified patterns for males and females right after COVID-19 disappeared as the pandemic continued. H1a, H1b, and H4a were supported.

[Figure 4]

5.2. Age

For the first group of interaction variables (Age*Right after COVID-19), the impact was significant only for those in their 50s (*b* = 0.411*,* $p < 0.05$) and 60s (*b* = 0.416*,* $p < 0.05$) (Table 3). The extent to which people in their 50s and 60s increased their restaurant visits right after COVID-19 was higher than the reference group by about 40%. For the second group of interaction variables (Age*Long after COVID-19), no significant impact was found. Consistent trends were shown in all age groups, but the strongest changes were shown in the 50s and 60s age groups (Figure 5).

[Table 3]

[Figure 5]

The red circles represent people in their 20s (1st row of Figure 6), orange, 30s (2nd row of Figure 6); yellow, 40s (3rd row of Figure 6); green, 50s (4th row of Figure 6); and blue, 60s (5th row of Figure 6). In general, more 2nd, 3rd, and 4th level circles appeared and circles became more evenly distributed right after COVID-19. However, such tendencies were more evident in those in their 50s and 60s (Figures 6k and 6n) than those in their 20s, 30s, and 40s (Figures 6b, 6e, and 6h). The diversified patterns in the periods right after COVID-19 disappeared for all ages when the pandemic was prolonged (Figure 6c, 6f, 6i, 6l, and 6o).

These findings imply that 1) older adults tended to be more active in diversifying their spatial choice for dining activities during the pandemic compared to younger adults, supporting H2a and H2b, and that 2) all age groups tended to return to their original restaurant visit patterns when they became accustomed to COVID-19, supporting H4b.

[Figure 6]

5.4. Status

The impact of the first interaction variable (Residents*Right after COVID-19) on the dependent variable was significant ($b = 0.791$, $p < 0.01$) (Table 4). Also, the impact of the second interaction variable (Residents*Long after COVID-19) was significant ($b = 0.681$, $p < 0.01$). The extent to which residents increased restaurant visits right and long after COVID-19 was higher than the extent to which tourists did by about 80% and 70%, respectively. The line for residents ascended right after COVID-19 and remained at a similar level long after (Figure 7). However, the line for tourists did not show much change over the period.

[Table 4]

[Figure 7]

The red circles represent residents (top of Figure 8), while the blue circles represent tourists (bottom of Figure 8). As shown in Figure 8b, more 2nd, 3rd, and 4th level red circles appeared and those red circles became evenly distributed right after COVID-19, compared to before. However, restaurant visit patterns visualized in Figure 8e were very similar to those in Figure 8d, indicating that tourists did not change their restaurant visit patterns across the periods. Similar trends were found even when the pandemic became prolonged. Regarding residents' restaurant visit patterns, more 2nd, 3rd, and 4th level red circles appeared across the Island long after COVID-19 (Figure 8c) than before (Figure 8a). For tourists' patterns, no clear differences were identified between the periods (Figure 8d and 8f).

These results imply that while residents dealt with the pandemic situation by diversifying their spatial choice for dining activities, tourists were not active in taking this approach. H3a and H3b were supported. Even when the pandemic situation became prolonged, residents maintained their diversified restaurant visit patterns. In the same period, tourists also maintained their original restaurant visit patterns. H4c was partially supported.

[Figure 8]

6. Conclusions

6.1. Theoretical Implications

First, this research clarified the factors influencing people's differences in movement patterns within a destination during the COVID-19 pandemic. The previous research described how people's movement patterns changed after the outbreak of COVID-19 (Falk et al., 2022, Li et al., 2022). Little is known about what leads people to make an unusual spatial decision during the pandemic. This research showed that how people changed their spatial behavior during the pandemic was dependent on the level of risk they perceived. These findings also contribute to the literature on people's perceived risk of COVID-19, which investigated the risk's impact primarily with people's cognitive and affective perceptions (Kim et al., 2022, Wang et al., 2021, Joo et al., 2021).

Second, this research showed how pandemic fatigue is manifested in people's movements. Some recent studies attempted to demonstrate pandemic fatigue via a range of indications (Zaman et al., 2021). This research adds to the literature by providing further evidence of pandemic fatigue: the extent to which people revert to their pre-pandemic behaviors. While the previous research could not indicate when people start to experience pandemic fatigue (Kim et al., 2022), this research provided some clues: about 3 months after the outbreak of COVID-19. Furthermore, our findings indicated that residents continued to be active in diversifying their movements even after 3 months from the outbreak of COVID-19. This finding extends the literature on pandemic fatigue by proposing a possible moderator: residents accommodating an influx of tourists may be less prone to pandemic fatigue (Zenker and Kock, 2020).

Third, this research methodologically contributes to the literature on the impact of COVID-19 on people's spatial behaviour in several ways. On one hand, many previous studies examined people's movement during the COVID-19 using proxy data, such as the revenue or the number of overnight stays in accommodation facilities (Falk et al., 2022, Jang et al., 2021). Compared to the proxy data, the data from a smartphone driver navigation application are more effective in capturing people's movements with detail and precision (Chen et al., 2021). On the other hand, most previous studies comparing people's spatial behaviour before and after the COVID-19 outbreak targeted different months of the year (Falk et al., 2022, Li et al., 2022). By targeting the same month of the year, this research tries to control the potential confounding effect of seasonality.

6.2. Practical Implications

This research suggests that restaurant managers should adapt their operational strategies by understanding the location of their properties and identifying those who are sensitive to infection risk. According to our findings, restaurants located in popular areas would be visited less during the early period of a disease outbreak. In contrast, restaurants in less popular areas may have more visitors during the early period of a disease outbreak, and those visitors are likely to be those who are sensitive to infection risk. Based on these findings, restaurant managers could prepare for potential changes in the customer base according to their properties' locations. For example, the managers of restaurants located in the popular (vs. less popular) areas could consider decreasing (vs. increasing) ingredient orders or hiring fewer (vs. more) temporary staff. The restaurant managers located in the less popular areas could focus on enhancing the attributes that are important to groups of people who are highly sensitive to infection risk right after the outbreak of a disease. Furthermore, this research indicates that people revert to their normal restaurant visit patterns around 3 months after the outbreak of a disease. If another pandemic situation happens in the future, this finding could allow restaurant managers to estimate when they can return to their original management operations.

Based on our findings, destination managers could determine which groups of people mainly visit which areas in their restaurant visits and, accordingly, implement location-based management. For example, destination managers could enforce stricter monitoring of people’s compliance with social-distancing rules for restaurants located in regions that are mainly visited by older adults when a pandemic occurs. With regard to restaurants located in regions that are mainly visited by tourists during the early period of a disease outbreak, tourists’ irresponsible behaviour may damage both the businesses and the region. Thus, destination managers can provide local restaurants with indirect educational resources (e.g., video campaigns or brochures) to encourage tourists to be more responsible toward the businesses and the region (Kane et al., 2021). Building on the findings about people’s tendency to revert to their normal restaurant visiting patterns, destination managers could set a possible duration for social distancing policies, which can be a reference for future pandemic situation.

6.3. Limitations

First, our results are limited to specific periods of the COVID-19 pandemic, and one geographic area. Future research needs to increase the generalizability of this study by targeting different periods and areas. Second, there can be other socio-demographic characteristics that influence individuals’ risk perception. Future research should target other socio-demographic characteristics related to individuals’ risk perception. Finally, this research only targeted people’s movement via private vehicles. While the majority of people’s movement may be covered by private vehicles on account of their preference for using such vehicles during COVID-19, other travel modes should be investigated to fully explain human movement.

References

Abraham, V., Bremser, K., Carreno, M., Crowley-Cyr, L. and Moreno, M. (2020), "Exploring the consequences of COVID-19 on tourist behaviors: Perceived travel risk, animosity and intentions to travel", *Tourism Review,* Vol. 76 No. 4, pp. 701-717.

Bae, S. Y. and Chang, P. J. (2021), "The effect of coronavirus disease-19 (COVID-19) risk perception on behavioural intention towards 'untact'tourism in South Korea during the first wave of the pandemic (March 2020)", *Current Issues in Tourism,* Vol. 24 No. 7, pp. 1017-1035.

Bauder, M. and Freytag, T. (2015), "Visitor mobility in the city and the effects of travel preparation", *Tourism Geographies,* Vol. 17 No. 5, pp. 682-700.

Campisi, T., Basbas, S., Trouva, M., Papas, T., Akgün-Tanbay, N., Stamatiadis, N. and Tesoriere, G. (2022), "Anxiety, fear and stress feelings of road users during daily walking in COVID-19 pandemic: Sicilian cities", *Transportation Research Procedia,* Vol. 62, pp. 107-114.

Cantallops, A. S. and Salvi, F. (2014), "New consumer behavior: A review of research on eWOM and hotels", *International Journal of Hospitality Management,* Vol. 36, pp. 41-51.

Chen, J., Becken, S. and Stantic, B. (2021), "Harnessing social media to understand tourist mobility: The role of information technology and big data", *Tourism Review,* Vol. 77 No. 4, pp. 1219-1233.

Chi, C. G., Ekinci, Y., Ramkissoon, H. and Thorpe, A. (2022), "Evolving effects of COVID-19 safety precaution expectations, risk avoidance, and socio-demographics factors on customer hesitation toward patronizing restaurants and hotels", *Journal of Hospitality Marketing & Management,* Vol. 31 No. 4, pp. 396-412.

Chow, T. E., Choi, Y., Yang, M., Mills, D. and Yue, R. (2021), "Geographic pattern of human mobility and COVID-19 before and after Hubei lockdown", *Annals of GIS,* Vol. 27 No. 2, pp. 127-138.

Ellegård, K. and Svedin, U. (2012), "Torsten Hägerstrand's time-geography as the cradle of the activity approach in transport geography", *Journal of Transport Geography,* Vol. 23, pp. 17-25.

Falk, M., Hagsten, E. and Lin, X. (2022), "Uneven domestic tourism demand in times of pandemic", *Tourism Economics*, pp. 1-16.

Florido-Benítez, L. (2021), "The effects of COVID-19 on Andalusian tourism and aviation sector", *Tourism Review,* Vol. 76 No. 4, pp. 829-857.

Gogoi, M., Webb, A., Pareek, M., Bayliss, C. D. and Gies, L. (2022), "University students' mental health and well-being during the COVID-19 pandemic: Findings from the UniCoVac qualitative study", *International Journal of Environmental Research and Public Health,* Vol. 19 No. 15, 9322.

Grinberger, A. Y. and Shoval, N. (2019), "Spatiotemporal contingencies in tourists' intradiurnal mobility patterns", *Journal of Travel Research,* Vol. 58 No. 3, pp. 512-530.

Han, H., Kim, S. and Otoo, F. E. (2018), "Spatial movement patterns among intra-destinations using social network analysis", *Asia Pacific Journal of Tourism Research,* Vol. 23 No. 8, pp. 806-822.

Isaac, R. K. and Van den Bedem, A. (2020), "The impacts of terrorism on risk perception and travel behaviour of the Dutch market: Sri Lanka as a case study", *International Journal of Tourism Cities,* Vol. 7 No. 1, pp. 63-91.

Jang, J. J. and Jeong, H. S. (2011), "A survey on the knowledge and preferences for Korean food targeting Germans residing in Korea", *Culinary Science and Hospitality Research,* Vol. 17 No. 5, pp. 1-14.

Jang, S., Kim, J., Kim, J. and Kim, S. S. (2021), "Spatial and experimental analysis of peer-to-peer accommodation consumption during COVID-19", *Journal of Destination Marketing & Management,* Vol. 20, 100563.

Joo, D., Xu, W., Lee, J., Lee, C.-K. and Woosnam, K. M. (2021), "Residents' perceived risk, emotional solidarity, and support for tourism amidst the COVID-19 pandemic", *Journal of Destination Marketing & Management,* Vol. 19, 100553.

Kane, B., Zajchowski, C. A., Allen, T. R., McLeod, G. and Allen, N. H. (2021), "Is it safer at the beach? Spatial and temporal analyses of beachgoer behaviors during the COVID-19 pandemic", *Ocean & Coastal Management,* Vol. 205, 105533.

Kang, C., Shi, L., Wang, F. and Liu, Y. (2020), "How urban places are visited by social groups? Evidence from matrix factorization on mobile phone data", *Transactions in GIS,* Vol. 24 No. 6, pp. 1504-1525.

Kim, E. E. K., Seo, K. and Choi, Y. (2022), "Compensatory travel post COVID-19: Cognitive and emotional effects of risk perception", *Journal of Travel Research,* Vol. 61 No. 8, pp. 1895-1909.

Kim, S. (2022), "Built-in car navigation companies are digging a different way to survive", *MTNnews,* 9 September.

Lee, D. (2022), "Comparing top 3 map or navigation app in South Korea", *Maeil Business News Korea*, 7 March.

Li, L., Tao, Z., Lu, L., Liu, H., Zhang, J. and Zhang, M. (2022), "The impact of COVID-19 on the regional tourism flow network: An empirical study in Hubei Province", *Current Issues in Tourism,* Vol. 25 No. 2, pp. 287-302.

Li, Z., Zhang, X., Yang, K., Singer, R. and Cui, R. (2021), "Urban and rural tourism under COVID-19 in China: Research on the recovery measures and tourism development", *Tourism Review,* Vol. 76 No. 4, pp. 718-736.

Malik, A. A., McFadden, S. M., Elharake, J. and Omer, S. B. (2020), "Determinants of COVID-19 vaccine acceptance in the US", *EClinicalMedicine,* Vol. 26, 100495.

McKercher, B. and Lew, A. A. (2004), "Tourist flows and the spatial distribution of tourists", Lew, A., Hall, M. and Williams, A. (Eds.), *A Companion to Tourism,* Blackwell Publishing, London, UK, pp. 36-48.

Moreira, P. (2008), "Stealth risks and catastrophic risks: On risk perception and crisis recovery strategies", *Journal of Travel & Tourism Marketing,* Vol. 23 No. 2-4, pp. 15-27.

Neuburger, L. and Egger, R. (2021). "Travel risk perception and travel behaviour during the COVID-19 pandemic 2020: A case study of the DACH region", *Current Issues in Tourism*, Vol. 24 No. 7, pp. 1003-1016.

Park, C. (2004), "Efficient or enjoyable? Consumer values of eating-out and fast food restaurant consumption in Korea", *International Journal of Hospitality Management,* Vol. 23 No. 1, pp. 87-94.

Park, I. J., Kim, J., Kim, S. S., Lee, J. C. and Giroux, M. (2021), "Impact of the COVID-19 pandemic on travelers' preference for crowded versus non-crowded options", *Tourism Management,* Vol. 87, 104398.

Pope, N., Brown, M. and Forrest, E. (1999), "Risk, innovativeness, gender, and involvement factors affecting the intention to purchase sport product online", *Sport Marketing Quarterly,* Vol. 8 No. 2, pp. 25-34.

Radic, A., Lück, M., Al-Ansi, A., Chua, B.-L., Seeler, S. and Han, H. (2021), "Cruise ship dining experiencescape: The perspective of female cruise travelers in the midst of the COVID-19 pandemic", *International Journal of Hospitality Management,* Vol. 95, 102923.

Reisinger, Y. and Mavondo, F. (2006), "Cultural differences in travel risk perception", *Journal of Travel & Tourism Marketing,* Vol. 20 No. 1, pp. 13-31.

Ryu, K. and Han, H. (2010), "Influence of the quality of food, service, and physical environment on customer satisfaction and behavioral intention in quick-casual restaurants: Moderating role of perceived price", *Journal of Hospitality & Tourism Research,* Vol. 34 No. 3, pp. 310-329.

Shahid, Z., Kalayanamitra, R., McClafferty, B., Kepko, D., Ramgobin, D., Patel, R., Aggarwal, C. S., Vunnam, R., Sahu, N. and Bhatt, D. (2020), "COVID‐19 and older adults: What we know", *Journal of the American Geriatrics Society,* Vol. 68 No. 5, pp. 926-929.

Taylor, J. W. (1974), "The role of risk in consumer behavior: A comprehensive and operational theory of risk taking in consumer behavior", *Journal of Marketing,* Vol. 38 No. 2, pp. 54-60.

Wang, J. and Xia, L. (2021), "Revenge travel: Nostalgia and desire for leisure travel post COVID-19", *Journal of Travel & Tourism Marketing,* Vol. 38 No. 9, pp. 935-955.

Wang, L., Wong, P. P. W. and Zhang, Q. (2021), "Travellers' destination choice among university students in China amid COVID-19: Extending the theory of planned behaviour", *Tourism Review,* Vol. 76 No. 4, pp. 749-763.

Wen, J., Kozak, M., Yang, S. and Liu, F. (2020), "COVID-19: Potential effects on Chinese citizens' lifestyle and travel", *Tourism Review,* Vol. 76 No. 1, pp. 74-87.

Wong, I. A., Zhang, G., Zhang, Y. and Huang, G. I. (2021), "The dual distance model of tourism movement in intra-regional travel", *Current Issues in Tourism,* Vol. 24 No. 9, pp. 1190-1198.

Zaman, U., Raza, S. H., Abbasi, S., Aktan, M. and Farías, P. (2021), "Sustainable or a butterfly effect in global tourism? Nexus of pandemic fatigue, covid-19-branded destination safety, travel stimulus incentives, and post-pandemic revenge travel", *Sustainability,* Vol. 13 No. 22, 12834.

Zenker, S. and Kock, F. (2020), "The coronavirus pandemic–A critical discussion of a tourism research agenda", *Tourism Management,* Vol. 81, 104164.

Zhan, L., Zeng, X., Morrison, A. M., Liang, H. and Coca-Stefaniak, J. A. (2022), "A risk perception scale for travel to a crisis epicentre: Visiting Wuhan after COVID-19", *Current Issues in Tourism,* Vol. 25 No. 1, pp. 150-167.

Zhao, X., Lu, X., Liu, Y., Lin, J. and An, J. (2018), "Tourist movement patterns understanding from the perspective of travel party size using mobile tracking data: A case study of Xi'an, China", *Tourism Management,* Vol. 69, pp. 368-383.

Zheng, W., Li, M., Lin, Z. and Zhang, Y. (2022), "Leveraging tourist trajectory data for effective destination planning and management: A new heuristic approach", *Tourism Management,* Vol. 89, 104437.

Table 1. Descriptive statistics

Variables (Restaurant level)	Min	Max	Mean	SD
Number of nearby restaurants (kilometres)	0	29	8.192	5.883
Proximity to nearby beach (kilometres)	0.071	24.422	9.878	5.104
Proximity to the airport (kilometres)	0.602	52.114	17.554	7.416
Normalized restaurant visits (proportion) (total)*	0	1	0.018	0.047
Normalized restaurant visits by month (proportion)				
• Before COVID-19	0	1	0.024	0.054
• Right after COVID-19	0	1	0.024	0.052
• Long after COVID-19	0	1	0.024	0.051
Normalized restaurant visits by sex (proportion)				
• Males	0	1	0.021	0.051
• Females	0	1	0.017	0.048
Normalized restaurant visits by age (proportion)				
• 20s	0	1	0.014	0.046
• 30s	0	1	0.019	0.051
• 40s	0	1	0.021	0.049
• 50s	0	1	0.019	0.057
• 60s	0	1	0.024	0.069
Normalized restaurant visits by status (proportion)				
• Residents	0	1	0.058	0.094
• Tourists	0	1	0.012	0.053

*According to the result of the Chi-square test for analyzing the distribution of data by comparing observed and expected intensity of the data, the dependent variable was found to follow Poisson distribution (x^2 = 121.18, p = 0.104) (Rahnama-Moghadam et al., 2001).

Table 2. Poisson regression: Males' and females' restaurant visit patterns during COVID-19

	Coefficient (Z value)	Standard error
Intercept	-3.917*** (-34.858)	0.143
Month		
• Right after COVID-19	0.235 (1.036)	0.192
• Long after COVID-19	0.173 (1.001)	0.194
Sex		
• Males	0.222 (0.716)	0.192
Males*Right after COVID-19	0.541* (1.976)	2.717
Males*Long after COVID-19	-0.147 (-0.716)	0.554
Number of nearby restaurants	0.447* (2.115)	2.158
Proximity to nearby beach	-0.701** (-2.929)	1.229
Proximity to the airport	-0.663** (-3.012)	2.891
Efron's pseudo R^2	0.158	

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Table 3. Poisson regression: Restaurant visit patterns of customers aged in their 20s, 30s, 40s, 50s, and 60s during COVID-19

	Coefficient (Z value)	Standard error
Intercept	-4.111 (-27.374)	0.143
Month		
• Right after COVID-19	0.744** (2.870)	0.602
• Long after COVID-19	0.158 (1.645)	0.214
Sex		
• 30s	0.339 (0.338)	0.206
• 40s	0.354 (0.737)	0.205
• 50s	0.421* (2.079)	0.203
• 60s	0.665** (2.687)	0.197
30s*Right after COVID-19	-0.161 (-0.873)	0.291
40s*Right after COVID-19	0.102 (0.818)	0.279
50s*Right after COVID-19	0.411*	0.282

	(1.852)	
60s*Right after COVID-19	0.416* (1.997)	0.272
30s*Long after COVID-19	-0.246 (-0.737)	0.287
40s*Long after COVID-19	0.035 (0.438)	0.275
50s*Long after COVID-19	-0.036 (-0.553)	0.282
60s*Long after COVID-19	-0.196 (-0.664)	0.274
Number of nearby restaurants	0.655* (2.117)	2.216
Proximity to nearby beach	-0.598* (-1.958)	-1.267
Proximity to the airport	-0.681* (-2.001)	-2.577
Efron's pseudo R^2	0.218	

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Table 4. Poisson regression: Residents' and tourists' restaurant visit patterns during COVID-19

	Coefficient (Z value)	Standard error
Intercept	-2.816*** (-34.217)	0.083
Month		
• Right after COVID-19	1.254 (0.042)	0.168
• Long after COVID-19	0.099 (0.029)	0.139
Sex		
• Residents	1.169 (0.873)	0.114
Residents*Right after COVID-19	0.791** (2.873)	0.240
Residents*Long after COVID-19	0.681** (2.898)	0.234
Number of nearby restaurants	0.710** (3.033)	0.977
Proximity to nearby beach	-0.668** (-2.976)	0.383
Proximity to the airport	-0.702** (-3.052)	0.974
Efron's pseudo R^2	0.211	

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

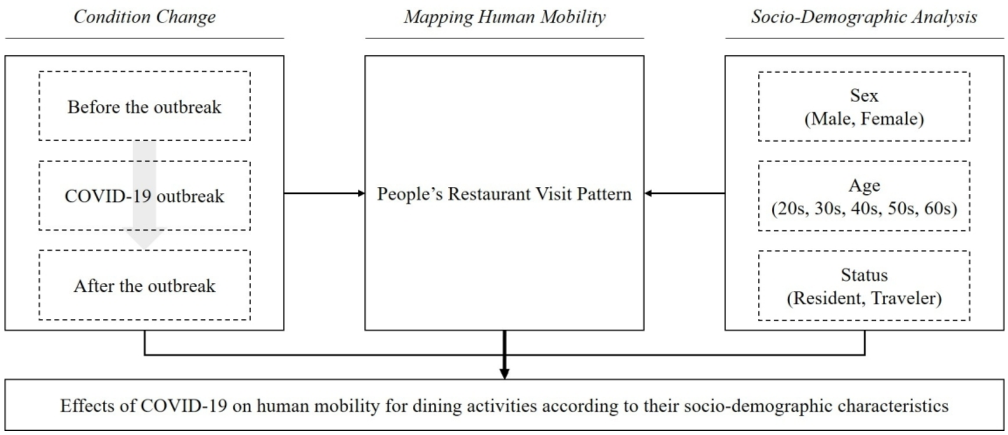

Figure 1. Conceptual framework

291x126mm (150 x 150 DPI)

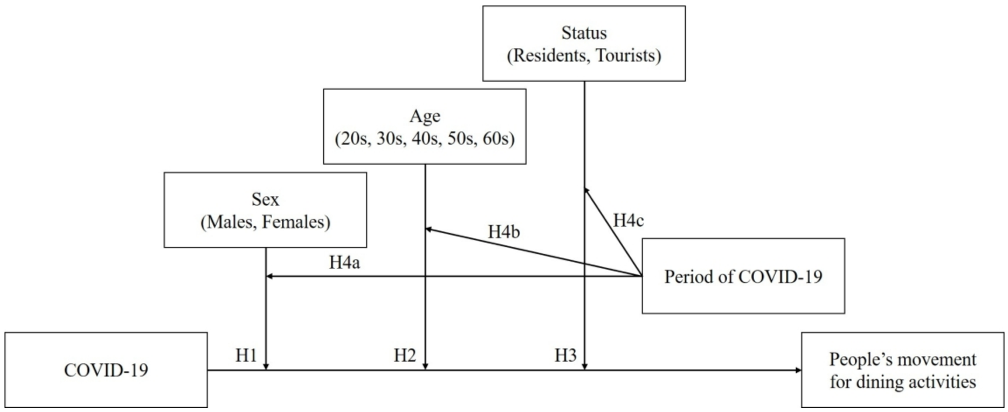

Figure 2. Research model

339x136mm (150 x 150 DPI)

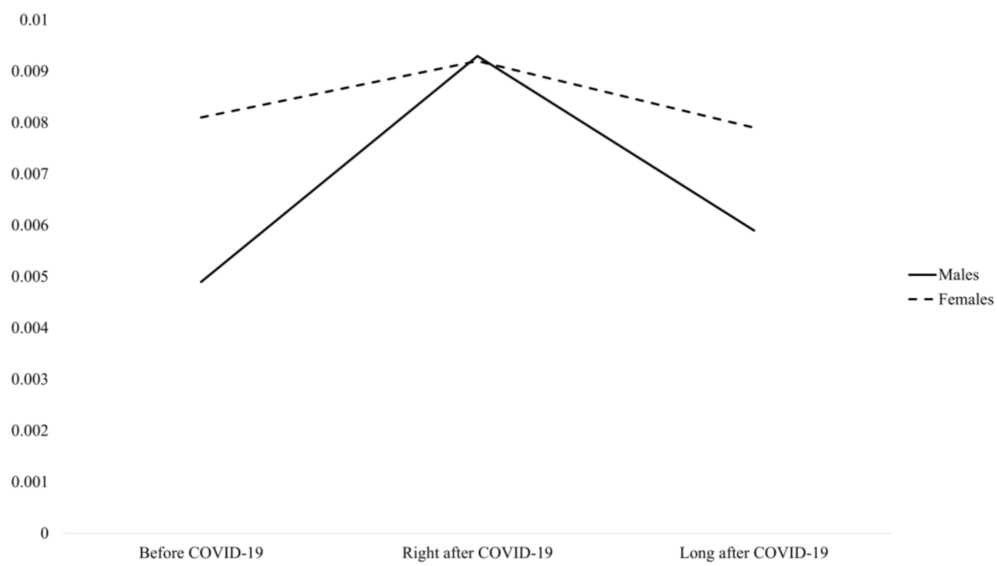

Figure 3. Interaction plot of Regression model 1

338x190mm (300 x 300 DPI)

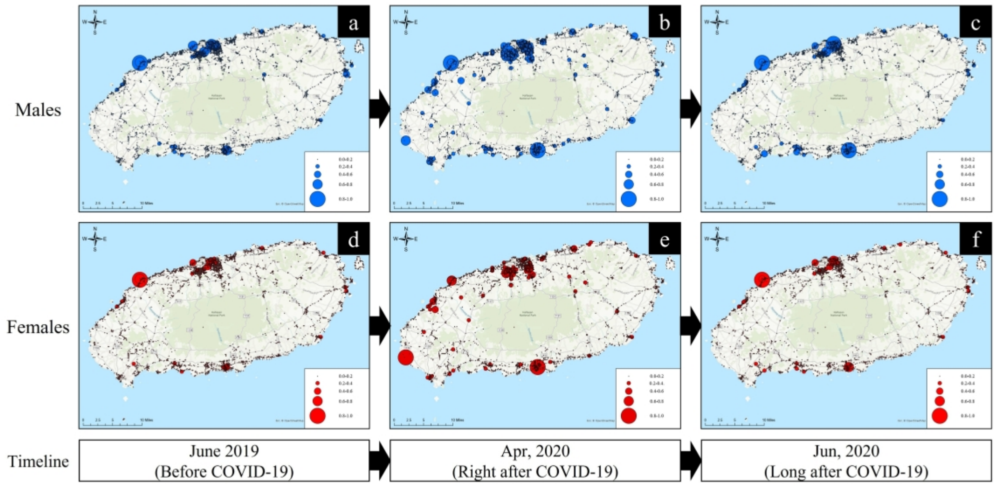

Figure 4. Males' and females' restaurant visit patterns during COVID-19

371x181mm (300 x 300 DPI)

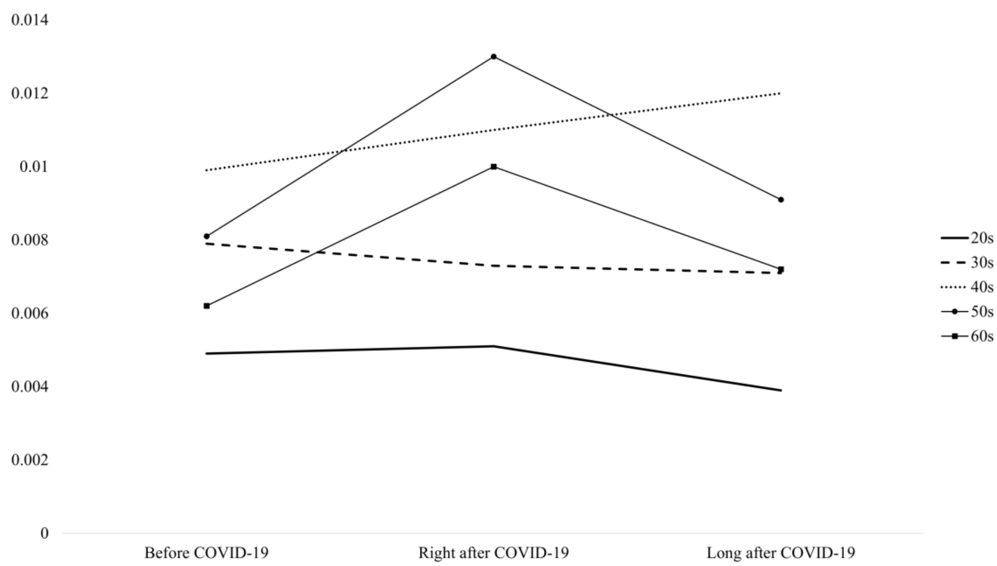

Figure 5. Interaction plot of Regression model 2

338x190mm (300 x 300 DPI)

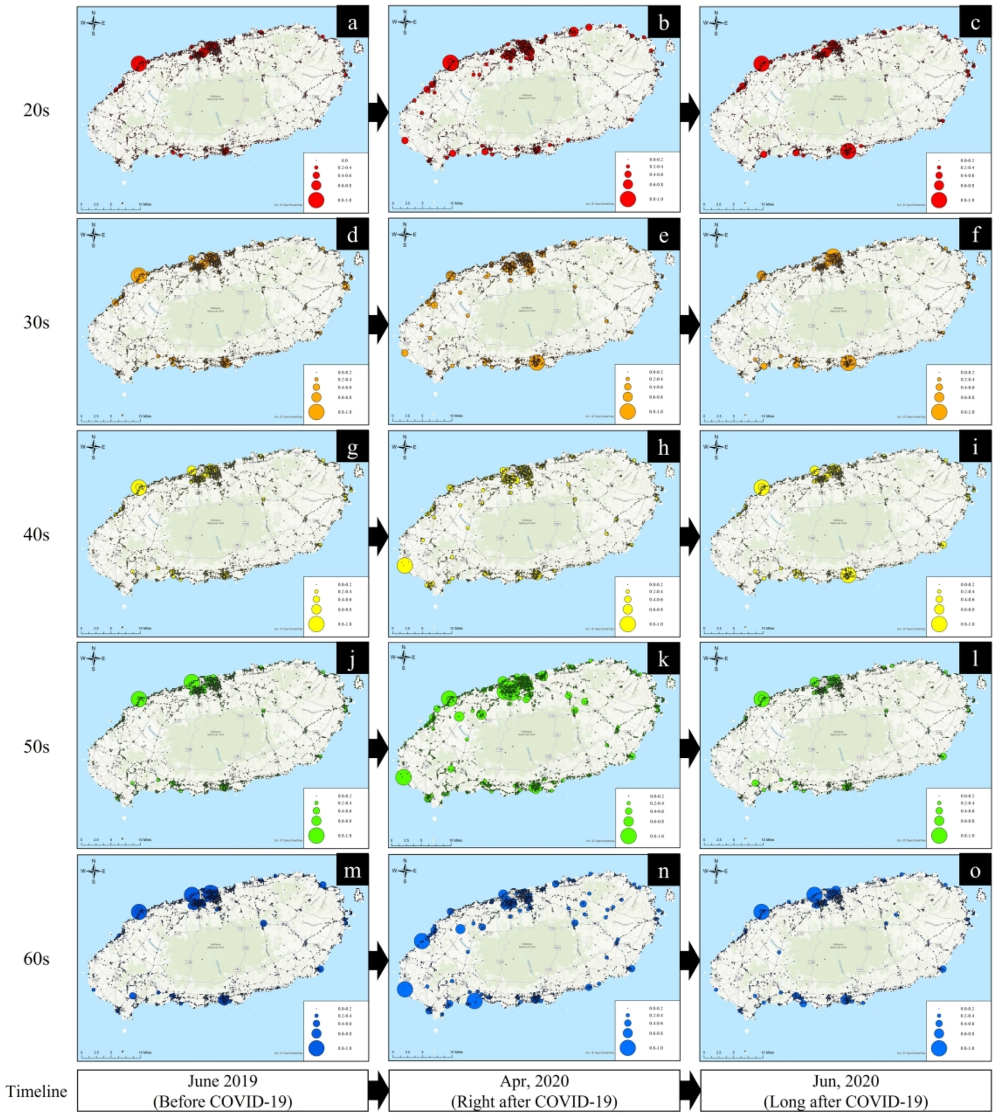

Figure 6. Restaurant visit patterns of people in their 20s, 30s, 40s, 50s, and 60s during COVID-19

370x414mm (300 x 300 DPI)

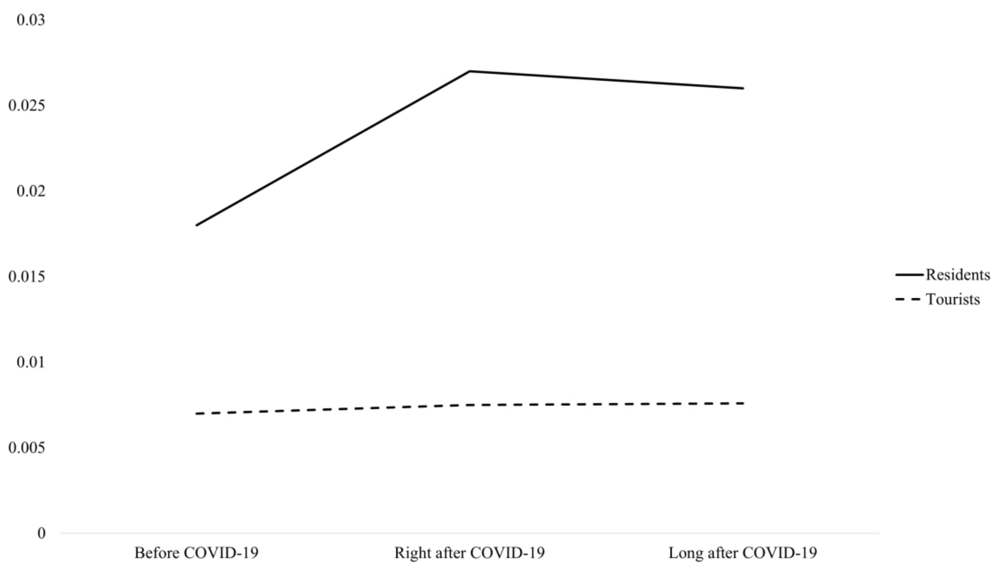

Figure 7. Interaction plot of Regression model 3

338x190mm (300 x 300 DPI)

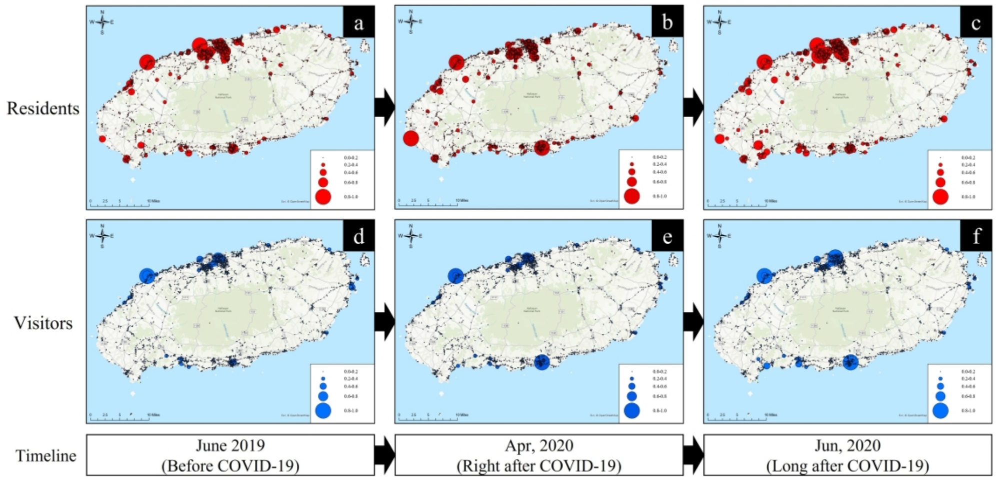

Figure 8. Residents' and tourists' restaurant visit patterns during COVID-19

374x181mm (300 x 300 DPI)

Appendix. Preview of the data of a smartphone driver navigation application (Tmap)

	A	B	C	D	E	F	G
1	Date(YYYYMMDD)	User's stauts	User's sex	User's age	Origin (Grid ID)	Destination (Grid ID)	Destination (Category)
2	20190601	local	M	10	Grid120_431	Grid128_465	Restaurant
3	20190601	local	M	10	Grid127_467	Grid121_430	Subway station
4	20190601	local	F	20	Grid128_465	Grid128_468	Gas station
5	20190601	local	F	30	Grid196_382	Grid201_380	Museum
6	20190601	local	F	10	Grid206_394	Grid132_419	Gallery
7	20190601	visitor	M	50	Grid220_397	Grid259_363	Accommodation
8	20190601	local	M	40	Grid226_508	Grid199_511	National park
9	20190601	local	M	10	Grid230_377	Grid231_378	Beach
10	20190601	visitor	M	60	Grid248_373	Grid322_347	Sport facility