Sufficient and reliable health care access is necessary for people to be able to maintain good health. Hence, investigating the uncertainty embedded in the temporal changes of inputs would be beneficial for understanding their impact on spatial accessibility. However, previous studies are limited to implementing only the uncertainty of mobility, while health care resource availability is a significant concern during the coronavirus disease (COVID-19) pandemic. Our study examined the stochastic distribution of spatial accessibility under the uncertainties underlying the availability of intensive care unit (ICU) beds and ease of mobility in the Greater Houston area of Texas. Based on the randomized supply and mobility from their historical changes, we employed Monte Carlo simulation to measure ICU bed accessibility with an enhanced two-step floating catchment area (E2SFCA) method. We then conducted hierarchical clustering to classify regions of adequate (sufficient and reliable) accessibility and inadequate (insufficient and unreliable) accessibility. Lastly, we investigated the relationship between the accessibility measures and the case fatality ratio of COVID-19. As result, locations of sufficient access also had reliable accessibility; downtown and outer counties, respectively, had adequate and inadequate accessibility. We also raised the possibility that inadequate health care accessibility may cause higher COVID-19 fatality ratios.

Introduction

In addition to sufficient access to health care resources, the provision of reliable health care is critical to promoting the overall health of the public (Chen et al. 2020; Lee and Miller 2020). The merit of high accessibility to hospitals would be depreciated if the available resources in hospitals are depleted, even if several hospitals exist around residential locations. This issue is particularly emphasized during the global pandemic; particularly, the state of Texas has been suffering from the limited availability of hospitals, which resulted in a high fatality from the
coronavirus disease (COVID-19) (Walters, Najmabadi, and Platoff 2020). In detail, Texas was hit hard by the second wave of the COVID-19 spread, where approximately 10,000 new cases daily and a total of 350,000 confirmed cases were reported. Owing to the extraordinary outbreak of COVID-19, the US Department of Health and Human Services (2020) estimated that 70.1% of inpatient beds (95% confidence interval [CI]: 70.2%–71.1%) and 77.9% of intensive care unit (ICU) beds (95% CI: 76.9%–78.9%) were occupied in the state of Texas as of July 14, 2020. Therefore, the limited availability of health care resources should be taken into account in spatial accessibility measurement to promote policy implications such as identification of spatial disparity or effective allocation of infrastructures (Park and Goldberg 2021).

Up to three variables (supply, demand, and mobility) are used to examine spatial accessibility on the basis of their interactions (Shen 1998; Luo and Wang 2003; Wang 2012). Here, supply refers to the infrastructure of interest, such as hospitals or grocery stores; demand represents the spatial distribution of people who are expected to use the facility; and mobility is the travel cost (i.e., distance or time) to access the supply location from the demand location. While some form of spatial accessibility measurements, such as cumulative opportunity (Kelobonye et al. 2020) or gravity model (Hansen 1959) employs supply and mobility, the two-step floating catchment area (2SFCA) method utilizes all three variables to consider the competition between the supply and demand (Luo and Wang 2003). Since the advent of the initial 2SFCA method, two significant trajectories have emerged to advance the accuracy of spatial accessibility measurements. First, studies pursued to enhance the prediction of people traveling to infrastructures based on various distance decay functions (Dai 2010; Dai and Wang 2011; Delamater et al. 2013; Tang et al. 2017; Gong et al. 2021) and threshold travel time (Luo and Whippo 2012; McGrail and Humphreys 2014). In addition, they aimed to alleviate the potential demand overestimation issues of the 2SFCA method by implementing the selection weights of each facility (Wan, Zou, and Sternberg 2012), the use of an additional distance decay function (Delamater 2013), and the normalized weights of both supply and demand (Paez, Higgins, and Vivona 2019; Pereira et al. 2021). Second, studies investigated the 24-h variation of spatial accessibility, along with the argument of high-frequency cities (Batty 2020; Kandt and Batty 2021). Given that the supply, demand, and mobility statuses are subject to change over 24 h (Järv et al. 2018; Park et al. 2021), much attention has been paid to the temporal dynamics of spatial accessibility caused by the temporal changes of the three input variables (Chen et al. 2017; Lee, Sohn, and Heo 2018; Hu and Downs 2019; Xia et al. 2019).

Compared with the notable trajectories for accuracy improvements, the impact of uncertainty on the spatial accessibility measurement is underexamined. To our knowledge, only a few research studies have examined uncertainty in the context of spatial accessibility. However, these studies still focused on the influence of uncertain mobility on accessibility measures. Ertugay and Duzgun (2011) were among the first to develop an approach for investigating how the service area was mutated on the basis of the probability distribution of the observed travel speed. They drew the shape and size of catchment areas randomly through Monte Carlo simulation and concluded that the locations consistently included in the catchment areas had sufficient and reliable accessibility. In addition, Lee and Miller (2020) incorporated the notions of risk-seeking and risk-averse on the arrival probability into the measurement and defined robust accessibility as the accessibility of a location regardless of uncertain mobility. While Ertugay and Duzgun (2011) and Lee and Miller (2020) only examined the characteristics of catchment areas, Chen et al. (2020) proposed a reliability-based 2SFCA method and assessed the impact of uncertain mobility with their interaction with supply and mobility. They underscored that
uncertain mobility had a notable impact on the accessibility measures, as it could provide mixed consequences depending on the location. A reduction in catchment area could prevent facilitated access to infrastructures from a location but could be beneficial to other locations, as it could lower the local competition for the same facility.

As the three variables of spatial accessibility (i.e., supply, demand, and mobility) change temporally, they are subject to underlying uncertainty, which may significantly impact accessibility measurements (Park and Goldberg 2021). While conventional accessibility approaches (i.e., without the incorporation of uncertainty or temporal dynamics) have a tendency to exaggerate the degree of access (Kang et al. 2020), the examination of uncertainty could provide better insights using a stochastic distribution. As discussed in several studies, mobility uncertainty could change the size and shape of the service area that a facility provides (Ertugay and Duzgun 2011; Chen et al. 2020; Sahebgharani and Haghshenas 2021). Besides the notable mobility influence, uncertainties of supply and demand would affect the degree of local competition (i.e., supply-to-demand ratio within a certain area). In the context of health care accessibility, the competition may intensify if either health care availability decreases or the number of patients increases. Uncertainty examples of both variables can be easily found from dynamic changes in health care availability (SETRAC 2020) and the number of COVID-19 patients (Kim et al. 2021).

This study examines the stochastic distribution of spatial accessibility to ICU beds during the COVID-19 pandemic in the Greater Houston area. As discussed above, input variable uncertainty is may influence accessibility measurement results. Here, we explore the impact of uncertainty on spatial accessibility from a systems perspective, addressing the adequacy of health care access people would receive under temporal changes of ICU bed availability and travel time. While all three input variables possess underlying uncertainty, we mainly focus on addressing the uncertainties of two variables (i.e., availability of supply and degree of mobility) based on an Enhanced 2SFCA method. Demand uncertainty could not be directly incorporated into our study, due to the coarse geographical unit of COVID-19 confirmed cases (i.e., county level); it is rather implemented in our study indirectly along with the uncertainty of supply, given that the temporal changes of ICU bed availability are attributed to the surge and decline of COVID-19 cases. In addition, we aim to investigate vulnerable locations in case they have had an acute surge of COVID-19 cases under these uncertainties. To be specific, our analysis proceeded with the following three steps: First, we calculated the probability distribution of supply and mobility based on their historical changes in the Greater Houston area. Second, we used Monte Carlo simulation to randomize the levels of supply and mobility for the 2SFCA method and measure spatial accessibility to ICU beds 999 times. Given that the stochastic distribution of accessibility provided by the simulation varied by location, we conducted hierarchical clustering to delineate areas of adequate (i.e., sufficient and reliable) accessibility and inadequate (i.e., insufficient and unreliable) accessibility. Our study particularly focuses on the following three research questions: (1) How does spatial accessibility stochastically vary under the temporal uncertainty of supply and mobility? (2) Where are locations of adequate accessibility and inadequate accessibility indicated by the stochastic distribution? (3) Are the characteristics of accessibility related to the case fatality ratio of COVID-19?

Research workflow

We used the following three steps to measure spatial accessibility to ICU beds under the temporal uncertainty of supply and mobility (Fig. 1): calculation of probability distribution, accessibility
measurement with Monte Carlo simulation, and spatial clustering. The first step is to calculate the probability distribution of supply and mobility, which would be used as the randomized input variables in the Monte Carlo simulation in the next step. The second step was to assess spatial accessibility to ICU beds 999 times (i.e., Monte-Carlo simulation) to investigate the impacts of the two randomized variables on the measures. The simulation provided the stochastic distribution of the measures for each location. Spatial clustering was implemented in the last step to group locations based on the measures and to demonstrate which locations had sufficient and reliable accessibility.

**Study area and data**

Our study area is the Greater Houston area (Fig. 2), which consists of nine counties (Harris, Fort Bend, Brazoria, Galveston, Chambers, Liberty, Montgomery, Waller, and Austin) in the state of Texas. The study area is the fifth largest metropolitan area in the United States, with more than 7 million residents (U.S. Census Bureau 2021). When the second wave of the COVID-19 spread hit the state of Texas in July 2020, the study area was suffering from a limited availability of ICU beds. In addition, the case fatality ratio of COVID-19 was significantly high during the period even though the number of cases during the second peak was lower than those during the third (December 2020) and fourth waves (August 2021). This may be attributed to the limited availability of beds. Moreover, the city of Houston has notorious traffic congestions, which may prevent on-time arrival to health care resources. Therefore, the study area would be an excellent example for investigating the impacts of the uncertainties of supply and mobility on the measures of spatial accessibility.

We utilized three spatial data sources to obtain the necessitated inputs (supply, demand, and mobility) for spatial accessibility measurements. First, we used health care resources data provided by Definitive Healthcare (2020) to represent supply facilities; the data included the locations of hospitals and the number of staffed ICU beds. The study area has 83 hospitals equipped with ICU beds among 115 hospitals and a total of 2,039 staffed ICU beds. Second, to demonstrate demand, we used LandScan, a database of estimated global population distribution
data (Rose et al. 2020). The dataset would enhance the accuracy of measurements given its finer spatial resolution (1 km × 1 km) (Luo and Qi 2009; Kobayashi, Medina, and Cova 2011). As LandScan data were provided as points, we aggregated the population with 2,000-acre hexagons (i.e., the average size of the census block group in the study area) to incorporate them into the accessibility measurement. Given that the 2SFCA method assesses accessibility levels based on the centroids of geographical units, the use of continuous and homogeneous grid cells (i.e., LandScan and hexagon grids) is expected to improve analysis quality (Park et al. 2021). Lastly, the mobility data were obtained from OpenStreetMap with a Python package (OSMnx) (Boeing 2017). The road networks provided by the dataset were used to calculate the travel time from a demand location to hospitals (i.e., ICU beds).

Calculating the probability distributions of supply and mobility

To prepare the randomized input for the Monte Carlo simulation, we first computed the probability distributions of supply and mobility on the basis of the historical temporal changes of the number of ICU beds in use and the travel speed of freeways, respectively (Fig. 1). Given that the amount of service and ease of mobility are temporally dynamic, the levels of supply and mobility at a certain time would be ambiguous. Therefore, we used the historical variations of supply and mobility to determine the probability that each variable has a particular value.

We generated the probability distribution of supply in three steps as follows: Data on the temporal variation of ICU beds in use (i.e., supply) were collected from the South East Texas Regional Advisory Council within the period from May 1, 2020, and September 30, 2020 (SETRAC 2020). Given that the second wave of the COVID-19 spread peaked in July 2020 in
Texas, the duration was chosen to cover the surge and decline of the number of ICU beds in use. First, we summed the numbers of empty beds and those occupied by COVID-19 patients (i.e., confirmed and suspected) and then divided them by the total number of staffed ICU beds. Given that most of the waves in ICU bed usage were derived from COVID-19 patients, the summation of the ICU beds in use by COVID-19 patients to the empty units would allow us to consider the uncertainty of demand indirectly; the surge and decline of COVID-19 patients in ICU beds would reflect the degree of demand and its uncertainty. Second, the percentages of ICU beds available for patients with COVID-19 were divided into 10 classes (0%–10%, 10%–20%, … 90%–100%). Third, we calculated the frequency of a certain availability rate from the entire period (from May 1 to September 30, 2020). For example, in Harris County, 312 ICU beds were empty and 221 ICU beds were occupied with COVID-19-related patients as of May 1, 2020, and the total number of staffed ICU beds was 1,614. Hence, the availability rate of ICU beds was 33% (i.e., \[\frac{312 + 221}{1,614}\]) at that moment. The rate (33%) was classified as an availability group of 30%–40%. We repeated the calculation of availability over 153 days (from May 1 to September 30, 2020) and computed the frequency of the groups. We also applied this process for six (Harris, Fort Bend, Brazoria, Galveston, Chambers, and Montgomery) of the nine counties in the study area. The historical usage data for Austin and Liberty counties were missing, so we assumed that the probability distributions in the counties follow the overall variation in the other six counties. In addition, Waller County did not have any staffed ICU beds.

The probability distribution of mobility was calculated in four steps as follows: Its temporal variation was retrieved from the historical travel speed of freeways in 2019 (Houston Transtar 2020). The mobility data in 2019 were the latest available dataset at the time of analysis. The temporal granularity of the data was 15 min, from 5:00 a.m. to 7:00 p.m. We first matched the historical travel speed of a chunk of a freeway to the corresponding edges on the road network obtained from OpenStreetMap. Second, we divided the travel speed measured every 15 min into the fastest travel speed within a day, given the ratio to the free flow. We then divided the ratios into four classes (1–0.75: free flow, 0.75–0.5: light congestion, 0.5–0.25: moderate congestion, and 0.25–0: severe congestion) and estimated the delay in travel time compared with the free flow. Lastly, we determined the frequency of having a certain degree of mobility for each road. For example, the fastest travel speed on Interstate Highway 10 from Beltway 8 to downtown Houston was 66 mph at 5:00 a.m. The travel speed at 8:00 a.m. was 28 mph. Therefore, the ratio to the free flow is 0.42, indicating moderate congestion. As a result, the interstate highway has a 50% chance of free flow, a 21% chance of light congestion, and a 29% chance of moderate congestion. In addition, we assumed that non-freeway roads would have a 25% chance of having light congestion to maximize the impact of the uncertainty in mobility (Wang et al. 2018).

Monte Carlo simulation: Measurement of spatial accessibility under uncertainty
Monte Carlo simulation was used to incorporate the temporal uncertainties of supply and mobility into the spatial accessibility measurements. The simulation is useful for investigating the impact of the ambiguity of inputs on the output, as it takes randomized variables for each measurement and processes with 999 iterations (Ertugay and Duzgun 2011). As the spatial accessibility requires three input variables (supply, demand, and mobility), we produced randomized supply and mobility from their probability distribution, computed on the basis of their historical changes. To be specific, in each iteration, the number of available ICU beds for each hospital (i.e., supply) fluctuated, and the estimated travel time via the road network (i.e., mobility) varied.
With the randomized inputs, we assessed the spatial accessibility to ICU beds, implementing the E2SFCA method (Luo and Qi 2009; Kang et al. 2020) to evaluate spatial accessibility in two steps as follows: (1) calculate the supply-to-demand ratio for each facility and (2) aggregate the ratio of reachable facilities. Distance decay was considered in the method by assigning different weights for subzones. While the original E2SFCA method determined spatial impedance on the basis of the Gaussian distribution, we used log-logistic distribution given that it provided a good prediction of the travel behavior of people visiting healthcare resources both in urban and rural areas (Luo and Qi 2009; Delamater et al. 2013; Jia, Wang, and Xierali 2017). In detail, in the first step of the E2SFCA method, the supply-to-demand ratio of a hospital \( R_j \) was computed. Then, the product between the number of staffed ICU beds in each hospital \( S_j \) and their availability rate \( E_j \) was divided by the number of residential populations within its service area \( D_k \), where the facility is accessible within a threshold travel time. The first step is defined in the following equation:

\[
R_j = \frac{S_j E_j}{\sum_{k \in \{t_{kj} \leq t_0\}} D_k f(t_{kj}, t_0)},
\]

where supply-and-demand locations are represented by \( j \) and \( k \), and the log-logistic distance decay function is denoted by \( f(t_{ij}, t_0) \).

The second step of the E2SFCA method summed the supply-to-demand ratio of hospitals \( (R_j) \) that were accessible from a demand location, providing the accessibility measure \( A_i \), computed using the following equation:

\[
A_i = \sum_{j \in \{t_{ij} \leq t_0\}} R_j f(t_{ij}, t_0) = \sum_{j \in \{t_{ij} \leq t_0\}} \frac{S_j E_j f(t_{ij}, t_0)}{\sum_{k \in \{t_{kj} \leq t_0\}} D_k f(t_{kj}, t_0)},
\]

where a demand location is presented by \( i \).

The log-logistic distance decay function was implemented in both steps to depreciate the influence from either demand (Equation 1) or supply (Equation 2). The distance decay function is based on the cumulative distribution function of log-logistic distribution and is defined as follows:

\[
f(t_{ij}, t_0) = \begin{cases} 
\frac{1}{1 + \left( \frac{t_{ij}}{\theta} \right)^\beta} & \text{if } t_{ij} \leq t_0 \\
0 & \text{if } t_{ij} > t_0
\end{cases}
\]

where \( t_{ij} \) and \( t_0 \) represent the travel time from demand location \( i \) to supply location \( j \) and the threshold travel time, respectively; and \( \theta \) and \( \beta \) indicate the scale and shape parameters, respectively. In our implementation, we defined threshold travel time, \( \theta \), and \( \beta \), as 60 min, 13.89, and 1.82, respectively, on the basis of the actual travel pattern of patients (Delamater et al. 2013). Consequently, the following weights for 10 subzones were incorporated into the E2SFCA method to represent spatial impedance: 0.9459 for the 0- to 5-min subzone; 0.7544 for the 5- to 10-min subzone; 0.5511 for the 10- to 15-min subzone; 0.3993 for the 15- to 20-min subzone; 0.2957 for the 20- to 25-min subzone; 0.2253 for the 25- to 30-min subzone; 0.1765 for the 30- to 35-min subzone; 0.1417 for the 35- to 40-min subzone; 0.1161 for the 40- to 45-min subzone; and 0.0832 for the 45- to 60-min subzone.
Geographical Analysis

Figure 3. Stochastic distributions of accessibility to ICU beds: (a) distinctive distribution of each hexagon and the accessibility for probability rate of (b) 50%, (c) 5%, and (d) 95%. [Colour figure can be viewed at wileyonlinelibrary.com].

Spatial clustering

In the final step, hierarchical clustering was implemented to spatially cluster hexagons according to their stochastic distributions of accessibility as granted from the Monte Carlo simulation. Given that a stochastic distribution would provide distinctive variations based on the locations, we utilized agglomerative hierarchical clustering, which initiates with the accessibility distribution of each hexagon and aggregates the hexagons into a higher cluster on the basis of the similarities of distribution. The representative value of the distributions per hexagon was computed with Ward’s method instead of using a median or mean, given that the value from Ward’s method minimizes within-cluster variance (Ward 1963). In addition, the silhouette method was used to indicate the optimal number of spatial clusters (Rousseeuw 1987), which is expected to delineate spatial segregation the most.

Results

Stochastic distribution of accessibility to ICU beds

The implementation of the Monte Carlo simulation provided a stochastic distribution of accessibility that varies depending on the temporal uncertainties in supply and mobility (Fig. 3). Given that the levels of supply and mobility dynamically change over the 999 iterations, the hexagons of the different locations showed distinctive distributions of accessibility (Fig. 3a). Overall, the accessibility to ICU beds tended to be high in the center of the study area and was gradually
Figure 4. Hierarchical clustering results based on the stochastic distribution of accessibility: (a) spatial distribution of clusters, (b) dendrogram of hierarchical clustering, (c) silhouette method for determining the optimal number of clusters, and (d) the attributes of the hexagon classified in each cluster. ** Hexagons with excessive coefficient of variation (CV > 1) were omitted at (d). [Colour figure can be viewed at wileyonlinelibrary.com].

decreased to the peripheral regions. For example, a site in Waller County (blue point) had a sharp distribution of poor accessibility (mean: 3.55; standard deviation [SD]: 0.22). By contrast, a location in Harris County (red point) had a smooth distribution of sufficient accessibility (mean: 21.51; SD: 1.68).

The pattern of spatial accessibility was greatly affected by the different levels of reliability (i.e., the probability that a location has a certain degree of accessibility). The three maps in Fig. 3 illustrate the spatial accessibility that can be obtained at probability rates of 50% (Fig. 3b), 5% (Fig. 3c), and 95% (Fig. 3d). The gradation of the maps indicates the available ICU bed count per 100,000 people that residents in the hexagon have access to. An inverse correlation was observed between the reliability level and the number of available ICU beds. For instance, 10 ICU beds per 100,000 people are assumed to be sufficient, given the median number of available ICU beds for patients with COVID-19. The ratio of all staffed ICU beds to the population in the study area was 28.94 per 100,000 people, and the median availability rate of ICU beds for patients with COVID-19 in the study period was 35%. For 5% reliability, 474 hexagons with 5.1 million people had sufficient access to ICU beds. However, the numbers were limited to 368 hexagons of 4.4 million people and 262 hexagons of 3.6 million people in the case of 50% and 95% reliability rates, respectively.

Spatial clustering
The agglomerative hierarchical clustering produced two major spatial clusters (Fig. 4b), one with adequate (i.e., sufficient and reliable) access to ICU beds and the other with inadequate (i.e., insufficient and unstable) accessibility. Although the optimal number of clusters as determined by the silhouette method was two clusters (silhouette coefficient: 0.619; Fig. 4c), we further divided the two major clusters into a couple of subgroups, given that the five clusters provided
Geographical Analysis

Figure 5. Attributes of accessibility to ICU beds: (a) relationship to the case fatality ratio of COVID-19 and (b) Gini index per various reliability level. [Colour figure can be viewed at wileyonlinelibrary.com].

the second highest silhouette coefficient (0.529). The cluster of inadequate accessibility was broken down into two subclusters (clusters L1 and L2), and the other cluster consisted of three partitions (clusters H1, H2, and H3).

The five spatial clusters were delineated in Fig. 4a. They had different characteristics for the sufficiency (mean) and reliability (coefficient of variation [CV]) of accessibility (Fig. 4d). Given that the scatterplot has sufficiency of accessibility as x-axis and unreliability of accessibility as y-axis, the upper-left corner indicates inadequate accessibility, and the lower-right corner presents adequate accessibility. The first cluster (L1) was at the outermost region in the study area, covering 762 hexagons with approximately 89,000 residents. It had very poor ($\bar{A}_i \leq 2.2$) and unreliable ($CV \approx 0.26$) accessibility. The second cluster, L2, was mainly in the rural area (988 hexagons with 0.5 million residents), having low accessibility ($1.9 < A_i \leq 5.7$) and reliability ($CV \approx 0.10$). The third cluster (H3) overlaid the suburban areas of Greater Houston, such as the city of Galveston, Galveston County, the Woodlands, Montgomery County, and the city of Sugar Land, Fort Bend County. It included 485 hexagons of 1.4 million people and presented moderate ($5.7 < A_i \leq 9.3$) and stable ($CV \approx 0.08$) accessibility. Cluster H3 was extruded to the southwest of the study area because of the freeway (Interstate 45) toward Galveston County, while the other directions of the cluster were constrained in a circular shape. The fourth cluster was an urbanized area and a group of peripheral neighborhoods in Houston (369 hexagons with 3.3 million residents), with sufficient ($9.0 < A_i \leq 15.0$) and reliable ($CV \approx 0.07$) accessibility. The last cluster was the urban core of Houston. It produced outstanding ($15.1 < A_i$) and solid ($CV \approx 0.07$) accessibility, although it was the most populous area (1.8 million residents in 85 hexagons). The cluster was slightly extended southwest, as a colossal hospital cluster (Texas medical center) was located in the direction.

Impact of accessibility to ICU beds on COVID-19 and its spatial inequality

We observed a trend where the case fatality ratio of COVID-19 can be attributed to unsatisfactory accessibility even though it may not be statistically significant because of the limited number of
samples \((n = 9\) counties; Fig. 5a). Three of nine counties showed a higher case fatality rate than the average in the study area. While \(18\%\) (18 fatalities per 1,000 people) of the case fatality rate was observed as of September 30, 2020, Liberty, Austin, and Harris counties had case fatality rates of \(23\%\), \(20\%\), and \(19\%\), respectively. Liberty and Austin counties had insufficient (mean accessibility: 2.09 and 1.64) and unreliable (mean CV of accessibility: 0.13 and 0.27) accessibility. Therefore, their high rates can be related to the attributes of their accessibility. However, Harris County had a robust accessibility (mean accessibility: 10.39, and mean CV: 0.07). Its casualty could be caused by the intensive transmission of the virus within a short period, which was often reported in a high-density city such as New York.

The spatial disparity of accessibility would deteriorate as the reliability level increases (i.e., the probability that a location has a certain degree of accessibility), which possibly impacts the inequity of the case fatality rate of COVID-19. Stochastic distributions obtained from the Monte Carlo simulation provided that the degree of accessibility would be changed according to the reliability level. The Gini index values of accessibility for the reliability levels of \(0.05\%, 0.50\%,\) and \(0.95\%\) were 0.43, 0.45, and 0.47, respectively (Fig. 5b). Despite the fact that the difference was marginal, the spatial inequality of access was intensified as the reliability level increased. This alluded that the inequality of fatality may deteriorate in the future if the spatial disparity continues.

**Discussion**

A direct relationship was observed between sufficient and reliable accessibility. That is, the center of the study area (cluster H1; downtown Houston) had adequate accessibility with sufficiency and reliability. However, the peripheral locations had inadequate accessibility (cluster L1), showing insufficient and unreliable characteristics. Our result was consistent with that of previous studies that showed spatial disparity of access between urbanized and rural areas (Luo and Whippo 2012; McGrail and Humphreys 2014; Kim et al. 2021). In addition, we uncovered that the spatial inequality of access would persist or intensify under the uncertainties of supply (availability of resources) and mobility (travel time for accessing hospitals). If a policymaker focuses on a spatial accessibility distribution that would be consistently obtained (i.e., \(A_i[0.95]\)), compared with the distribution obtained for the probability rate of 50\% (i.e., \(A_i[0.5]\)), not only does measurement have a low overall accessibility but also the disparity between locations would also be severe.

As claimed by previous studies, sufficient access to healthcare resources, particularly ICU beds, is critical to patients with COVID-19, and insufficient accessibility may result in a higher case fatality rate (Kang et al. 2020; Gboranzadeh et al. 2021; Kim et al. 2021). Our comparison for nine counties presented direct relationships between the characteristics of accessibility and the case fatality rate of COVID-19. Our results are considered significant because they show that the higher fatality rate of COVID-19 could be expected to the locations of inadequate (i.e., insufficient and unreliable) accessibility. While previous studies investigated a direct relationship between a snapshot of spatial accessibility to healthcare and COVID-19 fatality, our study concluded that the higher fatality could be attributed to the unreliable availability and insufficient accessibility.

The disparity in accessibility may be attributed to the different densities of hospitals across the study area. For example, if a hospital is running out of vacant ICU beds, a downtown resident could access other hospitals close to their locations, but this may not be the case for rural residents because of the sparse density of hospitals. As shown in our results, rural areas are more...
susceptible to the effects of unreliable availability of ICU beds; thus, more attention should be paid to the location. The measure of spatial accessibility typically indicates that locations need additional infrastructure; however, the cost of a new hospital installation is significant. Therefore, policymakers could enhance the number of operational beds in the rural area to prevent rural residents from unstable reliability of the availability of ICU beds.

**Conclusion**

Our study examined the stochastic distributions of the spatial accessibility to ICU beds and investigated the impact of accessibility on the case fatality rate of COVID-19. To be specific, we aimed to address uncertainties in the availability of ICU beds and travel time to healthcare resources in the Greater Houston area. As far as we know, our study is the first to discover the uncertainties of supply and mobility for spatial accessibility measurements. We used the Monte Carlo simulation to examine the stochastic distribution of accessibility granted from the randomized supply and mobility. Hierarchical clustering grouped locations according to stochastic distribution and discovered the locations of adequate (i.e., sufficient and reliable) and inadequate (i.e., insufficient and unreliable) accessibility. Our results demonstrate that the reliability of accessibility is proportional to the sufficiency of accessibility, indicating that spatial disparity of access would persist regardless of uncertainty. In addition, our results show that the high case fatality rate of COVID-19 in the peripheral counties may be attributed to the inadequate accessibility of the locations.

Our study has the following limitations: First, it would be challenging to reproduce and replicate because of the issue of computational intensity. Given that we used the Monte Carlo simulation with 999 iterations, the analysis took 3 months even though we conducted parallel computing of four computers with 16 cores. Second, only supply and mobility uncertainty was directly implemented into our analysis, whereas the uncertainty of demand was indirectly considered along with the uncertainty of ICU bed availability due to the lack of high granularity census data (i.e., the data was provided as zip code level for Harris County and county level for the other counties at the time of analysis). We excluded the COVID-19 case uncertainty, as having a discrepancy in data granularity would be harmful to the quality of simulation, given that the geographical scales of supply and mobility were the exact locations of hospitals and the roads, respectively. Third, our comparison was not statistically significant although the result showed a possibility of a negative correlation that inadequate accessibility may trigger higher fatality rates. It is likely attributed to the limited extent and granularity of the employed spatial data; only nine counties (i.e., a geographical unit for collecting the fatality of COVID-19) exist within the study area.

Our next step is to expand the spatial extent with the implementation of underlying temporal changes of input variables and investigate the retrospective relationship between ICU bed accessibility upon its availability and the case fatality ratio of COVID-19. Including our study, numerous studies have highlighted the importance of ICU bed accessibility to treat the patients well and reduce fatalities (Kang et al. 2020; Ghorbanzadeh et al. 2021; Kim et al. 2021; Pereira et al. 2021). However, a substantial relationship has not been discovered yet due to the limited computational resources and insufficient availability of high granularity data. High-performance computing, such as CyberGIS (Wang 2010), can facilitate at-scale analysis. Upon the increased computational capacity, examining temporal dynamics at scale (e.g., a national level) could uncover new geographical findings beyond other factors in the dissemination of infectious
diseases. Consequently, it would help policymakers effectively allocate additional infrastructures and possibly reduce fatalities for COVID-19 or the next pandemic.

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Data availability statement

The data and codes that support the finding of this study are published with a DOI at https://doi.org/10.6084/m9.figshare.19165670.

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