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Examining the impact of COVID-19 vaccination rates on differential access to critical care

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A R T I C L E   I N F O

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A B S T R A C T

The measurement of potential access to health care has focused primarily on what might be called “place-based” access or the differential access among geographic locations rather than between different populations. The vaccination program to inoculate the population against the effects of the COVID-19 virus has created two different at-risk populations. This research examines the impact of COVID-19 vaccination rates on access to critical care for persons fully-vaccinated versus those not fully-vaccinated. In this situation, additional tools are necessary to understand: 1) if there is a significant difference in accessibility between different populations, 2) the magnitude of this difference and how it is distributed across accessibility levels, and 3) how the differences between groups are distributed across the state. A study of access to intensive care unit (ICU) beds by these two populations for the state of Illinois found that although there was a statistically significant difference in access, the magnitude of differences was small. A more important difference was being located in the Chicago Area of the state. The not-fully vaccinated in the Chicago Area had higher than expected spatial access due to the lower need for ICU beds by a higher percentage of fully vaccinated people.

1. Introduction

Spatial accessibility is the relationship between the location of supply and the location of demand that considers an individual’s travel time, cost, and distance (Penchansky & Thomas, 1981). Spatial accessibility, as a form of spatial interaction, measures then how easily an individual at a location can overcome the friction of distance to access resources. Geographic proximity to resources and a diverse set of resource destinations impact potential accessibility. Geographic information systems (GIS) have enabled an integrative data management and analysis environment to examine the relationships between place, population, and access (Graves, 2008).

While accessibility to ICU beds and hospitals has been an area of research during the COVID-19 pandemic, little research has focused on the role of vaccination in easing the congestion related to ICU bed access during the pandemic. Public health professionals have repeatedly discussed the concept of “flattening-the-curve” (Kenyon, 2020) to reduce pressure on hospital capacity. Evenning congestion concerning ICUs among hospitals is a spatial method for flattening the curve. This study focuses on vaccination’s role in easing congestion and, therefore, increasing access to ICU beds. As Zhang et al. (2020) pointed out, increased capacity and access to ICUs decrease fatality rates for COVID-19; a corollary would be that strategies that lessen the strain on capacity should reduce fatality rates COVID-19. Evening congestion, therefore, can be thought of as an important dimension of healthcare beyond direct spatial access with regards to mitigating mortality in the COVID-19 pandemic.

This article also analyzes accessibility differences between population groups as an important counterpoint to a “place-based” approach. More attention to accessibility differences between population groups is necessary for several reasons. First, the literature frequently focuses on different groups by age and race/ethnicity concerning disease and health care. Differences in spatial access to medical care by different socioeconomic groups is an important area of inquiry. Second, spatial access to facilities is a component of a more significant spatial equity issue concerning resources (Green et al., 2018; Kim et al., 2021). A third issue is a major focus of this research –the impact of differential at-risk exposures to the disease on spatial accessibility concerning critical care units. Every accessibility model begins with an estimated population at risk. Often total population is used as the at-risk population. In the early stages of COVID-19, the at-risk population focused more on older age groups. With the development of vaccinations for ameliorating the effect...
of this virus, differentials in risk are also highly associated with vaccination rates. Vaccination is another strategy for reducing the strain on ICU capacity at hospitals. This study examines methods for assessing accessibility and potential congestion at hospitals concerning populations with varying vaccination levels for the highly contagious COVID-19 virus. It determines if there is a significant difference in access between fully vaccinated and not fully vaccinated populations and the magnitude and spatial pattern of the accessibility differences.

2. Background

Accessibility measures examine different aspects of the spatial relationships between supply and demand for services. This requires considering other variables and representations of supply and demand (Langford & Higgs, 2006). One aspect of accessibility is the travel cost to services (Apparicio et al., 2008; Bennet et al., 2012; Brabyn & Gower, 2004; Guagliardo, 2004; Pearce et al., 2006). This can be measured either simply as distance to the nearest service (Brabyn & Gower, 2004) or the total or mean distance to all service providers or the number of services within a threshold distance (Gordon-Larsen et al., 2006; Hansen, 1959; Horner et al., 2012; Talen & Anselin, 1998). A number of different functional forms have been used, including inverse distance, Gaussian, binary discrete, and multiple discrete functions (Wang, 2012), to model the distance-decay in travel to services.

A larger group of measures are based on supply-to-demand ratios (or simply ratios) that measure access as the amount of a service relative to a demand population. The early container-based approach (Page et al., 2019) linked the amount of service to the population within bounded units such as neighborhoods to measure accessibility as in physician-to-population ratios. However, container-based ratios have been criticized for failing to account for actual patient flows across the container unit’s hard boundaries. Joseph and Bantock (1982) overcame these hard boundary issues by expanding Hansen’s interaction model (Hansen, 1959) to discount services’ availability by the potential population demanding those services. Others (Guagliardo, 2004; Guagliardo et al., 2004) calculated supply-to-population ratios as a kernel density (KD) surface of physicians divided by a population’s KD surface.

The most prominent set of ratio measures belong to the two-step floating catchment area (2SFCA) family of methods. Luo and Wang (2003) initiated the development of these measures by adapting Radke and Mu’s (2000) floating catchment area (FCA) design to the problem of access to health services. Luo and Wang (2003) also showed that this threshold-based model is a special case of Joseph and Bantock’s (1982) more general interaction model. The 2SFCA family of methods has grown over time as numerous adaptations have emerged, including different distance decay representations (Dai & Wang, 2011; Luo & Qi, 2009), disaggregation of demand by age group (Ngui & Apparicio, 2011), variable catchment area sizes (Luo & Whippo, 2012; Matthews et al., 2019; McGrail & Humphreys, 2009), commuting side-trips (Franssen et al., 2013), hierarchical systems of facilities (Tao et al., 2020), multiple site characteristics (Chen, 2017), and the effect of geographical scale (Bryant & Delamater, 2019).

Over time, however, there has been a growing concern regarding some deficiencies in the 2SFCA approach. Wan, Zou, and Sternberg (2012) noted a potential misspecification of demand because of competition among supply sites. Their three-step floating catchment area (3SFCA) method added a selection weight to adjust for this misspecification. Next, Delamater (2013) noted that all supply opportunities are fully allocated to demand regardless of the actual distances involved. He constructed a modified version (the M2SFCA) to address the issue of how interaction is discounted over distance. Lin and Cromley (2022) noted that Delamater’s concern could be eliminated by recognizing that accessibility is a bivariate concept, and there is a distinction between supply accessibility (amount of resources per unit of demand) and cost accessibility (average cost of acquiring those resources per unit of demand).

More recently, there has also been an increasing consideration of the role of congestion in measuring accessibility. Wang (2018) developed the inverted 2SFCA (i2SFCA) to measure congestion levels at hospitals. Wang (2021) later showed the symbiotic relationship between the generalized i2SFCA and the 2SFCA models. In the generalized models (Wang, 2021), impedance, \( f_i = f(e_i) \) is defined as:

\[
 f_i = f(e_i) \quad (1)
\]

where \( f(\cdot) \) is a decay function, and \( c_i \) is the cost of movement measured in distance, time, or money units. Although Wang showed that the accessibility index of the 2SFCA and crowdedness index of the i2SFCA are ‘two sides of the same coin,’ he still maintained them as separate models of different concerns. However, Páez et al. (2019) used congestion to balance accessibility in a single model, which they called the balanced floating catchment area (BFCA) model. The BFCA has been used to measure spatial access to healthcare during the COVID-19 pandemic in Brazil (Pereira et al., 2021). Lin and Cromley (2022) modified the BFCA to create the adjusted BFCA (ABFCA) by using the i2SFCA is in the first stage to calculate service-provider ratios for estimating accessibility in a second stage. However, even though congestion is used to estimate accessibility based on congestion levels, congestion was not used in selecting service providers. However, Lin and Cromley (2022) used congestion levels as part of the attractiveness of the hospitals in conjunction with their overall supply level in a congested supply accessibility (CSA) model. Finally, an alternative approach to 2SFCA models was proposed by Saxon and Snow’s (2020); their rational agent accessibility model (RAAM) measures accessibility as a trade-off between congestion and movement cost.

The discussion thus far has focused primarily on place-based measures of accessibility. Less consideration has been given to accessibility between different population groups. Studies have used multivariate statistical analyses to associate the effects of different socioeconomic variables on spatial accessibility (Dai & Wang, 2011; Páez et al., 2010, 2012; Wang et al., 2008; Zenk et al., 2005). Guagliardo et al. (2004) compared the accessibility map for the general population against a second map of the spatial distribution of a particular population group. In another study, Bell et al. (2013) constructed separate accessibility-to-physician maps for different language groups; differences in physicians’ access to the different language populations were determined by comparing the accessibility maps for each distinct population.

3. Data

This study is organized into several components to examine the different issues related to differential accessibility using a case illustration of access to ICU beds by fully and not-fully vaccinated populations in the state of Illinois. A vaccination dataset for Illinois was downloaded on November 7, 2021, from the website www.healthgrades.com. This dataset covered all vaccines administered to persons in the state of Illinois from the beginning of vaccination to the date of data download on November 7, 2021. These estimates do not include non-residents who work in Illinois and were vaccinated in Illinois (IDPH). The original dataset contained information on the number and percent of the population receiving a single vaccine dose and the number and percent of the population that was considered fully vaccinated aggregated at the zip code level. The total population count for each zip code was then derived from these percentages. The Illinois Department of Public Health (IDPH) states that ‘fully vaccinated’ versus ‘not-fully vaccinated’ is defined by the type of vaccine administered and the number of doses required to reach full vaccination (IDPH). The count of not-fully vaccinated people was calculated as the difference between the estimated total population and the count of fully vaccinated persons. The count of not-fully vaccinated included the unvaccinated and those who received a single dose. Statewide, 56.5% of the population was fully vaccinated at that time.
The spatial distribution of the percent fully vaccinated by zip code ranged from 5.1% to 100% (Fig. 1a). The statewide rate was as high as it was because of the higher vaccination rates in the Chicago Area. Geographically, most of the state was less than 50% vaccinated, especially in the southern portion of Illinois, where many areas were less than 36.5%.

Data on hospitals, their coordinate location, and the number of the intensive care unit (ICU) beds in these hospitals were originally collected by the Illinois Department of Public Health (IDPH) and later made publicly available by Kang et al. (2020). This dataset reported 183 hospitals with 7764 ICU beds for the state of Illinois. The spatial distribution shows that hospitals with the more beds are located in the Chicago Area in northeastern Illinois (Fig. 1b). Overall the 81 hospitals in the Chicago Area (defined here as all hospitals within 30 min travel time of Cook County) have 69% of the total number of ICU beds. Zip code centroids were used as the demand locations. Travel times from the zip code centroids to the respective hospitals were computed based on the OpenStreetMap road network using a Python package OSMnx developed by Boeing (2017).

A fully vaccinated population is still at-risk for so-called ‘breakthrough’ cases. However, different reports (Washington State Department of Health, 2021; CDC COVID-19 Vaccine Breakthrough Case Investigations Team, 2021) have shown that the likelihood of breakthrough cases is much lower than cases among an unvaccinated or partially vaccinated population. In a report monitoring the incidence of COVID-19 hospitalizations by vaccination status for thirteen jurisdictions in the United States (Scobie et al., 2021), the data showed that across all ages 18 and over, the not-fully vaccinated were 8.3 times more likely to be hospitalized than those who were fully vaccinated. In this research, the at-risk population among the fully vaccinated for each zip code is established by dividing the fully vaccinated population by 8.3 so that there is a similar likelihood of hospitalizations between the not-fully vaccinated. This transformation is similar to the iceberg transport model used in trade economics (see Krugman, 1998), in which a constant amount of goods ‘melts’ in transit. In this case, full vaccination ‘melts’ the at-risk population for hospitalization. One would expect higher levels of accessibility as vaccination rates increase even without any increase in supply.

4. Methods

Three different accessibility models are used here to estimate congestion levels at hospitals and the difference in the supply and cost accessibility differences between the two at-risk groups – the ABFCA (Lin & Cromley, 2022), the CSA (Lin & Cromley, 2022), and the RAAM (Saxon & Snow, 2020). These models were chosen because they explicitly use congestion in some manner to estimate accessibility. Each model uses a different approach to understand how congestion influences accessibility. By comparing these three methods, one can better interpret results than from an individual method and gauge the sensitivity of the results with respect to these models. In the ABFCA, the probability that the at-risk population at \( i \) will be allocated to the \( j \)th hospital, \( q_{ij} \), is modified from that of the BFCA (Paez et al., 2019) by adding the attraction of a facility into the calculation (Lin & Cromley, 2022):

\[
q_{ij} = \frac{S_j \times f_{ij}}{\sum_j (S_j \times f_{ij})}
\]
where, \( S_j \) is the number of ICU beds at the \( j \)th hospital and \( f_q \) is the impedance factor defined in Equation (1). This probability is then used to calculate the flow of patients to each hospital \((D_i \times q_j)\), and Wang’s (2018) congestion (or crowdedness) index, \( M_j \), for the \( j \)th service center:

\[
M_j = \sum (q_j \times D_i) / S_j
\]  

(3)

The supply accessibility, \( S_{A_i} \), is then calculated as:

\[
S_{A_i} = \sum S_j \times q_j / \sum (D_i \times q_j)
\]  

(4)

Although this metric uses congestion in calculating supply accessibility, it does not use congestion to determine which hospitals patients would travel to. In the congested accessibility model, the attractiveness of each hospital is adjusted for the expected congestion level at each hospital. The i2SFCA is again run first, but this time the congestion of each hospital is adjusted for the expected congestion level at each hospital to calculate the flow of patients to each hospital \((\tau \times D_i \times q_j)\). This probability is then used to calculate the new values for \( q_j \) and \( M_j \). The new values for \( q_j \) are also then used in Equation (4) to calculate supply accessibility.

In contrast, RAAM has a cost equalizing and cost-minimizing objective in which an individual’s access cost of service is a function of both congestion and travel time:

\[
Access = \frac{\sum X_i \times S_j \times c_i \times \tau}{\lambda}
\]  

(5)

where, \( X_i \) is the flow of patients from zip code \( i \) to hospital \( j \); \( c_i \) is the travel cost from \( i \) to \( j \); \( S_j \) is the number of ICU beds in hospital \( j \); and, \( \lambda \) and \( \tau \) are parameters that determine the trade-off between congestion and travel cost. Saxon and Snow (2020) note that by fixing \( \lambda \) (it is set to the system-wide congestion level here), \( \tau \) is the only free parameter necessary to investigate the relationships between congestion and travel costs. The procedures begin with all patients assigned to the hospital nearest their home zip code. Using this initial allocation, RAAM reallocates demand from the hospital with the highest combined congestion and travel cost to a cheaper one through a cycle of iterations. These cycles over zip code locations terminate when no further cost reductions are possible for any of the zip codes. Full equalization of congestion levels among hospitals is not the primary objective but rather the equalization of congestion and travel cost among individuals. However, congestion levels will be more equal as the value of \( \tau \) increases and the cost of congestion becomes the dominant portion of access cost in Equation (5).

For each model, the allocation of patients to hospitals is then used to calculate the average travel cost for each zip code which is its cost accessibility (Lin & Cromley, 2022):

\[
CA_i = \frac{\sum (X_i \times c_i)}{D_i}
\]  

(6)

where, \( X_i \), \( c_i \), and \( D_i \) are the same as Equations (4) and (5). Maps displaying the patterns of supply accessibility and cost accessibility can then be constructed as in the application of any accessibility method. An analysis of place-based supply and cost accessibility might end here, but several additional issues must be considered in examining differential accessibility between the sub-groups. First, is there a significant difference in access between fully vaccinated and not fully vaccinated populations? Earlier studies have measured the strength of the relationship using correlation coefficients (or adjusted correlation coefficients) to indicate a statistical association between accessibility and population groups (Grumbach et al., 1997; Lineberry, 1977; McLafferty & Ghosh, 1982; Madlener, 1978). Correlation is commonly visualized using scatterplots. Although scatterplots are easy to compute and display, they have some shortcomings. One shortcoming is scalability (Andrienko & Andrienko, 2004). As the number of observations increases, the cloud of points can become too dense. To address scalability, Andrienko and Andrienko (2004) suggested using a series of cumulative frequency curves (CFCs). CFCs have been used to compare accessibility patterns of different populations (Cromley, 2019; Grengs, 2010). In this study, CFCs for the fully and not-fully vaccinated populations with respect to the three accessibility/congestion models are plotted. The accumulated frequency of observations is plotted on the y-axis against the variate value plotted along the x-axis. A two-sample, nonparametric Kolmogorov-Smirnov (K-S) test is then calculated to determine if there is a significant difference in addition to a visual depiction of differences. The two-sample K-S test statistic is the maximum absolute vertical deviation (D) between the two observed cumulative frequency curves.

Next, the magnitude of the differences concerning accessibility between groups is measured. Accessibility metrics have the same interpretation – either the amount of health service per unit of population or the average of service per unit of population. Wan, Zhan, et al. (2012) computed potential accessibility for different population groups based on the E2SFCa measure, although few details were given on how this was done. A demographically weighted accessibility index (DWAI) is calculated here for each population group and supply/cost accessibility metric:

\[
DWAI = \sum (P_i \times SPA_i)
\]  

(7)

where \( P_i \) is the proportion of a population found in the \( i \)th zip code area, and \( SPA_i \) is the spatial accessibility index for zip code area \( i \). A DWAI for the general population would use the proportion that each area’s total population is of the total population of the study area as the demographic weight. In contrast, for a specific sub-group, the proportion of that sub-group in each area relative to the sub-group population in the entire study area would be the demographic weight. The statistical distributions of the DWAI for vaccine sub-groups are visualized using spatial accessibility quantile profiles (SPAQP) developed in this research. A SPAQP is based on a bar chart representing the components of the DWAI. Each term of the DWAI is represented by a bar with a height equal to the accessibility score \( (SPA) \) and a width equal to the proportion of a specified population associated with a unit \( (P) \). The total width of all bars equals one, and the area of the set of bars equals the value of the corresponding DWAI. The SPAQP is the line over the top of these bars ordered from shortest to highest. The area under the SPAQP equals its DWAI value, and the shape of the SPAQP shows the statistical distribution of the DWAI components. As the number of data units increases and the width of each bar decreases, a SPAQP will approach a quantile function (see Hao & Naiman, 2010) for a complete discussion of quantile functions. A quantile function is similar to a CFC, but the axes are reversed.

5. Results

For the ABFCA and CSA models, this study uses a four-step function to model the distance decay in patient-hospital interactions in which the weights (1, 0.68, 0.22, and 0.10) are applied to four travel time zones (0–10, 10–20, 20–30, and 30–70 min). These weights and zones are the same as those of Kang et al. (2020), except that the fourth outer zone is added to ensure that all zip codes would be in the access radius of some hospitals (the largest minimum travel time between a zip code centroid and a hospital was 69 min). The first analysis examines congestion levels among hospitals across the state. The statewide congestion level is 830.4 potential patients per ICU bed. If the Chicago Area were a container unit, it would have a congestion index of 700.1 compared with 1120.4 for the rest of the state because of higher vaccination rates and a higher proportion of the ICU beds. Consequently, congestion at hospitals in the Chicago Area was substantially lower than for the rest of the state across...
all three models (Table 1). Every Chicago Area hospital had a congestion index less than the statewide rate for the CSA model. In addition, all CSA congestion values in the Chicago Area were higher than the region’s container-based congestion rate. This suggests a boundary effect around the Chicago Area in which more patients are traveling from outside of the Chicago Area to hospitals inside the area than patients from inside the Chicago Area are traveling to hospitals located outside the area.

The CSA model also produced the most even distribution of congestion within the state as measured by a Gini Coefficient of 0.0788. The Gini Coefficient is a standard measure of evenness/concentration within a distribution (Fellman, 2018). This was slightly less than the RAAM model. As might be expected, the ABFCA had the highest level of unevenness in congestion because congestion is not used in the model to direct patients.

The impact of congestion on supply accessibility can be seen in the spatial distribution of supply accessibility. An extension of the Chicago Area and the western region centered on Adams County were the main places where the supply accessibility values exceeded the statewide supply accessibility of 1.204 beds per 1000 population (Fig. 2). The supply accessibility scores for the northeastern region were spottier for the RAAM because its objective function also included travel costs. However, these were discounted by setting the τ value to 300 (Fig. 2c).

Concerning cost accessibility, the RAAM was much more effective in reducing travel times than either the ABCFA or the CSA models. The average travel time for the RAAM was almost 10 min less on average than the other two models (see Table 2). Because total travel cost is not fixed across the state in the same manner as total demand and supply, there is no single statewide average cost. The only normative metric would be the statewide average travel cost if all patients traveled to their nearest hospital. For Illinois, that value is 8.49 min. The RAAM results were more than double this amount, and the ABFCA and CSA models were more than triple this amount. In terms of the spatial pattern of cost accessibility, all models show the lowest cost accessibility scores surrounding urban centers where the hospitals are located (Fig. 3). The patterns for the ABCFA and the CSA models were almost the same, as shown in Fig. 3a and b. In contrast, the RAAM pattern was more bipolar, with the most average travel times either below 30 min or above 50 min (Fig. 3c). The highest value for the RAAM was more than twice as high as that for the other two models.

Next, the relationship between the CFCs of the fully and not-fully vaccinated populations is displayed in Fig. 4. With respect to supply accessibility, the two CFCs for the ABFCA and CSA models were similar. For the BCFA, both curves start with the same accessibility score, 0.39, but they begin to diverge after a supply accessibility value of 0.75. The not-fully vaccinated CFC increases more rapidly than the fully vaccinated CFC reaching the maximum separation between the two CFCs at a supply accessibility score of 1.27; the two CFCs then converge again at a CFC score of 1.31 and remain together after that. The maximum difference, D, between the two CFCs is 9.44%; this test statistic was significant at a level of less than 0.001, implying a significant difference between the two sub-groups in the level of accessibility to ICU beds based on the ABCFA measure. The D statistic was even higher for the CSA model, 10.6%, again implying a significant difference between the two sub-groups. Finally, for the RAAM, the CFC for the not-fully vaccinated began to diverge at a value of 0.93. It remained above the fully vaccinated CFC until a supply accessibility value of 1.40. The D value was 10.0%, which is significant at the 0.001 level. Regardless of the model, there was always a significant difference in supply accessibility between the two sub-groups. With respect to cost accessibility, the CFC for the not-fully vaccinated was higher than that for the fully vaccinated over a much wider range of accessibility values (Fig. 5). Overall the separation between the two groups was not as great as in the case of supply accessibility. The greatest D value among the three models was 5.4% for the ABFCA model. The differences were significant but not to the same level as supply accessibility.

Next, these differences are quantified by calculating the DWAI for the total population at-risk, the fully vaccinated population, and the not-fully vaccinated population. Illinois’s ICU bed/population-at-risk container has an overall ratio of 1.204 beds per 1000 population, which is the statewide DWAI for all models. At the state level, all three models produced very similar results for the fully vaccinated population with respect to supply accessibility, ranging only from 1.228 to 1.231 (Table 2). For the not-fully vaccinated, supply accessibility was the same with respect to the three models. In contrast, cost accessibility fluctuated more between models and groups. For the fully vaccinated, cost accessibility was slightly over an average of 18 min for the RAAM but 28.2 min for the CSA model. For the not-fully vaccinated, cost accessibility ranged from 20.26 to 29.51 min. Next, the results were examined regarding supply efficiency, which is the average minutes necessary to acquire a supply unit (in this case, one ICU bed). Given its lower cost accessibility values, the RAAM also had the lowest supply efficiency values, ranging from 16.88 min for the not-fully vaccinated to 14.69 for the fully vaccinated. None of the relationships between models and groups changed with respect to supply efficiency. In no instance was the difference in supply that different from the difference in travel cost.

The statistical distribution of the demographically weighted supply accessibility can be seen graphically in the SPAQPs for the two groups - the fully vaccinated population had a larger area under its profile than the not-fully vaccinated had under its profile (Fig. 6). The SPAQPs also show for both populations how uneven spatial accessibility is for both populations. For the ABFCA and CSA, almost all of the difference between the two groups is associated with the quantile range of less than 0.4, which has the lowest supply accessibility scores. The area under the SPAQ for the fully vaccinated population between the 0.0 and 0.33 quantile level is 0.344 physicians per 10,000 population, whereas the same range for the not-fully vaccinated has supply accessibility of 0.316. The SPAQ for the RAAM also shows more difference between the lower half of the quantiles than in the upper half (Fig. 6c). With respect to cost accessibility (Fig. 7), the fully vaccinated SPAQP was never in relative terms that much greater than for the not-fully vaccinated population. The difference was also spread over a wider range of quantiles.

In decomposing the different DWAI metrics, supply accessibility is used to define the zip codes in each group. It should be noted that the zip codes in the bottom, middle, and top thirds with respect to fully vaccinated, not-fully vaccinated, and total at-risk involve slightly different sets of zip codes. For example, the bottom third for the ABFCA concerning being fully vaccinated contained 960 zip codes. The bottom third for not-fully vaccinated contained 853 zip codes, and the total at-risk had 898 zip codes because a third of each population was spread differently across the zip codes. However, the same groups were then used for decomposing cost accessibility and supply efficiency. While the bottom third always had the lowest supply accessibility because of how it was defined, it did not always have the lowest cost accessibility. For the ABFCA, the highest average travel costs occurred in the top third

### Table 1

| Table 1 | Differences in congestion levels between the Chicago Area and the rest of Illinois. |
|---------|-----------------------------------------------|
|         | Chicago Area | Rest of Illinois | Statewide Gini Coefficient |
|         | Min | Median | Max | Min | Median | Max |               |
| ABFCA   | 535.8 | 776.4 | 906.5 | 353.3 | 900.7 | 3946.0 | 0.1202       |
| CSA     | 729.7 | 759.7 | 777.9 | 646.8 | 997.9 | 1848.7 | 0.0788       |
| RAAM    | 481.2 | 761.3 | 1328.0 | 721.0 | 1090.3 | 1851.4 | 0.0891       |
across all groups. The lowest average costs were in the middle third for the ABFCA. The same was true for the middle third of the fully vaccinated in the CSA model. With respect to supply efficiency, the bottom third always had the lowest scores because their lower supply accessibility scores outweighed any advantage in travel cost. Finally, the RAAM had the lowest supply efficiency scores across all quantile groups and vaccination status (Table 3).

The differences between groups based on the statistical

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**Table 2**

| Demographically weighted accessibility indices. | Supply Accessibility* | Cost Accessibility** | Supply Efficiency*** |
|-----------------------------------------------|-----------------------|----------------------|---------------------|
|                                               | ABFCA | CA       | RAAM | ABFCA | CA       | RAAM | ABFCA | CA       | RAAM | ABFCA | CA       | RAAM |
| Fully Vaccinated                             | 1.228 | 1.231    | 1.229 | 27.77 | 28.20    | 18.05 | 22.61 | 22.91    | 14.69 |       |          |      |
| Not-Fully Vaccinated                         | 1.200 | 1.200    | 1.200 | 29.14 | 29.51    | 20.26 | 24.83 | 24.59    | 16.88 |       |          |      |
| Total At-Risk                                | 1.204 | 1.204    | 1.204 | 28.95 | 29.33    | 19.96 | 24.04 | 24.36    | 16.58 |       |          |      |

*ICU Beds Per 1000 Population ** Average Minutes Per Unit of Demand ***Average Minutes Per Unit of Supply.

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**Fig. 2.** ICU bed accessibility for the at-risk population at the zip code level from a) the ABFCA model, b) the CSA model, and c) the RAAM model. The RAAM model in panel c has a much narrower value range, eliminating any observations in either the highest or lowest class interval.

**Fig. 3.** The cost accessibility associated with each zip code from a) the ABFCA model, b) the CSA model, and c) the RAAM model.
decomposition were not that high. An alternative decomposition is to decompose the demographically weighted indices based on the grouping of zip codes in the Chicago Area versus those in the rest of the state. The lack of lower supply accessibility scores in the Chicago Area displayed in Fig. 2a and b can also be seen in the SPAQP diagrams in Fig. 6a and b for the ABFCA and CSA models. The gray lines (thin rectangles) in these two diagrams represent the DWAI components for the fully vaccinated population residing in the Chicago Area. The thickness of lines would be slightly different for the not-fully vaccinated population because, as mentioned previously, the widths of the rectangles vary by the percent...
of a particular group being investigated. However, only one set of lines can be displayed in one diagram. The spottier concentration of higher supply accessibility values in the Chicago Area in the RAAM (Fig. 2c) is seen again in Fig. 6c as thin rectangles are scattered in the low end of the supply accessibility range.

Table 4 shows this geographical decomposition for all models and population groups. Across all groups, the supply accessibility scores for each model are higher in the Chicago Area than in the rest of the state. It should be noted that the supply accessibility for the not-fully vaccinated was slightly higher than for the fully vaccinated. The advantage for the fully-vaccinated in the Chicago Area lies in lower-cost accessibility scores and lower supply efficiency because the lower cost accessibility was relatively greater than the higher supply accessibility. In the rest of Illinois, the not-fully vaccinated had the lowest supply accessibility, the

Table 3
Statistically decomposed accessibility and efficiency indices.

|                      | Supply Accessibility* | Cost Accessibility** | Supply Efficiency*** |
|----------------------|------------------------|----------------------|---------------------|
|                      | ABFCA                  | CSA                  | RAAM                |
|                      | Bottom Third Middle Third Top Third Bottom Third Middle Third Top Third Bottom Third Middle Third Top Third |
| Fully Vaccinated     | 0.344 0.434 0.451      | 9.23 7.73 10.81      | 26.83 17.81 23.97  |
| Not-Fully Vaccinated | 0.316 0.430 0.455      | 9.80 9.24 10.10      | 31.01 21.49 22.25  |
| Total At-Risk        | 0.319 0.434 0.451      | 9.99 7.95 11.01      | 31.28 18.34 24.41  |
|                      | Bottom Third Middle Third Top Third Bottom Third Middle Third Top Third Bottom Third Middle Third Top Third |
| Fully Vaccinated     | 0.351 0.437 0.444      | 11.19 7.72 9.28      | 31.92 17.68 20.90  |
| Not-Fully Vaccinated | 0.320 0.434 0.446      | 10.29 9.72 9.49      | 32.15 22.39 21.30  |
| Total At-Risk        | 0.323 0.438 0.443      | 10.34 9.60 9.40      | 31.98 21.90 21.21  |
|                      | Bottom Third Middle Third Top Third Bottom Third Middle Third Top Third Bottom Third Middle Third Top Third |
| Fully Vaccinated     | 0.353 0.424 0.451      | 8.63 5.37 4.05       | 24.46 12.65 8.97   |
| Not-Fully Vaccinated | 0.339 0.414 0.447      | 7.74 7.77 4.75       | 22.81 18.78 10.61  |
| Total At-Risk        | 0.341 0.415 0.448      | 8.07 7.12 4.76       | 23.66 17.17 10.63  |

*ICU Beds Per 1000 Population ** Average Minutes Per Unit of Demand *** Average Minutes Per Unit of Supply.

Table 4
Geographically decomposed accessibility and efficiency indices.

|                      | Supply Accessibility* | Cost Accessibility** | Supply Efficiency*** |
|----------------------|------------------------|----------------------|---------------------|
|                      | ABFCA                  | CSA                  | RAAM                |
|                      | Bottom Third Middle Third Top Third Bottom Third Middle Third Top Third Bottom Third Middle Third Top Third |
| Fully Vaccinated     | 1.310 1.319 1.308      | 19.31 19.55 7.84     | 14.74 14.83 5.99    |
| Not-Fully Vaccinated | 1.312 1.320 1.311      | 19.72 19.94 8.23     | 15.03 15.11 6.28    |
| Total At-Risk        | 1.312 1.319 1.311      | 19.66 19.88 8.17     | 14.99 15.06 6.23    |
|                      | Bottom Third Middle Third Top Third Bottom Third Middle Third Top Third Bottom Third Middle Third Top Third |
| Fully Vaccinated     | 1.166 1.165 1.168      | 34.21 34.77 25.81    | 29.34 29.84 22.09   |
| Not-Fully Vaccinated | 1.136 1.131 1.137      | 34.54 35.00 27.16    | 30.39 30.94 23.90   |
| Total At-Risk        | 1.140 1.135 1.141      | 34.50 34.97 27.00    | 30.26 30.80 23.67   |

*ICU Beds Per 1000 Population ** Average Minutes Per Unit of Demand *** Average Minutes Per Unit of Supply.

Fig. 7. The SPAQPs of the fully and not-fully vaccinated populations for the cost accessibility derived from a) the ABFCA model, b) the CSA model, and c) the RAAM model.
highest cost accessibility, and the highest supply efficiency scores. Overall, the rest of Illinois had supply accessibility scores that were about 13% lower, cost accessibility scores that were 75% higher, and supply efficiency scores that were at least 102% higher than for the Chicago Area. These results provide insight into differences between and within population groups and between different state regions.

6. Conclusions

The COVID-19 pandemic continues to place strain on health care resources. The development of vaccines to protect individuals against the effects of this disease assist in reducing that strain by reducing the number of patients needing ICU care. This study examined the potential impact that vaccination rates can have on differential access to ICU beds in the state of Illinois. Results suggest a statistically significant supply and cost accessibility difference between the fully vaccinated and not-fully vaccinated population. However, the magnitude of this difference is not that great because more vaccinated people reduce the demand for services that benefit both vaccinated and not-fully vaccinated populations. A greater difference occurred between populations located in the Chicago Area than the rest of the state. A combination of proportionally more ICU beds located in the Chicago Area and higher vaccination rates among its population resulted in higher accessibility scores across all models used in this study. In fact, the not-fully vaccinated population in the Chicago Area had marginally higher accessibility scores than the vaccinated had. These results highlight another aspect of herd immunity – the fully-vaccinated provide positive externalities to the not-fully vaccinated by reducing congestion due to a lower need for hospitalization among the fully vaccinated.

The study compared results with respect to three different models for calculating supply and cost accessibility and supply efficiency for the zip code demand region and congestion levels at hospitals. All three models produced fairly even congestion levels among hospitals aiding in flattening the curve of care at any particular hospital. Evening congestion is even more important given more highly contagious new strains of COVID-19, such as the recent omicron variant. Each model produced similar levels of supply accessibility, but the RAAM generated cost accessibility scores that were approximately 30–40% lower than the ABFCA and CSA models. Both the CSA and RAAM models produced a more even level of congestion within the system of hospitals than the ABCFA because congestion was included in the travel decisions for the RAAM and CSA models. Given these two factors, the RAAM had the best overall representation with respect to a normative consideration.

This study also highlights an essential difference between visualizing access to health services versus visualizing access to health services between population groups. The former focuses on the development and use of numerical indices using traditional choropleth maps in a supporting role to display the spatial distribution of the accessibility metric. In contrast, the latter must perform that task and examine the association between accessibility and population groups. This study has identified geovisual tools that can aid in interpreting that association. In addition to the traditional choropleth map, additional insight into the relationship of differential accessibility between population groups was gained from methods related to the graphing of cumulative density functions: CFCs and SPAQPs. Each of these graphs possesses the quality of being scalable, where the line becomes increasingly smooth as additional observations are added to the graph. CFCs and SPAQPs were used to determine whether differences in accessibility between population groups are significant and how contributions to accessibility are distributed within the respective populations and geographic location. The SPAQ, developed in this research, is a tool that permits a visual understanding of the statistical distribution of accessibility measures and determines which ends of the distribution favor which groups in comparisons between a pair of population groups.

Finally, the spatial supply and cost accessibility patterns were very different across Illinois. Both forms of accessibility were better in urban areas than rural areas, but supply accessibility was only better in the Chicago Area and the west centered on Adams County. In contrast, cost accessibility was better in most urban centers of any size because that is the dominant location of hospitals. Although there are urban/rural disparities, no clear statement regarding underlying disparities in non-spatial factors such as the concentration of disadvantaged groups can be made based on the data used here although many disadvantaged groups tend to be more concentrated in urban areas. Future work will investigate the relationship between the spatial aspects of accessibility discussed here and these non-spatial factors.

Author statement

Gordon Cromley: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Data Curation, Writing- Original draft preparation, Writing - Review & Editing. Jie Lin: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing - Review & Editing, Visualization.

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G. Cromley and J. Lin

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