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Refining 2SVCA method for measuring telehealth accessibility of primary care physicians in Baton Rouge, Louisiana

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ABSTRACT

Equity in health care delivery is a longstanding concern of public health policy. Telehealth is considered an important way to level the playing field by broadening health services access and improving quality of care and health outcomes. This study refines the recently developed "2-Step Virtual Catchment Area (2SVCA) method" to assess the telehealth accessibility of primary care in the Baton Rouge Metropolitan Statistical Area, Louisiana. The result is compared to that of spatial accessibility via physical visits to care providers based on the popular 2-Step Floating Catchment Area (2SFCA) method. The study shows that both spatial and telehealth accessibilities decline from urban to low-density and then rural areas. Moreover, disproportionally higher percentages of African Americans are in areas with higher spatial accessibility scores; but such an advantage is not realized in telehealth accessibility. In the study area, absence of broadband availability is mainly a rural problem and leads to a lower average telehealth accessibility than physical accessibility in rural areas. On the other side, lack of broadband affordability is a challenge across the rural-urban continuum and is disproportionally associated with high concentrations of disadvantaged population groups such as households under the poverty level and Blacks.

1. Introduction

Equity in health care delivery is a longstanding concern of public health policy (Administration HRS, 2021). The disparity in health care accessibility is considered a main barrier as distributions of health care resources and population are rarely even across space (Wang, 2012). With the advancements in internet service, communication technology, and medical device innovation, telehealth has been considered a major pathway to overcome geographic barriers (Kruse et al., 2017; Moffatt & Eley, 2010), broaden health care access, and improve quality of care and health outcomes (Chang et al., 2021). Potential beneficiaries include disadvantaged population groups such as the elderly (Noel et al., 2004), rural residents (Gagnon et al., 2006), and those with transportation barriers. Several studies dampen such a hope since telehealth can be only effective for certain patients or medical services (Dinesen et al., 2016), and not available for some communities with limited internet service (Catalyst, 2018; Myers, 2019). Moreover, virtual visits do not completely replace physical visits (Kaiser, 2014), and most people still prefer face-to-face consultation and treatment (Balestra, 2018; Shigekawa et al., 2018).

During the COVID-19 pandemic, telehealth has received increased support and developed rapidly out of necessity (An et al., 2021; Gajarawala & Pelkowski, 2021; Koonin et al., 2020; Monaghesh & Hajizadeh, 2020; Shachar et al., 2020; Snoswell et al., 2020; Wosik et al., 2020). Some recent studies suggest that it may even exacerbate the existing disparity of health care accessibility (Campos-Castillo & Anthony, 2021; Chuo et al., 2020), for certain racial-ethnic groups (Zhang et al., 2021), the elderly and low income group (Ng & Park, 2021), and in rural areas (Ng et al., 2022). The widening digital divide (Cortelyou-Ward et al., 2020; Lythreatis et al., 2022) plays an important role (Nadkarni et al., 2020), including unaffordable internet to minority populations (Cortelyou-Ward et al., 2020) and user barriers to people of low educational attainment and the elderly (Fischer et al., 2020). Wearable technologies and smart homes also have higher requirements for broadband quality

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and deprive low-income residents of adequate access to telehealth (Blandford et al., 2020; Hirko et al., 2020).

The distance-dependence of patients to telehealth providers may also reinforce preexisting geographic disparities. In Queensland, Australia, an average distance for receiving a telehealth consultation at an outreach clinic was 173 km (Edirippulige et al., 2015). Most people consider telehealth as supplementary to regular medical services from nearby providers, such as services after normal clinic hours and refilling prescriptions (Tuckson et al., 2017). Many prefer local telehealth providers for the challenge of conducting a physical exam online, maintaining emotional connection, or unreliable internet service (Dorsey & Topol, 2016; Kaplan, 2021). Telemedicine does not seem to alter the spatial range patients search for medical care (Skinner et al., 2022).

Among models measuring spatial accessibility, the "*2-Step Floating Catchment Area (2SFCA) method*" has been used widely since 2003 (Luo & Wang, 2003; Wang, 2021). Built upon the 2SFCA method for measuring *physical access*, a recent study proposes the "*2-Step Virtual Catchment Area (2SVCA) method*" for measuring *telehealth access* by taking account of aforementioned interdependence between telehealth and physical visits in health care delivery (Alford-Teaster et al., 2021). However, there has been no systematic research on how telehealth accessibility varies across areas in the rural-urban spectrum and of diverse socio-demographic structures. This paper refines the 2SVCA method to account for additional elements omitted in the previous formulation. The improved method is then applied to measuring the telehealth accessibility of the primary care physicians (PCPs) in the Baton Rouge Metropolitan Statistical Area (BRMSA), Louisiana. The case study focuses on the disparities across geographic areas and socio-demographic groups and identifies underlying causes. The results shed light on possible strategies for improving telehealth accessibility in underserved areas and population.

2. Study area and data sources

The study area is the Baton Rouge Metropolitan Statistical Area (BRMSA) hereafter simply referred to as "Baton Rouge." As shown in Fig. 1(a), this region consists of nine parishes with areas falling in a full rural–urban spectrum. "Parish" is the county equivalent unit in Louisiana. The City of Baton Rouge, the state's capital city, resides in East Baton Rouge Parish. According to a recent report (Parish EBR, 2022), East Baton Rouge Parish has double the national average rates in low birth-weight, 1.5 times in uninsured population, and 5.6 times in sexually transmitted diseases. All highlight the importance of health research, including primary care accessibility, in the study area.

Data for the analysis are composed of four parts: supply (physician facilities), demand (population), broadband availability and subscription, and the road network.

(1) Physician data. The data of individual physicians (including specialty and geographic location) in Louisiana in 2022 are obtained from the Doctors and Clinicians National Downloadable File released by the Centers for Medicare and Medicaid Services (CMS). There are 594 primary care physicians (PCP) aggregated to 172 census blocks (Fig. 1). When physicians have multiple practice locations, they are converted to full-time equivalent (FTE) PCPs.

(2) Population and socioeconomic data. The 2020 Census Redistricting data at the census block level are used to define population-weighted centroids for the census block group areas. There are 574 block groups in the study area with total population of 849,530. Poverty

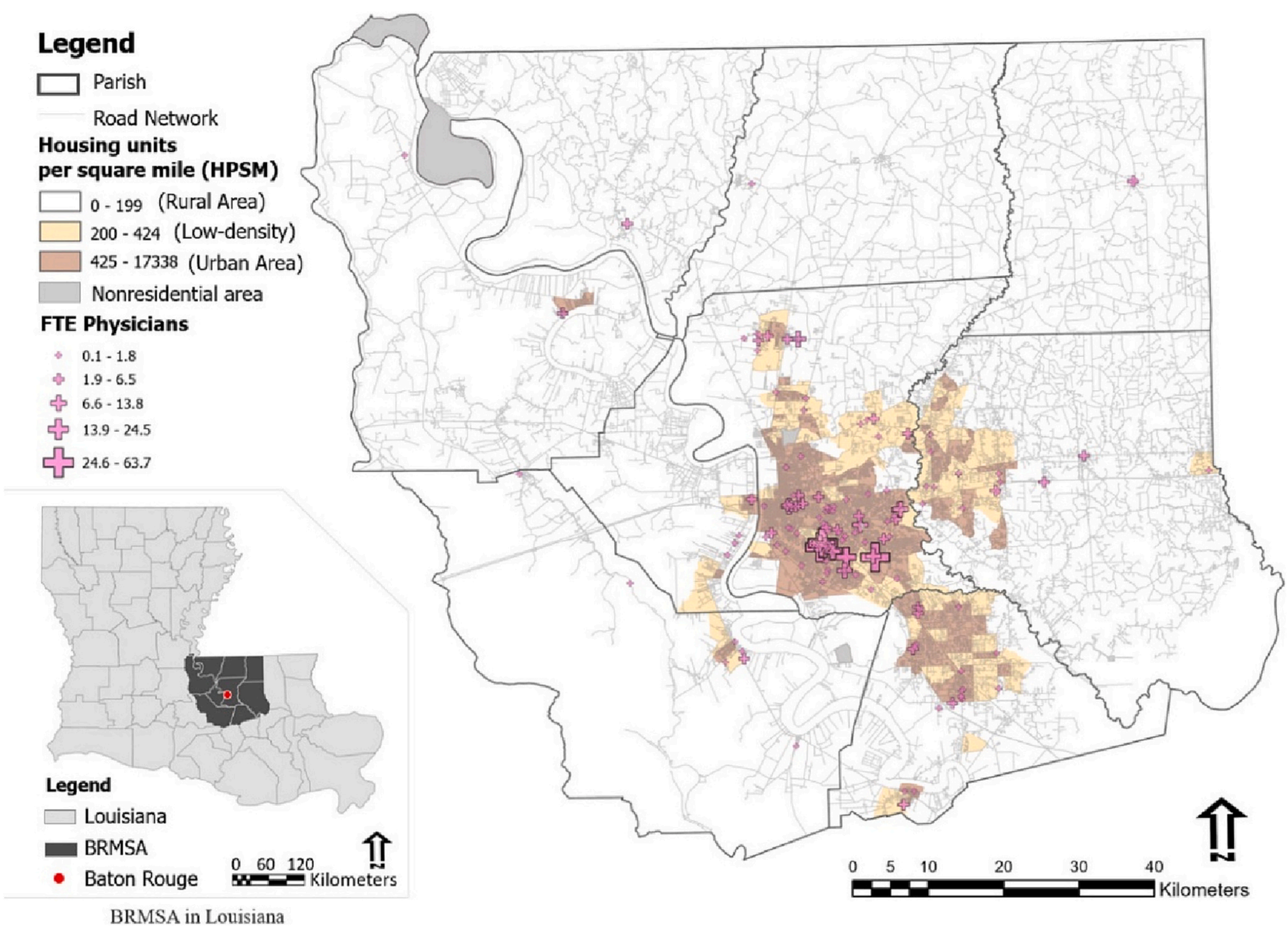


Fig. 1. Primary care physicians and urban areas in Baton Rouge MSA.

status data is extracted from the 2016–2020 Five-Year American Community Survey (ACS), wherein block group is the smallest area unit. The BRMSA is composed of 58.4 % white (non-Hispanic) residents and 35.2 % African American (non-Hispanic) residents. Other racial-ethnic groups are not considered in analysis of racial-ethnic disparity because of their relative low percentages. Fig. 2 shows the geographic distribution of African Americans across the BRMSA. The highest concentration of African Americans (with rates higher than 83 %) is in the northwest part of the City of Baton Rouge. The U shape of the statistical distribution of block groups across various percentages of African Americans highlights a segregated pattern of the BRMSA with the highest numbers of block groups being either 0–5 % or 95–100 %. For analysis of disparity across socioeconomic groups, this research focuses on households under poverty, and the BRMSA has an average poverty rate of 14.6 %.

(3) Broadband availability data. The dataset is extracted from the Federal Communications Commission (FCC) Fixed Broadband Deployment Block Data [https://www.fcc.gov/general/broadband-deployment-data-fcc-form-477]. The FCC broadband data contains maximum upload and download speed records by different service providers (consumer vs. business). It is firstly aggregated to mean speeds at the 2010 block level by the two types of service providers. Such data for consumer at the 2010 block level are further aggregated to the 2020 block group level if the former's centroids fall within the boundary of the latter (Fig. 3). The broadband speed for each PCP is assigned by its nearest 2010 census block centroid with broadband speed data for business.

(4) Broadband subscription data. Household broadband subscription rate at the census block group level is extracted from the 2016–2020 Five-Year American Community Survey (ACS), as shown in Fig. 4. Specifically, broadband includes such as cable, fiber optic, or DSL, identified as variable "B28011_004E" in the ACS.

(5) Road network data. The road-network dataset is from the U.S. Census Bureau (Lee, 1991), and then processed by the ArcGIS Network Analysts to estimate the shortest-path travel time from each demand location (i.e., population-weighted centroid of block group) to each supply location (i.e., average location of non-zero PCPs in a block). It produces a travel time matrix of 570 × 172 or 98,556 origin-destination (O-D) pairs.

(6) Urbanicity data. Urban areas are also based on data from the U.S. Census. Based on the 2020 Census Urban and Rural Classification with definition standard by housing units per square mile (HPSM) [https://www.federalregister.gov/documents/2022/03/24/2022-06180/urban-area-criteria-for-the-2020-census-final-criteria], a census block group is defined as (1) urban area (UA) if density ≥ 425 HPSM, (2) Low-Density Fill zones (LD) if density = 200–425 HPSM and contiguous to UA units, and otherwise (3) rural area (RA). Four block groups are eliminated in the analysis due to their nonresidential nature (total households ≤2, or total population ≤ 1), such as farmland, airport, prison, and commercial district. As shown in Fig. 1 and Table 1, most of the block groups (410) in the BRMSA are UA, followed by RA (164) and then LD (82). RA has the highest percentage of White (65.1 %), followed by LD (60.5 %) and then UA (41.8 %); and the order is reversed for percentages of Black. UA has the highest percentage of households under poverty, followed by RA and then LD. In terms of broadband subscription rate, LD enjoys the highest average, followed by UA and then RA.

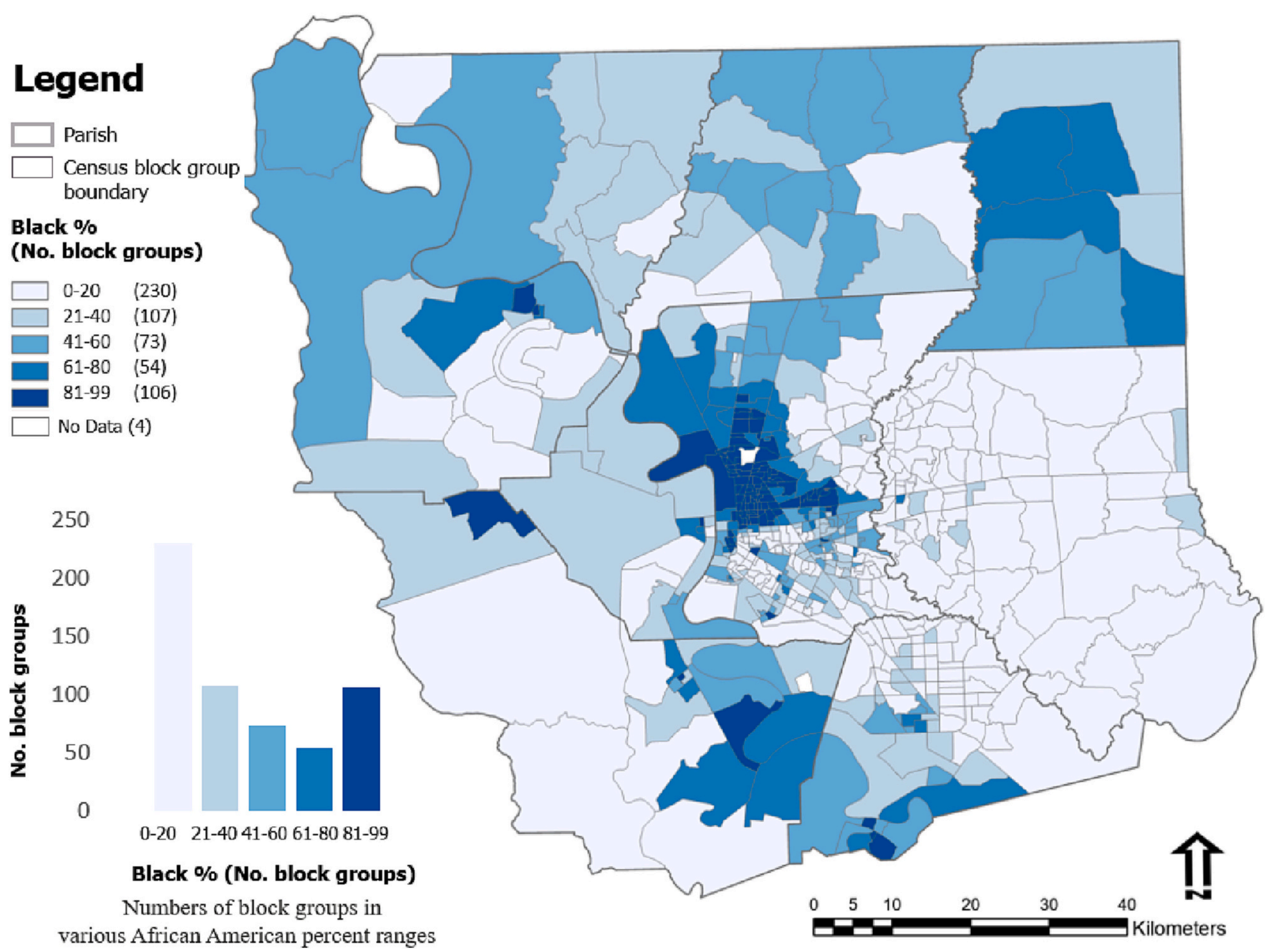


Fig. 2. African American percent across block groups in Baton Rouge MSA 2020.

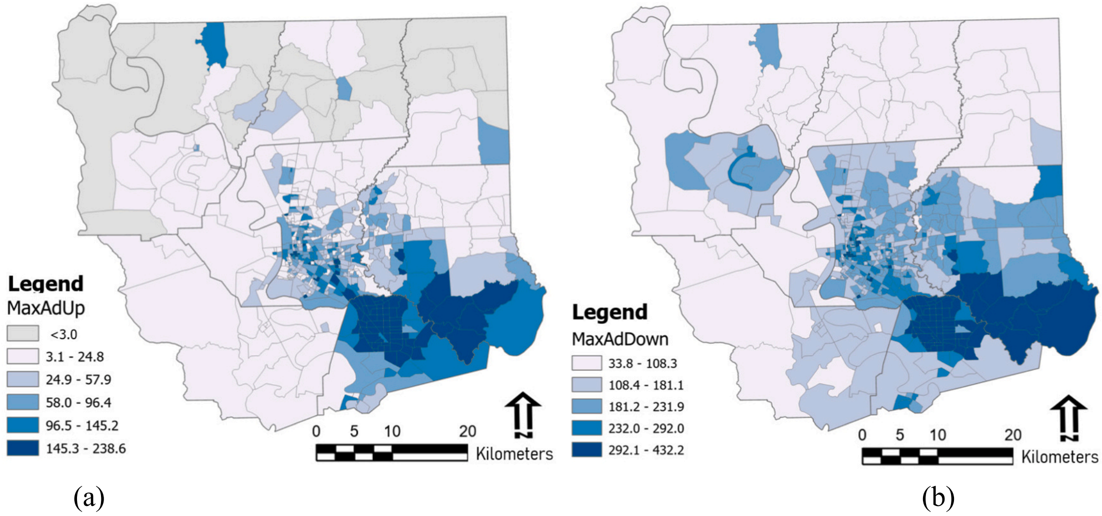


Fig. 3. (a) Mean upload FBB speeds, and (b) mean download FBB speeds in BRMSA 2020.

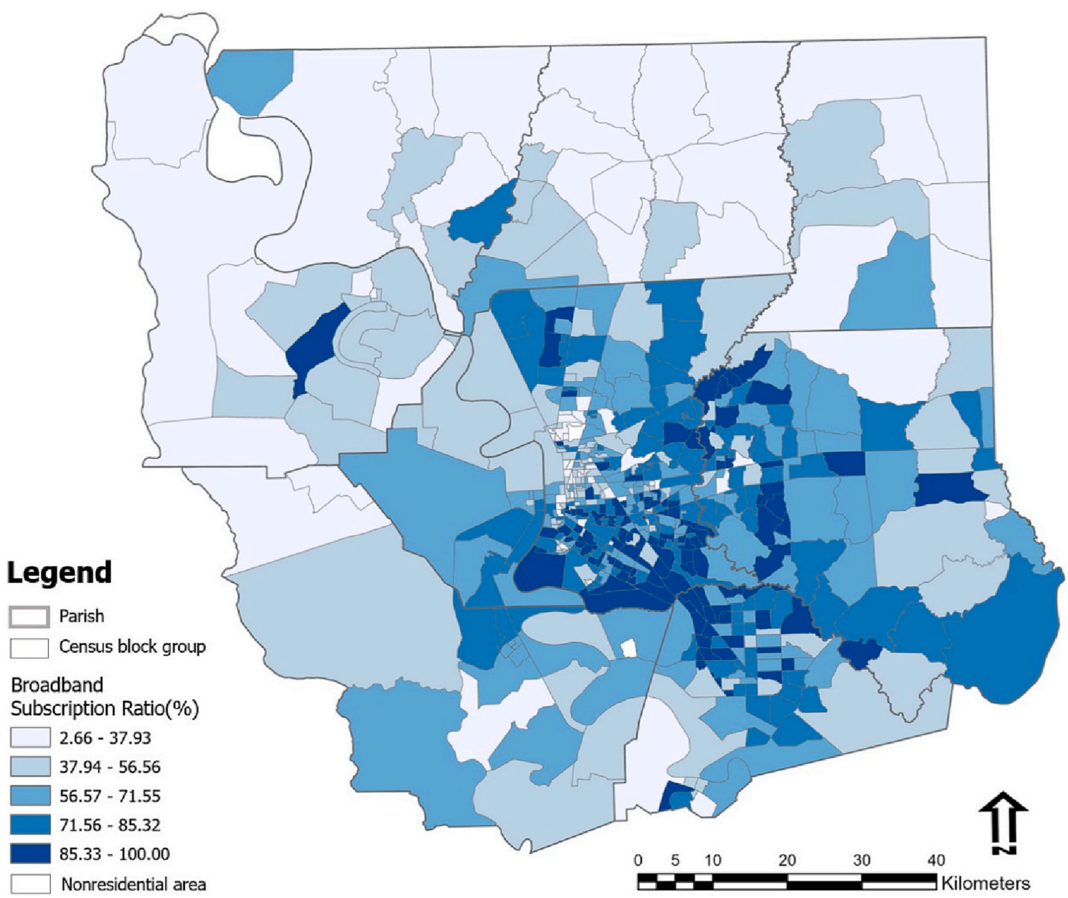


Fig. 4. Household broadband subscription rate in BRMSA 2020.

3. Methods

3.1. Refining 2SVCA method for measuring telehealth accessibility

The General 2-Step Floating Catchment Area (2SFCA) model for physical accessibility at demand location i, PA_i, is written as

$$PA_i = \sum_{j=1}^{n} \left[S_j f(d_{ij}) \Big/ \sum_{k=1}^{m} \left(D_k f(d_{kj}) \right) \right] \tag{1}$$

where supply capacity of PCPs at location j is denoted by S_j, population at location k (or i) is denoted by D_k (or D_i), and the interactions between them is a declining function of their physical distance d_{kj} (or d_{ij}). For simplicity in this case study, we assume that the distance decay function

Table 1
Demography and broadband access across areas of urbanicity.

Area (no. block groups)	Population	Area (km^2)	White %	Black %	Poverty %	Broadband subscription %	MaxDownload (mbps)			MaxUpload (mbps)		
							Min	Mean	Max	Min	Median	Max
Total (n = 570)	849,233	10,776	51.2	38.8	16.8	65.6	33.8	208.7	432.2	2.2	65.6	238.6
Rural (n = 164)	247,593 (29.2 %)	9807 (91.0 %)	65.1	27.7	15.4	57.3	33.8	158.3	369.1	2.2	36.9	226.8
Low density (n = 82)	133,907 (15.8 %)	472 (4.4 %)	60.5	29.1	10.4	70.9	104.5	232.1	358.7	5.2	80.32	228.5
Urban (n = 324)	467,733 (55.0 %)	497 (4.6 %)	41.8	46.8	19.1	68.5	42.3	228.3	432.2	2.4	76.4	238.6

$f(d_{kj})$ or $f(d_{ij})$ takes binary values 0 or 1 when d_{kj} (or d_{ij}) is within or beyond d_0. In that case, Eq. (1) is regressed to "traditional 2SFCA", written as

$$PA_i = \sum\nolimits_{j\in(d_{ij}\le d_0)}^{n} \left[S_j \middle/ \sum\nolimits_{k\in(d_{kj}\le d_0)}^{m} D_k \right] \tag{2}$$

As stated previously, telehealth often works contingently upon physical visits of service providers (Sorensen et al., 2020), and thus takes effect within a provider's physical catchment area. Therefore, the "2-step virtual catchment area (2SVCA)" method, proposed by Alford-Teaster et al. (2021), builds upon the 2SFCA in Eq. (2), and formulates the virtual accessibility via telehealth such as

$$VA_i = \sum\nolimits_{j\in(d_{ij}\le d_0)}^{n} \left[S_j f(b_i b_j) \middle/ \sum\nolimits_{k\in(d_{kj}\le d_0)}^{m} \left(D_k f(b_k b_j)\right) \right] \tag{3}$$

where both the supply S and demand D are rescaled by a factor f, which is a function of the digital transmission speeds at both locations b_i (or b_k) and b_j. The conceptual model of 2SVCA is illustrated in Fig. 5.

We further refine the 2SVCA by (1) separating the effects of broadband qualities at supply and demand locations, b_j and b_k, and (2) accounting for the effect of broadband subscription rate at demand location, denoted by parameter a. The refined 2SVCA for virtual accessibility is formulated as

$$VA_i = a_i \sum\nolimits_{j\in(d_{ij}\le d_0)}^{n} \left[a_j S_j f(b_j) \middle/ \sum\nolimits_{k\in(d_{kj}\le d_0)}^{m} \left(a_k D_k f(b_k)\right) \right] \tag{4}$$

where the degrees of a facility S_j and a demand location D_k participating in telehealth services between them is a function of their broadband strengths $f(b_j)$ and $f(b_k)$. There are three additional parameters associated with broadband subscription rates: (1) a_j is applied on facility S_j so that only a portion of the facility with commercial broadband subscription provides quality telehealth service, (2) a_k is applied on demand D_k to capture that only those residents with consumer broadband subscription would contribute to quality telehealth services offered by S_j, and (3) a_i is applied to discount the initial virtual accessibility score assigned to demand location i because only this portion of residents have the consumer broadband subscription. Our case study assumes that broadband is affordable for any PCP facilities and thus a uniform $a_j = 1$. All other notations remain the same as in Eq. (3).

The refinement to the original 2SVCA method is significant. The broadband quality variable b is associated with locations and reflects *where it is available*, and its subscription rate a is associated with population and captures *to whom it is affordable*. The new formulation enables us to decompose contributing causes to disparity of telehealth accessibility.

Similar to the notion of assigning a binary 0–1 value to the distance decay function $f(d_{kj})$ or $f(d_{ij})$ in Eq. (2), a baseline 2SVCA method sets $f(b_j) = 1$ or $f(b_k) = 1$ in Eq. (4) for simplicity when broadband is available at supply location j or demand location k, respectively, and set their value as 0 otherwise. In a rare case, if the denominator in Eq. (4), $\sum\nolimits_{k\in(d_{kj}\le d_0)}^{m} \left(a_k D_k f(b_k)\right) = 0$, a supply facility S_j is surrounded with no valid demand via virtual connectivity, the term $S_j f(b_j) / \sum\nolimits_{k\in(d_{kj}\le d_0)}^{m} \left(a_k D_k f(b_k)\right)$ is invalid, coded as 0, and does not contribute to the overall accessibility. Here, any location with a minimum download and upload speed of 25 and 3 Mbps, respectively, is considered having the broadband access.

In implementing the 2SVCA, step 1 calculates the ratio of supply capacity at location j, S_j, over its surrounding total demands, D_k, within a physical catchment area d_0, but only those demand locations with available broadband service and the portion of demand with broadband subscription participate in the summation. For each demand location, step 2 sums up such ratios associated with its surrounding supplies, again within the same physical catchment area d_0; and once again, only those supply locations with valid broadband access participate in the

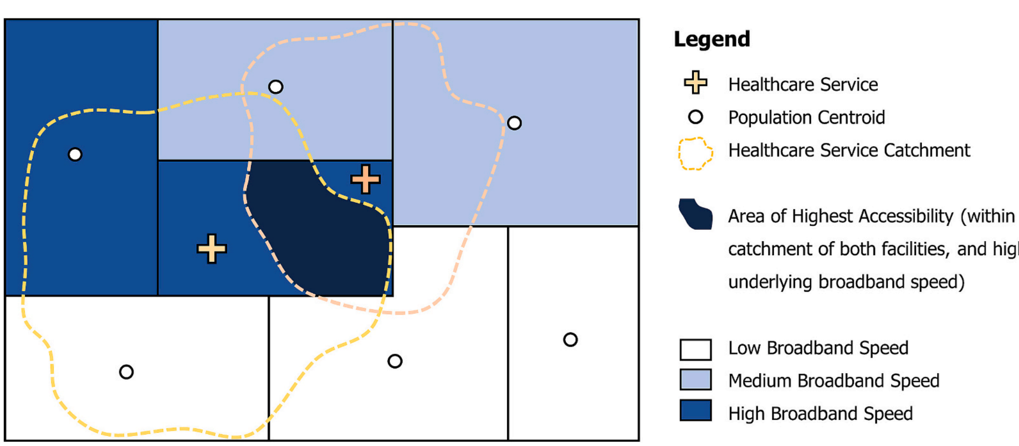


Fig. 5. Conceptualization of the 2-step virtual catchment area method (refined from Alford-Teaster et al., 2021).

summation. The result is further adjusted by the portion of demand there with broadband subscription. In other words, the virtual accessibility VA_i in Eq. (4) remains the summed-up supply-demand ratios like PA_i in Eq. (2) that is first filtered by a physical distance range, and then further limited to only the pairs where both supply and demand locations have broadband (i.e., with virtual connectivity). Refer to Wang and Liu (2023) for a step-by-step implementation of the 2SVCA method and its automated tool in ArcGIS Pro.

3.2. Regression model for detecting statistical significance in disparity

A regression model on an accessibility measure can be designed to analyze the disparity across rural-urban settings. Specifically, block groups in the reference category "rural" is coded as $x_1 = 0$, $x_2 = 0$; the category "low-density" is coded as $x_1 = 1$, $x_2 = 0$; and "urban" as $x_1 = 0$, $x_2 = 1$. The regression model is written as:

$$A = b_0 + b_1 x_1 + b_2 x_2 \tag{5}$$

where A is an accessibility score in a block group, the intercept term b_0 is the average score in reference category, namely "rural areas", coefficient b_1 is the difference of scores between the reference category and "low-density areas", and b_2 is the difference of scores between the reference category and "urban areas". The t-values for the corresponding coefficients indicate whether the average of accessibility score of a specific category differs from that of the reference category significantly.

4. 2SVCA sensitivity analysis

The formulation of 2SVCA in Eq. (4) has two parameters capturing how broadband quality and affordability are factored into telehealth accessibility, namely (i) parameter b indicating whether and at what quality broadband service is provided at a location, and (ii) its subscription rate a by residents. Here we examine the impacts of these two parameters on measures of telehealth accessibility.

Prior to any sensitivity analysis, we need to establish the baseline scenario for both the 2SFCA-derived physical accessibility based on Eq. (2) and the 2SVCA-derived virtual accessibility based on Eq. (4). Both contain a travel time catchment size d_0. Lee (1991) recommended a catchment of 30 min for primary care in the U.S. However, travel time estimated in ArcGIS assumes free-flow travel speed and is likely to be underestimated. In the study area, a prior study found an underestimation as much as about 5 min on average (Wang & Xu, 2011). As stated in Section 2, our estimation of the travel time matrix is in ArcGIS, and thus d_0 is set as 30–5 = 25 min. In this study, all PCP facilities have sufficient commercial broadband width speeds for uploads and downloads, thus $f(b_j) = 1$ for any supply locations S_j. Our sensitivity analysis focuses on $f(b_k)$ associated with demand location D_k. As all the locations in BRMSA have mean maximum download speed above 25 Mbps, we choose the mean maximum upload speed to measure broadband availability and define b_k, and its threshold setting $b_0 = 3$ Mbps according to FCC (Commission FC, 2015). The baseline scenario assigns $f(b_k) = 1$ if $b_k \geq 3$ Mbps, and 0 otherwise for demand locations D_k.

In order to examine the impact of broadband quality, a logistic growth function $f(b_k) = 1 - 1/\left(1 + e^{\beta(b_k - b_0)}\right)$ is proposed to capture a gradual response of the telehealth communication strength to consumer broadband width upload speed b_k. As shown in Fig. 6(a), $f(b_k)$ is binary (= 0 or 1) as a baseline, whereas in Fig. 6(b), $f(b_k)$ increases from 0 to 1 gradually with the growth rate parameter β controlling the increasing gradient.

Fig. 7 shows the density plots of the telehealth accessibility across block groups in various combinations of parameters d_0, b_0 and function $f(b_k)$ in comparison to the baseline (i.e., $d_0 = 25$, $b_0 = 3$ and $f(b_k)$=0 or 1). Almost all models reflect the same bimodal pattern with the exception of $d_0 = 5$, reflecting the relative robustness of the parameters in the 2SVCA model. As shown in Fig. 7(a), (b), and (d), an increase in the

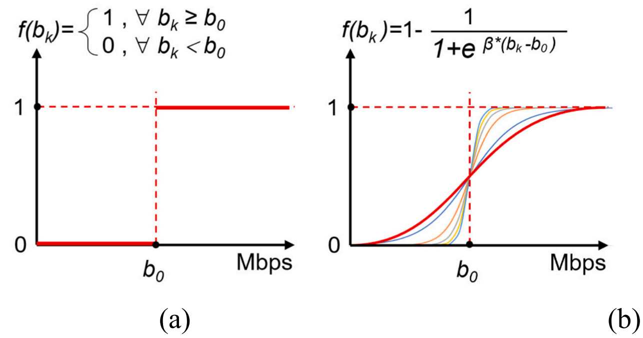


Fig. 6. Illustration of $f(b_k)$ defined as (a) binary, (b) logistic growth function.

broadband speed threshold b_0 (thus disqualifying more residents with broadband access) or a decrease in the travel time threshold d_0 (thus excluding more residents beyond the service catchment) tends to widen the disparity of virtual accessibility with similar impacts. A comparison between Fig. 7(a) and (b) indicates that the variation of virtual accessibility is more sensitive to the change in bandwidth speed threshold b_0 (every 2 M) than the change in travel time d_0 (every 5 min). Fig. 7(c) indicates that the growth rate β does not play a major in altering the variation pattern of accessibility when using a logistic growth function to define $f(b_k)$, and the patterns are largely consistent with those when using the simple binary $f(b_k)$. The results help support the choice of defining $f(b_k)$ as binary.

In order to detect the impacts of broadband availability $f(b_k)$ versus broadband affordability captured in subscription rate a, we calibrate the 2SVCA accessibility in absence of either and compare the results to that of the baseline with both considered. In other words, two hypothetical virtual accessibility (VC) measures are derived from Eq. (4) by assuming (1) uniform broadband subscription, i.e., $a = 1$ for all block groups (thus highlighting the impact of b alone), and (2) ubiquitous geographic availability of broadband, i.e., $f(b_k)$=1 for all block groups (thus highlighting the impact of a alone). The results are compared to the baseline. As shown in Fig. 8(a), the impact of $f(b_k)$ is limited as the results between the baseline and the scenario with varying broadband availability across block groups are largely consistent with a small number of diversions. This is understandable as only a small number (22) of the 570 block groups do not have any broadband service available (Fig. 3a). The results accounting for its effect or not differ little and their correlation coefficient is as high as 0.99. In contrast, Fig. 8(b) shows that the results with vs. without accounting for variability of broadband subscription rate differ significantly, and the diversions expand as the accessibility scores increase. In the study area, an average of 34.4 % households do not have broadband subscription, and 22.6 % block groups have a subscription rate lower than 50 %. This highlights that broadband affordability is a more prominent issue than its availability and affects far more population and especially the areas with concentrated disadvantaged population groups.

5. Results and discussion

This section presents the results on spatial and telehealth accessibility of primary care in the BRMSA. They are derived by the 2SFCA and 2SVCA methods with the parameter settings discussed previously as baseline: $d_0 = 25$ min, $f(b_k)$=0 or 1 based on threshold mean maximum upload speed $b_0 = 3$ Mbp, and a_i and a_k defined by broadband subscription rate at the census block group level. The results are shown in Fig. 9(a)-(b). The patterns for the two accessibility scores are largely consistent with higher values in the central urban areas including a narrow stripe extending southeast and lower values in surrounding rural areas. However, the pattern of physical accessibility is more smoothed

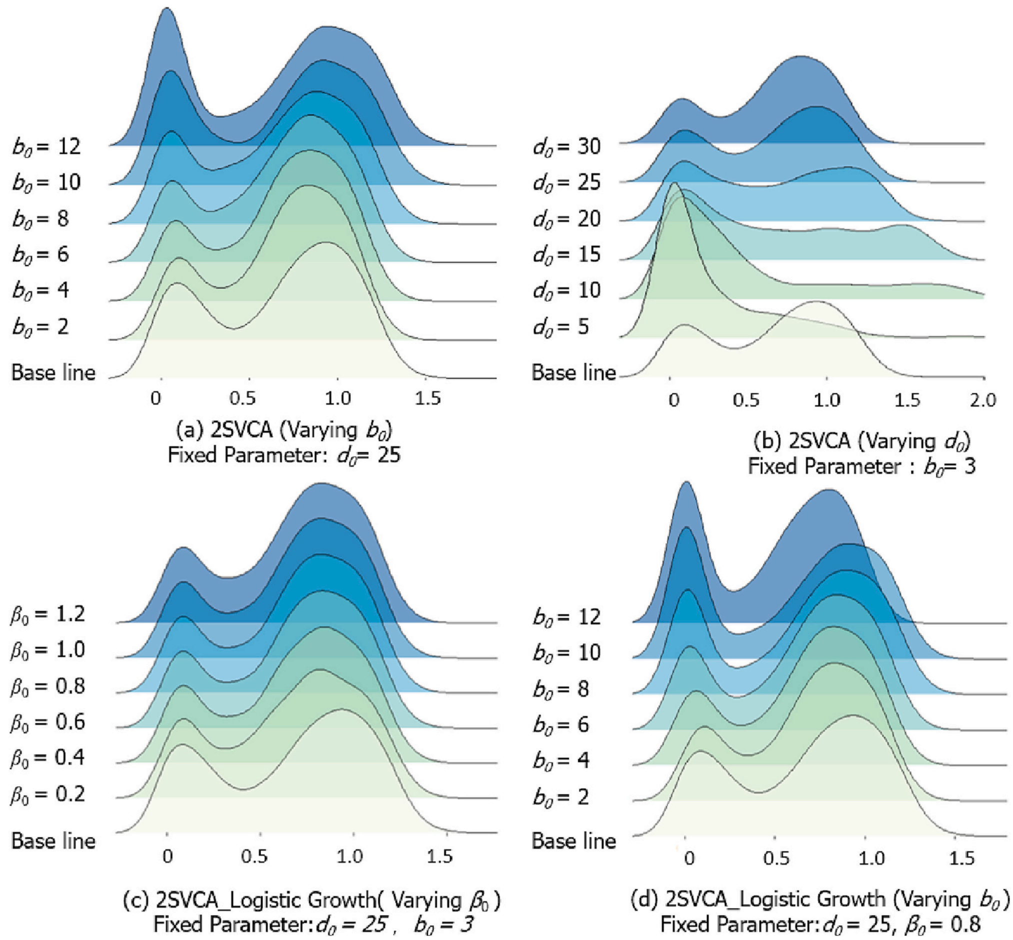


Fig. 7. Density plots of telehealth accessibility by the 2SVCA method with various parameters (the X-axis indicates accessibility scores.

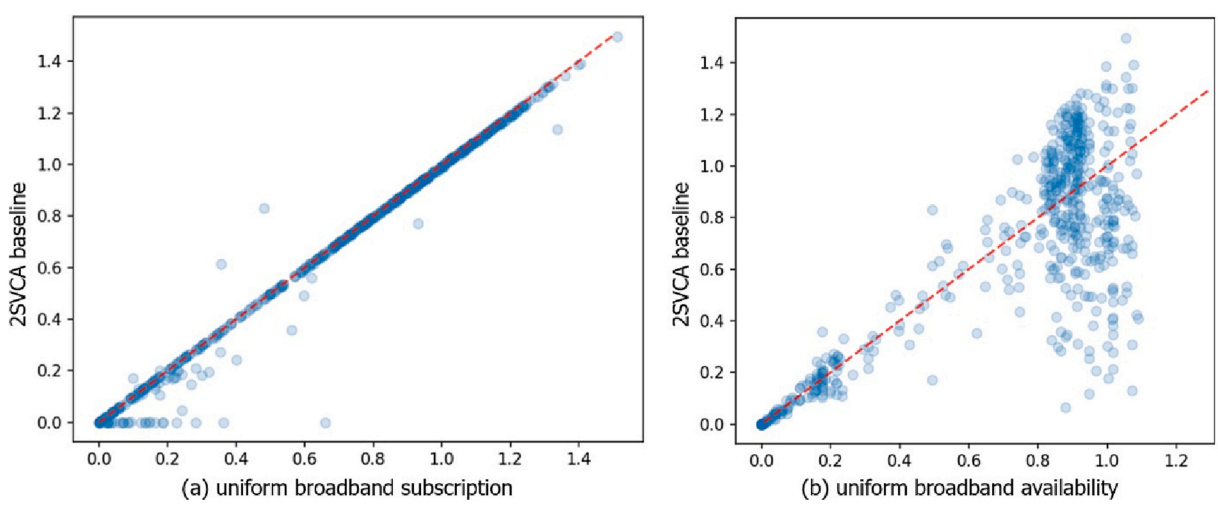


Fig. 8. 2SVCA accessibility comparisons: (a) baseline vs. uniform broadband subscription, (b) baseline vs. ubiquitous broadband availability.

within a narrower range (0–1.16) than that of virtual accessibility ranging (0–1.50), and the latter is more fragmented. The following examines the variations in more depth.

5.1. Variation of spatial and telehealth accessibility by urbanicity

We begin the examination of accessibility variations across areas of various urbanicity levels. Public health has a long tradition of examining the effect of urbanicity (i.e. degree of urbanization) on health behavior and outcome (Iyanda et al., 2022; Levit et al., 2020; Luo et al., 2022; Wang, 2020; Xu & Wang, 2015). In addition to the two measures by 2SFCA and 2SVCA, the average travel time to the nearest PCP is included as it has been the simplest and basic measure of accessibility. For the 2SVCA measures on telehealth accessibility, we also simulate the scenarios while assuming ubiquitous geographic availability of broadband or uniform broadband subscription in comparison to the baseline. The

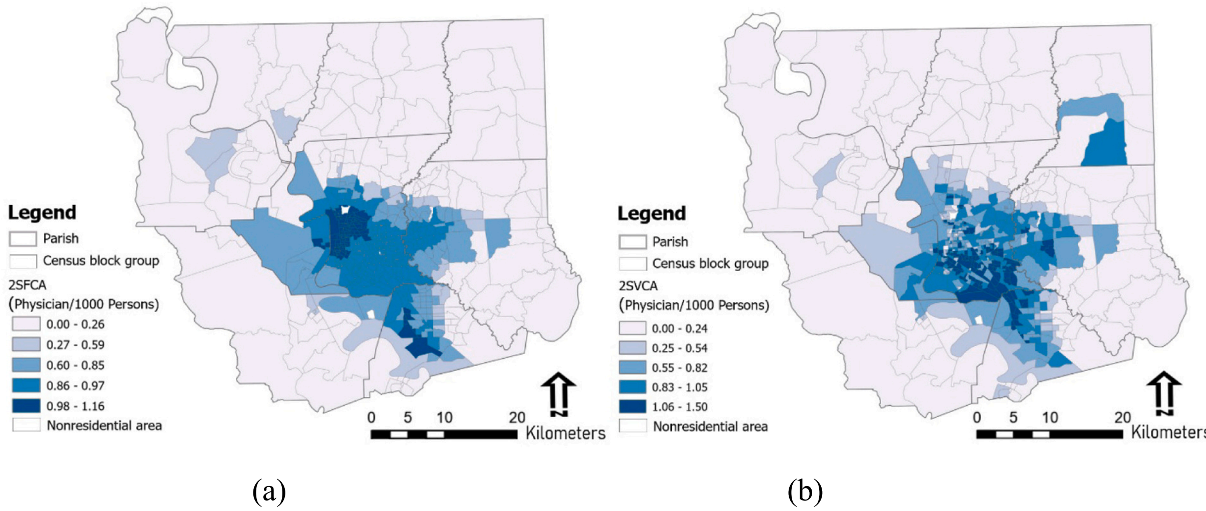


Fig. 9. (a) physical accessibility by 2SFCA ($d_0 = 25$ min), (b) Virtual accessibility by 2SVCA ($d_0 = 25$ min, $b_0 = 3$Mbps).

two hypothetical scenarios give us a glimpse of possible outcome when either barrier is removed for telehealth accessibility.

As illustrated in Sub-section 3.2, a regression model is constructed to test the statistical significance of differences in accessibility scores across urbanicity categories. The results are reported in Table 2. For example, for "Travel time from the nearest PCP", its average value for residents in rural areas is 10.6 min, those in low-density and urban areas travel 7.6 and 8.6 min less than rural residents on average, respectively, and such differences are statistically significant.[1] In all cases, the average accessibility scores by 2SFCA and 2SVCA show a consistent trend that rural areas have the lowest accessibility, followed by low-density areas, and then urban areas with the highest accessibility. Among the three 2SVCA measures, the simulation with a ubiquitous broadband availability would improve the average accessibility in rural areas from 0.279 to 0.303, and lower the accessibility in low-density and urban areas (via enabling more residents participating in and competing for telehealth service), and therefore narrow the urban-rural disparity. In other words, lack of broadband availability is mainly a rural problem and leads to a lower average virtual accessibility score than physical accessibility in the rural areas. The simulation with a uniform broadband subscription rate would improve the virtual accessibility across all areas (rural, low-density and urban). That implies that lack broadband affordability is likely an obstacle across the rural-urban continuum.

We now focus on the difference between 2SFCA and 2SVCA (baseline) and the variability across rural-urban categories. As show in Fig. 10 (a), the two are generally correlated with each other (with a correlation coefficient of 0.90). However, as stated previously, the 2SVCA scores have a wider variability range and a lower average than the 2SFCA. As further illustrated in Fig. 10(b), this pattern is consistent across all three urban-rural categories, and the 2SVCA scores have a lower mean and a wider band than those of 2SFCA in each. The rural-urban disparity in primary care accessibility experienced by residents via physical visits (i.e., urban > low-density > rural) remains and such a gap is even widened for telehealth access; and the variability within each rural-urban category is also higher for telehealth.

[1] For reasons stated previously, ArcGIS tends underestimate travel time consistently. Here travel time from the nearest PCP on average increases from 2.0 min in urban areas (UA) to 3.0 min in low density area (LD), and jumps to 10.6 min in rural areas (RA).

5.2. Disparities of spatial and telehealth accessibility across demographic groups

This sub-section examines disparities in accessibility by race (here Black is chosen as an example) and by socioeconomic status (here poverty status is chosen as an example). Note that the accessibility index is area based (census block groups), not individuals, and has an ecological nature. In other words, various racial-ethnical groups and both households of various poverty statuses may be present in a census block group. It is the variability of their concentrations (i.e., percentages) across areas that leads to disparity. Our approach here is to assess whether one group is disproportionally represented in areas of different levels of accessibility.

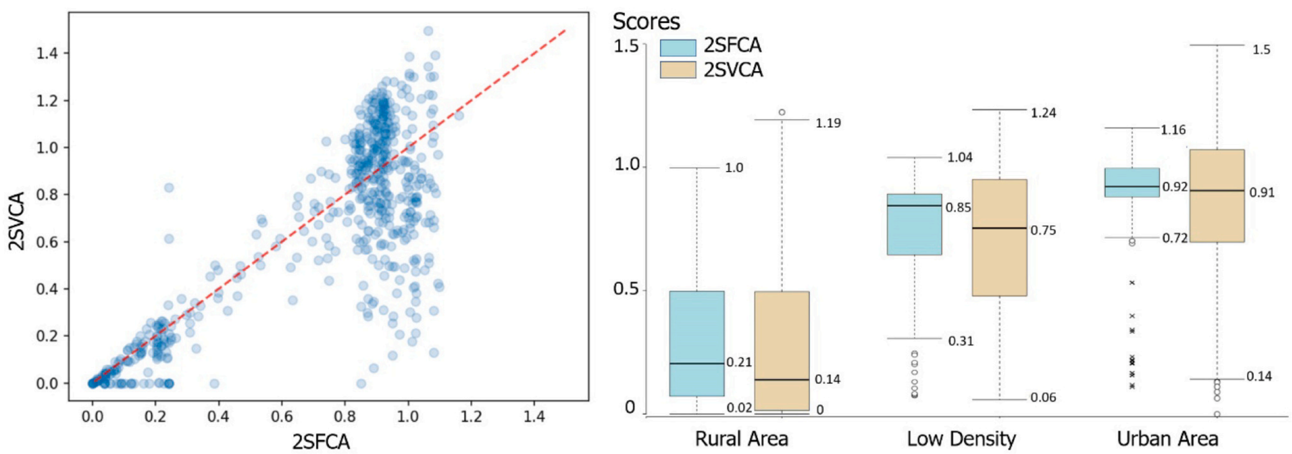
We begin with comparing the average accessibility values for different socio-demographic groups to gain some preliminary understanding of the issue. Specifically, the weighted average for each group across all block groups is calibrated by using the number of that group in an area as the weight. As reported in Table 3, Blacks in the study area on average have a shorter travel time from the nearest PCP and also a higher physical accessibility score by the 2SFCA than the overall population, and a similar trend is observed for households under the poverty line (shorter travel time and higher 2SFCA score). This observation indicates that disadvantaged population groups such as Blacks or those in poverty actually come ahead in terms of spatial accessibility either in proximity to PCP or PCPs per 1000. This may be attributable to that disproportionally high numbers of these groups tend to concentrate more in central city areas, and thus enjoy better spatial accessibility.

But such an advantage evaporates and is even reversed for virtual accessibility measured by the 2SVCA as both groups have lower accessibility scores than the overall population. The disadvantage is more pronounced in households under poverty than Blacks as the order of weighted average 2SVCA accessibility is: 0.608 for households under poverty <0.681 for Blacks <0.686 for all population. This reverse of fortune is largely attributable to an intersection of lower broadband subscription rates and lack of broadband service providers in the neighborhoods where they are disproportionally concentrated. The stronger negative effect on telehealth accessibility for households under poverty than Blacks suggest that poorer broadband affordability might be a major underlying cause. A definite answer awaits validation by future studies of data of individuals with socio-demographic attributes and associated broadband access.

Table 2
Disparity in average travel time and accessibility across areas of urbanicity.

	Travel time from the nearest PCP (minutes)	2SFCA accessibility score (physicians per 1000)	2SVCA accessibility score (physicians per 1000)		
			Baseline	If ubiquitous broadband ($f(b)$ = 1)	If uniform subscription (a = 1)
Reference: Rural (n = 164)	10.6*** (34.363)	0.318*** (17.139)	0.279*** (11.504)	0.303*** (12.647)	0.290*** (15.080)
Low density (n = 82)	−7.6*** (−14.111)	0.405*** (12.605)	0.416*** (9.992)	0.401*** (9.665)	0.427*** (12.826)
Urban (n = 324)	−8.6*** (−22.733)	0.582*** (25.555)	0.573*** (19.261)	0.559*** (19.022)	0.601*** (25.462)

Note: t-value in parenthesis.
*** Significant at 0.001.



(a) (b)

Fig. 10. Comparison between the 2SFCA and 2SVCA accessibility scores: (a) scatter plot, (b) box plots by rural-urban categories.

Table 3
Weighted average travel time and accessibility scores by demographic groups.

	Travel time from the nearest primary care provider (minutes)	2SFCA accessibility score (physicians per 1000) $d_0 = 25$	2SVCA accessibility score (physicians per 1000) $d_0 = 25$
All population	4.7	0.699	0.686
Black	3.9	0.778	0.681
Household under poverty	4.4	0.730	0.608

5.3. Integrated analysis on disparity of spatial and telehealth accessibility

Note that the above observations are preliminary and suggestive as they are based only on the weighted average scores. More in-depth analysis follows to examine the combined effects of urbanicity and socio-demographic structure on the variations of the accessibility scores of 2SVCA and 2SFCA and their differences. Similar to the regression model with dummy variables in Eq. (5), we design:

(1) one dummy variable for two categories of “household under poverty” (reference category: block groups with poverty rate below average rate 16.8 %),
(2) two dummy variables for three urbanicity types (reference category: rural), and
(3) four dummy variables for five categories of Black % (reference category: Black ≤20 %).

The results are summarized in Table 4. The effects of variables of household poverty level and urbanicity are consistent between 2SFCA and 2SVCA scores. Areas with an above average % of households under

Table 4
Regressions on 2SVCA and 2SFCA accessibility scores and their differences.

	2SFCA accessibility	2SVCA accessibility	2SVCA - 2SFCA
Intercept	0.298 (13.8)***	0.348 (12.7)***	0.050 (2.7)**
Household under poverty	−0.047 (−2.1)*	−0.173 (−6.0)***	−0.126 (−6.6)***
Low-density (LD)	0.395 (12.4)***	0.396 (9.9)***	0.002 (0.1)
Urban area (UA)	0.556 (24.0)***	0.615 (21.0)***	0.059 (3.0)**
Black 20–40 %	0.070 (2.5)*	0.016 (0.5)	−0.053 (−2.3)*
Black 40–60 %	0 (0.01)	−0.066 (−1.6)*	−0.066 (−2.5)*
Black 60–80 %	0.133 (3.7)***	−0.013 (−0.3)	−0.147 (−4.8)***
Black 80–100 %	0.153 (4.9)***	−0.102 (−2.6)*	−0.255 (−9.7)***
Adjusted R^2	*0.556*	*0.458*	*0.297*

Notes: t-value in parenthesis; Dummy variable reference category: “household under poverty” ≤ 16.8 %, “rural areas (RA)” for variables LD and UA, “Black 0–20 %” for the other 4 categories on Black %.
* Significant at 0.1.
** Significant at 0.01.
*** Significant at 0.001.

poverty have lower physical and virtual accessibility scores than their counterparts. The disparity in 2SVCA between the two categories of household poverty level is much more evident both in magnitude of difference and statistical significance. This provides stronger evidence for the previous observation that the disadvantage of economically deprived neighborhoods in telehealth accessibility is more pronounced than physical accessibility. Urban areas enjoy the highest physical and virtual accessibility, followed by low-density areas and then rural areas. The advantage of urban areas in 2SVCA accessibility over other areas is stronger than that in 2SFCA accessibility. Similar to the observation from the previous analysis on weighted averages of accessibility scores, the areas with higher concentration of Blacks tend to enjoy better physical accessibility (Black 80–100 % areas > Black 60–80 % areas > Black 20–40 % areas > Black 0–20 %). However, such an advantage is not transferred to telehealth accessibility as areas with Black 40–60 % experience a slight but significant drop from areas with the lowest Black rate (0–20 %) and areas with the highest concentration of Blacks (>80 %) have a more notable drop.

The regression result on the difference between the two accessibility measures (2SVCA-2SFCA) reinforces the findings. It is the areas with above average household poverty that experience a more evident drop from physical to telehealth accessibility. The most significant drop from physical accessibility to virtual accessibility are observed in the highest concentrations of African Americans (>60 %). Once again, it supports the finding that areas with higher concentrations of Black tend to have better physical accessibility, and the opposite can be said on virtual accessibility.

6. Conclusions

The concept of virtual accessibility reflects the relative ease (and quality) by which an activity or service can be accessed from a given location digitally, thus virtually. Similar to physical (or spatial) accessibility whereas a service is visited in person, virtual accessibility is an important location amenity for residents. For telehealth, studies suggest that it is often contingent upon physical visits of a service provider, and thus takes place within its spatial catchment area, e.g., a travel time or distance range. For measuring physical accessibility, the two-step floating catchment area (2SFCA) method accounts for the ratio of supply (physicians) and demand (population) that interact within a threshold travel time and yields an accessibility score interpreted as physicians per 1000 residents. The two-step virtual catchment area (2SVCA) method builds upon the 2SFCA and further considers additional constraints associated with broadband service availability and quality. This paper makes some significant refinements to the original 2SVCA method proposed by Alford-Teaster et al. (2021) Specifically, the refined 2SVCA differentiates whether the barriers to telehealth access come from absence of broadband service providers in an area or lack of affordability for any population groups. The former reflects where it is available, and the latter captures to whom it is affordable. The new formulation decomposes contributing factors to disparity of telehealth accessibility.

This study examines telehealth accessibility to primary medical care, in comparison to spatial accessibility, in Baton Rouge MSA, Louisiana, in 2020. Based on the results from both methods, we examine the disparities across geographic areas of various urbanicity levels and with various concentration levels of demographic groups (e.g., poverty status, Blacks). In the study area, absence of broadband service is mainly a rural problem and leads to a lower average virtual accessibility score than physical accessibility in rural areas. On the other side, lack of broadband affordability is a challenge across the rural-urban continuum, and is disproportionally associated with high concentrations of disadvantaged population groups such as households under the poverty level and Blacks.

Overall, both physical and telehealth accessibility scores decline from urban areas to low-density areas and then rural areas, and such an urban advantage is even larger in telehealth accessibility than physical accessibility. In other words, the poorer accessibility in rural areas is more pronounced for telehealth than physical visits. This observation dampens the hope that telehealth would help level the playfield as rural residents in Louisiana face double challenges of poor availability and affordability of broadband service. For physical accessibility, neighborhoods of higher concentrations of Black have better proximity as well as higher 2SFCA accessibility scores for visiting primary care physicians, consistent with a finding termed “reversed racial advantage” in a previous study (Wang et al., 2020). Such an advantage in physical accessibility is not transferred to areas with higher concentration of poverty level, neither replicates when it comes to telehealth accessibility. In fact, areas with higher concentration of poverty suffer from disadvantages in both accessibility measures and more severe in telehealth access; and areas of higher Black concentration correspond to poorer telehealth accessibility. In short, when it comes to telehealth, even greater disparities are observed across rural-urban continuum and across areas with various concentrations of disadvantaged population groups.

There are several limitations and possible extensions to this study. First, the current formulation of 2SVCA for measuring virtual accessibility assumes that patients seek telehealth service within the same physical catchment area. Telehealth, governed by state and federal policies, has expanded significantly in response to COVID-19 (U.S. Department of Health & Human Services, 2022), and may reach market beyond the areas served traditionally by physical visits. Further refinements for the method need to be informed by empirical studies that capture these changes. Secondly, both our measures of accessibility (2SFCA and 2SVCA) are location based, and thus reflect location merits associated with a geographic area. Therefore, our study on the disparity of accessibility in socio-demographic groups emphasizes variability across areas of various concentration levels of these groups. Within each area, there is presence of different groups. In other words, the study has an ecological nature and cannot be strictly interpreted as differences between individuals of these socio-demographic attributes or individual behaviors (Robinson, 1950). Stronger evidence needs to come from studies based on data of individuals. Finally, the purpose of this study is to build the foundation for follow-up work to examine how disparity of accessibility impacts people’s actual utilization of the service (here, primary care), which then affects outcome of the care. Examining the linages in the full spectrum of accessibility-utilization-outcome in health care is critical for public health as any reduction in health disparity begins with closing the gap in health care access (Wang & Onega, 2015).

There are several implications for public policy. First, our conceptualization of telehealth accessibility is built on the observation that telehealth is often supplementary to physical visits to service providers, and thus contingent upon and inherit the same constraints associated with physical accessibility. This assumption may well change as telehealth continues to evolve as technologies advance and policy adapts. Secondly, while physical access is driven by where service providers and residents are and transportation connections between them, telehealth access is affected by more forces such as internet availability and affordability. Whether these overlapping effects alleviate or aggravate the existing disparity in health care access largely relies on where we invest and prioritize our resource in transportation and telecommunication. A balanced approach calls for an integrated analysis and assessment of physical and virtual accessibility as adopted by this study. Finally, for telehealth to play an important role in driving up overall access as well as improving health care equity, policy needs to be twofold: expanding quality internet services to the blind spots in geographic coverage and bringing down the financial and cultural barriers for targeted population groups to adopt the services.

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CRediT authorship contribution statement

All authors read and approved the manuscript, and each author participated sufficiently in, and stands by, the validity of this work. LL implemented the study and drafted the manuscript. JA-T and TO participated in conceptual development and provided manuscript and scientific review. FW designed the study, directed its implementation, revised the manuscript, and gave final approval for the submission.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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Data availability

The data underlying this article will be shared on reasonable request to the corresponding author.

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