
Full Paper

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Abstract

The Affordable Care Act (ACA) has altered the healthcare landscape in the US. ACA mandated US residents to obtain health insurance. However, having insurance does not necessarily provide access to healthcare. These legislation changes made it imperative for researchers to explore into more detail the problem of healthcare accessibility. Recent advances in measuring healthcare accessibility have been fueled by a rapid improvement of the Floating Catchment Area (FCA) methodologies. This current study summarizes the abundance of existing knowledge on metrics of spatial accessibility and more specifically, the FCA family. Organization of previous studies in a more comprehensive manner can assist both researchers and practitioners who are struggling to identify which FCA methodology would best fit their needs. And finally, the study provides a step-by-step analysis methodology, which is beneficial for decision makers when considering solutions to the problem of physician shortage areas.

Keywords

Spatial Business Intelligence, Business Analytics, Knowledge Management, Big Data and Knowledge Management

Introduction

Recent healthcare reforms in the US, especially the Affordable Care Act, have made it imperative for professionals to provide better quality of care and reach out to a much larger population. In spite of the ever-increasing amount of funds allocated to healthcare (17.9% of the nation’s GDP according to the World Bank), population wellness and healthcare are still insufficient when compared with other countries. In fact, the US healthcare system is ranked 37th in performance (Murray & Frenk, 2010) which demonstrates that the state of US healthcare is not adequately meeting the needs of the population. Thus, there are heeding calls to address the gap in providing better health services to a larger portion of the population.

This study explores the outreach of healthcare services and addresses the population’s overall access to healthcare. A comprehensive investigation of different models for quantifying healthcare accessibility was conducted. Consequently, the findings of this research can provide a better understanding of the challenges associated with healthcare accessibility. There are a number of innovative approaches for assessing healthcare accessibility. These methods compute an accessibility index within several geographical settings. Collectively, they are known as the floating catchment area (FCA) methodologies “family”.

FCA methodologies are vector-based algorithms that utilize concepts in geography, econometrics, and applied physics. The raster-based algorithm family is out of the scope of this study, as FCA is a more
preferable method for measuring healthcare accessibility (Guagliardo 2004). Since the inception of the two-step floating catchment method (2SFCA) (Luo and Wang 2003; Radke and Mu 2000), there are many variations of the models, suggesting different ways of improvement. Given their immediate applicability in accessing various accessibility metrics, the purpose of this study is to raise awareness in the healthcare community regarding these methodologies. Consequently, the goals are to introduce the FCA methodologies, suggesting a step-by-step approach when performing them, highlight their utility and weaknesses, and provide future research directions.

To demonstrate the efficacy of the FCA methodologies family, we chose Los Angeles County, California as the research setting because it represents a population as diverse as the US. It is expected that this analysis can be utilized by researchers and practitioners to aid in the decision-making process of improving healthcare accessibility and improving the quality of care in the US.

The current study contributes to existing knowledge in several aspects. First, it provides a comprehensive literature review of the FCA methodologies family and it assesses the advantages and disadvantages of the different methods. Second, it presents the processes associated with two FCA methodologies in a more comprehensive manner and it describes the analysis methodology, enabling faster adoption and inviting more robust improvement of the FCA methodologies family. Third, it points out publicly available resources used in this research. And finally, its conclusion reflects on how the assessment of these methodologies can inform other researchers in deciding which methodology to use and provides an overview of these methodologies’ applicability to other disciplines.

**Background**

The increasing availability of geographic information systems (GIS) in health organizations, together with the proliferation of spatially disaggregate data, has led to a number of studies that have been concerned with developing measures of access to healthcare services (Higgs 2004). In order to summarize the existing literature and propose a step-by-step method for measuring healthcare accessibility, the first need is to understand what approaches have been suggested in prior studies and to conduct a comprehensive investigation of these models. There is an abundance of accessibility research, predominantly focused on the healthcare domain. Thus, the aim is to organize the work and offer a more comprehensive method for exploring the relationship between geographic access, utilization, quality of care, and healthcare outcomes. An examination of prior work and a critical evaluation of some of the most common accessibility measures was conducted. Further, areas were identified where more research is needed to improve the process of quantifying healthcare accessibility. More specifically, there was a focus on the FCA family of metrics, as it employs principles from gravity-based models to incorporate supply, demand, and distance in their characterization of the spatial accessibility of healthcare resources. Unlike traditional gravity models, the FCA metrics provide an output in highly interpretable container-like units, e.g., physicians per person (Delamater 2013) which are more easily understood by non-specialists. The following literature review summarizes these studies and identifies gaps which can be addressed to improve the accuracy of the healthcare accessibility index.

**Healthcare Accessibility**

There are a number of definitions related to accessibility in the healthcare context. Some of them consider the consumers’ willingness to enter the healthcare system, or the fit between the clients and the system (Penchansky and Thomas 1981), or the influence of financial, informational, and behavior modalities which go beyond the geographical access (Aday and Andersen 1974). Another study (Gulliford et al. 2002) investigates the difference between “having access” to healthcare and “gaining access”, where the former is related to the availability of services and the latter refers to whether individuals have the resources to overcome financial, organizational and socio-cultural barriers in order to utilize that service. For the purposes of this paper, the definitions proposed by Khan (1992), which are based on the interaction between the individual and the healthcare system, are used. More specifically, the notion that accessibility is the “availability of a service moderated by space, or the distance variable” (p. 275) is used and this information is represented using travel time, road, or map distances as suggested by Higgs (2004). As mentioned earlier, there are a number of barriers that patients need to overcome in addition to the physical distance to access healthcare services. In the following sections these measures of accessibility are examined in more detail, focusing in particular on the role of geographical factors.
Spatial Decompositions

Measuring and predicting access to healthcare services is important for decision makers, so they can better plan better the distribution of facilities and practitioners so that all individuals in the community have access to them. This is especially important for underserved populations which often times have greater needs but more limited access to social programs. One such method to delineate the service area of providers delivering social services and to produce a probability metric that maps the equity of the program of services for each household is suggested by Radke and Mu (2000).

The method they propose measures access to social services for each household and makes adjustments among service providers to better accommodate under-served regions. Radke and Mu (2000) considered the problem of location-allocation and decomposing service regions to predict access and generate equity. Overall, their model computes the ratio of suppliers to residents within a service area centered at the supplier's location and sums up the ratios of residents living in areas where different providers overlap (Luo and Wang 2003). Although the results support the creation of polygon-polygon representations of the location-allocation substitution model, there is uncertainty in the application of the model. For example, it relies to a great extent on the delineation of a service area defined for specific domain and any modification would impact the empirical outcome of the model. Further, the model does not take into consideration the regions not serviced by the original supply set. Thus, the proposed method for measuring spatial decompositions does not offer the most accurate prediction of access to social programs.

Another approach for measuring spatial accessibility is by using the FCA methods. FCA has been used to inform the US Department of Health and Human Service to designate the Health Professional Shortage Areas (Luo 2014; Luo and Wang 2003). The following literature review summarizes prominent FCA methodologies and identifies gaps which can be addressed to improve the accuracy of the healthcare accessibility index.

Floating Catchment Area Methodologies Family Review

Since their inception, FCA methodologies have proliferated and increased in both sophistication and rigor. However, the adoption of the methodologies remains fragmented. There are no uniform application criteria. This review is intended to inform researchers and practitioners about different types of FCA methodologies and provide a comprehensive summary of the advantages and disadvantages of each method.

Two-Step Floating Catchment Area (2SFCA)

The FCA methodologies family started with the two-step floating catchment area method (2SFCA) proposed by Luo and Wang (2003). This method consists of two steps dealing with healthcare access; the first step is concerned with the supply and the second step is concerned with the demand. The relationship between supply and demand is underpinned by the gravity models, i.e. how both groups interact with each other. Travel distance and drive time analysis form “catchments”, encompassing supply-to-demand and demand-to-supply areas of effects. In short, the two-step floating catchment area method can be interpreted as follows:

- Step 1: Given a default 30-minute drive time (catchment) from a particular healthcare provider, sum up the total population that the supplier can reach within that drive time, then compute a provider-to-population ratio. In the case of an individual physician, the provider ratio is 1 to the total population reached.
- Step 2: Given a 30-minute drive time (catchment) from a particular population center, obtain the previously computed provider-to-population ratio of each healthcare provider that is located within that drive time. Compute the accessibility index by summing up all provider-to-population ratios.

Advantages:

The index created by the 2SFCA is easy to interpret, as opposed to its predecessor, the polygon-polygon representation (Radke & Mu, 2000). By utilizing drive time analysis, 2SFCA embeds driving obstacles and impedances, an improvement over buffer zones. The method also considers the interaction between supply and demand.
Disadvantages:

Even though 2SFCA is an innovative method, it has several limitations. First, 2SFCA assumes that all providers and population centers that reside within the designated drive time are equal in access. In other words, there is no difference between a 10-minute drive and a 25-minute drive. Additionally, the 2SFCA does not perform well in rural areas, since the 30-minute catchment size does not capture sparse population well (Haggerty et al. 2014; McGrail and Humphreys 2009). Furthermore, the 2SFCA is concerned with only one source of transportation, i.e. personal vehicles. Obviously, an expansion to other modes of transportation is needed.

Enhanced Two-Step Floating Catchment Area (E2SFCA) Method

To address some of the limitations of the two-step FCA, Luo and Qi (2009) present the enhanced Two-Step Floating Catchment Area (E2SFCA) method. As the name suggests, the enhanced version is built upon previous research and segregates different travel times. By assigning different weights associated with different travel time zones, it accounts for distance decay. Travel preference is thought to be decreasing while moving further away from the point of origin, hence the coinage of the term “distance decay”. The E2SFCA can be interpreted as follows:

- Step 1: Given three drive time zones (catchment) from a particular healthcare provider: 0-10, 10-20, and 20-30 minutes, sum up the total population that the supplier can reach within each zone, then compute a provider-to-population ratio. In the case of an individual physician, the provider ratio is 1 to the total population reached for each zone.
- Step 2: Given three drive time zones (catchment) from a particular population center: 0-10, 10-20, and 20-30 minutes, obtain the previously computed provider-to-population ratio of each healthcare provider that resides within each zone. Compute the accessibility index by summing up all provider-to-population ratios.

Advantages:

This enhancement is another special case of the gravity model discussed above. Luo and Qi (2009) discovered that the E2SFCA reveals a spatial accessibility pattern that is more consistent with intuition and delineates even more precisely spatially explicit health professional shortage areas. The advantage of E2SFCA is that it considers distance decay in both steps, mimicking travel preferences between close and far destinations.

Disadvantages:

The weights between different travel time zones are not properly addressed in E2FSCA. By providing a set of Gaussian weights for each time zone, the authors composed an initial weights composition. Gaussian weights were derived from a normality assumption of the data. In other words, for each time zone, population’s and providers’ distribution lie along the bell curve distribution. The smaller distance between providers and population centers is, the smaller the statistical variance would be. This variance then inform the data distribution percentage, which in turn inform the Gaussian weights. However, the article does not explain why the weights were chosen. Nevertheless, the study called for future research with applying different sets of weights. Despite these shortcomings, E2FSCA is the most preferred method of the family.

Various Improvements to 2FSCA and E2SFCA

The advent of 2SFCA and E2SFCA has enabled the need for extending the efficacy of the FCA methodologies family. Improvements upon both methods come from many different aspects. Below is a brief discussion of the most notable improvements.

- *Optimized 2SFCA* (Ngui and Apparicio 2011): The focal improvement of the Optimized 2SFCA is weighted calculation of travel times. By using the Canadian Health Survey in 2005, the authors calculated demand by considering the proportion of medical users. In addition, in contrast with using individual physicians, the method utilized aggregated physician counts in the associated medical clinics. However, the method is only accurate for small distances, which are lower than 500 meters (approximately 550 yards).
Two-Step Floating Catchment Family Methodologies

- **Kernel Density 2SFCA** (Dai and Wang 2011; Polzin et al. 2014): Using kernel density (Epanechnikov function) as a catalyst to improve 2SFCA, the method transformed the discrete and stepwise accessibility distance decay in E2SFCA into a continuous and step-less distance decay. The improvement of the Kernel Density 2SFCA also introduced a health needs index and a commuting index by ways of considering principle component analysis on various demographics and socioeconomic variables. The indices were borrowed and condensed from (Wang and Luo 2005) applying the US notion of Health Professionals Shortage Areas to Portugal.

- **Variable Catchment size for 2SFCA** (Luo and Whippo 2012; McGrail and Humphreys 2014): This method proposed a flow diagram in determining the catchment size between supply and demand. The flow diagram depicted a decision process to increase the catchment size in small increments until a predetermined base population and a provider-to-population ratio is reached. The added two steps of calculating the catchment sizes precede the E2SFCA steps. A further exploration of robust catchment size determination has also been proposed in the study.

- **Three-step FCA** (Wan et al. 2012): The three-step FCA was designed to compensate for the overestimation in the demand. The method accounts for surrounding supply sites as competition by computing a selection weight. The selection weight was implemented into both catchment calculations.

- **Modified 2SFCA** (Delamater 2013): Modified 2SFCA addresses the inherent underestimation and overestimation in three-step FCA (Delamater, 2013). Modified 2SFCA employs both relative and absolute distance between supply and demand in a pairwise mechanism. This builds upon the three-step FCA method and provides a compensation for the suboptimal supplier distribution.

- **Multi-transportation mode 2SFCA** (Mao and Nekorchuk 2013): This variation of the E2SFCA utilizes different types of transportation as weights. It assigns a weight for each mode of transportation in the calculation of the provider-to-population ratio and the spatial accessibility index.

- **Huff model-based 2SFCA** (Luo 2014): The Huff Model is a probabilistic gravity model that was designed to predict consumer behavior within competing retail locations (Huff 1963; Huff 1964). Essentially, the Huff Model provides a probability value for a particular demand area in relation to a particular supply location. The probability calculation adjusts for population demand, and is integrated into both catchments.

- **Commuter-based 2SFCA** (Fransen et al. 2015): Focusing on bidirectional travel, the commuter-based 2SCFA considers the routine trip observed in frequent travel to and from a supply location. Commuter-based 2SFCA is an extension of the family to a different domain, i.e. daycare center access. Though commuting behavior does not coincide with healthcare visits in patient scenarios, it should be taken into consideration for the current study.

**Proposed Solution**

The myriad methods in the FCA family that have proliferated in recent years have not paved the way for a better assessment or more accurate measures of healthcare accessibility. Rather, it has actually hampered the robustness of the newly developed FCA methods. FCA is an inherent transdisciplinary method (utilization of econometrics, applied physics, and geography in the public health domain), and as such, it proposes that an analysis methodology can constructed to facilitate and permeate future FCA research.

The proposed methodology is designed to encourage the use of GIS. First, the two FCA methods, viz. the original 2SFCA and ESFCA, are reexamined to provide the overall narration as well as the mathematical notation. These two techniques were chosen as they encompass the majority of steps required for subsequent FCA methods. Second, a brief description of the most common GIS datatypes is provided. Each datatype bears a pseudo symbol to help non-specialists following the analysis from obtaining the data to displaying the results.
Two-Step Floating Catchment Area (Luo and Wang 2003)

Overview
Generate a 30-minute drive time zone (catchment) with respect to the provider site.
Compute the provider-to-population ratio at each provider location.
Generate another 30-minute drive time catchment with respect to the population site.
Compute the spatial accessibility index for each population site.

Step 1
Calculate provider-to-population ratio $R_j$ at each provider location $j$:
\[
R_j = \frac{S_j}{\sum_{k \in \text{Distance}(k,j) \leq d_0} P_k}
\]

Step 2
Calculate the spatial accessibility index $A_i^F$ for each population site $i$:
\[
A_i^F = \sum_{j \in \text{Distance}(i,j) \leq d_0} R_j
\]

Mathematical Notation Explained
- $S_j$: medical capacity at each provider $j$
- $R_j$: provider-to-population ratio
- $P_k$: population site $k$
- $d_0$: travel threshold
- $\text{Distance}(k,j)$: travel time between $k$ and $j$
- $A_i^F$: Spatial accessibility index of each population site $j$
- $\text{Distance}(i,j)$: travel time between $i$ and $j$

Enhanced Two-Step Floating Catchment Area (Luo and Qi 2009)

Generate three drive time zones, 0-10, 10-20, and 20-30 minutes with respect to the provider site. Assign Gaussian weights for each zone (1.00; 0.42; 0.03) (Luo 2011)

Compute the provider-to-population ratio at each provider location with the assigned weights.

Generate three drive time catchments similar to that of the provider. Compute the spatial accessibility index for each population site with the assigned weights.

Step 1
Calculate provider-to-population ratio $R_j$ at each provider location $j$:
\[
R_j = \frac{S_j}{\sum_{r=1}^{3} \sum_{k \in \text{Distance}(k,j) \leq d_0} P_k W_r}
\]

Step 2
Calculate the spatial accessibility index $A_i^F$ for each population site $i$:
\[
A_i^F = \sum_{r=1}^{3} \sum_{j \in \text{Distance}(i,j) \leq d_0} R_j W_r
\]

Mathematical Notation Explained
- $S_j$: medical capacity at each provider $j$
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- $d_0$: travel threshold
- $\text{Distance}(k,j)$: travel time between $k$ and $j$
- $A_i^F$: Spatial accessibility index of each population site $j$
- $\text{Distance}(i,j)$: travel time between $i$ and $j$
- $W_r$: Gaussian weight for each zone (1.00; 0.42; 0.03)
GIS Datatypes Description

Overall, there are four different datatypes. They are depicted as follows:

<table>
<thead>
<tr>
<th>Type</th>
<th>Symbol used</th>
<th>Description</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tabular</td>
<td>(t)</td>
<td>Generic datatype in table and row format</td>
<td>Census data</td>
</tr>
<tr>
<td>Point</td>
<td>(p)</td>
<td>A single location on the map</td>
<td>Physician location</td>
</tr>
<tr>
<td>Line</td>
<td>(l)</td>
<td>A vector from point A to point B</td>
<td>A road</td>
</tr>
<tr>
<td>Polygon</td>
<td>(g)</td>
<td>An enclosed shape on the map</td>
<td>A Census tract</td>
</tr>
</tbody>
</table>

Analysis Methodology

We conducted an analysis comparing these two methods. This was performed on an Intel Xeon 2.1 GHz chipset on a Windows 8.1 PC with 16 GB RAM. We used Esri’s ArcGIS Desktop 10.2.2 with the Network Analyst Extension. The overall computer processing time for 2SFCA was about six hours and the E2SFCA was about ten hours. Following are the steps we performed.

1. Obtain Census Data (t)
The appropriate population Census data (t) was obtained for the study site - Los Angeles County, California. The 2010 Census total population data was obtained at two levels: Census tracts and block groups (http://factfinder.census.gov/).

2. Obtain TIGER Shapefiles (g)
TIGER Shapefiles (g) (https://www.census.gov/geo/maps-data/data/tiger-line.html) contain geographic boundaries of the US. The Census tracts and block groups (t), filtered for Los Angeles County, were joined with the corresponding TIGER Shapefiles (g). We cleaned the data by removing all non-alphanumeric characters and incorrect geographical joins.

This 2012 Center for Medicare and Medicaid Services (CMS) dataset provides addresses of all physicians who claim Medicare payments. After limiting the data to only Los Angeles County and including only physicians who practice “Emergency Medicine, General Practice, and Family Practice”, there were a total of 2,669 physicians. Then we geocoded the addresses. Geocoding involves taking an address and providing the corresponding longitude and latitude coordinates.

4. Obtain the road network datasets
We obtained road network datasets (l) from ESRI Streetmap Premium Services.

We transformed the Census block shapefile (g) to obtain the longitude and latitude of the centroid (p). We used the information to calculate the population-weighted centroid of the Census tract. The calculation is as follows:

\[
\text{Longitude } x_t = \frac{\sum_{i=1}^{N_b} p_i x_i}{\sum_{i=1}^{N_b} p_i} \quad \text{Latitude } y_t = \frac{\sum_{i=1}^{N_b} p_i y_i}{\sum_{i=1}^{N_b} p_i}
\]

Where \( i \) is the Census block inside a particular Census tract; \( p_i \) is the population of each Census block; \( x_i \) and \( y_i \) are the longitude and latitude of each Census block, respectively. The calculation derives the longitude, \( x_t \), and latitude, \( y_t \), of the Census tract (t). These longitude and latitude coordinates are designed to compensate for the difference in population concentration in each Census tract. This calculation omits non-residential Census tracts such as airfield and military bases. Including such tracts is interesting and...
worthy of discussion in regards to healthcare access, most notably in emergency medicine. However, we excluded these tracts in the current analysis.

6. Allot the first catchment area (g)
The first catchment area was performed by using ArcGIS’s Network Analyst tool. The drive time analysis was done in the Service Area option utilizing Dijkstra’s algorithm. The geocoded physician data (p) mentioned above was used to perform the analysis with a 30-minute drive time for 2SFCA and discrete rings of 0-10, 10-20, and 20-30 minute drive time for E2SFCA.

7. Calculate the provider-to-population ratio
A spatial join linked the first catchment (g) and the population-weighed centroids of the Census tracts (p) which resided within the catchment. This procedure aggregated the total population of all joined Census tracts within the catchment. For E2SFCA, the total population was multiplied with the weights: 1.00, 0.2, and 0.03 with respect to 0-10, 10-20, and 20-30 catchments. These catchments (g) were then joined with the physician data (p). For 2SFCA, since each physician was the sole healthcare provider at his or her location, the provider-to-population ratio calculation was equal to the reciprocal of total population. For E2SFCA, the provider-to-population ratio was equal to the summation of the weighed total population.

8. Allot the second catchment area (g)
Similar to the first catchment, the second catchment (g) analysis was performed using Network Analyst. It is notable that the population-weighed centroids (p) may or may not reside on an optimal location alongside the road data (l). There are three ways to account for this shortcoming: (1) increase the location tolerance; (2) manually move centroids; or (3) create a new road that connects to the centroid (l). The current analysis doubled the tolerance and utilized the second option.

9. Calculate spatial accessibility index
We performed another spatial join to link each catchment (g) with each physician location (p). For 2SFCA, we summed all provider-to-population ratios to compute the spatial accessibility index. For E2SFCA, the provider-to-population ratios of physicians who reside in different travel zones were multiplied by the appropriate weights (similar to step 7). Then, the total weighted provider-to-population ratios resulted in a spatial accessibility index. The catchments (g), which contained this information, were joined with the Census tract (g).

10. Display 2SFCA on a map.
Each Census tract (g) should contain a spatial accessibility index. A choropleth map was produced by using color-coded quintiles with the Jenks natural breaks method, where the lighter the color, the lower the health accessibility index.
Figure 1 and Figure 2 offer different healthcare accessibility indices. The E2SFCA displays certain pockets that have high accessibility index while the 2SFCA presents a centrality of healthcare accessibility. The E2SFCA provides more subtle accessibility because of drive time zone differentiation. This improvement is imperative for decision makers concerned with total population healthcare accessibility index.
Furthermore, the analysis methodology offers a solid foundation for conducting FCA methodology family research. Other FCA methods mentioned above can be applied by modifying some of the steps in this analysis.

**Practical Implications**

The current paper not only contributes to research, but also it provides important implications for practice. First, the study offers decision makers a comprehensive summary of existing methods for measuring healthcare accessibility. This information can be of critical significance when assessing physician shortage areas. These areas would have higher priority for decision makers when considering building new facilities or offering incentives for relocating. In addition, the current study organizes existing knowledge on healthcare accessibility by providing a corpus of the FCA methodology family.

Second, we offer an easy to follow analysis methodology, encouraging replication and improvement. This methodology contains detailed instructions and explanations which are accessible to a much broader audience compared to prior studies. Our study can be used as a guideline by both researchers and practitioners who are interested in pursuing further research on healthcare accessibility.

**Discussion and Limitations**

The guidelines provided for measuring accessibility may also be extended to other domains beyond healthcare. We hope that others would consider the FCA methodology family and employ it in a variety of disciplines such as education, finance, or public administration.

The current study does not come without limitations. First, we used only physician data. Including hospital data in the analysis would be more informative. Hospitals can provide unequivocal healthcare services compared individual physicians. However, in order to be consistent with prior studies, only physician data was used.

The second limitation of this study is the generalizability of the results. We used only data from Los Angeles County. However, the County is the most populous and diverse in the US according to the 2010 US Census (http://quickfacts.census.gov/qfd/states/06/06037.html), it could be considered representative of the total population. On the other hand, we used a small dataset to evaluate the utility of the FCA methodologies. Other researchers are encouraged to build upon our findings on a larger scale.

And finally, this study is subjected to the edge effect. This problem occurs when administrative boundaries define spatial data. In the case of an urbanized area such as Los Angeles, the edge effect is unavoidable. Thus, the patterns of patient-physician interaction along the borders of the bounded region are likely to be ignored or distorted. This phenomenon may have some effect on the measured healthcare accessibility.

**Conclusion**

The current study makes several important contributions to spatial business intelligence. First, it summarizes the abundance of existing knowledge on metrics of spatial accessibility and more specifically, the FCA family. It employs principles from gravity-based models to incorporate supply, demand, and distance in their characterization of the spatial accessibility of healthcare resources.

Second, this research organizes previous studies in a comprehensive manner. Such a structured literature review can assist both researchers and practitioners who are struggling to identify which FCA methodology would best fit their needs.

And finally, the study provides a step-by-step analysis methodology, which can be immensely beneficial for decision makers when considering solutions to the problem of physician shortage areas. The proposed methodology is based on prior literature and it builds upon the strengths of current studies while at the same time addressing their weaknesses and limitations.

In conclusion, measuring healthcare accessibility is of growing importance to the US government and it is vital for researchers and practitioners to use reliable datasets and be consistent in their analyses. Thus, the current study provides valuable aids for them to extend this work and measure healthcare accessibility in
other counties and states. This would also have a positive effect on healthcare services and would provide more useful resources for managers when making decisions regarding new facilities.

References


