JOURNAL OF
EMERGING INVESTIGATORS

Article

Accessibility to urgent care services for disadvantaged populations: An analysis of healthcare disparities

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SUMMARY

Healthcare is important for an individual's well-being as well as the social and economic health of the community. Due to COVID-19, healthcare has been even more crucial. In this study we analyzed urgent care facility accessibility for disadvantaged individuals in a large Virginian, United States urban area to discover potential healthcare disparities. We categorized census zones by the percentage of residing disadvantaged individuals using K-means clustering. In this study, a disadvantaged individual was defined as anyone who was impoverished or a minority. We put each zone into one of three derived groups: 1) Poverty, 2) Financially Independent (FI) minorities, 3) FI non-minorities. The census data counted minorities as non-Caucasian males. After reviewing previous research, we hypothesized that FI minority zones would have a longer travel time to urgent care facilities compared with the other two groups. We conducted network analysis in TransCAD to calculate the accessibility score during peak traffic hours, which is the travel time from each census zone to the nearest urgent care facility. The lower the travel time, the better the score. We conducted a one-tailed t-test that showed FI non-minority zones had the best accessibility score, then Poverty, and finally FI minority zones with the longest travel time. Most minorities resided in the city, which during peak traffic times is more congested than the suburbs, thus causing longer travel times and worse accessibility scores. Our analysis could be used to identify and spread awareness about healthcare disparities.

INTRODUCTION

In light of events such as COVID-19, healthcare equality is more important than ever. Accessibility to healthcare is crucial for an individual's well-being, but, despite the importance of healthcare, there is prominent inequality in accessibility between socioeconomic classes (1). This trend can be seen throughout developing and developed countries alike such as Brazil and Portugal (1, 2).

To promote equality in healthcare accessibility, our study analyzed the ease of access for disadvantaged communities to urgent care facilities within the Richmond metropolitan area. The Richmond metropolitan area includes Richmond City, Henrico County, and Chesterfield County (**Figure 1**). We chose this area because of the wide diversity of socioeconomic classes that can be generalized to represent a wider geographic area. Accessibility can be divided into two factors: facility distribution and transportation access. Facility distribution is the dispersion of healthcare facilities and was chosen as it is the dominant factor, accounting for 61.3% of accessibility (3). Virginia Department of Transportation (VDOT) used the 2020 census data to create census blocks which will be referred to as zones (**Figure 1**).

Based on census data, disadvantaged individuals were determined with two categories: financial and racial status. We chose these two categories due to their correlation with an individual's socioeconomic class (4). The census data accounts for the number of individuals in a zone that is composed of either a racial minority population or in financial poverty. K-means clustering allows for the grouping of these zones based on the percentage of minority or individuals in poverty. Previous research showed that accessibility to healthcare equipment was found to be substantially lower within poor and minority communities in Brazil (1). To determine whether a similar trend was present in our target area, we hypothesized that Financially Independent (FI) minority zones would have a worse accessibility score, the time to go from a zone to the nearest urgent care facility, compared to zones with a lower percentage of minorities, FI non-minority, and Poverty. We chose urgent care centers because of the low cost as well as the ability to walk in as opposed to appointment-based centers and hospitals. The results of this study can bring awareness to the disparity in healthcare and encourage the building of medical facilities in

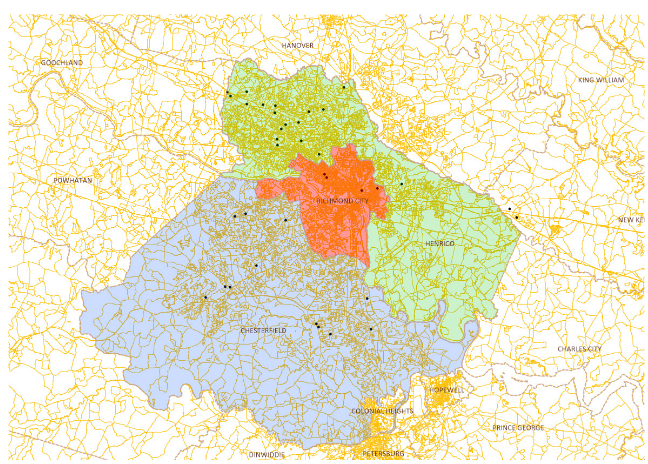

Figure 1. GIS geographical map of target area. Target counties are highlighted and urgent care facilities are marked with a black dot. Using a geographical information system (GIS) program provided by VDOT, a visual representation of the research area was found. Green is Henrico County, red is Richmond City, and blue is Charlottesville. The orange outlines are the separate zones.

DOI: https://doi.org/10.59720/23-074

the Richmond Metropolitan Area to increase accessibility for all classes.

RESULTS

Due to the increased need for healthcare caused by the COVID-19 pandemic, accessibility to healthcare has been more important than ever. We studied the accessibility to urgent care facilities in the Richmond Metropolitan Area to explore any potential healthcare disparities. We observed that urgent care facilities were generally concentrated toward areas with greater population density (**Figure 1**). This was expected as those are the places where most people will need healthcare. We used K-means clustering, which minimizes the squared Euclidean distance between a point and its centroid in a cluster, to split the population into three groups based on the percentage of both poverty and racial status (**Figure 2**). The Poverty group consisted of impoverished individuals represented by the green dots, the FI non-minorities were represented by red dots, and the FI minorities were represented by blue dots (**Figure 3**). We discovered that Poverty was the least populous with roughly 2,000 zones, FI minorities in second with 2,500 zones, and FI non-minorities taking up the majority with 5,100 zones. FI minorities had the worst accessibility score while the FI non-minorities had the best despite having a large number of outliers (**Figure 4**).

The Poverty zones were centralized around Richmond City while the FI minority zones were centered around northern Chesterfield and east Henrico. The FI non-minority zones took up most of west Henrico and the rest of Chesterfield (**Figure 5**). This shows common grouping between similar socioeconomic groups which was expected.

We conducted a one-tailed *t*-test using Python to compare the directional relationship of each type of zone with another. FI non-minority zones had a significantly better accessibility score compared to Poverty zones (p = 7.693e^{-50}) and FI minority zones (p = 7.898e^{-155}). Poverty had the second-best accessibility compared to FI minority (p = 4.251e^{-28}). FI minority had the longest travel times. This level of significant difference in access to urgent care facilities for different demographics raises concerns over healthcare access disparities.

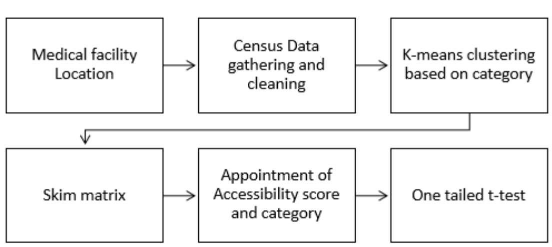

Figure 2. Analysis procedure. A flowchart showing the step-by-step procedure for this research analysis. We collected geographic data on urgent care clinics in the Richmond metropolitan area and utilized Census data to calculate poverty and minority percentages for each zone. Following data standardization, adjustment for outliers, and deletion of zones without a population, we applied K-means clustering to classify zones into three groups: 1) Poverty, 2) Financially Independent (FI) minorities, 3) FI non-minorities. TransCAD's network analysis generated a skim matrix, outlining travel times to medical zones. Subsequently, we computed minimum accessibility scores for each zone and performed a one-tailed *t*-test in SciPy to compare medical accessibility among these groups.

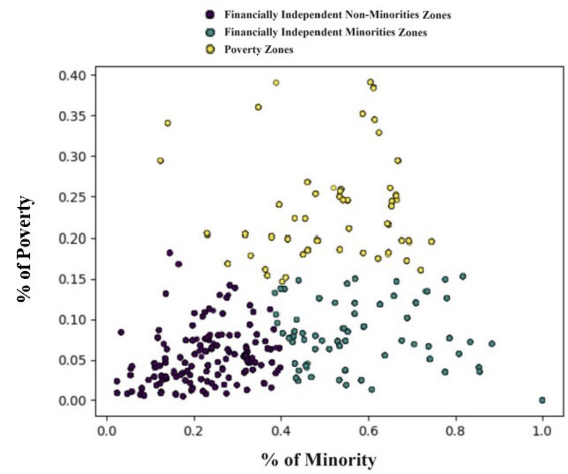

Figure 3. Distribution of groups based on poverty and minority percentages. The three groups based on percentage of poverty and minorities present. Python code was used to graph a 2D plot and K-means clustering was used to cluster groups. Data was split into three groups and labeled based on the racial and financial status of each group.

DISCUSSION

Using TransCAD, we analyzed the distribution and accessibility of urgent care facilities in the Richmond metropolitan area for different demographics to spread awareness. The distribution of urgent care facilities was generally grouped toward west Henrico and north Chesterfield County (**Figure 1**). This clustering is positively correlated with the population density of the area. A similar pattern can also be observed in low-density territories, such as Baixo Alentejo, Portugal where it is more difficult to access health care (2). According to the results, FI non-minorities had the best accessibility score while FI minorities had the worst

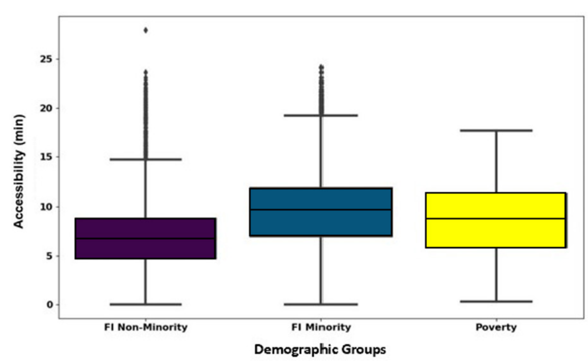

Figure 4. Comparison between accessibility scores over three different groups. Comparison using K-means clustering. Matplotlib in Python was used to plot a box and whisker plot with the three groups. Financially independent (FI) minorities have the greatest median in accessibility, then individuals in poverty, and finally FI non-minorities.

DOI: https://doi.org/10.59720/23-074

accessibility score. This proved to be a significant difference; therefore, the research hypothesis was supported. This analysis hopes to spread awareness regarding the potential healthcare disparities in the Richmond Metropolitan area.

Some limitations of this study could include: the lack of representation for non-English speakers, the use of peak traffic hours, and K-means clustering. Beyond physical accessibility, non-English speakers also need additional language accessibility. Different factors like on-site or phone-based translator availability could be more important for non-English speaker communities. Since a majority of FI minorities resided in or near the city, the roads would be more congested during peak hours compared to the suburbs where most FI non-minorities resided, thus causing the accessibility score to be worse. Additionally, financial/ethnic status are complex variables, K-means clustering only allows for a preliminary understanding of the potential relationships between these variables and healthcare disparity.

Potential reasons why Poverty had a better accessibility score compared to FI non-minorities could be due to the healthcare benefits granted by the government and Virginia Commonwealth University to those with low income (5). Moreover, the Poverty group included anyone who was under the poverty threshold, both non-minorities and minorities, due to the distribution of data and the K-means grouping, which could also potentially explain the results.

Additional analysis based on non-peak hours can be conducted to verify the conclusion of this study. For future research, the target area can be increased to include all zones in Virginia. TransCAD could be utilized to find the optimal locations for urgent care facilities to minimize travel time. Also, instead of travel time to urgent care facilities, the travel time for ambulances can be analyzed.

The intended purpose of our study was to find potential healthcare disparities in the Richmond Metropolitan area. The distribution of urgent care facilities and the accessibility score of different demographics shows the need to build urgent care facilities in high minority and impoverished zones. It also shows the need to bring diversity and inclusiveness into the consideration of selecting locations of health care facilities. Providing more mobile or other kinds of heath care services could be another way to reduce the disparity. Those services would bring basic health care to a patient's home and be an efficient means for providing certain types of routine health services like annual checkups. Beyond facility distribution, the enhancement of transportation networks or the provision of low-cost public transportation to medical facilities would help increase accessibility. Additionally, the spreading of awareness regarding the importance of regular healthcare checks to underrepresented communities could potentially be a solution. Finally, addressing the social determinants of the need for healthcare could be an effective long-term solution. This includes initiatives like improving education and job opportunities, reducing environmental hazards, and supporting common practices related to hygiene.

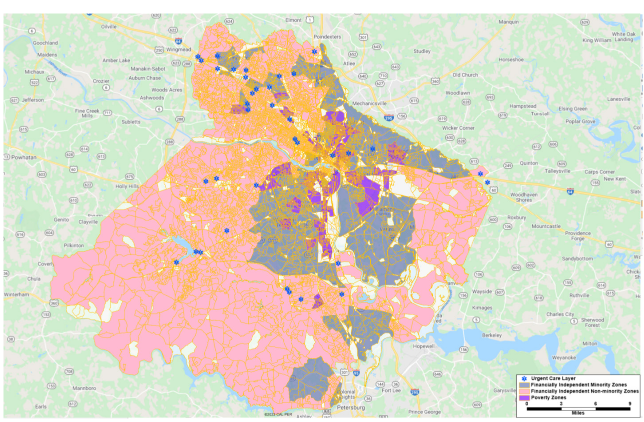

Figure 5. GIS map split by groups. Urgent care facilities are marked in blue, and the target area is split by the concentration of the different groups. GIS program provided by VDOT was used to make a visual representation of the results from the analysis.

MATERIALS AND METHODS

Data Gathering

This study covered the Richmond metropolitan area which encompasses Henrico County, Richmond City, and Chesterfield County. Census zones were provided by the Census Bureau. Census data was used due to the limitations of using macro-level data to calculate accessibility (6). A centroid was set for each zone that represented the location of the zone and where the accessibility score would be calculated from. The geographical location of all urgent care/medical walk-in clinics was collected and stored in an Excel file. Each medical facility was paired with the zone it was located in using a program called TransCAD. TransCAD is a Geographical Information System designed to store and analyze transportation data (7). A zone with a medical facility was labeled as a Mzone. Using the census data, the percentage of poverty and minorities for each zone was calculated. The usage of Ckmeans was considered but K-means clustering was used instead, since Ckmean only clusters univariate data. However, similar to Ckmean, K-means clustering is sensitive to outliers (8).

Data Preparation

The disadvantaged groups were split into two categories: financial and racial status. To determine whether a zone was disadvantaged, a commonly agreed upon qualifying value was set: the individual had to either be in poverty or a minority. Before conducting K-means clustering, all data values outside of the 1st and 99th percentile were floored or capped within the designated range to reduce the impact of outliers. The data was standardized by finding and plotting the z-score of each data value. This was done as z-score allows the comparison of populations with different means. K-means clustering is a popular machine learning algorithm that randomly selects a set number of centroids and performs repetitive calculations to optimize the position of those centroids (9). Essentially, it groups data based on similar characteristics and tries to minimize the distance between each data point and the cluster centroid. Utilizing K-means clustering, three groups were made: Poverty, FI minority, and FI non-minority.

Accessibility Analysis

Network analysis in TransCAD was used to calculate the shortest travel time from zone to zone during peak traffic hours (Zone 1 to Zone 2, Zone 1 to Zone 3, etc.) and the results were made into a skim matrix (7). Peak traffic hours were

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used to determine accessibility in the worst-case scenario which would account for potential medical emergencies. This was done by calculating the average speed of cars on a certain path and determining the path that took the shortest amount of time while considering other factors like cost and congestion. The travel time from a zone to itself (Zone 1 to Zone 1) was calculated by dividing the shortest travel time of that zone to the nearest zone by two. The resulting skim matrix was then sorted so each zone would be compared to an Mzone. The overall minimum accessibility score for each zone was singled out. To get a better illustration of this data, a box plot was created to compare the medians which showed that FI non-minority zones had the best accessibility score followed by individuals in poverty and finally FI minority zones with the worst accessibility score.

Statistical Analysis

Using a package in Python called SciPy, a one-tailed t-test was conducted. A one-tailed t-test was chosen to determine the directional significance between the groups. Each group was compared with one another. The t-test was conducted using standard methods with the sample size being counted by zone and the t-statistic as well as the p-value were obtained. An alpha level of 0.05 was taken as significant.

Received: March 25, 2023
Accepted: August 3, 2023
Published: October 20, 2023

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