Identifying Pharmacy Deserts on Residential Distribution

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INTRODUCTION

Background: Pharmacy deserts (PDs), referring to geographic areas with limited access to nearby pharmacies, significantly impact pharmacy services and subsequent public health outcomes [1]. Pharmacy communities offer diverse healthcare services, encompassing medication delivery, consultations, immunizations, and educational programs [2-5]. Despite the widespread presence of pharmacies, evidence indicates that certain individuals may face barriers to equitable access.

Socioeconomic factors influence the presence of PDs, with studies showing associations between these factors and PDs in various regions, including Toronto, Los Angeles, Baton Rouge, Chicago, and Nova Scotia [1, 6-14]. Research indicates that patients' health outcomes are linked to their proximity to healthcare facilities across different geographic levels [5]. Disparities in access to pharmacy services are also tied to residents' ethnicity and income levels. For instance, PDs are more prevalent among Black and Latino communities in cities like Chicago, Los Angeles, and Albuquerque [17]. PDs exhibit fluctuations over time and regions, remaining stable despite increased access to pharmacies in certain areas like New York City, while others, e.g., Los Angeles and Houston, maintain consistent pharmacy desert status [18].

Identifying PDs presents a critical challenge, leading to the utilization of various methodologies such as geospatial analysis. One such method is the centroid model, which examines the spatial relationship between residential areas and census tracts, indicating the overall distribution of residential buildings within each tract. To implement this model, the centroid (geometric center) and the location of each residential building within a census tract are determined. Subsequently, the distance between the centroid and pharmacy is calculated, typically using Euclidean or Haversine distance from each centroid to the nearest pharmacy. It's important to note that this distance does not represent the actual path for traveling to reach the pharmacy, potentially leading to over- or underestimation of pharmacy proximity due to data aggregation [19]. Some reports emphasize the use of driving distance metrics, which focus solely on driving paths [20]. However, this approach may overlook non-traveling distances and might not be suitable for urban areas or scenarios involving private transportation [20]. Another method involves assessing the density of pharmacies, which measures the number of pharmacies per unit area [10]. While this metric provides valuable information, it does not directly account for travel distance. Lastly, the household approach calculates the minimum distance from each household to the nearest pharmacy, serving as a basis for mapping PDs. This model has been applied in Pennsylvania, where it was utilized for 172,967 elderly households enrolled in the Pennsylvania State Pharmaceutical Assistance Program (SPAP) [14]. However, the scope of this study may be limited.

Motivation: Among the various geospatial analysis methods available for identifying PDs, the household model offers more precise insights into the spatial distribution of pharmacy access. The translation of accurate results can enhance decision-making processes concerning healthcare resource allocation and accessibility planning in both urban and rural areas.

Problem Definition: Numerous reports have identified PDs using the household model. However, the method of measuring the nearest distance between two points represents traveling distance. The authors discovered that 39% of Census Tracts were classified as PDs, primarily concentrated in rural regions with a higher proportion of elderly white married females and fewer black and Hispanic households. PDs exhibited fewer chain and independent pharmacies, along with limited delivery and 24-hour services, highlighting the necessity for improvements in these areas. The study's methodology could be adapted to evaluate the coverage of other public health programs [14]. By employing this approach in conjunction with the Haversine method and Dijkstra's algorithm to measure the shortest traveling distance between pharmacies and their neighboring residential households, we aim to compare the precision of identifying PDs while also developing a user interface (UI) tool for identifying the locations of pharmacy deserts and neighboring non-desert areas within specific tracts. By integrating PDs information, this interface will empower users, including policymakers, healthcare providers, and community members, to easily and effectively pinpoint pharmacy desert locations on the map. The intuitive visualizations and actionable insights at the county levelhelps users to gain valuable insights into areas lacking adequate pharmacy access.

List of Innovations

- Using Dijkstra's Algorithm to determine the nearest pharmacy for each residence within a city.
- Investigating the impact of varying distance constraints on the identification of PDs.
- Comparing the accuracy of identifying PDs between the Dijkstra and Haversine models.
- Creating interactive maps illustrating PDs in selected regions.
  - Maps present pharmacy deserts along with demographic and socio-economic features for different regions within an intuitive UI.
  - Maps facilitate the comparison of PDs across different regions via a user-friendly interface.

METHODOLOGY

1. Data Processing: The criteria of travelling and non-travelling distance to the nearest pharmacy, population density, demographics were considered for identifying PDs. The data pertaining to pharmacies, residents, and demographic details were gathered for three major cities: Boston (from MA), Chicago (from IL), and Washington (from DC). The primary variables of interest included the X and Y coordinates (longitude and latitude) along with location-specific identifiers such as zip codes for both pharmacies and household locations. Additionally, demographic information such as gender, ethnicity, race, and annual income were collected [24-36]. Following data cleaning, the data was segmented into 13 distinct datasets for further analysis (Table 1).

Table 1. Tables of the database and their dimensions and features.

City	Table	Dimension	Features
Boston	bos_addr_to_tract	399994 x 3	index, bos_rowid, tract
	bos_distances	399994 x 6	index, bos_rowid, pharm_rowid, hav_dist, path_dist, dist_rank
	boston	399994 x 16	PID, ST_NUM, ST_NAME, UNIT_NUM, CITY, ZIP_CODE, LU, BED_RMS, MAP_PAR_ID, Shape_STArea__, Shape_STLength__, ShapeSTArea, ShapeSTLength, X, Y, PARCEL
	bos_tract_distances	207 x 12	index, tract, x, y, pharm_rowid, pharm_x, pharm_y, hav_dist, dist_rank, orig_node dest_node, path_dist
Chicago	chi_addr_to_tract	1864201 x 3	index, chi_rowid, tract
	chicago	1864201 x 14	pin, property_address, property_city, property_zip, longitude, latitude, tract_geoid, tract_pop, tract_white_perc, tract_black_perc, tract_asian_perc, tract_his_perc, tract_other_perc, tract_midincome
	chi_distances	0 x 8	index, chi_rowid, chi_x, chi_y, pharm_rowid, pharm_x, pharm_y, distance
Washington	dc_addr_to_tract	144,440 x 3	index, dc_rowid, tract
	dc_distances	144,440 x 6	index, dc_rowid, pharm_rowid, hav_dist, path_dist, dist_rank
	wash_dc	144,440 x 12	X, Y, ADDRESS, ADDRESS_NUMBER, ADDRESS_NUMBER_SUFFIX, STREET_NAME, CITY, STATE, ZIPCODE, SSL, PRICE, LANDAREA
	dc_tract_distances	207 x 12	index, tract, x, y, pharm_rowid, pharm_x, pharm_y, hav_dist, dist_rank, orig_node, dest_node, path_dist
-	pharmacy_locations*	62973 x 10	NAME, ADDRESS, ADDRESS2, CITY, STATE, ZIP, ZIPP4, COUNTY, X, Y
-	temp	25047 x 8	index, tract, x, y, pharm_rowid, pharm_x, pharm_y, hav_dist
-	census	1773 x 27	index, Name, n, n_sex_male, n_sex_female, n_race_white, n_race_black, n_race_amer_indian, n_race_asian, n_race_nhopi, n_race_multiple, n_ethnicity_not_hispanic, n_ethnicity_hispanic, n_income_0, n_income_0_10k, n_income_10k_15k, n_income_15k_25k, n_income_25k_35k, n_income_35k_50k, n_income_50k_65k, n_income_65k_75k, n_income_greater_75k, n_vehicle_none, n_vehicle_one, state, county, tract

2. *Identification of PDs:* Upon mapping the geographical locations of pharmacies and residential buildings, the nearest traveling and non-traveling distances to pharmacies within the three cities were calculated using both the Haversine and Dijkstra methods. Subsequently, demographic and socioeconomic information was integrated for the analysis of PDs.

Haversine Distance measures the distance between two points on the curvature of the Earth's surface using latitude and longitude coordinates. It aggregates the distances obtained from calculating the centroid census tract distance from residential buildings via mean, median, or maximum distance to estimate the shortest path for traveling between two locations.

$$Distance = 2R * \arcsin(\sin^2((lat_h - lat_{ph})/2) + \cos(lat_h)*\cos(lat_{ph})*\sin^2((long_h - long_{ph})/2))$$

R: Polar radius of earth in miles (3949.99)
lat_{ph}: Latitude of pharmacy location in radius
lat_h: Latitude of household location in radius
$long_{ph}$: Longitude of household location in radius
$long_h$: Longitude of pharmacy location in radius

Dijkstra Distance measures the shortest traveling path distance between two locations on a graph. Street networks were sourced from OpenStreetMap to analyze the traveling distance in miles [38]. This model is useful for computing the most efficient route between to points in urban areas with complex street layouts, and different modes of transportation. This method computes the shortest traveling distance, denoted as $\mathbf{d_{start}}$, from each residence serving as a single source node to all other nodes representing pharmacies within a weighted graph. The process encompasses the following steps:

1. **Initialization:**
   - All nodes are initially marked as unvisited: **unvisited(v) = True** for all nodes **v.**
   - Initialization of $\mathbf{d_{start}}$:
     - For the source node **s**, set $\mathbf{d_{start}}$ to 0 and assign it as ***Current Node***: $\mathbf{d_{start}(s) = 0}$.
     - For all other nodes **v**, set $\mathbf{d_{start}}$ to infinity since their distances from the source are initially unknown: $\mathbf{d_{start}(v) = \infty}$.
2. **Neighbor Evaluation:**
   - Computing the tentative distances: unvisited neighbor **u** of the ***Current Node*** **v**, calculate the tentative distance as: **tentative_distance(v, u) =** $\mathbf{d_{start}(v)}$ **+ weight(v, u),** where **weight(v, u)** is the weight (travel distance) of the edge connecting nodes **v** and **u**.
   - Update the $\mathbf{d_{start}}$ value: If **tentative_distance(v, u) <** $\mathbf{d_{start}(u)}$, update $\mathbf{d_{start}(u)}$ to the tentative distance: $\mathbf{d_{start}(u)}$ **= tentative_distance(v, u)**
3. **Node Visitation:** Mark the ***Current Node*** **v** with the shortest $\mathbf{d_{start}}$ as visited after evaluating all unvisited neighbors: **unvisited(v) = False**
4. **Iteration and Termination:** Iterate over all unvisited nodes to select the one with the shortest $\mathbf{d_{start}}$ value as the new Current Node. Steps 2 and 3 are iteratively repeated until all nodes in the graph are either visited or unreachable from the source node. At this point, the algorithm terminates

3. *Analysis of PDs:* Utilizing the centroid, Haversine, and Dijkstra's models, each area in the city was categorized as a PD if the distance to the nearest pharmacy building exceeded one mile. The proportion of PDs (PPDs) was determined as follows:

$$PPDs = \frac{\text{Number of census tracts identified as pharmacy deserts in the city}}{\text{Total number of census tracts present in the city}}$$

$$PPDs\% = PPDs \text{ x } 100$$

The threshold for identifying PDs distances was 1.0, 1.5 and 2.0 miles, and subsequently, PPDs were computed for each model under the thresholds within each city (Figure 1).

4. Statistical Analysis: Descriptive statistics were conducted to examine the spatial distribution of residential buildings and pharmacies in each city, along with demographic and socio-economic characteristics, focusing on PDs. The PPDs were compared among the three models, applying various thresholds within each city and across the three cities. Additionally, a comparison of socio-economic profiles, including gender, ethnicity, race, and annual income, was conducted within the pharmacy desert areas over the three cities.

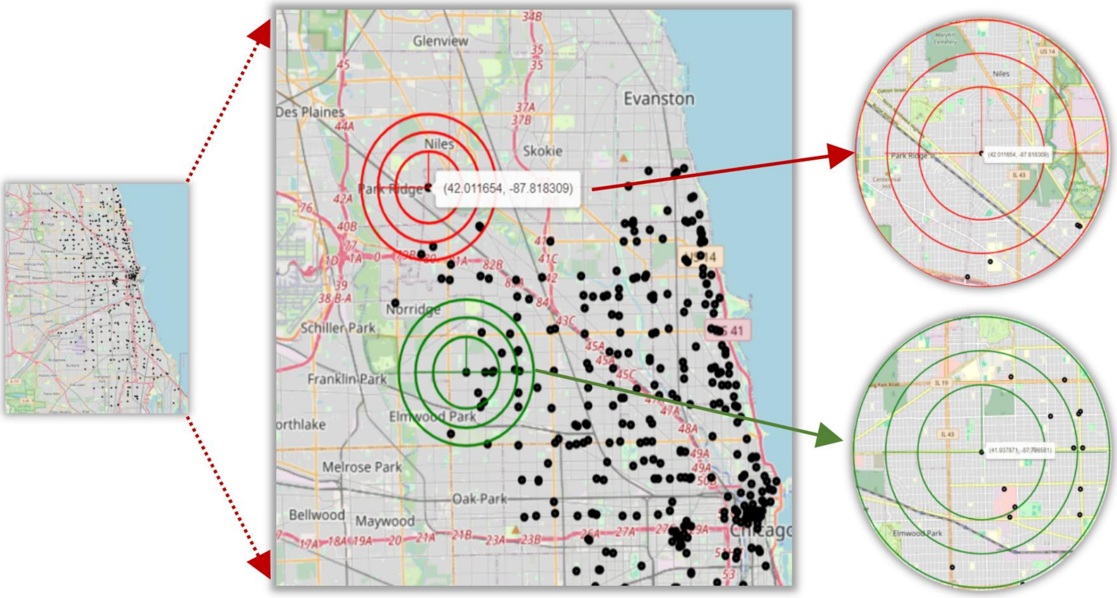


Figure 1. Illustration of the identification of threshold distances at 1.0, 1.5, and 2 miles for each pharmacy. If the nearest distance between the pharmacy and residential building exceeds the circle representing the threshold, it is classified as a PD; otherwise, classified as pharmacy non-deserts.

5. UI PDs: A UI for identifying PDs by city was developed to visualize the distribution of pharmacies across different tracts in each city on the map using Python, D3, and choropleth mapping methods and visualized at the levels of a county and census tract heatmaps. Demographic and socio-economic features are accessible via buttons for specific points on the heatmap, activated by tapping or hovering over it (Appendix: Figure 1).

RESULTS AND DISCUSSIONS

1. Exploratory Analysis: The characteristics of households and pharmacies, along with their densities, in three selected cities Boston, Chicago, and Washington are summarized in Table 2.

Table 2. City Characteristics

City	Area (mi^2)	Census Tract (n)	Residences (n)	Pharmacy (n)	Residence Density ($/mi^2$)	Pharmacy Density ($/mi^2$)	Ratio of Residences per Pharmacy
Boston	48.4	207	399,994	46	8264.34	0.95	8696
Chicago	228	866	1,864,201	442	8176.32	1.94	4218
Washington	68.4	179	144,440	121	2113.24	1.77	1193

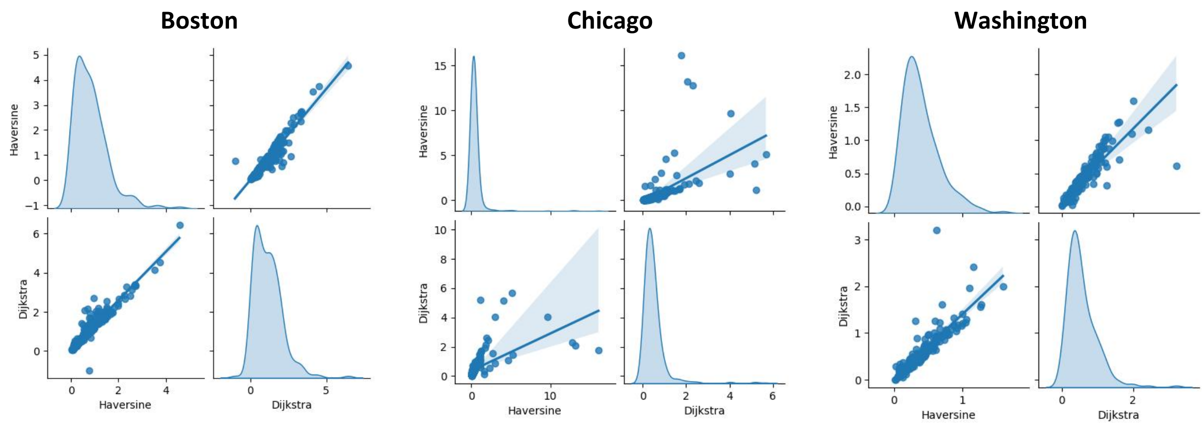
As depicted in Table 2, Chicago exhibits a larger area and number of residences compared to Boston and Washington D.C. However, its residence density falls short of Boston's but exceeds that of Washington D.C. The density of pharmacies in Washington D.C. surpasses both Chicago and Boston, indicating a higher availability of pharmacies in the city. Specifically, in Washington D.C., there is one pharmacy available for every 1,193 residences, whereas in Chicago and Boston, the ratios stand at 1:4,218 and 1:8,696, respectively. Hence, it seems that Washington D.C. has a more favorable pharmacy availability status compared to the other cities.

2. ***Spatial Distribution of Pharmacies and Residential Buildings:*** The locations of pharmacies and households were mapped using their geographical coordinates (longitude and latitude) or addresses and zip codes in each related dataset (Figure 2) [37].

Figure 2. Spatial distribution of pharmacies across Boston, Chicago, and Washington.

As Figure 2 depicts, the density of pharmacies in Chicago is much higher than other cities.

3. ***PDs:*** The PDs were computed using both Haversine and Dijkstra distances based on the centroid census tract distance approach, and then their accuracy was compared across the cities (Figure 3).



Haversine mean ± SD = 0.84 ± 0.72	Haversine mean ± SD = 0.5 ± 1.34	Haversine mean ± SD = 0.4 ± 0.27
Dijkstra's mean ± SD = 1.16 ± 0.93	Dijkstra's mean ± SD = 0.49 ± 0.59	Dijkstra's mean ± SD = 0.57 ± 0.43
Correlation = 0.95	Correlation = 0.57	Correlation = 0.87
p-value = 4.81e-104	p-value = 2.07e-39	p-value = 3.14e-63

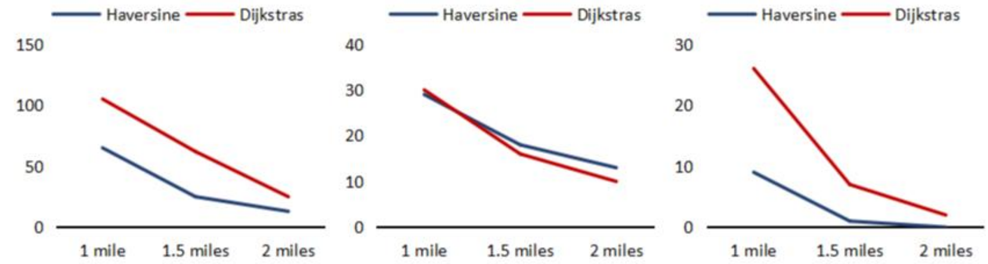
Figure 3. Comparison of Haversine and Dijkstra's correlation between the three cities.

As illustrated in Figure 3, the performance difference between the two models was minimal in Chicago (0.5 ± 1.34 vs. 0.49 ± 0.59). However, the Haversine model tended to yield lower average nearest distances than Dijkstra's algorithm in both Boston and Washington (0.84 ± 0.72 vs. 1.16 ± 0.95 and 0.4 ± 0.27 vs. 0.57 ± 0.43, respectively). A strong positive correlation was observed between the Haversine and Dijkstra's distances in the three cities, albeit lower in Chicago compared to Boston and Washington (p-values: 2.07e-39 vs. 4.81e-104 and 3.14e-63, respectively).

In this study, accuracy was defined as the ratio between the number of tracts that both models return the same PD classification and the total number of tracts in the segment. Both Haversine and Dijkstra's distances were utilized for evaluating the accuracy in identifying PDs under distance thresholds of 1.0 mile, 1.5 miles, and 2.0 miles across the tracts of the three cities showed in Table 3. This table showcases the discrepancy in pharmacy desert (PD) identification across different distance thresholds by the two models and their respective accuracies. It reveals that Dijkstra's algorithm consistently outperforms the Haversine model in identifying PDs across all thresholds for Boston, Chicago, and Washington. Notably, at a 1-mile threshold, the accuracy is lower compared to thresholds of 1.5 miles and 2.0 miles for all cities. This disparity arises due to the increased distance between pharmacies and households, leading to both models identifying the same PDs more frequently.

Table 3. Identification of PDs by Haversine (H) and Dijkstra's (D) models by thresholds in three cities.

Boston				Chicago				Washington			
Threshold	Model	PDs(%)	Accuracy	Threshold	Model	PDs(%)	Accuracy	Threshold	Model	PDs(%)	Accuracy
1.0	H	65 (31)	80.7	1.0	H	29 (7)	80.7	1.0	H	9(4)	80.7
	D	105 (51)			D	30 (7)			D	26 (13)	
1.5	H	25 (12)	82.1	1.5	H	18 (4)	82.1	1.5	H	1 (0)	82.1
	D	62 (30)			D	16 (4)			D	7 (3)	
2.0	H	13 (6)	94.2	2.0	H	13 (3)	94.2	2.0	H	0 (0)	94.2
	D	25 (12)			D	10 (2)			D	2 (1)	



Dijkstra's algorithm exhibits superior performance in PD identification, particularly evident in Boston and Washington, albeit less effective in Chicago. Overall, as the distance threshold increases, the number of PDs identified by both models decreases. Because of complexity of data layers, the demographic and socioeconomic features data were visually presented under 1.0-mile threshold only in the UI.

UI of PDs: Based on the enhanced prototype, the final version of the UI for PDs (**UIPDs**) was developed to reflect the study's outcomes (Appendix: Figures 1-4) [39]. The UI design aimed for simplicity, functionality, and consistency across city, tracts, distances, thresholds, and PDs, and demographics and socioeconomic six layers of data incorporating feedback from team members at each development stage. The PDs calculated by Haversine and Dijkstra's distances in each tract of the related city were displayed on the map at the top-middle of the page for each city. The demographic and socioeconomic data, including gender, race, ethnicity, and annual income by tracts were visually compared at the bottom section. The tool-tip located on the middle-right side facilitated the specific identification of layers under a specific tract. The presentation of results over six layers in a simple UI format enhanced the accessibility and understanding of the findings, reducing complexity for data and fostering user-friendliness.

In summary, the study highlights the effectiveness of Dijkstra's algorithm in identifying PDs within the 1-2.0 mile threshold range, with improved accuracy as distance thresholds increase. Despite measuring longer travel distances compared to Haversine, Dijkstra's algorithm outperforms the latter in PD identification accuracy. Furthermore, with increasing distance thresholds, the occurrence of false positives or negatives diminishes.

CONCLUSION

The study revealed notable disparities in using Haversine and Dijkstra's methodologies across various thresholds, alongside demographic and socioeconomic factors, to identify PD distributions in Boston, Chicago, and Washington. The integration of centroid and household models, visualized through a user-friendly interface, presents an opportunity to inform public health initiatives. However, further extensive studies on a larger scale are necessary to validate these findings and enhance strategies aimed at addressing the impact of PDs on public health and well-being.

CONFLICT OF INTEREST

All team members have contributed a similar amount of effort and have no conflict of interest.

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APPENDIX

The developed UI for identifying PDs in Boston, Chicago, and Washington

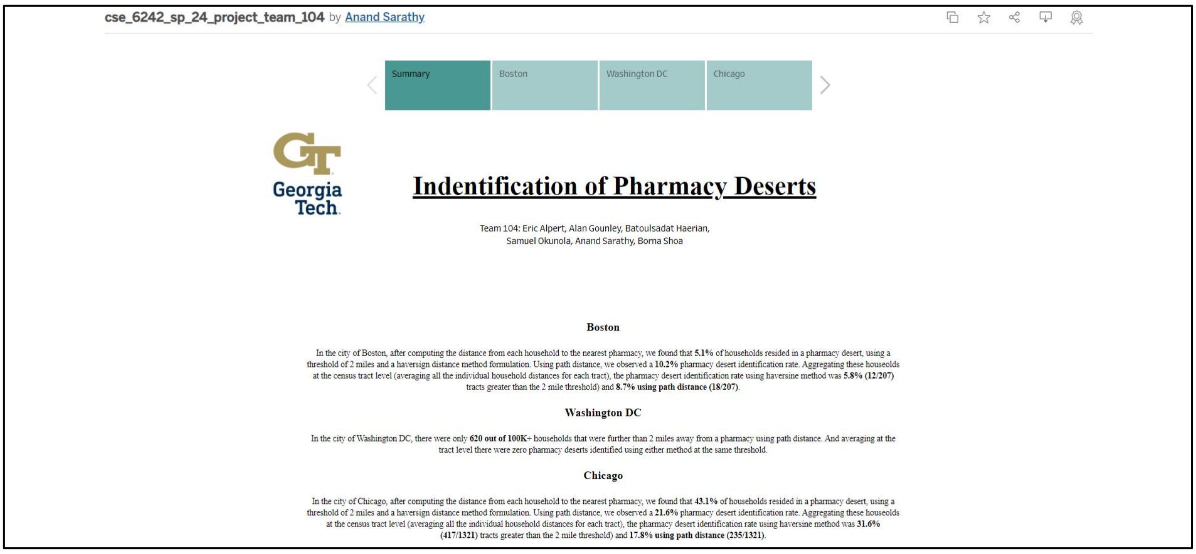

Figure 1. Summary page of the UI

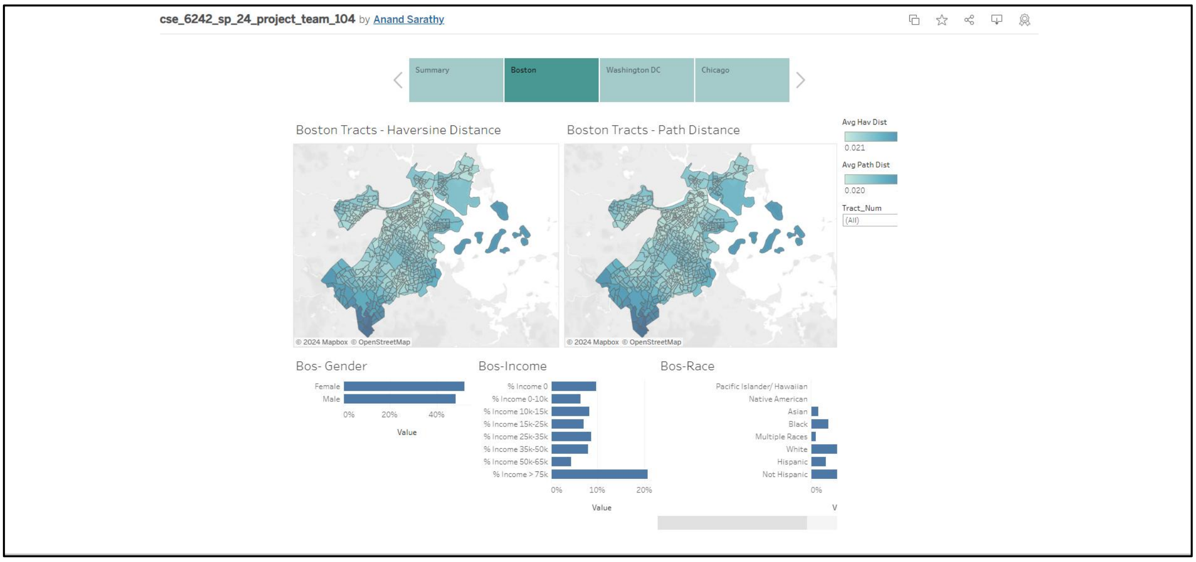

Figure 2. Identified PDs by gender, annual income, and race and ethnicity in Boston

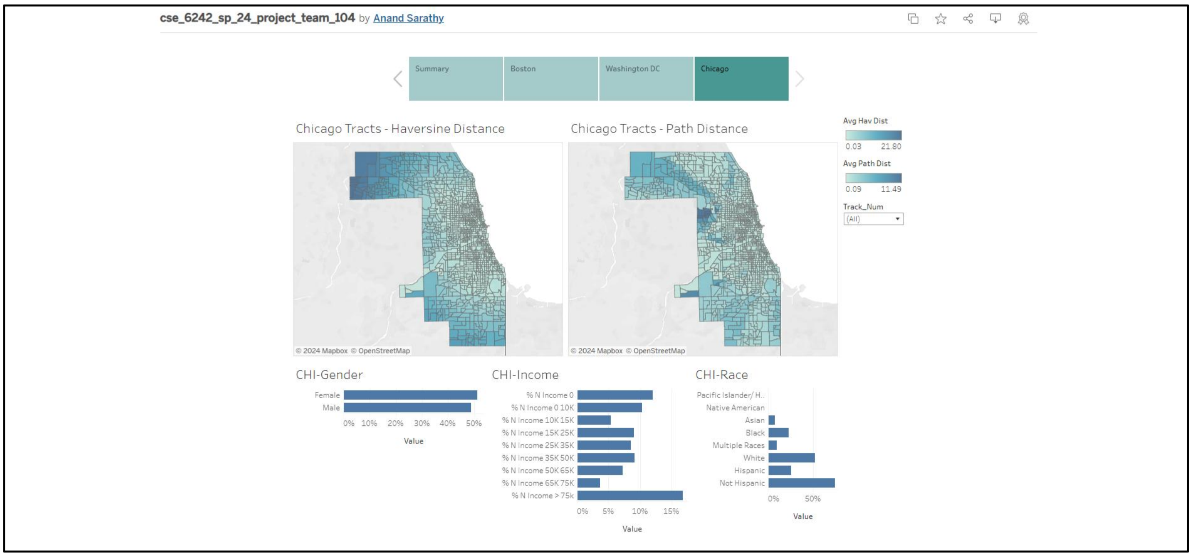

Figure 3. Identified PDs by gender, annual income, and race and ethnicity in Chicago

Figure 4. Identified PDs by gender, annual income, and race and ethnicity in Washington