



# End Project – End Report

## Medical Care Supply in Graz, Austria

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# Contents

<b>1</b>	<b>Introduction and Research Question</b>	<b>1</b>
<b>2</b>	<b>Data and Methods used</b>	<b>1</b>
2.1	Data sources . . . . .	1
2.2	Programming in Python . . . . .	2
2.3	Analytical Hierarchy Process (AHP) for Healthcare Facility Weighting . . . .	2
2.3.1	Theoretical Foundation . . . . .	2
2.3.2	Hierarchical Structure for Medical Accessibility . . . . .	2
2.3.3	Pairwise Comparison Matrix and Weight Derivation . . . . .	3
2.3.4	Consistency Verification . . . . .	3
2.3.5	Application in Distance-Decay Accessibility Scoring . . . . .	4
2.4	Calculation of distribution quality metric . . . . .	4
2.4.1	Population-Weighted Accessibility Index . . . . .	4
2.4.2	District-Level Aggregation . . . . .	5
2.4.3	Network Distance Thresholds . . . . .	5
2.5	Application on the data of Graz . . . . .	6
2.6	Optimization for new facility location . . . . .	6
2.6.1	Selecting potential locations . . . . .	6
2.6.2	Testing each candidate . . . . .	7
2.6.3	Finding the best option . . . . .	7
<b>3</b>	<b>Results</b>	<b>8</b>
3.1	Medical facility distribution in Graz . . . . .	8
3.2	Distribution quality score in Graz . . . . .	9
3.3	Optimal location for new facility . . . . .	11
<b>4</b>	<b>Discussion</b>	<b>13</b>
<b>5</b>	<b>Conclusion and Outlook</b>	<b>13</b>
	<b>References</b>	<b>14</b>
	<b>Appendix</b>	<b>16</b>

## List of Figures

1	Kernel Density Estimation (KDE) of medical facilities . . . . .	9
2	Population-weighted cost for distribution quality . . . . .	10
3	Inverse population-weighted cost per district . . . . .	10
4	Top: Current accessibility with proposed hospital location (blue star). Bottom: Improvement in accessibility scores after adding the new hospital. . . . .	12

## List of Tables

1	AHP matrix for medical facility types . . . . .	3
2	Maximum network distance thresholds by facility type. . . . .	6
3	District-level accessibility improvement from the proposed hospital. Values represent mean accessibility scores (0-1 scale). . . . .	11

# 1 Introduction and Research Question

Living in a city, it is important to have some vital facilities in a nearby area, which applies especially to medical facilities, since it guaranties the health of the population. This not only concerns hospitals, but also clinics, doctors and pharmacies. Due to the often uneven distribution of such places, the quantification of this inequality is important to be able to take measures on reducing it. Therefore this work tries an approach on quantifying the distribution of medical facilities applied on the city of Graz, Austria. The aim is to only use open data to make this study reproducible by other researchers and other places. To do so, the following three research questions were formulated:

- How is the distribution of medical care facilities in Graz?
- How is the quality of distribution in each district or neighbourhood and which are disadvantaged?
- Where should new facilities be built and what impact would that have on the distribution?

## 2 Data and Methods used

### 2.1 Data sources

This research integrates vector and raster geospatial datasets from two primary open-access repositories:

- OpenStreetMap (OSM): Vector datasets were accessed via OSM including:
  - Medical facilities (amenity tags: hospital, clinic, doctors, pharmacy)
  - Street network (routing graph with weighted edges)
  - Administrative boundaries (city districts and municipal borders)
  - Residential areas (landuse classification)
- Copernicus Global Human Settlement Layer (GHSL):

GHSL is a gridded population dataset with 100-meter spatial resolution, providing normalized population density across the study area. The global dataset was cropped to the Graz metropolitan area and surrounding regions.

All datasets are publicly available, ensuring study reproducibility and compliance with open science principles.

## 2.2 Programming in Python

All spatial operations were performed using the Austria Lambert Conformal Conic projection (EPSG:31256, MGI/Austria Lambert), the official CRS for Austria, ensuring metric distance calculations and compatibility with Austrian administrative datasets. Data quality assurance included removal of erroneous geometries, validation of facility classifications, and exclusion of emergency services (fire station) to maintain analytical focus on civilian healthcare infrastructure. The entire workflow was implemented in Python 3.11 using the following specialized libraries:

- OSMnx (Boeing, 2017): Retrieval of OSM data and street network analysis
- NetworkX (Hagberg et al., 2008): Graph-based routing computations using Dijkstra's algorithm
- GeoPandas: Vector geodata manipulation and spatial joins
- Rasterio: Raster data processing and band operations
- SciPy: Spatial interpolation (griddata) for raster generation
- Matplotlib and Folium: Static and interactive cartographic visualization
- KeplerGL: Web-based interactive data exploration

## 2.3 Analytical Hierarchy Process (AHP) for Healthcare Facility Weighting

### 2.3.1 Theoretical Foundation

The Analytical Hierarchy Process (AHP) is a structured decision-making methodology that decomposes complex problems into a hierarchy and derives relative weights through pairwise comparisons and eigenvector analysis (Saaty, 1977, 1990). In the context of healthcare accessibility, AHP is particularly suitable because different facility types provide qualitatively different services and thus should not be treated as equivalent (Tavana et al., 2023). A hospital providing emergency and specialist care has a different impact on population health than a pharmacy offering routine medication, and AHP formalizes these differences using a transparent, reproducible procedure instead of ad-hoc weighting.

### 2.3.2 Hierarchical Structure for Medical Accessibility

The AHP hierarchy for this study consists of three levels:

- Level 1 (Goal): Maximize healthcare accessibility and service quality across Graz population
- Level 2 (Criteria): Facility types, each representing distinct healthcare services:

Hospitals (tertiary care, emergency services, specialized departments); Clinics (primary and secondary care, specialized outpatient services); General Practitioners/Doctors (primary pre-

ventive care, initial consultation); Pharmacies (medication dispensing, pharmaceutical counseling)

- Level 3 (Alternatives): Geographic locations (street network nodes) evaluated for accessibility to facility types

### 2.3.3 Pairwise Comparison Matrix and Weight Derivation

Following Saaty’s fundamental scale (1–9), expert judgment and established medical and accessibility literature were synthesized to construct the pairwise comparison matrix shown in Table 1 (Saaty, 1977, 1990). The weighting prioritizes facilities according to their medical significance and population relevance, with hospitals and primary care facilities receiving higher importance due to their influence on survival and health outcomes. Empirical evidence shows that increased distance to emergency hospitals is associated with higher mortality risks; for instance, Bertoli and Grembi (2017) report that a 5 km increase in distance to the nearest hospital raises the fatality rate in road-traffic accidents by nearly one percentage point.

Facility Type	Hospital	Clinic	Doctor	Pharmacy
Hospital	1	2	2	4
Clinic	0.5	1	1	2
Doctor	0.5	1	1	2
Pharmacy	0.25	0.5	0.5	1

Table 1: AHP matrix for medical facility types

The matrix was calibrated so that the resulting principal eigenvector aligns with weight ranges reported in GIS-AHP healthcare accessibility studies, where hospitals typically receive 25–40 % of the total weight (Rabiei-Dastjerdi et al., 2023; Asadi et al., 2021). The resulting normalized weights are:

- Hospital: 0.40 – Emergency care and specialist services
- Clinic: 0.25 – Secondary care provision
- Doctor: 0.25 – Primary care and diagnostics
- Pharmacy: 0.10 – Medication access and pharmaceutical services

This weighting structure reflects the stronger influence of hospitals and primary care on population health outcomes compared to pharmacies (Berke et al., 2008; Chen et al., 2022), consistent with recent GIS-AHP healthcare accessibility applications (Janssen et al., 2021).

### 2.3.4 Consistency Verification

The consistency of pairwise judgments was assessed using the Consistency Index (CI) and Consistency Ratio (CR), derived from the maximum eigenvalue  $\lambda_{\max}$  of the AHP matrix (Saaty, 1990). The resulting CR was below 0.10, indicating acceptable internal consistency

and providing a reliable basis for subsequent accessibility calculations (Veldwijk et al., 2015; Tavana et al., 2023).

### 2.3.5 Application in Distance-Decay Accessibility Scoring

AHP-derived weights were applied within a distance-decay framework to quantify healthcare accessibility along the pedestrian street network. Facilities were associated with the nearest network nodes, and shortest-path distances were computed for each facility type using Dijkstra’s algorithm.

Accessibility contributions from each facility type  $i$  were modeled with a quadratic decay function:

$$f_i(d_i) = \max \left( 0, 1 - \left( \frac{d_i}{d_{\max,i}} \right)^2 \right), \quad (1)$$

where  $d_i$  is the network distance to the nearest facility, and  $d_{\max,i}$  represents the maximum acceptable distance for each facility type (previously defined). The quadratic form captures the rapid decline in accessibility beyond optimal service ranges (Schuurman et al., 2010; Statistics Canada, 2021; Todd et al., 2015; MapOG, 2024).

The overall accessibility score at each node is then calculated as the weighted sum of contributions from all facility types:

$$A(x, y) = \sum_i w_i f_i(d_i), \quad (2)$$

where  $w_i$  are the AHP-derived weights. Scores were normalized to the range [0,1] for interpretation. This formulation combines facility importance with spatial impedance, providing a nuanced measure of accessibility that differentiates between emergency, primary, and routine care providers across the network.

## 2.4 Calculation of distribution quality metric

### 2.4.1 Population-Weighted Accessibility Index

The distribution quality of medical facilities was quantified using a population-weighted accessibility index, which combines node-based network accessibility  $A(x, y)$  with spatial population density from the Copernicus GHSL 100 m raster. Unlike purely distance-based measures, this metric accounts for population distribution: two areas may have identical network distances to facilities but differ vastly in practical accessibility depending on population density.

Node-level accessibility values were interpolated to the population raster grid, yielding a continuous accessibility surface  $A_i$  for each raster cell  $i$ . The population-weighted quality metric  $Q$  is then defined as

$$Q = \frac{\sum_{i=1}^n A_i \cdot P_i}{\sum_{i=1}^n P_i}, \quad (3)$$

where  $A_i$  is the normalized accessibility score (range 0–1),  $P_i$  is the population in cell  $i$ , and  $n$  is the number of raster cells. Equation (3) ensures that:

- high-accessibility, high-population zones contribute most strongly to overall quality;
- low-accessibility areas with few residents have limited influence;
- zero-population cells (parks, industrial zones, water bodies) are automatically excluded.

This population-weighted formulation aligns with gravity-based accessibility measures that integrate supply, distance, and demand (Schuurman et al., 2010; Chen et al., 2022), ensuring that accessibility assessments reflect both spatial proximity and demographic relevance.

#### 2.4.2 District-Level Aggregation

For administrative interpretation, node-level accessibility scores were aggregated to the 17 official districts of Graz. Each network node was assigned to its corresponding district, and the mean accessibility for the district was calculated as

$$A_{\text{district}} = \frac{\sum_{\text{nodes} \in \text{district}} A_{\text{node}}}{|\text{nodes} \in \text{district}|}, \quad (4)$$

where  $A_{\text{node}}$  is the accessibility score at a given node, and  $|\text{nodes} \in \text{district}|$  denotes the total number of nodes within that district.

This produces a district-level indicator of average accessibility. Districts with lower mean scores indicate reduced access to healthcare, highlighting areas that may benefit from new or improved facilities.

#### 2.4.3 Network Distance Thresholds

Distance-decay scoring employs evidence-based maximum distances tailored to facility type and urban context, as summarized in Table 2. These thresholds reflect typical travel tolerances for different healthcare services in urban settings.

The quadratic decay function (1) was applied, wherein accessibility declines sharply beyond the facility-specific maximum thresholds listed in Table 2, reflecting realistic distance friction in urban pedestrian and vehicular networks.



Facility Type	Max Distance	Justification	References
Hospital	3000 m	Emergency and tertiary care; 30-min response time; urban-scale tolerance	Mseke (2024), Schuurman et al. (2010), Bertoli & Grembi (2017)
Clinic	1200 m	Urgent/intermediate care; $\approx 15$ -min travel	Todd et al. (2015)
Doctor	1000 m	Primary care; $\approx 15$ – $20$ -min walk	Statistics Canada (2021)
Pharmacy	800 m	Routine medication; neighbourhood-scale optimal access	MapOG (2024)

Table 2: Maximum network distance thresholds by facility type.

## 2.5 Application on the data of Graz

To apply this metric on Graz, firstly for each node the distance to the closest facility had to be calculated. To do so, the closest path via the street network using the dijkstra algorithm was used. Having computed the general distribution quality for each node, it was necessary to include the population data for weighting, since more highly populated areas have more impact on the overall quality.

Since the population data is raster data, the general distribution quality, which is only represented by the nodes of the street network had to be converted to a corresponding raster by, in this case, linear interpolation. Then, the distribution quality ( $Q$ ) was multiplied by the population ( $P$ ) raster and normalized by dividing by the maximum population per raster cell to calculate the normalized population-weighted distribution quality:  $Q_p = \frac{Q \cdot P}{\max(P)}$

## 2.6 Optimization for new facility location

After calculating the accessibility scores for Graz, the next step was to find out where a new medical facility should be built to improve the overall situation as much as possible. The goal was to answer two questions: What type of facility (hospital, clinic, doctor, or pharmacy) would help the most? And where exactly should it be located? There are many ways to solve this type of location problem in existing research (Al-Rabiaah et al. 2022, Pourrezaie-Khaligh et al. 2022, Salami et al. 2023). For this project, the approach used can be described as a greedy heuristic to solve a version of the p-median problem (Gwalani et al. 2021). This approach iteratively selects locations that minimize the total weighted distance between citizens and healthcare facilities, ensuring the most impactful placement.

### 2.6.1 Selecting potential locations

Testing every single point in Graz would take too long computationally. Instead, the search was limited to areas that already have poor accessibility – after all, building a new hospital

next to an existing one would not help much. To find these underserved areas, the following approach was used:

1. First, all accessibility scores were sorted, and the 30th percentile was calculated. This means that 30% of all locations have scores below this value.
2. All street network nodes with scores below this threshold were marked as “underserved”.
3. For each underserved node, a “deficit” value was calculated: how far below the threshold is this location? Locations with very poor accessibility get higher deficit values.
4. From these underserved nodes, 150 candidate locations were randomly selected. However, locations with higher deficits had a higher chance of being selected, ensuring that the worst areas are more likely to be tested.

### 2.6.2 Testing each candidate

For each of the 150 candidate locations, the algorithm simulated what would happen if a new facility were built there. This was done separately for each facility type (hospital, clinic, doctor, pharmacy), resulting in  $150 \times 4 = 600$  tests in total.

For each test, the following steps were performed:

1. **Calculate new distances:** Using Dijkstra’s algorithm, the walking distance from the candidate location to every other point in the street network was calculated.
2. **Update the distance values:** For each node in the network, check if the new facility would be closer than the current nearest facility of that type. If yes, update the distance. Mathematically, this is:

$$d'_{t,i} = \min(d_{t,i}, d_{\text{new} \rightarrow i})$$

where  $d_{t,i}$  is the current distance to the nearest facility of type  $t$ , and  $d_{\text{new} \rightarrow i}$  is the distance from the proposed new facility to node  $i$ .

3. **Recalculate accessibility scores:** Using the updated distances, the accessibility score for each affected node was recalculated using the same distance-decay function described earlier.
4. **Calculate the new overall score:** The population-weighted average of all accessibility scores was computed to get a single number representing the overall healthcare accessibility in Graz.

### 2.6.3 Finding the best option

After testing all 600 combinations, the algorithm compared the results to find which combination of location and facility type produced the highest improvement. The improvement was measured as the difference between the new overall score and the baseline (current) score:

$$\text{Improvement} = Q_{\text{new}} - Q_{\text{baseline}}$$

where:

- $Q_{\text{baseline}}$  is the current population-weighted accessibility score before adding any facility
- $Q_{\text{new}}$  is the score after adding the proposed facility

The combination with the highest improvement value was selected as the optimal solution. This tells us both where to build (the location) and what to build (the facility type) to maximize the benefit for Graz's population.

### 3 Results

In the following chapter, the results of this work will be depicted and described.

#### 3.1 Medical facility distribution in Graz

Firstly, the general distribution of medical facilities is shown in Figure 1. Here, it can be seen, that the highest density can be detected in the inner city towards St. Leonhard in the south-east. Also some hot-spots in areas further outwards can be seen, indicating some sub-centres concerning medical care. Nevertheless, it has to be noted that this distribution does not guarantee high scores since different types of facilities have to be present, with hospitals being the most important, which are not located in the centre.

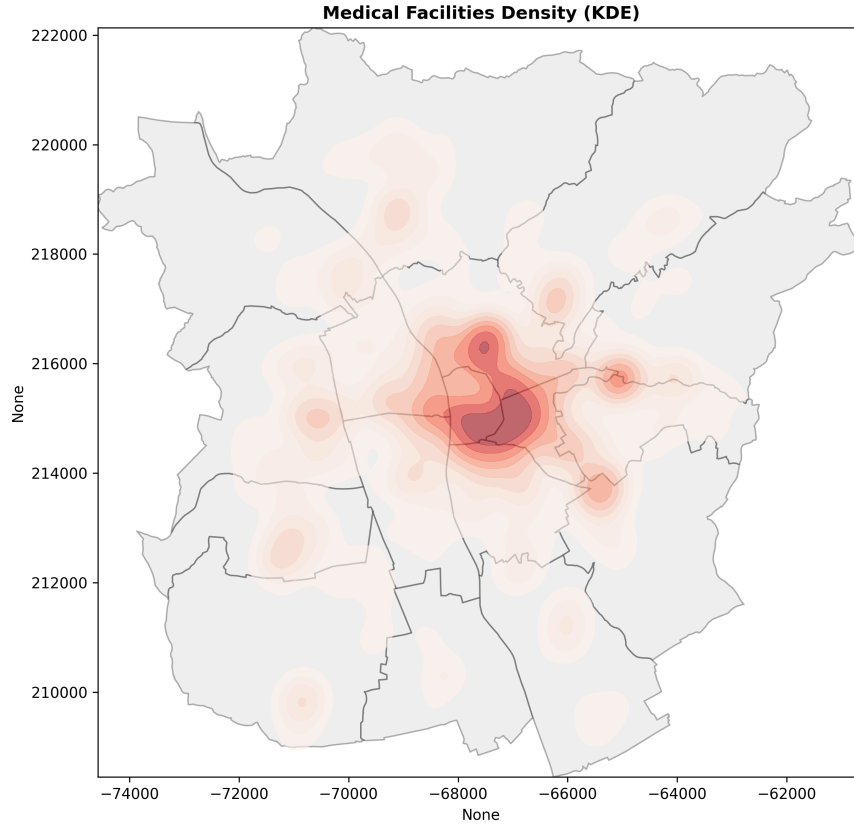


Figure 1: Kernel Density Estimation (KDE) of medical facilities

### 3.2 Distribution quality score in Graz

Having the developed metric applied on Graz and weighted by its population, the following result can be obtained (Figure 2). Here, it can be seen that the centre shows a quite low score, while the outer districts in the north-east have the best scores with low population and a hospital located in this area. In general area to the south especially to the south-east show worse scores but also some badly served areas can be detected to in north.

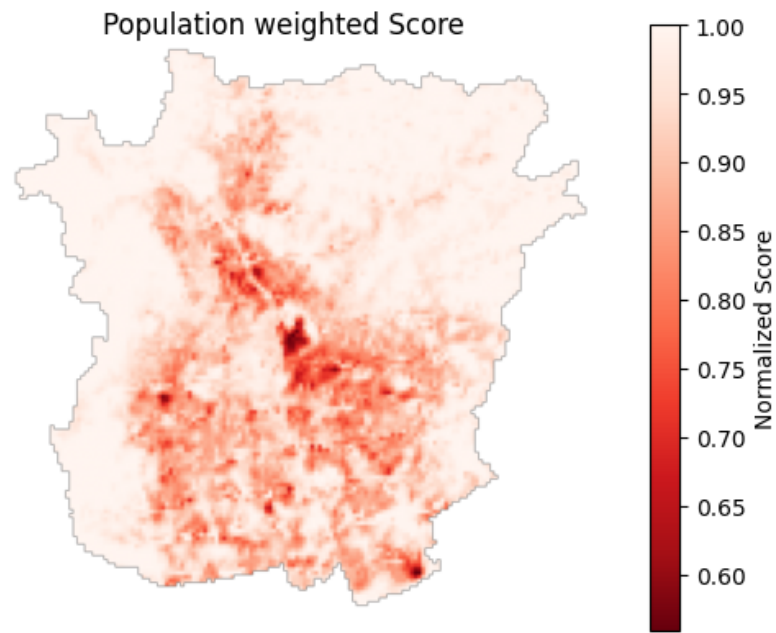


Figure 2: Population-weighted cost for distribution quality

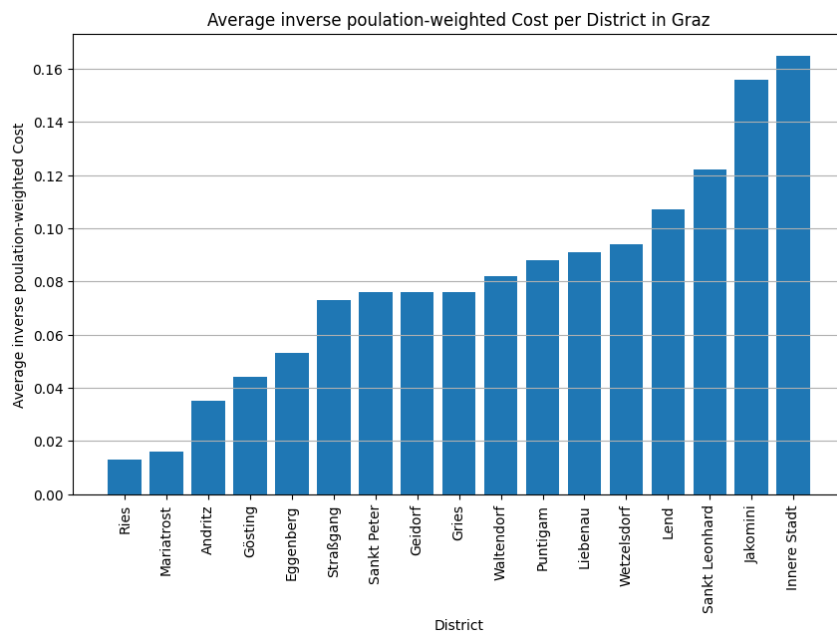


Figure 3: Inverse population-weighted cost per district

In Figure 3 above, this score for each district is shown inversely to indicate the missing score for optimal coverage. Ries and Mariatrost show the best results with almost perfect coverage while Jakomini and Innere Stadt are worst according to this score. The absolute differences are quite small since the score had to be normalized consistently for all areas

### 3.3 Optimal location for new facility

The optimization algorithm tested 600 combinations (150 candidate locations  $\times$  4 facility types) to find the placement that would maximize the improvement in overall accessibility.

The results (Figure 4) show that the optimal new facility would be a hospital located in the southeastern part of Graz, near the border between the Jakomini and Sankt Peter districts. The exact coordinates are 47.058248°N, 15.460684°E (WGS84).

The key findings from the optimization are:

- Baseline accessibility score: 93.38%
- New accessibility score after adding the facility: 93.85%
- Overall improvement: +0.47%

While the overall improvement of 0.47% may seem small, this is because Graz already has relatively good healthcare coverage in most areas. The impact becomes much more visible when looking at individual districts. Table 3 shows the districts that would benefit most from the new hospital:

District	Before	After	Improvement
Jakomini	0.305	0.560	+25.50%
Sankt Peter	0.138	0.351	+21.29%
Waltendorf	0.300	0.496	+19.62%
Sankt Leonhard	0.527	0.723	+19.55%
Innere Stadt	0.314	0.354	+3.99%

Table 3: District-level accessibility improvement from the proposed hospital. Values represent mean accessibility scores (0-1 scale).

The districts with no improvement (such as Andritz, Eggenberg, and Wetzelsdorf) are located too far from the proposed location to benefit, as they fall outside the 3000m maximum distance threshold for hospitals.

The reason a hospital was selected over other facility types is related to the AHP weights and the current distribution. Hospitals have the highest weight (0.526) in the accessibility calculation, meaning that improving access to hospitals has the largest impact on the overall score. Additionally, the chosen location is in an area that currently has poor access to hospitals – the nearest existing hospital is several kilometers away – while clinics, doctors, and pharmacies are already relatively well distributed in this area.

**Optimization Results: New Hospital improves overall accessibility by 0.468%**  
**Baseline Score: 93.38% → New Score: 93.85%**

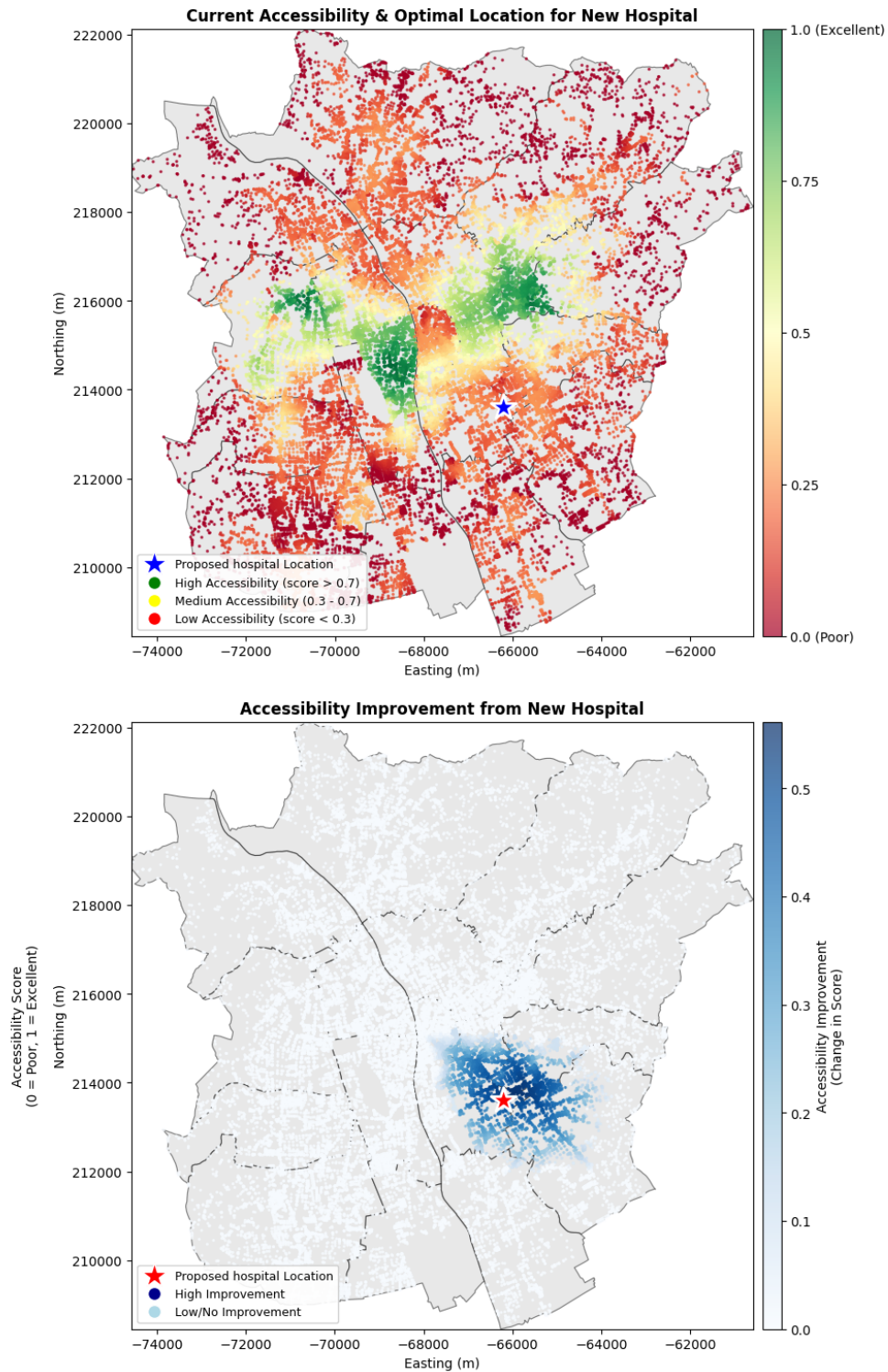


Figure 4: Top: Current accessibility with proposed hospital location (blue star). Bottom: Improvement in accessibility scores after adding the new hospital.

## 4 Discussion

The results shown above are not necessarily intuitive, since some areas which are quite central show quite bad distribution quality scores. Here it must be noticed that the high population living in this area is highly affecting this score, which would not be the case in lighter populated areas at the borders of the city. The new placed hospital and its impact highlights the lack of a quick access in areas like Jakomini although the placement of a hospital in an already densely populated area is very unlikely possible and therefore only pointing out potential changes. Also the score is derived from quite short maximum distances to hospitals which would be especially relevant in very urgent medical emergencies.

This work also has some limitations. Firstly, the use of OSM data yields the problem of data quality and might have some incomplete data. The network analysis also does not include public transport being incomplete in that context. Also this analysis only shows the current status and does not include temporal changes. Also some assumptions were made which must be considered here. The weighting and the distance thresholds highly influence the results and since they are partly subjective but also extracted from literature, which might not apply perfectly on Graz, this represents the main uncertainty.

## 5 Conclusion and Outlook

This work shows that the quality of distribution of medical facilities lacks in quality in the central and the southern districts of Graz, while being almost optimal in the outer suburban parts in the north-east. An optimal new facility to increase the overall quality would be a hospital in Jakomini serving also the surrounding districts.

These results could be improved in future work by doing a validation of the results and by including more information related to this topic. This could be done by comparing actual health conditions and their spatial distribution. On the other hand including data concerning age with focus on elderly people could give more insights. Also including socioeconomic factors would help interpreting the results. To make the results more precise concerning everyday life including multimodal transport is an important aspect.



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# Appendix

## Distribution of tasks

- Adilya Kocheganova
  - Code: Steps 1 and 2
  - Report: Chapter 2 (2.1 - 2.4)
- Bernadette Kakuska
  - Code: Step 3
  - Report: Chapter 2.3, 2.4
- Julian Breitler
  - Code: Step 5
  - Report: Chapter 2.6, 3.3
- Tobias Hochreiter
  - Code: Step 4
  - Report: Chapter 1, 2.5, 3.1 & 3.2, 4, 5

## AI Prompts: Adilya Kocheganova

- How do I load medical facilities (hospital, clinic, doctor, pharmacy) from OpenStreetMap using osmnx? (ChatGPT)

ox.features from place() worked, but needed to filter by multiple amenity tags in a dictionary

- I loaded districts from OSM and got 60+ polygons, but I only need the 17 official districts of Graz. How do I filter them? (Perplexity)

Had to filter by district name manually, some boundaries were duplicated

- I want to make a choropleth map showing facility counts per district. How do I aggregate points to polygon boundaries? (ChatGPT)

Used gpd.sjoin() for spatial join, then groupby() to count facilities per district

- How do I calculate population statistics for each district from a raster file? (Perplexity)

rasterstats.zonal\_statistics() worked but needed to ensure raster and vector geometries had same CRS first

- Used AI for translation (Russian - English)

## AI Prompts: Bernadette Kakuska

- Applying the finding of this case study to our project, how would you suggest the metrics?
- How do I check if there are subcategories to this dataset?
- How do I adapt my code snippet accordingly to the AHP concept?
- How do I include the street network to the AHP approach for accessibility scores?
- I want to calculate the scores based of the weights from the AHP approach and the street network and the population per districts, how do i implement this in my code snippet?
- Right now i calculate the distance with the euclidean distance, how can i implement the dijkstra to better use the street network with the nodes?
- I want to use the optimized dijkstra, what do i need to change in my code?
- How can I do this not hardcoded, but so it matches the user's path depending on who is working on this project?

AI tools (ChatGPT and Perplexity) helped with coding, debugging, text editing, explaining concepts, solving Git issues and literature searches. Results were better when problems were clearly described and relevant code or data was provided. Some AI prompts didn't work at first, for example when they used a different version of a Python library, but by asking follow-up questions and giving more specific instructions, most issues worked well. All AI suggestions were carefully checked before use. Overall, AI was most helpful for troubleshooting, generating code snippets, improving code, and assisting with writing and formatting.

## AI Prompts: Julian Breitler

LLM used: Claude Code

Prompt 1

- look at this projekt, and especially the notebook. i want to implement the point 5 in the project proposal pdf `Final_project-Medical_care_supply_in_Graz.pdf` . make a plan and think about whats a good method do do this task. report back on what to do and what the task is. Summerize everything in a context file you can use in the future.
- worked good, important step for future LLM calls. especially when using jupyter notebooks due to huge context size (json files)

Prompt 2

- can you also think about how to validate the results we have so far ? so before implementing the optimization and creating a new facility. What are possible methods do that. add it to the plan

- resulted in multiple good ideas for validation, but also some unrealistic ones.

#### Prompt 3

- take a look at the project again. the notebook should now include changes on the euclidean distance which now should be calculated via the dijkstra algorithm.add the changes to the plan file.
- keeping the project plan up-to-date is important, brought good results

#### Prompt 4

- if you would be a GIS specialist and you looked at our project. what would be critic points for this projects. what would be tips to improve our current state of this project ? save this critique in "project\_criteque.md"
- good result, brought good context and helped understand the problems of our approach.

#### Prompt 5

- ok lets try implenting the optimization for a new facility from the plan file.
- due to a detailed plan the implementation worked well. Lacked a bit of explanation and was quite complex.

#### Prompt 6

- can you create a detailed explanation on how these calculation works ? What is the input? What gets used from calculations before. save it to explanation.md
- due to complexity of implemntation I needed this prompt to understand what is happening

#### Prompt 7

- can you see the data folder ? It is unstrcuterized and a mess. help me create a better file structure. keep the "data" itself gitignored
- worked good to clean up the project. should have set it up better from the beginning

#### Prompt 8

- how is the data output of the current notebook handled ? i don't want to change to much in the cells due to possible merge conflicts for my colleagues. Is it possible to create a single output cell that handles the outputs ? explain options without implementing.
- discussing options for handling data in and outputs without destroying my colleagues work

#### Prompt 9

- implement option 1 (non invasive input handling)

Prompt 10

- i got an error during importing a file. i guess due to our new file structure. lets check the in/outputs for issues
- didn't work to good so had to make changes

Prompt 11

- no forget the merge conflict concerns from before. lets set the inputs/outputs up more robust.
- still not perfect but handled in/output better. next time better setup from the beginning

Prompt 12

- ok lets take a look at the plan for this project final\_project\_Plan.md . there is a task to validate the existing results before calculating the optimal new facility. help me implement Method 1 and Method 3 for now.
- not implemented yet due to lack of time and understandig what is happening

Prompt 13

- why do not all scores change by 20% in the sensitivity analsis ? only the hospital score changes for 20% all others change in different values
- Prompt
  - Comment

## AI Prompts: Tobias Hochreiter

- I have two polygon rasters with different cells: a cost raster and a population density raster. I want to add the population density to the cost raster by averaging the covered raster cells weighted by area. how to do this in python? (ChatGPT)
  - Result not satisfying,description not clear, procedure probably unusual
- I have a raster file with population data and irregular point data with certain weights. I need to multiply those to add the population to the weight. How to do this? (ChatGPT)
  - Interpolation works, but problems with projection first
- Can i set the pop data in areas in which it does not intersect with the gdf residential to nan, so it is not included in the calculation (Perplexity)
  - Successful but not useful due to Resolution
- How can i vectorize the raster? (Perplexity)
  - Worked immediately