Extending Accessibility Analysis With True Multi-Modality

Master Thesis

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December 18, 2023

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Moritz Gottschling

Köln, den xx.xx.20xx

Abstract

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1 Introduction

Climate change poses a significant threat to our planet, and reducing emissions is crucial in addressing this global challenge. With its ambitious goals to reduce global warming, the Paris Agreement serves as a call to action. However, current trends suggest that achieving these goals without immediate action to reduce emissions is unlikely (Kriegler et al., 2018; Liu & Raftery, 2021). 61.8% of global emissions in 2015 came from cities and predictions for 2100 estimate the share to exceed 80% by 2100 (Gurney et al., 2021). The connection between the large share of city emissions and climate change has led to a critical examination of urban planning and transportation. In response to the urgent need to reduce emissions, the concept of emission-free cities has emerged as a pivotal strategy. Emission-free cities aim to create sustainable environments that minimize the carbon footprint, promote the health of residents, and align with the global efforts to mitigate climate change. Transitioning to these cities is a proactive step toward sustainable living and securing a healthier future for our urban spaces.

With vehicles on the roads accounting for 72% of all transport-related emissions (Sims et al., 2014), it is clear that urban transportation is a crucial area to reduce emissions. To reduce the amount of car traffic, cities need to be planned in a way that allows people to conveniently access everything they need with sustainable, and more environmentally friendly modes of transport. Therefore, one of the main areas of research in the field of urban planning is accessibility-based planning, which was investigated by many studies, including Proffitt et al. (2019); Geurs and van Wee (2004).

A modern way of to rethink urban planning is the 15-minute city concept. This approach is inspired by the 15-minute city concept, which recently gained traction during the COVID pandemic (Moreno et al., 2021). The 15-minute city envisions a lifestyle where all the essential components for a fulfilling life are conveniently reachable within a 15-minute walking or cycling radius. Traditionally, the modes of transport within the 15-minute city studies don't include public transportation or vehicle-sharing systems. However, we argue that to fully grasp the potential of sustainable transportation systems, it's essential to incorporate all available modes of modes, not merely a subset, in measuring accessibility. Little research has been done on the impact of sustainable transportation modes, beyond walking and using a personal bicycle, on a city's accessibility within the 15-minute city framework and how these modes interact. We therefore formulate our first research questions as follows:

RQ 1. How can bicycle sharing and public transport contribute to a city being a 15-minute city?

(a) In what cases is bicycle sharing or public transport more beneficial?

(b) Is a combination of bicycle sharing and public transport necessary, or are they substitutable?

RQ 1b aims to investigate the interactive effects of these transportation modes and examines how their combined or individual use impacts urban accessibility. Previous studies have noted synergistic effects between these modes (Yang et al., 2018; Murphy & Usher, 2015; Wagner & Zündorf, 2017; Fishman et al., 2013; Ma et al., 2015); however, there is a notable gap in research regarding their role specifically within the 15-minute city concept.

However, incorporating other modes of transport that potentially are fare-based poses a new challenge. To be able to use these modes of transport, people need to be able to afford them, which might cause inequality in accessibility. There has been research that investigates the influence of cost on accessibility (Conway & Stewart, 2019; El-Geneidy et al., 2016; Guzman et al., 2017; Cui & Levinson, 2018), but not in the domain of the 15-minute city concept. Therefore, we formulate our second research question as follows:

RQ 2. How does cost affect accessibility in the perspective of the 15-minute city, and how can practitioners enable more equal and fair mobility?

To answer these questions, we develop a new method for accessibility-based planning that incorporates an arbitrary amount of modes of travel. This method will compute a metric based on the concept of the 15-minute city, extending it to include all modes of transport and, therefore, presenting a more holistic view of accessibility via sustainable modes of transport. To also consider the interaction between cost and accessibility, our metric will also account for the cost of using the different modes of transport. To the best of our knowledge, no method exists that can compute accessibility metrics for an arbitrary combination of different transport modes while computing a metric with multiple objectives, like cost and time. Lastly, we apply our method to the city of Cologne to retrieve actual data. With that, we formulate our third and fourth research questions as follows:

RQ 3. How can we measure accessibility in a way that incorporates an arbitrary combination of transport modes while considering the associated costs?

RQ 4. What are specific recommendations for urban planning in Cologne?

Our research makes significant contributions both theoretically and practically. Theoretically, our contributions are threefold: Theoretically, we introduce a new method for accessibility-based urban planning that incorporates various transport modes and considers the cost of using these modes. Our second contribution is the development of a novel metric rooted in the 15-minute city concept, offering a fresh perspective on assessing urban accessibility. Thirdly, we analyze the influence and interaction between multiple transportation modes within the 15-minute city framework and examine how cost factors impact accessibility. Practically, our work yields a significant tool for urban planners. This tool facilitates the planning of cities with a focus on accessibility, aligning closely with the 15-minute city concept. It offers a pragmatic approach to urban design, enabling planners to create more accessible, efficient, cost-effective urban environments.

The remainder of this paper is structured as follows. Section 2 presents related work on accessibility-based planning, the 15-minute city concept, and routing algorithms. Then, in Section 3, we describe the specifics of our approach, including the data collection process, our routing algorithm, and our accessibility metric. After that, we introduce the use case on which we will apply our method in Section 4 and present the results in Section 5. Finally, we conclude with our discussion Section 6.

2 Related Work

Urban planning and transportation is evolving rapidly due to the increasing emphasis on sustainability and proximity-based accessibility. This section consists of a comprehensive literature review focusing on critical areas such as accessibility analysis, routing algorithms, and integrating public transport data with street network data. The objective is to build a theoretical foundation for developing methodologies to optimize urban accessibility. The first part of this section explores the paradigm shift from traditional mobility-based to accessibility-based planning. This shift is crucial in addressing modern urban challenges such as reducing greenhouse gas emissions and promoting sustainable transportation. Subsequently, we examine various routing algorithms central to assessing accessibility effectively. These include some well-established algorithms like Dijkstra, Multi-Label-Correcting (MLC), and innovative approaches tailored for public transport networks, such as RAPTOR, McRAPTOR, and Multi-modal Multicriteria RAPTOR (MCR). Furthermore, the integration of public transport data, primarily through the General Transit Feed Specification (GTFS), and street network data sourced from OpenStreetMap (OSM) are discussed. This integration is vital for a realistic simulation of urban dynamics and enables the reproducibility of our results. Finally, we address the significance of multimodality and intermodality in urban planning. This is important because considering diverse transport modes, including bicycle sharing and public transport, and investigating their synergies are vital to retrieving a holistic view of urban accessibility. This literature review sets the stage for the subsequent sections, where we develop and test a new tool for accessibility-based planning, incorporating multi-modal and intermodal transport options.

2.1 Accessibility-Based Planning

Traditional mobility-based planning primarily focuses on reducing congestion and facilitating movement, often prioritizing automobile travel (Proffitt et al., 2019). However, this approach is becoming increasingly outdated, failing to address modern challenges like reducing greenhouse gas emissions. This is where accessibility-based planning comes into play, which focuses on planning cities in a way that provides residents with fast access to all essential services (Proffitt et al., 2019). Having easy access to all essential services has the potential to reduce the need for car ownership and its frequent usage. This shift foregrounds accessibility as the primary goal, rather than merely focusing on mobility, recognizing that mobility is a means to an end and not the ultimate objective in urban planning.

Geurs and van Wee (2004) describe four types of accessibility-based planning, seen in Table 1. Infrastructure-based accessibility is an approach that evaluates the performance and service level of transportation infrastructure. It involves an analysis of various factors, such as the levels of congestion and average travel speeds. The primary goal of this approach is to optimize the physical layout and capacity of transport networks to improve access to various destinations. Even though Geurs and van Wee (2004) describe this as an accessibility-based approach, it more closely resembles the traditional mobility-based approach, as it focuses on the infrastructure itself rather than accessibility. Location-Based or Place-Based Accessibility focuses on the accessibility of essential services or employment opportunities within specific travel time or cost limits. This method calculates the number of critical destinations, such as schools, hospitals, or workplaces that are reachable within a reasonable commute. It emphasizes the spatial distribution of resources and services. Person-Based Accessibility centers on the individual's experience in accessing various activities. This perspective acknowledges that accessibility can vary significantly based on personal factors like age, income, or physical ability. It aims to tailor urban planning to address diverse personal needs and constraints, considering personal travel patterns and individual circumstances. Utility-based accessibility evaluates the economic benefits of transportation investments. This approach focuses on the returns of such investments regarding improved accessibility and their overall utility to the community. It includes considerations of how transportation improvements can enhance residents' quality of life and economic opportunities.

Table 1: Categories of Accessibility-Based Planning Measures

Category	Focus	Examples
Infrastructure-Based	- Traffic performance analysis - Service level of infrastructure	- Level of congestion - Average travel speed
Location-Based or Place-Based	- Level of accessibility to locations - w.r.t. time & cost	- Number of jobs within 30 minutes
Person-Based	- Individual travel time	- Individual's travel time between activities
Utility-Based	- Economic benefits	- Transportation investments returns

2.2 15-Minute City

A recent stream of research in the field of urban planning is the concept of the 15-minute city. The concept is based on the idea that all essential services and amenities should be reachable within a 15-minute walking radius, focusing on reducing travel times and enhancing urban livability. Even though it is a concept rather than a concrete metric, the 15-minute city is closely related to location-based planning measures. The 15-minute city concept was first introduced by Carlos Moreno, a professor at the Sorbonne University in Paris (Moreno et al., 2021). It was popularized by the mayor of Paris, Anne Hidalgo, who made it a central part of her re-election campaign (Gongadze & Maassen, Wed, 01/25/2023 - 15:46).

The 15-minute city model offers several advantages instrumental in shaping modern urban environments. Primarily, it cultivates stronger social relationships (Allam et al., 2020). Residents are more likely to encounter each other regularly in a city where essential amenities are within a 15-minute walking or cycling radius. This frequent interaction fosters community bonds and a sense of belonging, which benefits urban livability. Additionally, this model inevitably promotes a unique form of social distancing. As residents primarily travel by walking or cycling, there's a natural reduction in gathering large crowds, typically seen in mass transit systems. This not only aids in maintaining public health standards but also diminishes the stress often associated with crowded urban transportation (Allam et al., 2020). Moreover, the shift towards walking and cycling represents a more environmentally sustainable mode of urban transport. This transition aligns closely with Sustainable Development Goals 11 and 13, which advocate for sustainable cities and communities, and taking urgent action to combat climate change, respectively. By reducing reliance on motorized vehicles, the 15-minute city concept contributes to lowering carbon emissions and minimizing the overall environmental impact of urban areas (Allam et al., 2020; Papas et al., 2023).

Furthermore, an important economic benefit of the 15-minute city is the significant reduction in traffic. This decrease in traffic congestion not only enhances the efficiency of urban transport systems but also leads to economic savings for both individuals and the city as a whole, due to lower transportation costs and time savings. This aspect underscores the economic viability of the 15-minute city model in creating more efficient and cost-effective urban environments (Allam et al., 2020; Papas et al., 2023).

In addition, developing cities around the 15-minute city concept can play a crucial role in reducing social inequalities. Since walking is a free mode of transport, it becomes an accessible option for all socioeconomic groups, thereby leveling the playing field for urban residents. This inclusivity is central to the concept's appeal and effectiveness (Weng et al., 2019; Gustafson, 2022). However, when incorporating other fare-based modes of transport, such as bicycle sharing, it is vital to consider the fares and their impact on accessibility and equity. This consideration is a crucial reason for adopting multi-objective approaches in urban planning, ensuring that the benefits of the 15-minute city are equitably distributed across all sections of society.

2.3 Accessibility Metrics Based on the 15-Minute City

Quantitative studies have developed various ways to measure how well cities match the 15-minute city concept by developing metrics that encapsulate this principle. Olivari et al. (2023) contribute to this research by creating the NExt proXimity Index (NEXI), which has two components: the NEXI-Minutes and the NEXI-Global. The NEXI-Minutes looks at the accessibility of various urban amenities, ranging from educational institutions to entertainment venues and grocery stores, by calculating the time needed to reach the closest facility within each category. Complementing this, the NEXI-Global, inspired by the Walk Score method (*Walk Score Methodology*, 2023), combines these individual times through a weighted average into an overall score, giving a holistic view of the accessibility of a city.

NEXI is unique because it is both global and local. Namely, it is globally applicable due to its reliance on OpenStreetMap data, yet sufficiently detailed to assess local conditions. This has been proven by applying it all over Italy, where it's showcased on an interactive map through a hexagonal grid that makes it easy to see which areas are doing well and need improvement. The significance of the NEXI, as underscored by Olivari et al. (2023), is its role in enabling data-driven policy-making to develop cities in the fashion of the 15-minute city framework. Therefore, their index enables accessibility-based planning.

However, there are some limitations in the NEXI metrics. The NEXI-Minutes offers separate metrics for each category, which may lead to a fragmented understanding of urban accessibility. This multi-metric approach can make comprehensive evaluation challenging. In addition, the NEXI-Global, while aggregating these categories, introduces complexity through its weighted scoring system. The weighted average is hard for humans to interpret, and the score from 0 to 100 disconnects the metric from the intuitive meaning of minutes. This makes it more difficult for urban planners and policymakers to interpret and utilize the results effectively. These factors suggest a need for refinement in the NEXI methodology to enhance its practical utility in urban development and planning.

Another study by Nicoletti et al. (2023) introduces an accessibility metric that explores the connection between urban infrastructure and social inequality. The researchers developed an open, data-driven framework to analyze how different communities within cities access essential services, and they discovered that access to urban amenities like healthcare, education, and transportation is not evenly distributed. The study examined over 50 types of amenities across 54 cities worldwide and found a common pattern: in all cities, access to infrastructure followed a log-normal distribution, indicating that a small number of communities have very high access to amenities, while the majority have moderate to low access. The log-normal distribution suggests that improvements in accessibility are not proportionately distributed across the urban landscape. Instead, there are diminishing returns in accessibility as one moves from the most to the least accessible areas. This skew towards lower accessibility for most communities underscores systemic urban planning and infrastructure development issues that disproportionately affect disadvantaged populations. This pattern was consistent even when considering various socioeconomic factors.

This framework developed by Nicoletti et al. (2023) is flexible and adaptable, allowing city planners to tailor it to local needs and priorities. It's a tool that can help identify which groups in a city are most affected by inequality concerning accessibility to services. Similar to Olivari et al. (2023), they emphasize the role of open data to guide urban planning and policy. While Olivari et al. (2023) provide a tool to measure accessibility and leave the analysis and interpretation to practitioners, Nicoletti et al. (2023) directly reveal the disparities in accessibility and provide a framework to analyze them.

Another metric introduced by Ferrer-Ortiz et al. (2022) calculates whether a specific area has access to a particular category within 15 minutes for Barcelona. They derive their categories from the six 15-minute city "urban social functions" defined by Moreno. However, they only consider a small subset of four categories: care, education, provisioning, and entertainment. Their data is taken from a variety of sources, all of which are specific to Spain or Barcelona. This makes it challenging to apply their method to other cities. To calculate the distances between the amenities and the areas, they use ESRI's ArcGIS Network Analyst, which is proprietary software, making applying their method to other cities difficult. Interestingly, the study revealed a high level of service accessibility across Barcelona, with an average of the residents having access to most of the 24 services analyzed within the 15-minute threshold. However, disparities were observed between the city center and suburban areas, indicating spatial inequalities in accessibility. The findings underscore the critical role of urban planning in ensuring equitable access to amenities and demonstrate that most of Barcelona's areas align with the 15-Minute City ideal.

Meanwhile, the computation of travel time by all previously named authors is based on walking simulations. This fails to capture the reality of urban mobility, which consists of various modes of transport, such as public transport, cycling, and driving. Moreover, the NEXI's fragmented multi-metric approach and complex weighted scoring system can hinder practical interpretation and application. Acknowledging these shortcomings, we aim to introduce a novel multi-modal accessibility metric, which we present in Section 3.1. This proposed metric will encompass a broader spectrum of transportation modes and a more intuitive understanding, providing a more accurate and comprehensive evaluation of urban accessibility for effective urban planning.

2.4 Routing Algorithms

Following the discussion of accessibility metrics and their application in urban planning, particularly in the context of the 15-minute city model, this subsection transitions to a critical component necessary to calculate these metrics: routing algorithms. Here, the focus is to explore various routing algorithms instrumental in calculating the shortest and most efficient paths within urban environments.

2.4.1 Graph-based Algorithms

Before exploring the specific algorithms, it is vital to understand the theoretical foundations of graph-based routing algorithms, so we first present the theoretical background.

Theoretical Background The primary goal of routing algorithms is to identify the optimal path between a designated origin and a specific destination. Typically, this is captured using a graph representation:

$$G = (V, E)$$

where V represents a set of nodes or locations and E encapsulates the set of edges, which correspond to connections between these nodes.

For each edge $e \in E$, there's an associated weight $w(e) \in \mathbb{R}$ that characterizes the cost of traversing it. This cost might be determined by factors such as distance or travel time. Consequently, the shortest path can be expressed as:

$$\langle v_0, e_0, v_1, e_1, \ldots, v_n \rangle$$

Here, v_0 denotes the origin, v_n the destination, and the edges must connect the nodes in the sequence:

$$e_i = (v_i, v_{i+1}) \quad \text{for} \quad i \in \{0, \dots, n-1\}$$

In accessibility contexts, the primary concern frequently revolves around determining the accumulated cost, $d(v_n) = \sum_{e \in E} w(e)$, to reach the destination rather than the actual path.

The problem may also encompass multiple objectives, such as considering both time and monetary cost of travel. Under these circumstances, the edge weight is represented as a vector:

$$w(e) \in \mathbb{R}^k$$

where k stands for the total objectives count. Unlike the more straightforward single-objective case with a singular optimal path, the multi-objective optimization yields a Pareto set, constituting several optimal routes. A Pareto set refers to a set of solutions that are non-dominated by any other solution. This means that for each solution in the Pareto set, no other solution is better for all objectives. The Pareto set represents an optimal trade-off among the different objectives, where improving one aspect would worsen another. For example, a Pareto set could contain multiple paths, where one path is faster but more expensive, while another is slower but cheaper.

The value of these paths is depicted using a label: $l \in \mathbb{R}^k$ where $l_i \in \mathbb{R}$ denotes the value for the i-th objective. This label can be considered a multidimensional extension of $d(v_n)$ from the single-objective scenario. The Pareto set associated with destination node v_n is often termed as a bag, expressed as $B(v_n)$, comprising labels that are not dominated by each other. Domination is defined as follows: l' dominates l if $l'_i \leq l_i$ for all $i \in \{1, \dots, k\}$ and $l'_i < l_i$ for at least one $i \in \{1, \dots, k\}$. Intuitively, this means that l' is at least as good as l in all objectives and strictly better in at least one objective.

The goal of routing algorithms used in accessibility analysis is finding the distance in the single objective case and the bag in the multi-objective case, often discarding the actual paths. Also, specific to accessibility analysis is the altering of routing algorithms to not find the optimal paths between two nodes, referred to as one-to-one query, but the path from a single origin to all other nodes in the network, which we call one-to-all query.

Dijkstra The most straightforward approach to compute the shortest paths in a graph is the Dijkstra algorithm (Dijkstra, 1959). Dijkstra's algorithm initiates at a designated start node $s \in V$ and employs a priority queue to systematically determine the shortest path to each subsequent node $v \in V$.

Initially, the distance to the start node s is set to zero, while the distances to all other nodes are set to infinity. The algorithm dequeues the node u with the smallest known distance from the priority queue in each iteration. It then examines each outgoing edge $e = (u, v)$ from u, updating the distance to v if a shorter path through u is discovered. Specifically, if $\text{dist}(u) + w(e) < \text{dist}(v)$, then $\text{dist}(v)$ is updated to $\text{dist}(u) + w(e)$, and v is enqueued into the priority queue for future exploration. The node u is marked as visited by adding it to the set V_{visited}. Depending on the goal, the algorithm terminates when the destination node is dequeued (one-to-one) or when the priority queue is empty (one-to-all).

However, this simple approach has multiple problems. Firstly, the Dijkstra algorithm is not able to handle multiple criteria. Secondly, the runtime of Dijkstra's algorithm is $O(|E| + |V| \log |V|)$, which is slow for large graphs.

MLC The Multi-Label-Correcting (MLC) (Hansen, 1980) algorithm is an extension of Dijkstra's algorithm to handle multi-objective scenarios. As mentioned in Section 2.4, in the multi-objective case, we try to find the bag of the destination node. Specifically, for k criteria, each node v retains a bag of k-dimensional labels. Such a list encapsulates a set of Pareto-optimal paths from the starting node to v. Similarly to Dijkstra's algorithm, MLC initializes all nodes with an empty bag, except for the start node, which is initialized with a label of $(0, \ldots, 0) \in \mathbb{R}^k$. Each iteration extracts the lexicographically smallest label instead of selecting the node with the minimum distance. When a label is extracted and v is its corresponding node, updates are made for all connected edges (v, w). The update process consists of comparing a newly generated tentative label against all labels within the bag of w. This new label is only inserted into the bag if any existing label doesn't dominate it. Conversely, any label now dominated by the new entry is removed. Each time a label is inserted into a bag, it is also inserted into the priority queue. The algorithm terminates when the priority queue is empty.

The major drawback of the MLC algorithm is its runtime, which is even slower than Dijkstra's algorithm because each node can be visited multiple times.

Graph-based Algorithms in Public Transport In the context of accessibility analysis, the previously mentioned algorithms can be used directly for walking, cycling, and driving networks. However, public transport networks pose a challenge since they contain time-dependent information, such as the departure time of a trip. To overcome this challenge, two approaches are commonly used, the time-expanded and the time-dependent approach, as explained by Müller-Hannemann et al. (2007). The idea behind these methods is to artificially craft a graph that represents the public transport network in a way that allows the use of graph-based algorithms. While enabling the use of graph-based algorithms to solve routing in time-dependent transport networks, both approaches result in massive graphs and therefore suffer from runtime problems. Because of these runtime problems, we won't go into detail about them but rather introduce algorithms that take advantage of the specifics of time-dependent transport networks, resulting in much better runtimes.

2.4.2 Schedule-based Algorithms

Schedule-based Algorithms are a class of algorithms specifically designed to solve routing problems in time-dependent transport networks. We start with the most influential algorithm in this class, RAPTOR (Delling et al., 2015), and then introduce some of its extensions and other algorithms based on it.

RAPTOR To overcome the runtime problems of graph-based approaches, Delling et al. (2015) introduce one of the most prominent routing algorithms for public transport, called Round based Public Transit Optimized Router algorithm (RAPTOR). Unlike traditional Dijkstra-based algorithms, RAPTOR operates in rounds, looking at each route (such as a bus line) in the network at most once per round, where one round represents a single trip.

As RAPTOR does not operate on a graph, we first introduce the problem statement. Raptor operates on a scheduled network consisting of routes r, trips t, stops p, and stop times that associate trips with stops. A route is associated with a sequence of stops $stops(r) = \langle p_1, \ldots, p_n \rangle$. A route has multiple trips ordered by their departure time $trips(r) = \langle t_1, \ldots, t_m \rangle$. One trip associates arrival and departure times with each stop of the route, denoted by $arrivalTime(t, s) \in \mathbb{N}$ and $departureTime(t, s) \in \mathbb{N}$ respectively. Trips of the same must not overtake each other, formally:

$$departureTime(t_i, p_j) \leq arrivalTime(t_{i+1}, p_j)$$

for all $i \in \{1, \ldots, m-1\}$ and $j \in \{1, \ldots, n\}$. Each stop p has a minimal exchange time $\tau_{ch}(p) \in N$ associated with it. Often, the exchange time is set to a fixed time $\tau_{ch}(p) = \tau_{ch}$ for all stops p. When transferring from a trip t to another trip t' within a stop p, the exchange time has to be smaller than the difference in arrival and departure time of the two trips, formally:

$$arrivalTime(t, p) + \tau_{ch}(p) \leq departureTime(t', p)$$

In addition to transfer within stops, RAPTOR also allows footpaths. Footpaths allow transferring from one stop to another without using public transport. Therefore, they are time-independent. Each footpath is associated with a travel time $l(p, p')$. The input of the RAPTOR algorithm, in addition to the previously described scheduled network, are source stop p_s, and, in the case of a one-to-one query, target stop p_t, as well as the departure time at the source stop τ.

RAPTOR operates in rounds. Before the first round, some variables are initialized. We denote the earliest possible arrival time at iteration i with $\tau_i(p)$ and the best earliest possible arrival time over the course of all iterations with $\tau^\star(p)$. For the source stop, τ_p, we set $\tau_0(p) = \tau$ and $\tau^\star(p) = \tau$. For all other stops, we set $\tau_0 = \infty$ and $\tau^\star = \infty$. In addition, we initialize a set of marked nodes M only to contain the source stop p_s and a set of marked route-stop pairs, denoted by Q, to the empty set. A route-stop pair is simply a tuple that contains a route and one of its stops. The set of marked stops will contain all stops whose earliest possible arrival time has been updated in the current round. Similarly, the set of marked route-stop pairs contains the routes of the marked stops, together with the earliest stop of that route that has been marked.

Each round consists of three major steps. In the first step, the routes that have to be iterated are collected. In the second step, the routes are iterated by "hopping" on their trips. And in the third stage, potential footpaths are explored.

First, we clear the set of marked route-stop pairs Q. Then, we check the routes that are connected to each marked stop. For each of these routes, we store the route-stop pair in Q. However, the routes in Q should be unique. If there are two marked stops that are connected to the same route, we choose the stop that is earlier in the sequence of stops of that route. Now, we clear the set of marked stops.

We iterate the route-stop pairs in Q visually depicted in Figure 1. The following step can be regarded as hopping on the earliest possible trip that we can catch of that route at that stop. For each route-stop (r, p) pair, we iterate over the stops in r in the sequence that is associated with r, beginning with p. We check for the earliest possible trip that we can catch regarding the last arrival time at the current stop $\tau_{k-1}(p)$ and the minimum exchange time $\tau_{ch}(p)$. If there is a trip that is possible to catch, we save it as the current trip t_{curr} and continue to iterate the stops of the route r. Now that we are on a trip, we have to check whether we need to update the earliest possible arrival time of the current stop $\tau_k(p)$ and $\tau^\star(p)$ by comparing the stop time of the current trip with the best earliest arrival time of that stop

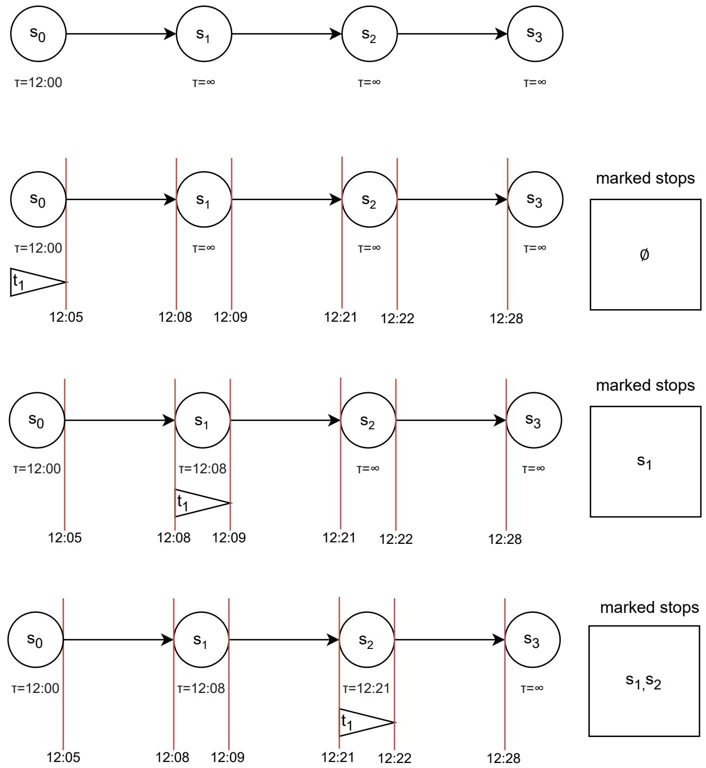


Figure 1: Iterating a Route in RAPTOR

$\tau^{\star}(p)$, formally:

$$\tau_k(p) = \min\{\tau_k(p), arrivalTime(t_{curr}, p)\}$$

If an update is necessary, we also add the current stop p to the marked stops. Lastly, we check all marked stops for potential footpaths. Remember: the marked stops are those for which the earliest possible arrival time was updated in this iteration. For each footpath that is connected to a marked stop, we check whether the earliest possible arrival time of the other stop could be improved by the footpath. If so, we update the earliest arrival times and mark that stop. If no stops are marked, there are no new routes to iterate, and the algorithm stops. After termination $\tau_k(p)$ contains the earliest possible arrival time at stop p with at most k transfers.

One limitation of RAPTOR is the transfer graph, which is used to represent footpaths. The transfer graph has to be transitively closed, which means that each node has to be connected with an edge to all other nodes that can be reached from that node. This has the advantage that in the algorithm, we only have to check for direct neighbors of a stop, which is very fast. In practice, there are many possibilities for how the transfer graph could look. A realistic transfer graph should be derived from a street network, as passengers should be able to walk from one stop to another using sidewalks. One could limit the maximum walking distance to keep the transfer graph small. However, this may remove optimal journeys from the search space. Creating the transfer graph involves a preprocessing step that becomes exponentially more resource-intensive as the size of the graph increases. This escalation in computational demand renders the task infeasible quickly as the graph grows larger and more reflective of real-world complexity.

Therefore, finding a fitting transfer graph is challenging. Through its round-based nature, RAPTOR is able to optimize for two criteria at the same time. However, RAPTOR cannot incorporate more criteria, and one of the criteria will always be the number of transfers.

McRAPTOR McRAPTOR (Delling et al., 2015) is an extension of RAPTOR that allows an arbitrary number of criteria. Like MLC, McRAPTOR also uses the notion of bags containing non-dominating labels. McRAPTOR does not pose any restrictions on how the objectives are updated during the algorithm.

The algorithm of McRAPTOR only requires slight modifications to the algorithm of RAPTOR. In the initialization step, each stop p is assigned an empty bag, except the source stop p_s, which is assigned a bag containing a starting label. The starting label can be defined as an input but is usually $(\tau, 0, 0, \dots, 0)$, where τ is the departure time at the source stop. When iterating over the route-stop pairs (r, p), McRAPTOR creates a route bag that contains all labels that are in the current bag of p. In addition, labels in the route bag are associated with a trip. During the creation of the route bag, each label in the route bag is associated with the first trip that is possible to catch according to the label's earliest arrival time at the current stop p. Then the route is processed, stop by stop, just like in RAPTOR. At each stop, the labels in the route bag are updated according to the current trip. This update must include updating the earliest arrival time but can also include updates to other criteria. After the route has been processed, the route bag is merged into the bag of the current stop. Merging a bag B_1 into a bag B_2 means that all labels in B_1 that are not dominated by any label in B_2 are added to B_2 and all labels in B_2 that are dominated by a label in B_1 are removed from B_2. After the route bag has been merged into the bag of the current stop, the bag of the current stop is merged into the route bag. Lastly, the trips associated with the labels in the route bag are updated according to the labels' earliest arrival time at the current stop. Each time a label is added to a stop bag, this stop is marked. If no stop is marked after a round, the algorithm terminates. Note that McRAPTOR allows updates to the route bags at any time during processing. When and how the route bag should be updated depends on the objective and its representation.

While McRAPTOR has a slower runtime than RAPTOR, it is still magnitudes faster than MLC. However, McRAPTOR still suffers from the same problem as RAPTOR: the transfer graph is hard to compute.

MCR To overcome the problem of RAPTOR Delling et al. (2013) introduce Multi-modal Multicriteria RAPTOR (MCR). MCR modifies McRAPTOR so that the transfer graph must not be transitively closed. MCR can use the street network as an input directly, so no preprocessing is necessary. Traversing the street network directly during the algorithm has the benefit of allowing it to update the objectives between trips. This is important if we want multiple modes of transfer that contain free-floating vehicle-sharing systems. For example, consider the following case. For an optimal journey a passenger has to first walk five minutes to a free-floating bicycle, with which the passenger then travels to the next stop. There is no way to represent this in RAPTOR because the specifics of the transfer depend on the current label, which is unknown before running the algorithm. Therefore, it is not possible to precompute the transfer graph.

MCR as an algorithm shares substantial similarities with McRAPTOR. The critical difference in MCR is the substitution of the footpath processing step with the MLC algorithm. Consequently, MCR can be conceptualized as an algorithm that seamlessly integrates MLC with McRAPTOR, employing each of them in an alternating manner. The authors find that the bottleneck of MCR is the MLC step. Therefore, they employ a technique called contraction (Geisberger et al., 2012) to speed up MLC. Contraction is a preprocessing technique that reduces the size of the graph by removing nodes and adding shortcut edges.

As previously mentioned, MCR is able to use the street network as the transfer graph and requires no preprocessing. However, when comparing the runtime of a simple query of MCR and McRAPTOR, MCR is slower, as MLC on the street network takes much more time than just checking the neighbors of a stop in the transfer graph. Generally, using MCR or McRAPTOR is a trade-off of runtime and preprocessing time.

ULTRA Baum et al. (2019) propose another algorithm building on MCR, called UnLimited TRAnsfers for Multi-Modal Route Planning (ULTRA). ULTRA builds on the observation that extensive exploration of the transfer graph, like in MCR, is often unnecessary for transfers between public transport trips but is more crucial for initial and final transfers. Therefore, they propose a preprocessing step that computes intermediate transfers, contributing to optimal journeys on the transfer graph. They then use these precomputed transfers as the transfer graph for RAPTOR. To account for initial and final transfers, ULTRA employs the Bucket Contraction-Hierarchies (Bucket-CH) algorithm (Geisberger et al., 2008), an efficient one-to-many approach, together with RAPTOR.

While ULTRA demonstrates a runtime improvement over MCR, it is limited to optimizing only time and the number of transfers. Using ULTRA in an accessibility analysis setting is also unsuitable because ULTRA runs a reverse Bucket-CH query from the end node to all stops to compute potential final transfers. This means that ULTRA, unlike MCR, is incompatible with one-to-many queries.

2.5 Public Transport Data

In practice, a standard data format is needed to retrieve and interpret the data needed to run routing algorithms on public transport networks. The General Transit Feed Specification (GTFS) (MobilityData, 2023a) serves as a standardized format for public transportation schedules and associated geographic details. It is divided into two main components: GTFS Schedule and GTFS Realtime. GTFS Realtime provides live transit updates. On the other hand, GTFS Schedule offers information about routes, schedules, fares, and geographic transit details. For our study and tool, we focus solely on GTFS Schedule and omit considerations related to GTFS Realtime.

Central to the GTFS format are several core concepts. A route defines the overall path a particular public transport service takes, identified by attributes like name, ID, and the mode of transport such as bus or subway. A route is not defined by a single path but rather a collection of possible paths. For example, in the real world a route often has two paths, one for each direction. Similarly, it can happen that a route has to be redirected due to construction work, which would result in a third and fourth path. A trip refers to a specific run of a vehicle along a route, distinguishing between different timings or sequences of service on the same route. A stop is a specific point along a route where passengers embark or disembark. Stops have unique IDs, names, and geographical coordinates. Stop times specify when a vehicle is expected to be at a particular stop during its trip. This data pinpoints both the arrival and departure timings at each stop.

In essence, GTFS provides a comprehensive overview of a transit agency's service, covering both the spatial aspects of transit and the temporal aspects.

2.6 Street Network Data

Just as GTFS provides a standardized format for public transport schedules, the need for a consistent data format for street network information is addressed by OpenStreetMap (OSM) (Foundation, 2023). OSM is a collaborative initiative that offers freely available geographic data. This data captures various features on the Earth's surface, including roads, trails, establishments, railway stations, and more. In the context of street networks, potentially used by routing algorithms, OSM represents roads and paths using interconnected nodes and ways. Nodes specify distinct geographical coordinates, defined by latitude and longitude, while ways connect these nodes to define linear structures or area boundaries. Importantly, these ways have meta-data assigned to them containing information about what vehicles can travel along them and how long they are. In addition, OSM offers vast amounts of data about points of interest, potentially valuable for accessibility analysis. OSM is extensive, regularly updated, and, most importantly, freely available, which makes it indispensable for projects seeking reproducibility and generalizability.

2.7 Importance of Multimodality & Intermodality

Various research has underlined the importance of considering multimodality and intermodality in urban planning and transportation. Recent studies have especially highlighted the synergistic relationship between bicycle sharing and public transport systems, demonstrating their combined potential in improving urban mobility.

Yang et al. (2018) illustrate the significant impact of bicycles in urban transport networks. Their results indicate that bicycles notably reduce average transfer times, the average journey length for passengers, and the Gini coefficient, an indicator of network efficiency. These findings underscore the role of bicycles in optimizing transit network performance. Further reinforcing this point, Radzimski and Dzięcielski (2021) identifies a positive correlation between public transport frequency and the number of bicycle trips, particularly for short and medium distances up to 3 km. This suggests that the availability of bicycles can complement public transport, particularly for covering the initial or final segments of a journey. Murphy and Usher (2015) conducted a survey in Dublin that revealed 39% of bicycle sharing users combined this service with another mode of transport, primarily public transport (91.5%) Murphy and Usher (2015). This indicates a high synergy between bicycle sharing and public transport, as commuters frequently use them together. Similarly, Fishman et al. (2013) reviewed literature on bicycle sharing and concluded that it is synergistic with public transport. This synergy is further elucidated by Ma et al. (2015) who, through a linear regression analysis, identified a positive correlation between public transport passenger numbers and bicycle sharing trips Ma et al. (2015). They suggest that bicycle sharing effectively addresses the first and last-mile problem, providing a crucial link to and from transit hubs. Wagner and Zündorf (2017) also contributes to this discussion by demonstrating that unrestricted walking, as part of a multi-modal transit system, significantly reduces travel times compared to limited walking scenarios. However, it's also noted that computing routes with unrestricted walking is more computationally intensive.

In summary, the interplay between bicycle sharing and public transport is not just complementary but essential for urban planning and transportation. Furthermore, incorporating unrestricted walking into transit planning, despite its computational challenges, can substantially reduce overall travel times. Thus, considering both multimodality (the use of multiple modes of transport) and intermodality (the chaining of different modes) is vital when designing urban transportation systems and evaluating accessibility.

3 Method

Our method is split into three parts. Initially, we establish a metric based on the concept of the 15-minute city and complement it with a cost metric. Following this, we focus on finding a fitting routing algorithm to calculate this metric. We do so by clearly stating our requirements for such an algorithm, explaining why existing algorithms don't meet our criteria, and introducing our algorithm, designed to meet our needs. The final stage explains how we use our routing algorithm to calculate our metric. This integrated approach allows us to thoroughly assess and improve accessibility in urban settings, offering valuable insights for urban planners and decision-makers.

3.1 Metric

Our metric consists of two dimensions: time and cost. The time dimension is based on the concept of the 15-minute city and expands on the findings of Olivari et al. (2023). The time dimension effectively measures how fast the access to various essential amenities is. To measure this, we categorize amenities into seven essential services: grocery, education, health, banks, parks, sustenance, and shops. Each category is populated with Points of Interest (POIs) sourced from OSM, providing a comprehensive database of locations. The POIs are identified by their respective OSM tags. OSM tags are descriptive labels used to define the attributes and characteristics of geographic features in the OSM database. They consist of a key and a value pair, like "amenity=restaurant", which enables categorizing map elements such as roads, buildings, and natural features for accurate and comprehensive mapping. In our case, we use the OSM tags to identify nodes that represent POIs, like a supermarket or a park. The categories and their respective tags can be seen in Appendix C.

The core of our metric is the determination of temporal proximity to these amenities. For each category, we calculate the minimum travel time required to reach at least one POI of that category. The metric is then defined as the maximum value among these minimal times across all categories, and we refer to it as the X-minute city metric, where X represents the maximum value among the minimum travel times. This approach yields a singular measure reflecting the most significant time distance barrier within an urban area, effectively capturing the least accessible category for any given region. We think that it is beneficial to focus on the least accessible category, as measuring accessibility in cities by averaging accessibility across all categories can mask disparities categories. This ensures that the metric is targeted to areas of greatest need. By leveraging this metric, we aim to help city planners create urban environments that prioritize sustainability, enhance the well-being of residents, and reduce dependency on vehicular transport, thus contributing to the broader goals of efficient urban planning and improved quality of urban life.

Our metric presents several advantages compared to the NEXI-minutes and NEXI-global, as outlined by Olivari et al. (2023). Firstly, unlike the NEXI-minutes, which calculates separate metrics for each of the seven categories, our metric evaluates all categories together. This unified approach makes it more straightforward to understand. In contrast, while NEXI-global considers all categories in one assessment, it converts the results into a 0-100 score. This percentage system can obscure the actual value of the data, making it more challenging to interpret.

Moreover, the NEXI-global's practice of assigning different weights to each category complicates its analysis. By focusing on the lowest-performing category across all areas, our metric simplifies the understanding and highlights where improvement is most needed. This method prevents the dominance of stronger areas over weaker ones, ensuring a more balanced and fair evaluation of urban development.

In addition to the time dimension, we incorporate a cost dimension into our metric. As we want to incorporate more modes than just walking, some of which may have a monetary cost associated with them, we need to consider the cost of the trip. We recognize that time and cost are measures of different units and cannot be combined sensibly. Therefore, we draw upon Pareto optimality to create a multi-objective metric considering time and cost. We define a Pareto set as a set of tuples where each tuple contains a time value and a cost value. A tuple can be considered the time needed to reach all categories given the cost value. The Pareto set will allow answering questions in the form of "What is the fastest time I can reach all categories given a certain cost?" or "What is the lowest cost I need to pay to reach all categories given a certain time?".

Traditionally, the 15-minute city concept is applied to walking and or cycling and ignores other modes of transport. In the context of location-based metrics, some researchers even go as far as to only calculate the beeline distance to the nearest amenity and ignore the street network altogether (Gastner & Newman, 2006). At the same time, most only consider walking (Olivari et al., 2023; Nicoletti et al., 2023). We, however, believe that to determine the accessibility of a city accurately, all modes of transport must be considered, and the routing needs to be as realistic as possible. Therefore, we continue discussing the requirements we pose on our routing algorithm next.

3.2 Routing Algorithm

This section will first define our requirements for our routing algorithm and explain why existing algorithms don't meet our criteria. Next, we will explain our algorithm in detail, based on a modular approach, where one module represents one mode of transport. After that, we will explain the modules we use in our experiments, which are based on MLC or McRAPTOR. Lastly, we will explain some enhancements we made to MLC and McRAPTOR to support multi-objective optimization with dynamic pricing schemes.

3.2.1 Requirements

To fully grasp the potential of the combination of the sustainable modes of transport, we require our routing algorithm to be **multi-modal**, **multi-objective**, **unrestricted inter-modal**, and **modular**.

Multi-modal means that our routing algorithm allows multiple modes of transport, including scheduled transport systems, like public transfer, and an arbitrary number of unscheduled transport systems, like walking, cycling, and driving. In addition, we require that free-floating vehicle-sharing systems are incorporated realistically. That means that our routing algorithm must consider that switching to a free-floating vehicle is possible at any location where a free-floating vehicle is available, and parking a free-floating vehicle is possible anywhere it's allowed.

Multi-objective means that our algorithm must find all Pareto optimal journeys according to an arbitrary amount of objectives. The algorithm must provide the possibility to update the values of any objective whenever a *movement* occurs. We define a movement as an edge traversal in an unscheduled network or a step in the route traversal during McRAPTOR. In the case of an edge traversal, the new objective must be a function of the old objective and the edge weights, formally: $l' = f(l, w(e))$, where l and l' are the old and new labels, respectively, and $w(e)$ are the weights of the edge that is traversed. In the case of an update during a step of the route traversal, the new objective must be a function of the old objective (to be continued).

Inter-modal means the different transport modes may be sequenced in any order. For example, when considering walking, cycling through a bicycle-sharing system, and public transport, the algorithm must consider journeys with bicycle rides between two consecutive public transport trips.

Unrestricted means that the algorithm thoroughly searches the unscheduled network graphs and does not pose restrictions like a maximum of 10 minutes walking distance.

Modular means that the algorithm should be easily adaptable to different modes of transport. It should be possible to easily add, remove, or chain different modes of transport.

Both Dijkstra and MLC are not considered due to their impractical runtime. Furthermore, the need for multi-objective solutions excludes Dijkstra, RAPTOR, and ULTRA. The requirement for unrestricted inter-modal travel makes RAPTOR and McRAPTOR unsuitable in practical scenarios. To explain this, let's examine a straightforward example. Consider the OSM graph of the key regions in Cologne, which comprises 125,176 nodes and 142,074 edges. For RAPTOR to compute a transitively closed graph requires calculating the walking distance between each node. This computation would yield $125,176^2 = 15,669,030,976$ edges, vastly greater than the original 142,074 edges. While MCR does support multi-objective solutions with unrestricted inter-modal transfers, it doesn't fully encapsulate the multi-modal concept we require. Although it theoretically permits various modes of unscheduled transport, it is primarily tailored for station-based vehicle-sharing systems. Our focus, however, is on the increasingly prevalent free-floating systems. In MCR, unscheduled networks are contracted, leading to the removal of specific nodes. If an optimal route requires a mode change at a deleted node, MCR will be unable to identify that path. As a result, MCR is not a viable option for our needs. Also, note that none of the algorithms mentioned so far are modular.

3.2.2 Scaffolding Algorithm

As mentioned, our algorithm should be easily adaptable to different modes of transport; therefore, we formulate it in a modular fashion. The algorithm described next presents a scaffolding that needs to be augmented by different modules, where a module represents a specific mode of transport, and running a module may be seen as fully exploring the network through this mode of transport. One module, for example, would be walking, and running the walking module would mean traversing the whole walking graph, given the current state of the bags.

A module always takes bags as an input and returns bags as an output. As explained in Section 2, a bag is a set of Pareto optimal labels concerning the objectives. In addition, in our work, a bag is associated with a node on some network. For the bags that are the input and output of the modules, we further require that they are associated with the same network. This is necessary to merge the bags of different modules. The most reasonable choice for the common network is the walking graph, which has a real-world interpretation because walking between different modes of transport is very

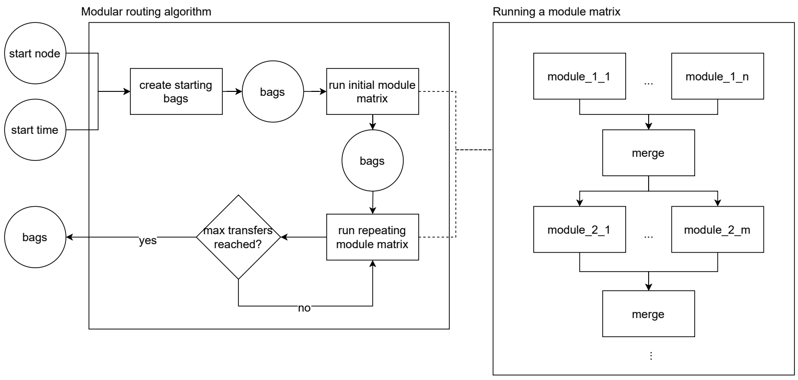


Figure 2: Modular Routing Algorithm

common.

To further explain how running a module looks like, consider the example of calling the walking module on the starting bags, which are a set of bags where every bag is empty, except for the one of the starting node, where precisely one label is present that contains the starting time and zero costs. The output would be a set of bags, where each node's bag contains exactly one label, where the time would be equal to the time it takes to walk to the node, and the cost would be zero, as walking never costs anything.

The scaffolding algorithm is shown in Figure 2. The algorithm takes a start node and time as input and returns bags. First, it creates the starting bags described above from the start node and the start time. Next, it runs the initial modules given by the initial module matrix.

A module matrix is an irregular matrix of modules. To run the module matrix, the first row's modules are run in parallel. Their respective outputs are then merged into a single set of bags. After that, the second row is run, and so forth. This process is also described in Figure 2.

After the initial modules are run, the same is done for the repeating modules for the specified number of times. By convention, we count each iteration of the repeating modules as one trip.

3.2.3 Modules

In our experiments, we categorize four modules into two types: unscheduled and scheduled. The unscheduled modules consist of walking, free-floating vehicle sharing, and personal vehicle use and are based on MLC, while the scheduled module is public transport, which is based on McRAPTOR.

Walking is the most straightforward unscheduled module, which consists of running MLC on the walking graph. The edges of the walking graph should contain the time it takes to traverse them by foot and should not have any monetary cost associated with them.

The free-floating vehicle-sharing module is more complex than the walking module. Before running MLC on the respective vehicle graph, the module filters all bags located at a node where no free-floating vehicle is available. In addition, the vehicle graph is augmented with a walking graph. This means that at nodes in the vehicle graph where the vehicle is allowed to be parked, there is an edge to the closest node in the walking graph. This augmentation is necessary, as the output bags of the free-floating vehicle-sharing module must be associated with nodes in the walking graph, as it is the common network. The module may also define cost depending on the time spent on the trip.

For the personal vehicle module, we assume that there is only one personal vehicle and that it is located at the starting node. Therefore, the module filters out all bags not located at the starting node. Obviously, this module is only helpful for the first trip, or more precisely, the module should only be used in the first row of the initial module matrix. After that, MLC is run on the vehicle graph again, augmented with the walking graph. This module is also based on MLC, so it may define costs like the free-floating vehicle-sharing module.

Compared to the unscheduled modules, the public transport module does not use MLC but McRAPTOR. As a first step, the module filters out all bags associated with a node that is not near a stop in the public transport system. Next, the module performs a single iteration of McRAPTOR, representing a single trip within the public transport system. Last, the resulting bags must be again associated with the walking network nodes. To do so, the modules use the node closest to the coordinates of the public transport stop. The public transport module may define costs like the free-floating vehicle sharing and personal vehicle modules. The cost may depend on the number of stops traversed during the trip.

3.2.4 Merging

The merging of bags after running multiple modules in parallel is quite simple. Each bag represents a set of Pareto optimal labels, and each bag is associated with a node. We, therefore, merge bag-wise. We differentiate between two cases:

1. There is only one bag associated with a node.

2. There are multiple bags associated with the same node.

In the first case, we put the bag into the output bags. In the second case, we create a new bag that contains all labels of all bags associated with the node, which might break the Pareto optimality of the labels. Therefore, to restore the Pareto optimality of the labels, we remove all labels dominated by another label.

3.2.5 Enhanced MLC & McRAPTOR

To address the multi-objective optimization involving both time and monetary cost, we introduce enhancements to MLC and McRAPTOR. The standard versions of MLC and McRAPTOR do not adequately capture dynamic pricing models, which is necessary to represent monetary costs realistically.

The original MLC associates a fixed cost with an edge, which cannot represent variable pricing, such as a bike-sharing tariff that costs €1 per 15-minute increment. Labels are only updated by adding the cost of a given edge to the label's values. Similarly, McRAPTOR updates the labels at each stop during route traversal only based on the information of the current trip and stop. With this, McRAPTOR cannot represent a pricing scheme that varies with the number of stops, like the one used by the Cologne Transport Authority. Our proposed modifications involve the use of 'hidden values' within the labels that are used by these algorithms. These hidden values carry additional information that is not considered when comparing labels, but that may be used to update costs dynamically.

In the case of MLC, the hidden values may be updated along any edge, just like the regular values of the label. A hidden value may carry information on how long the current trip with the shared vehicle is. We also allow defining a function that updates while traversing an edge and may use the values and hidden values before and after the traversal to do the update. With this functionality, it is easy to increment the cost by €1 every time the time spent on the trip exceeds the 15-minute interval.

Similarly, the hidden values may be updated during McRAPTOR after every iteration of a stop. We can, therefore, store how many stops the current trip has already traversed, and if that number exceeds four, we can increase the price from €2.20 to €3.20.

Additionally, as the concept of hidden values isn't specific to MLC or McRAPTOR, the hidden values can be transferred across iterations and modules. To understand the benefit, again consider the example of the pricing of the Cologne Transport Authority. The ticket that costs €3.20 allows traveling any number of trips within Cologne, no matter if changing to a different trip is necessary. Therefore, if we were to first travel to two stations with one trip and then get out to catch another trip that consists of five stops, we would still have the information that we already commuted two stops. Therefore, we can charge €3.20 instead of €2.20 twice, which is more realistic. These enhanced versions of MLC and McRAPTOR are used in our modules to use more realistic dynamic pricing schemes.

While running our experiment, we see that MLC based modules present a significant computational bottleneck.

We observe that to calculate our metric, we don't need the labels of every single node but only those that impact the X-minute city and time Pareto front. Therefore, we introduce a runtime optimization into MLC, which eliminates some bags from being processed that are guaranteed not to impact the Pareto front. While iterating the unprocessed bags in MLC, we keep track of the minimum time required to reach a POI node of each category for each cost value. If we encounter a bag whose time and cost values are greater than the minimum time and cost values for all categories, we can safely discard this bag, as it will not impact the Pareto front.

3.2.6 Example

To illustrate our algorithm, we will go through an example. The module configuration we use in our example represents traveling by free-floating vehicle sharing, public transport, and walking. The initial module matrix contains the walking module to reach the free-floating vehicles and the public transport stops. The repeating module matrix consists of first the free-floating vehicle sharing module and the public transport module in parallel and then the walking module. It can be seen in Figure 3.

$$\begin{pmatrix} \text{free-floating vehicle} & \text{public transport} \\ \text{sharing module} & \text{module} \\ & \\ \text{walking} & \end{pmatrix}$$

Figure 3: Example Repeating Module Matrix

In our example, we assume that both public transport and vehicle sharing have some form of cost associated with them. The objective is to minimize arrival time and cost. We also only consider a maximum of two trips.

First, we run the initial modules, which in our case is just the walking module on the starting bags. As the starting bags only consist of one non-empty bag at the starting node with precisely one label, running MLC on the walking graph is equivalent to running Dijkstra's algorithm. In the real world, this represents walking to all nodes in the walking network from the start node. Note that after the initial walking module, all bags only contain exactly one label, as the cost to go anywhere on foot is zero.

Next, the modules of the first row of the repeating matrix are run. In the real world, this means that after an initial walk, the traveler would either drive with a free-floating vehicle starting from a location where one is available or commute by public transport starting from one stop. For public transport, one could imagine that we commute with all possible trips from all stops and update the bags at the stops along each route accordingly. After running these modules and merging their result bags, each bag may contain more than one label, as public transport and driving with a vehicle may be faster than walking but also cost money. It may even be that some bags contain three different labels, if, for example, driving with a vehicle is the fastest but also costs the most money and commuting by public transport is faster than walking. The next step consists of running the second row of the repeating module matrix, which, in our case, is the walking module again. Running the walking module in the repeating module matrix is essential to reach nearby POIs after commuting through the public transport system. After that, the repeating module matrix is rerun, as we consider a maximum of two trips. The result of the second run of the repeating module matrix is our final result.

3.3 Integrated Accessibility Analysis Routine

We embed the routing algorithm described in Section 2.4 in our accessibility analysis routine to compute the metric described in Section 3.1. Our accessibility analysis routine consists of three parts: the input routine, the main routine, and the metrics routine.

In the input routine, depicted in Figure 4, we first create an even grid that covers the whole area of interest, for example, a city. We use H3 (*H3 / H3*, n.d.), which uses hexagons to discretize an area to create such a grid evenly. Our goal will be to calculate our metric for each hexagon to get detailed spatial information about the accessibility in the area of interest. The chosen H3 resolution determines the size of these hexagons: a higher resolution means smaller hexagons, enhancing the granularity of our analysis. As such, selecting an appropriate H3 resolution is pivotal as it allows us to calculate our metrics for each hexagon with increased spatial accuracy, yielding a detailed spatial dataset that reflects the accessibility variations within the area of interest. We recommend a resolution of nine, corresponding to a hexagon edge length of roughly 200 meters, as it is a good compromise between accuracy and computation time. The input routine also filters out

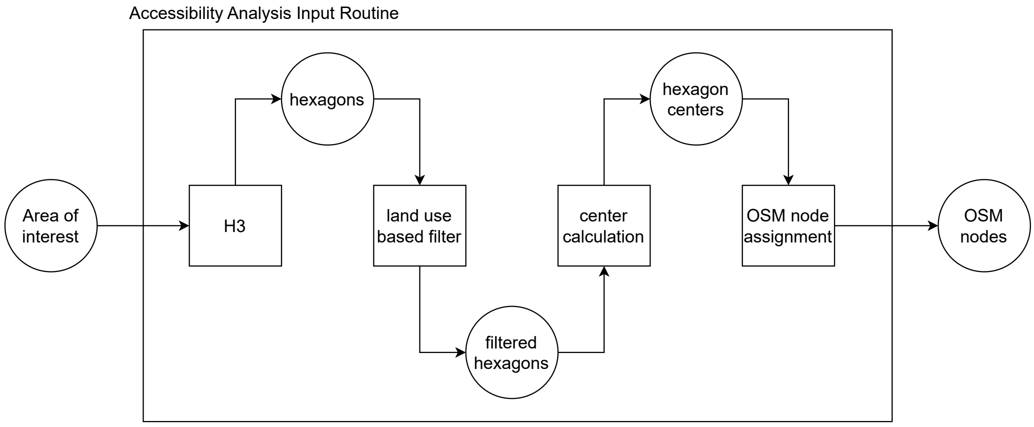


Figure 4: Input Routine

uninteresting hexagons. For example, we filter out hexagons containing no residential areas, as no people are living there. Next, the input routine retrieves the centroid of each hexagon and then calculates the Euclidean distance between the centroids and the OSM nodes to assign the closest OSM node to each centroid. The result of the input routine is a set of OSM nodes for which we want to compute the accessibility.

The main routine, depicted in Figure 5, calls our scaffolding routing algorithm described in Section 2.4 on each OSM node provided by the input routine. This results in a set of bags for each node.

The metrics routine, depicted in Figure 6, processes the bags into Pareto sets, where one entry in the Pareto set is a tuple of the X-minute city metric and the related cost. To do so, we process each collection of bags separately - one co-routine for each OSM node/collection.

The co-routine is depicted in Figure 7 and works as follows. We start by collecting all unique cost values on each label in each bag and then sorting them in ascending order. For each cost value, we then determine the associated X-minute city metric. We check whether every category is reachable given the cost value and an iteratively increasing time value. We start with a time value equal to the minimum time across all labels. If all categories are reachable, we've found the X-minute city metric, which, together with the cost value, is added to the Pareto set. If not, we increase the time value by one minute and check again. We repeat this until all cost values are processed. The result is a Pareto set for each OSM node/collection of bags.

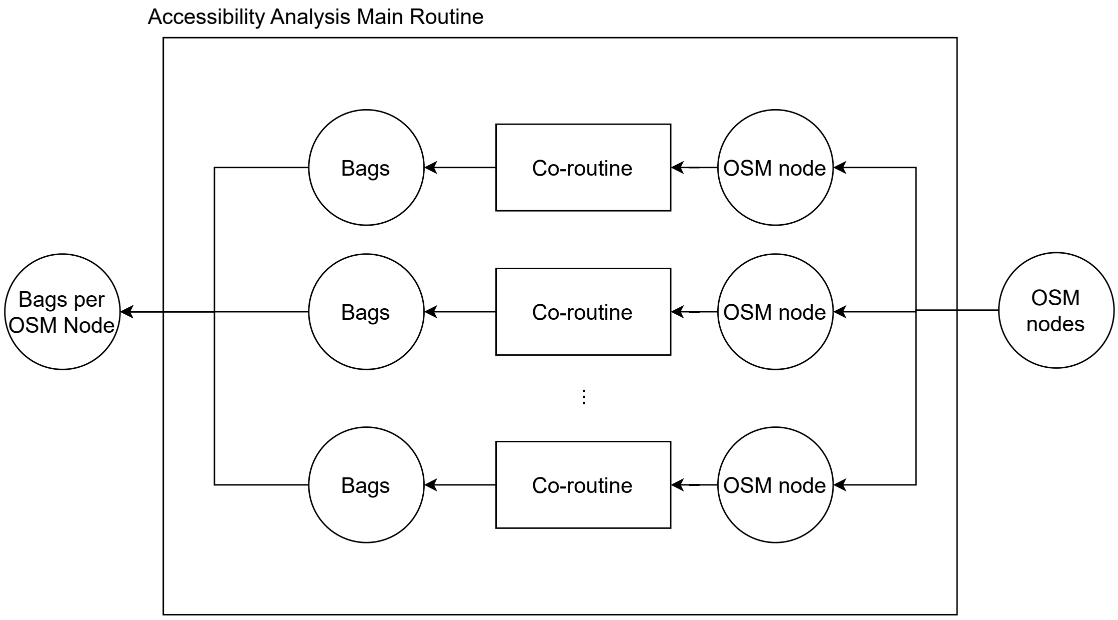


Figure 5: Main Routine

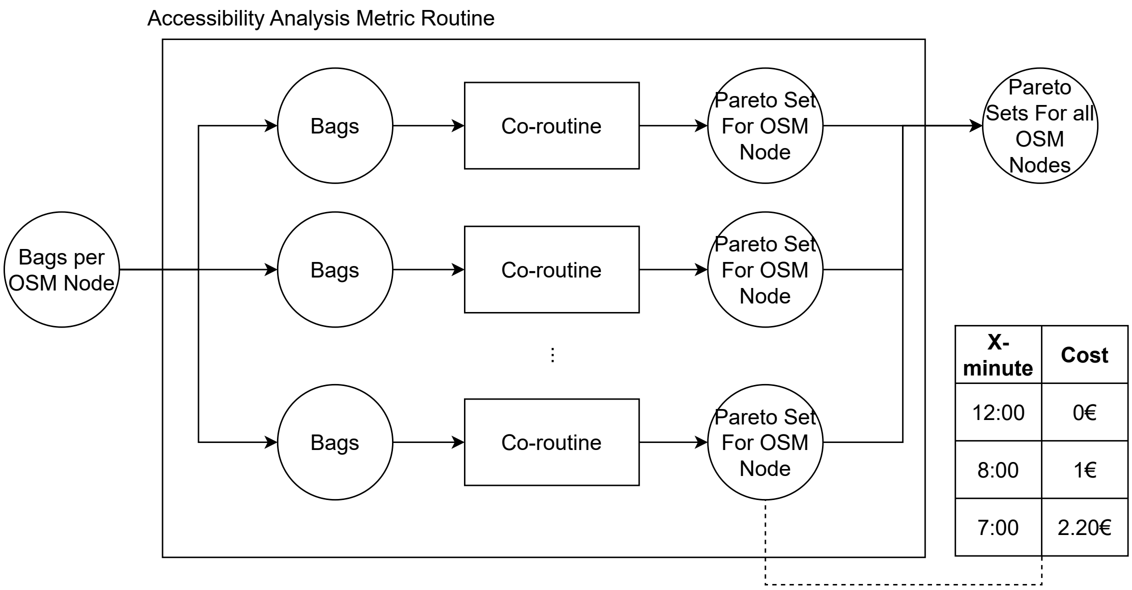


Figure 6: Metric Routine

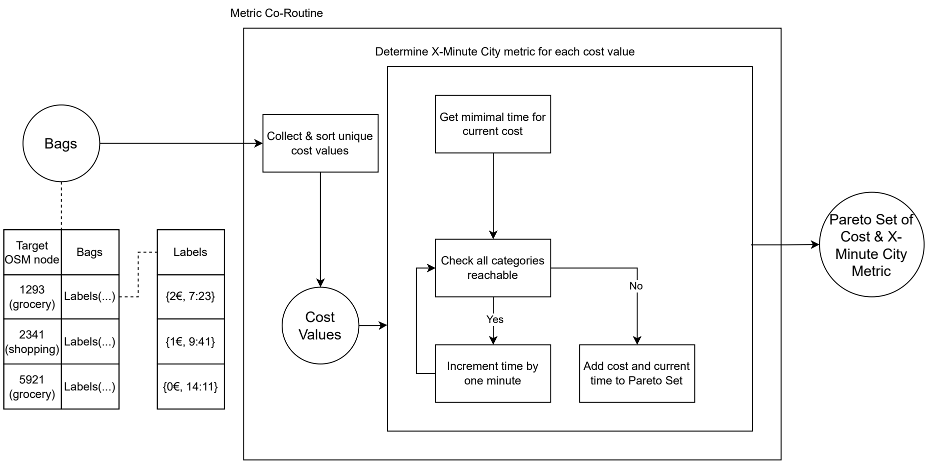


Figure 7: Metric Co-Routine

4 Experiment

We apply our method to the city of Cologne to retrieve insights about how different modes of transport interact and how they contribute to the city's accessibility. As we want to compare different modes of transport, we will calculate the metric multiple times for different scenarios, each with a different combination of modes of transport.

4.1 Scenarios

No matter what mode of transport we choose, we always allow for walking for two reasons. First, walking is the most accessible mode of transport, available to almost everyone and without additional costs. Second, most other modes of transport require walking at some point, be it to the next bus stop or the next available bicycle.

The first scenario we consider is our baseline, which only considers walking. This scenario measures what is possible without any additional infrastructure. Distinct from other scenarios, it does not require any additional cost, thus presenting the most basic form of urban mobility.

Building on this, the second scenario we consider is using a personal car. We consider this scenario the benchmark scenario, as we hope to achieve similar (or even better) results with more sustainable modes of transport. Therefore, we use it to answer the question of how competitive sustainable modes of transport are compared to the traditional mode of travel by car.

Transitioning from the simplest form of mobility, the third scenario focuses on public transport. It is essential to understand the effectiveness and accessibility of urban transit systems. This scenario evaluates how well-connected and time-efficient public transportation networks are and their role in reducing reliance on personal vehicles. It also investigates the impact of public transport on urban mobility and its potential to contribute to a more sustainable urban environment. Specifically, it assesses whether public transport is a viable alternative to the personal car and whether it offers significant advantages over walking, considering the X-minute city metric.

Next, in the fourth scenario, we focus on the dynamics of bicycle-sharing systems. This scenario is essential for assessing the feasibility and attractiveness of cycling as a primary mode of transportation in urban areas. We will directly compare it to the public transport scenario to understand which sustainable mode of transport is superior.

Finally, the fifth scenario combines public transport and bicycle sharing, offering insights into the synergy between these two modes of transport. For brevity, we refer to this scenario as the combined scenario. This integrated approach mirrors a growing trend in urban mobility solutions, where multi-modal transport options are increasingly favored. It underscores how this combination can bridge the gaps in accessibility and efficiency found when each mode is used independently. This scenario is expected to be the most competitive against cars, offering a comprehensive and sustainable urban transit model that could reshape the landscape of city mobility.

We summarize the scenarios in Table 2.

Scenario	**Modules**	**Key Points**
Walking	Walking	Baseline scenario
Personal Car	Personal Vehicle, Walking	Benchmark scenario
Public Transport	Public Transport, Walking	Evaluate the effectiveness public transport systems
Bicycle Sharing	Vehicle Sharing, Walking	Evaluate the effectiveness of bicycle sharing systems
Combined	Public Transport, Bicycle Sharing, Walking	Evaluate the effectiveness of sustainable multi-modal transport systems

Table 2: Scenarios for Urban Mobility Analysis

The specific configuration of the module matrices for each scenario can be found in Appendix D.

4.2 Data

We use four different datasets to calculate the Pareto sets of the X-minute city metric for the different scenarios. First, we require data that depicts the street network of the city of Cologne. Second, we need to know the locations of the POIs we want to reach. Third, we need to know the locations of the public transport stops and the schedules of the public transport. For the bicycle-sharing scenario, we also need to know the locations of the bicycles. Lastly, we also use land use data to identify where residential areas are located to calculate the X-minute city metric only for these areas.

As we will query spatial datasets of various formats from different sources, the area covered by the datasets will not be the same. Therefore, we first define an area of interest and trim the datasets to this area. In our case, this

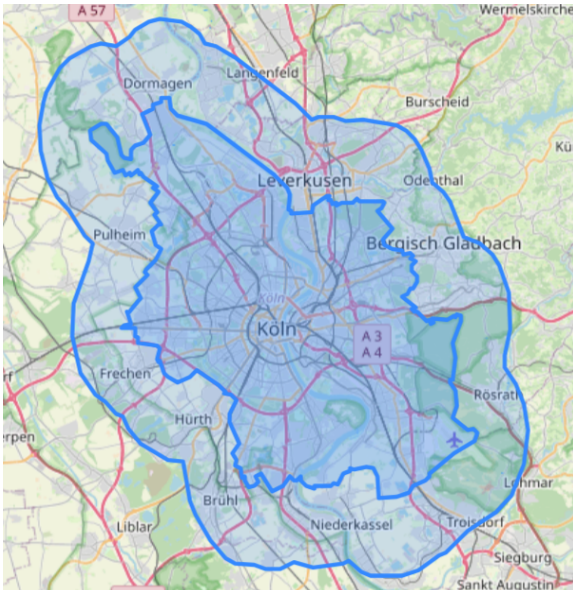


Figure 8: Area of Interest and Buffer Region

area is defined as the area of the administrative district of Cologne, specifically the "Stadtkreis Köln". We retrieve the specific boundary of this area with the help of the Overpass API (*Overpass API/Overpass QL – OpenStreetMap Wiki*, n.d.). The specific query can be found in Appendix A, and the resulting region can be seen in Figure 8.

The Figure additionally depicts a buffer zone surrounding the area of interest. This expanded area incorporates an additional buffer of approximately 5 km, which is essential as it directly impacts the plausibility of our accessibility analysis. Specifically, employing a larger underlying street network than the core area of interest circumvents the problem of underestimating accessibility in border regions.

4.2.1 Street Network & POIs

For the street network and the POIs, we use data from OpenStreetMap (OSM) (Foundation, 2023). Various tools and services have been developed to use OSM data in practice. Among these, we use pyrosm (Tenkanen, 2023), a Python library designed specifically for reading OSM data in different formats and conducting data processing operations. Through pyrosm, we can automatically fetch data from sources like Geofabrik (Geofabrik, 2018) and BBBike (Schneider, 2023), which are two of the most popular OSM data providers. In our case, we use the data for the city of Cologne from BBBike.

However, due to the flexibility of pyrosm, it is easily possible to use data from other sources and expand our analysis to other cities.

After retrieving the data, we retrieve a graph representation of the street network trimmed to the buffered area of interest. Using the buffered region is important because without it, calculating the X-minute city metric at the border of the area of interest would result in a higher value than the actual value. As a last cleaning step, we remove all nodes not part of the largest weakly connected component. A weakly connected component is a subgraph in which any two vertices from the subgraph would be connected if all directed edges were treated as undirected. Multiple weakly connected components in graphs derived from OSM data, mostly happen at the border of the considered area and can be neglected.

Because we consider multiple different modes of transport on the network, it is essential to filter out all edges that are not accessible by the respective mode of transport. To do so, we use Pyrosm's built-in filtering functionality. For reproducibility, we list the filters that Pyrosm uses in Appendix B.

To retrieve the POIs, we use the Overpass API (*Overpass API/Overpass QL – OpenStreetMap Wiki*, n.d.). We retrieve all POIs that fall into one of our predefined categories specified in Section 3.1 inside the area of interest plus the buffer mentioned before.

4.2.2 Public Transport

We use the General Transit Feed Specification (GTFS) (MobilityData, 2023a) to handle public transport data. We rely on the Mobility Database (MobilityData, 2023b) to retrieve it. This database serves as an open-source repository containing links to publicly available GTFS feeds globally, standing as the subsequent version of TransitFeeds (MobilityData, 2023c). Similarly to the OSM data, we trim the GTFS data to the area of interest plus the buffer. The GTFS data is also cleaned and converted into a format more suitable for our algorithm, specifically McRAPTOR, which is part of our algorithm. Specifically, two significant incompatibilities exist between the GTFS specification and RAPTOR's notion of routes and trips. Firstly, each trip belonging to a single route in RAPTOR visits the same stops in the same order. It is impossible for a trip to skip some stops that another trip of the same route visits, much less use a completely different sequence of routes. In GTFS, routes allow that, as they are much more a group of trips presented to the rider under the same name or identifier. Secondly, GTFS trips allow visiting the same stop multiple times, which is not permitted in RAPTOR. To overcome these differences, we split up routes into smaller routes following the same stop sequence. Additionally, we also remove circular trips, altogether.

4.2.3 Bicycle Sharing

Our bicycle-sharing data was retrieved from the NextBike API over one year. The data consists of all trips made with the NextBike system in Cologne from the 15th of January 2022 to the 31st of August 2023. To get representative samples of the locations of all bicycles, we employ the following strategy. We first discretize the data spatially and temporally. For the temporal discretization, we derive the location of each bicycle every hour. For the spatial discretization, we use H3 hexagons with a resolution of 9. The resulting data shows how many bicycles were at each hexagon at each hour. This data is then used as an input for k-medoids clustering (Rdusseeun & Kaufman, 1987) with a k of 4. K-medoids, also known as PAM (Partitioning Around Medoids) algorithm, is a clustering technique that partitions a dataset into K clusters, where each is assigned a medoid, the most centrally located object in a cluster. Unlike K-means, which uses mean values as cluster centers, K-medoids use an actual data point as the center of a cluster. This has the advantage that the centers are part of the dataset and, therefore, are realistic samples. We use the resulting medoids as different configurations of the locations of the bicycles.

4.2.4 Land Use

We use the land use data from the CORINE Land Cover (CLC) project (*CORINE Land Cover 2018 (Vector), Europe, 6-Yearly - Version 2020_20u1, May 2020*, n.d.) to identify the residential areas. The data covers the whole of Europe and is publicly available, making it possible to expand our analysis to other cities in Europe. We trimmed the data to the area of interest and then filtered for the land use types "Continuous Urban Fabric" and "Discontinuous Urban Fabric". These two land use types represent the residential areas of the city. The residential areas inside the area of interest are shown in Figure 9. Additionally, the Figure shows the hexagons of resolution nine found inside the residential areas.

4.3 Assumptions

To calculate the X-minute city metric, we have to abstract from reality to some degree. We do so by making the following plausible assumptions.

Firstly, we assume that traveling along an edge of the street network by walking, cycling, or driving is always proportional to the length of the edge. To obtain the time it takes to travel along an edge, we divide the length of the edge by the speed of the mode of transport. The different speeds for the

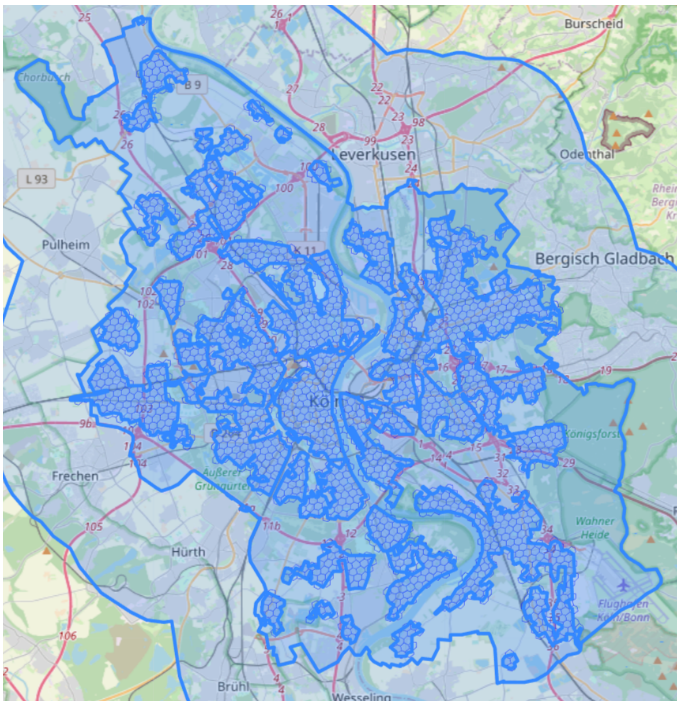


Figure 9: Area of Interest and Buffer Region with Residential Areas and Input Hexagons

different modes of transport are listed in Table 3.

Mode	Speed (m/s)
Walking	1.4
Cycling	4.0
Driving	11.0

Table 3: Speeds for Different Modes of Transport

The walking speed is consistent with the measurement that Willberg et al. (2023) made in their study.

We also pose some assumptions on the transitioning between different modes of transport and, in the case of public transport, the transfer time at the stops. We assume a fixed time of one minute for the transfer time at stops. To transition from any OSM network-based mode of transport to public transport, we assume that the stop is precisely at the location of the closest node of the OSM network. As OSM networks contain public transport stops, there should be no difference between the two. Similarly, we assume that the bicycles are located at the closest node of the OSM network. This assumption is reasonable because the OSM network, especially in the city, is very dense. We also assume that bicycles and cars can be parked anywhere on their network for simplicity.

4.3.1 Pricing

We implement a pricing scheme in our scenarios that represents the real-world circumstances as closely as possible.

For bicycle sharing, we use the pricing scheme of NextBike, which is €1 every 15 minutes. To depict this, we add a hidden value to the labels processed in MLC that shows how long the current bicycle trip is. As two consecutive bicycle trips are considered separately, we nullify this hidden value after each run of MLC.

For public transport, we use the pricing scheme of the Cologne Transport Authority (KVB), which is €2.20 for trips that span four stops or less. For any trip that spans more than four stops or any multitude of trips, the KVB charges €3.20. To depict this, we add hidden values to the labels processed in McRAPTOR, representing how many stops the traveler has already traversed. Because two consecutive trips are considered together, we don't need to nullify the hidden value.

For personal vehicles, we use a cost per minute of 19 cents, which we derived from the average cost per kilometer of 28 cents given by (Kiefer,

2023) and an average speed of $40\,\mathrm{km\,h^{-1}}$. These costs incorporate fuel, repair, insurance, and tax, but not acquisition costs.

5 Results

This section presents the findings of our comprehensive analysis, addressing the research questions outlined in the introduction. Recall, our primary inquiries revolved around understanding the role of bicycle sharing and public transport in shaping cities into 15-minute cities (1), the impact of cost on accessibility (2), the measurement of accessibility considering multiple transport modes and associated costs (3), and deriving specific urban planning recommendations for Cologne (4).

The results are the output of our experiment, which consists of a novel method for accessibility-based planning that incorporates multiple modes of transport, extending the 15-minute city concept to include a broader range of sustainable transport options while also considering cost. The data retrieved from our experiments consists of two parts: Firstly, for each (sub)-scenario and hexagon, we get the Pareto set of the X-minute city metric and cost. Secondly, we also retrieve the more fine granular version where we get a Pareto set of the time it takes to get to the closest POI for a specific category. In the following subsections, we delve into this data and observe our method's runtime and memory usage.

5.1 Runtime Observations

Observing the runtime and memory usage required to run our experiment enables us to evaluate the practicality of our approach. To execute our experiment, we used a machine with an AMD Ryzen 7 5800H CPU and 32 GB of RAM. As explained in Section 3 our routine is split into three parts, the input, main, and metric routine. The input routine took X minutes to run and required no more than Y gigabytes of memory. The main routine took the longest with X minutes and required Y gigabytes of memory, however, we only utilized eight of the 16 available cores for parallelization. Lastly, the metric routine took X minutes to run and required Y gigabytes of memory.

We found that the memory consumption primarily stems from the graph-based representation of the street network of Cologne.

5.2 15-Minute City Metric

Table 4 shows the mean, as well as, the 25%, 50%, and 75% quantiles of the optimal X-minute city disregarding the cost for each scenario over all hexagons.

Our findings indicate that cars enable the fastest access to all necessary Points of Interest (POIs), with an average accessibility time of 3.21 minutes.

Table 4: Optimal X-minute City Metric Over All Hexagons Disregarding Cost

	mean	25%	50%	75%
scenario				
bicycle	12.45	7.25	10.75	15.50
bicycle_public_transport	11.51	7.25	10.33	14.31
car	3.21	2.00	3.00	4.00
public_transport	12.78	9.00	12.00	16.00
walking	14.09	9.00	12.00	17.00

This mode of transport significantly outpaces other methods, establishing a benchmark for urban mobility efficiency. However, remember that our car scenario is very optimistic and these numbers should be taken cautiously.

In contrast, sustainable modes of transport, such as bicycles, public transport, a combination of bicycles and public transport, and walking, demonstrate similar accessibility times. These modes record average times ranging from 11.5 to 14 minutes, with walking being the least time-efficient mode at an average of 14.09 minutes.

Integrating bicycles with public transport emerges as the most time-efficient sustainable mode, with an average time of 11.51 minutes. A direct comparison between public transport and walking shows that the time savings offered by public transport stand at 1 minute and 28 seconds. However, this benefit is not evenly distributed across all areas. The analysis of quantiles reveals that the time improvement only establishes at the 75% quantile with a 2-minute gain, while the 25% and 50% quantiles don't show any improvements.

Similarly, adding public transport to bicycle sharing improves the average optimal time to reach all categories by 43 seconds. Again, this improvement is not evenly distributed but only applies to the 25% worst hexagons. Specifically, we see no improvement from bicycle sharing to public transport in the 25% and 50% quantiles, but a 1-minute improvement in the 75% quantile. While there is an improvement in the mean and 75% quantile, it is not as large as the improvement from walking to public transport.

We can make the same observation from the standpoint of adding bicycle sharing to walking and public transport. Adding bicycle sharing to public transport, the data indicates an improvement in the average accessibility time, reducing it by 1 minute and 16 seconds. In contrast to adding public transport to bicycles, this improvement already occurs for the 25% quantile

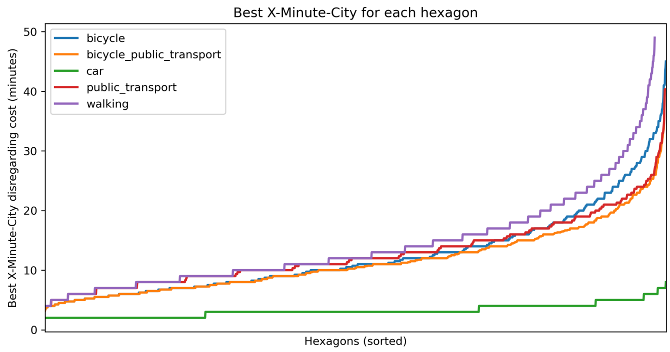


Figure 10: Distribution of Optimal X-Minute City Metric

and is, therefore, more evenly distributed across all hexagons. Adding bicycles to the walking scenario presents an average time reduction of 1 minute and 28 seconds, which denotes a significant enhancement in the accessibility metric. Again, this improvement already occurs at the 25% quantile, showing that the improvements gained through bicycle sharing are more evenly distributed across all hexagons.

We can observe a similar pattern when visualizing the distribution of the optimal X-minute city metric in Figure 10. As we can see initially (for the most accessible hexagons), public transport and walking are the same, but as we move to less accessible hexagons, public transport improves. In addition, the public transport scenario is worse than the pure bicycle sharing scenario but can catch up and even overtake it as we move to less accessible hexagons. The same pattern can be observed when comparing the bicycle-sharing scenario to the combined scenario of bicycle-sharing and public transport. Initially, the combined scenario is the same as the bicycle-sharing scenario, but as we move to less accessible hexagons the combined scenario becomes better. Similarly, when comparing the bicycle-sharing scenario to the combined scenario, we see that the combined scenario provides much better accessibility initially, but as we move to the least accessible hexagons, both become the same. Generally, adding public transport can flatten the drastic increase of the optimal X-minute city metric at the end of the distribution.

Figure 11 shows the optimal X-minute city metric for each hexagon over all sustainable modes of travel, i.e., excluding the car scenario. We can see that the least accessible hexagons require 44 minutes to reach all categories if only sustainable modes of travel are used. The least accessible regions are suburban areas in the north and south of Cologne. The region on the left bank of the Rhine River next to Leverkusen, which is the district of

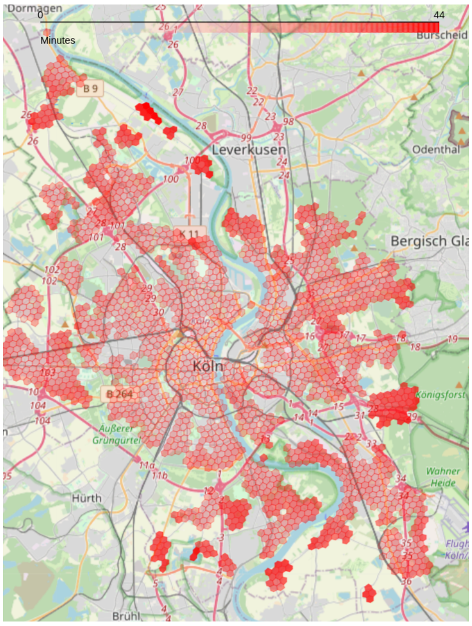


Figure 11: Map of Optimal X-Minute City Metric

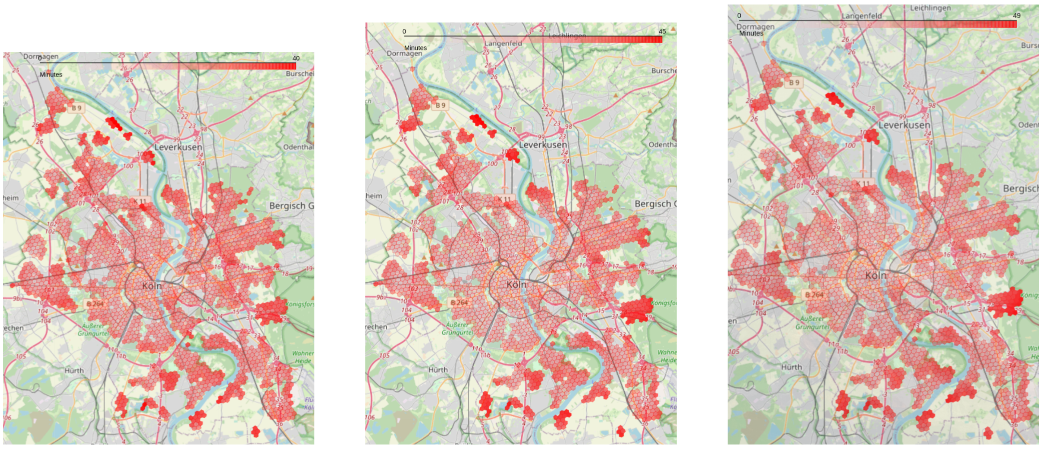
Merkenenich, is especially inaccessible.

Figure 12 shows multiple maps of the optimal X-minute city metric for each hexagon, one for bicycle sharing, one for public transport, and one for walking. The areas in and around the city center are more accessible by bicycle sharing than by public transport and walking. In the east of the city, near the forest "Königsforst", we see the district of Rath/Neumar, with low accessibility for all scenarios. However, one can see that the region is more accessible by public transport than by bicycle sharing and walking.

5.3 Cost of 15-Minute City

Table 5 shows the mean, the 25%, 50%, and 75% quantiles and the maximum of the costs that are required to achieve the optimal value for the X-minute city shown in Section 5.2. We can immediately see that there is no cost for hexagons at the 25% and 50% quantile when using public transport, implying that public transport is not used at all for those hexagons. Looking at the 75% quantile and the maximum required cost for an optimal x-minute city metric for public transport, we see that the benefits we observed earlier come at a cost. Similarly, bicycle sharing and the combined mode have zero cost at the 25% quantile, implying that they are not used for those hexagons.

Looking at the maximum cost values of each sustainable mode of trans-



(a) Public Transport (b) Bicycle Sharing (c) Walking

Figure 12: Map of Optimal X-Minute City Metric per Scenario

Table 5: Required Cost for Optimal Over All Hexagons

	mean	25%	50%	75%	max
scenario					
bicycle	0.39	0.00	0.50	0.75	1.00
bicycle public transport	0.87	0.00	0.75	1.30	3.95
car	0.37	0.19	0.38	0.38	1.33
public transport	0.65	0.00	0.00	1.47	3.20
walking	0.00	0.00	0.00	0.00	0.00

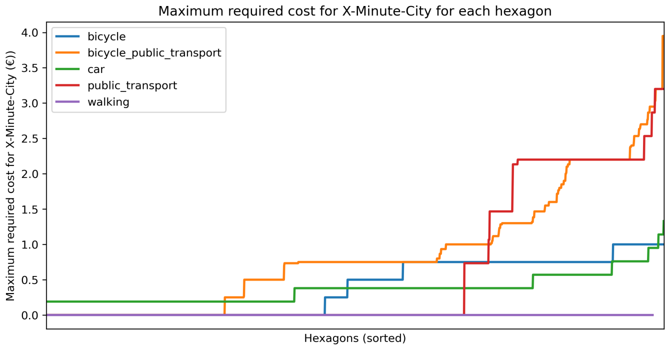
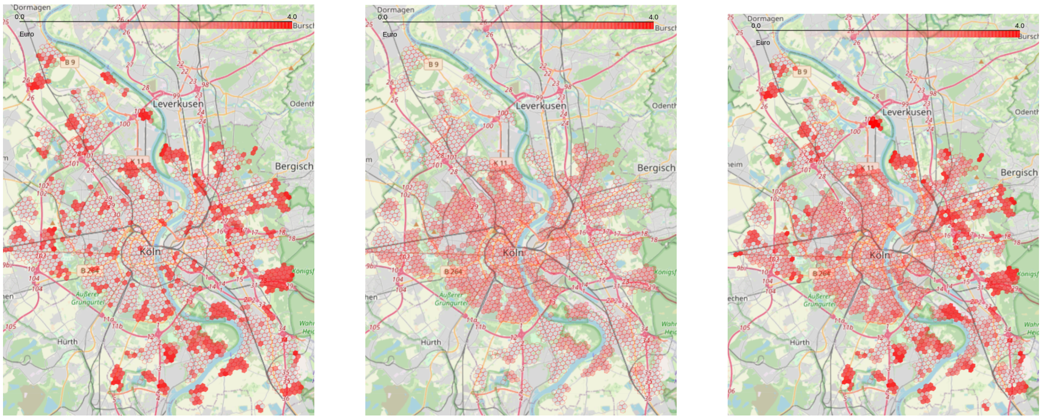


Figure 13: Maximum Required Cost for Optimal X-Minute City Metric

port shows us that bicycles never require more than €1. As €1 allows to travel a maximum of 15 minutes, it is never necessary to travel longer than 15 minutes after a bicycle is reached. The maximum cost incurred by public transport is €3.20, the long-distance ticket of public transport (more than four stops) is used. Similarly, in the combined scenario, the long-distance ticket is used with a 15-minute ride of bicycle sharing in at least one sub-scenario, resulting in the maximum price of €3.95.

We can make similar observations with more granularity when looking at the distribution of the required cost in Figure 13. A new pattern stands out when comparing public transport and the combined mode. We see that the combined mode has higher costs earlier, surpassed by public transport, only to be surpassed again by the combined mode. The first price increase in the combined mode can be explained by the €1 cost of 15-minute bicycle sharing. Then public transport surpasses the combined mode. This probably is because bicycle sharing is more cost-efficient and can compensate for public transport. The fact that the combined mode then surpasses public transport again most likely stems from the fact that the combined mode can achieve faster access than public transport by using bicycle sharing, which is more expensive than a short-distance ticket alone.

Figure 14 shows the cost required to reach the optimal X-minute city metric for each hexagon for public transport, bicycle sharing, and the combined scenario of bicycle sharing and public transport. Note that we don't show the cost for the walking scenario, as it is always €0. In these figures, we see that sometimes the cost is zero. As the portrayed scenarios all have costs associated with them, a cost of zero means that only walking is used. We see almost in all hexagons in and around the city center, where NextBike's flex zone is located, the cost for the bicycle sharing scenario is €1. This



(a) Public Transport (b) Bicycle Sharing (c) PT + Bicycle

Figure 14: Map of Required Cost for Optimal for Each Hexagon

sometimes also extends outside the city center.

The cost of public transport is more scattered around the whole region. We can mostly see single hexagons in the city's center and small groups of hexagons outside the city that have costs have than zero.

5.4 Interaction Between Cost and 15-Minute City Metric

Next, we will examine the interaction between the cost and the optimal X-minute city metric. To do so, we will investigate the mean Pareto front of the X-minute city metric and cost over all hexagons. To understand this graph, we first examine the Pareto front of a single hexagon.

Figure 15 shows the Pareto front for an example hexagon. The x-axis shows the cost, and the y-axis shows the X-minute city metric. The line shows us what X-minute city metric is achievable for a given cost in a specific scenario.

In our example, all modes begin with being able to reach all categories within 22 minutes for a cost of €0. Increasing the cost only yields improvements when reaching a cost of €1, where the bicycle and combined scenarios can reach all categories within approximately 10 minutes. Further, increasing the price to €2.20 improves the public transport scenario, where reaching all categories within approximately 19 minutes is now possible. Further cost increases do not yield any improvements for any scenario.

We can also quantify the value of the improvements as seen in Table 6. This table shows all the steps with their cost position and magnitude, visible

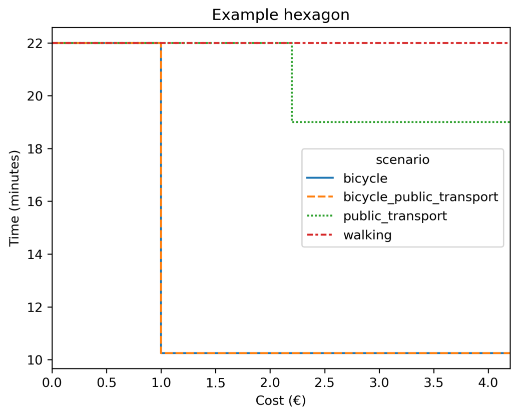


Figure 15: Example Pareto Front

Table 6: Steps in Example hexagon

improvement	at cost	minute per euro	scenario
11.75	1.00	11.75	Bicycle
11.75	1.00	11.75	Combined
3.00	2.20	1.36	Public Transport

in the previous graph. In addition, we can calculate the benefit in minutes per one euro of cost to make their value more comparable. As we can see, the bicycle scenarios' increase at a cost of €1 is larger than the public transport scenario's increase and has a higher value per euro.

To generalize these findings over all hexagons, we take the average over the X-minute city for each cost and scenario to generate an average Pareto front. The resulting Pareto front can be seen in Figure 16.

Similarly to the example of the single hexagon from before, we can see improvements for the bicycle scenario and the combined scenario at the cost of €1 of about 1.5 minutes. We can also see the improvements in public transport at a cost of €2.20. Unlike the example of the single hexagon, we can also see the improvement at the cost of €2.20 for the combined scenario. Lastly, there is a slight improvement for the public transport scenario and the combined scenario at a cost of €3.20.

To compare these improvements, we can again look at the differences in Table 7. We won't analyze the differences in the combined scenario, as prior improvements of other modes may skew them and are therefore hard

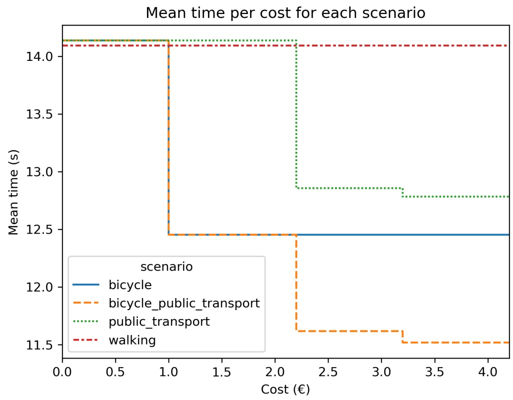


Figure 16: Mean Time per Cost for All Scenarios

Table 7: Steps in Mean Pareto Front

improvement	at cost	cost diff	minute per euro	scenario
1.684	1.000	1.000	1.684	bicycle
1.282	2.200	2.200	0.583	public transport
0.074	3.200	1.000	0.074	public transport

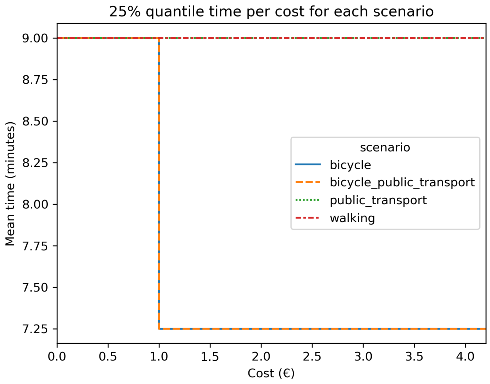
to interpret.

We see that the improvements of the bicycle scenarios at the cost of €1 are the largest, with an improvement of 1.68 minutes, and also the most cost-effective, with a value of 1.68 minutes per euro. They are followed by the improvements of the public transport scenario at a cost of €2.20 with an improvement of 1.28 minutes and a value of 0.58 minutes per euro. The improvement at a cost of €3.20 is minimal and the least cost-effective.

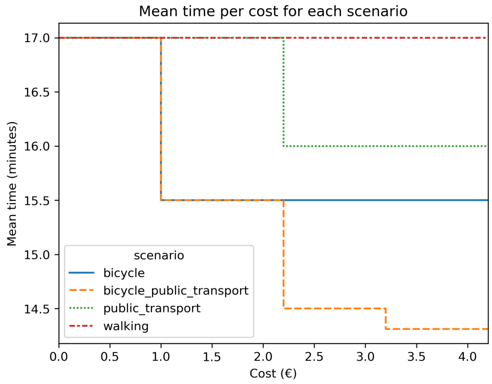
Next, we are going to look at the quantiles of the aggregated Pareto front. Figure 17 shows the 25%, 75%, and 90% quantiles of the aggregated Pareto front. The 25% quantile gives us insights about the more accessible areas in the city. Note that because we aggregate all the values of the X-minute city metric for a single cost and scenario at a time, the 25% quantile Pareto front does not necessarily reflect the same 25% of hexagons for each cost.

The 25% quantile Pareto front shown in Figure 17a only contains a single improvement at the cost of €1 for scenarios containing bicycle sharing of 1.75 minutes with a cost-effectiveness of 1.75 minutes per euro.

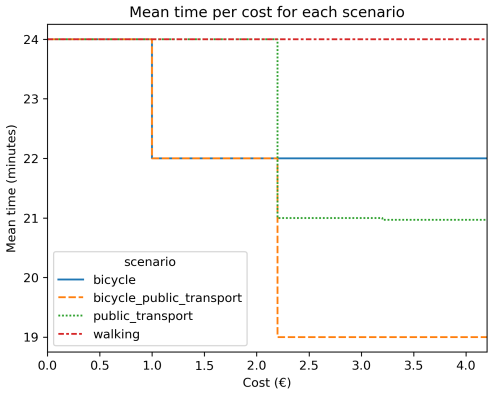
The 75% quantile Pareto front shown in Figure 17b with its steps shown in Table 8 also has a similar improvement of 1.5 minutes at the cost of €1



(a) 25% quantile time per cost for all scenarios



(b) 75% quantile time per cost for all scenarios



(c) 90% quantile time per cost for all scenarios

Figure 17: Map of Optimal X-minute City Metric per Scenario

Table 8: Steps in 75% Quantile Pareto Front

improvement	at cost	cost diff	minute per euro	scenario
1.500	1.000	1.000	1.500	bicycle
1.000	2.200	2.200	0.455	public transport

Table 9: Steps in 90% Quantile Pareto Front

improvement	at cost	cost diff	minute per euro	scenario
3.000	2.200	2.200	1.364	public transport
2.000	1.000	1.000	2.000	bicycle
0.033	3.200	1.000	0.033	public transport

for bicycle scenarios. In addition to that, it also shows a smaller increase at €2.20 for public transport scenarios of 1 minute and an even smaller increase at 3.20 euros for bicycle sharing and public transport scenarios.

The 90% quantile Pareto Front shown in Figure 17c with its steps shown in Table 9 shows a similar pattern to the 75% quantile Pareto front. The significant difference is that the increase at €2.20 for public transport scenarios is larger than the increase at 1 euro for bicycle scenarios. More precisely, while bicycle sharing is more effective in decreasing the 15-minute city metric on average and for the 75% most accessible regions, public transport is more effective than bicycle sharing for the 10% least accessible areas. We should note that even though the improvement in the public transport scenario is larger than in the other quantiles we examined, it is still less cost-effective than the improvement in the bicycle-sharing scenario.

5.5 Uncertainty in Sub-scenarios

As some of our input data is subject to uncertainties, we need to investigate the effects of this uncertainty to establish the robustness of our results.

First, we are going to look at the average standard deviation of the optimal value for the X-minute city metric in Table 10, which effectively shows the standard deviation of the values in Table 4. Note that we only display the average standard deviations of the bicycle, public transport, and combined scenarios, as those are the ones with uncertainty.

The mean average standard deviation for bicycle scenarios is around a

Table 10: Average Standard Deviation of Optimal Value for X-Minute City Metric

	mean	min	25%	50%	75%	max	CV
scenario							
bicycle	1.16	0.00	0.00	0.50	1.73	13.15	0.093403
bicycle public transport	0.94	0.00	0.00	0.74	1.48	6.73	0.082027
public transport	0.27	0.00	0.00	0.00	0.00	8.66	0.021151

minute, while it is 0.27 for the public transport scenario. We can also see that for the bicycle-related scenarios, the uncertainty does not affect the 25% most accessible hexagons, while for public transport, the 75% most accessible hexagons are not affected. In addition, outliers exist with more than 10 minutes of deviation for the pure bicycle scenario and more than 5 minutes for the public transport-related scenarios. Relating the standard deviation to the mean, we also calculated the Coefficient of Variation (CV) in the table, which is calculated as follows:

$$CV = \frac{\sigma}{\mu}$$

where μ is the mean and σ is the standard deviation. We see that it is approximately 9% for the bicycle-related scenarios and 2% for the public transport scenario.

To further investigate the effects of uncertainty on a more granular level, we plot the best and worst case distribution of the optimal X-minute city for each hexagon in Figure 18. These plots are essentially the upper and lower bounds of the graph, as seen in Figure 10. In addition, we've added a line at the 15-minute mark to better relate the results in the context of the 15-minute city. The best and worst-case values are calculated using the scenario that achieves the best X-minute city metric for a given hexagon. First, we see that the variation for bicycles is spread out over almost all hexagons, in comparison to public transport where the variation only really begins to happen after the 15-minute mark. For the combined scenario, we see the expected: The variances of the public transport scenario and the bicycle scenario add up.

5.6 Impact Of Sustainable Modes on 15-Minute Metric

To analyze the impact of sustainable modes of travel on the 15-minute city metric, we first uncover the problematic areas in which the X-minute city

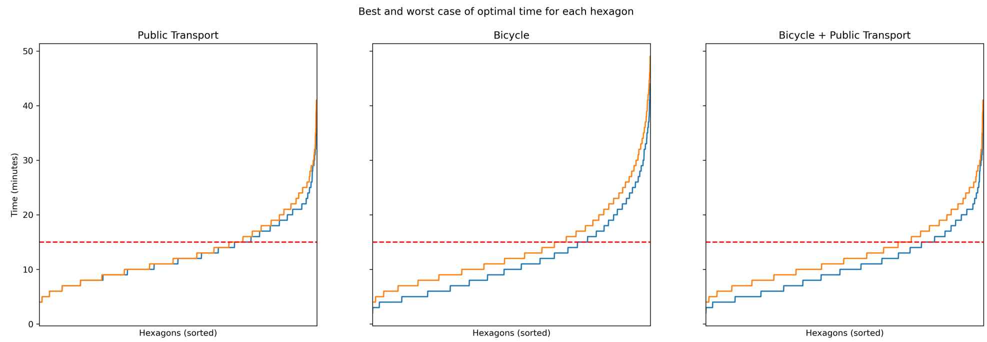


Figure 18: Best and Worst Case of Optimal Time for each Hexagon

metric is above 15 minutes for the walking mode. We then analyze how sustainable modes of travel can help reduce the X-minute city metric in those areas below 15 minutes.

In total, we find 552 hexagons, which have a walking time of more than 15 minutes to reach all categories, which is 30.98% of all hexagons. Table 11 presents the distribution of hexagons with a walking time above 15 minutes and how sustainable modes of transport can fix those hexagons. By fixing a hexagon, we mean that residents in the hexagon cannot reach all necessities in under 15 minutes by walking, but they can make it in under 15 minutes by some other mode of transport. A significant portion of these areas, amounting to 67.03%, cannot be reached within 15 minutes using sustainable modes with the current state of infrastructure. Conversely, the data indicates that for 13.04% of these hexagons, only bicycles can reduce travel time to under 15 minutes, while only public transport can achieve this for 10.69% of the hexagons. 7.43% of hexagons are reachable with either one of bicycles or public transport, while an additional 1.81% of hexagons are only accessible within this time frame when combining both modes.

Category	**Data**
Only bicycle below 15 mins	72 (13.04%)
Only public transport below 15 mins	59 (10.69%)
Both bicycle and public transport below 15 mins	41 (7.43%)
Combined mode below 15 mins	10 (1.81%)
Not reachable by sustainable modes below 15 mins	370 (67.03%)

Table 11: Impact of Sustainable Modes on Reducing Walking Time Above 15 Minutes

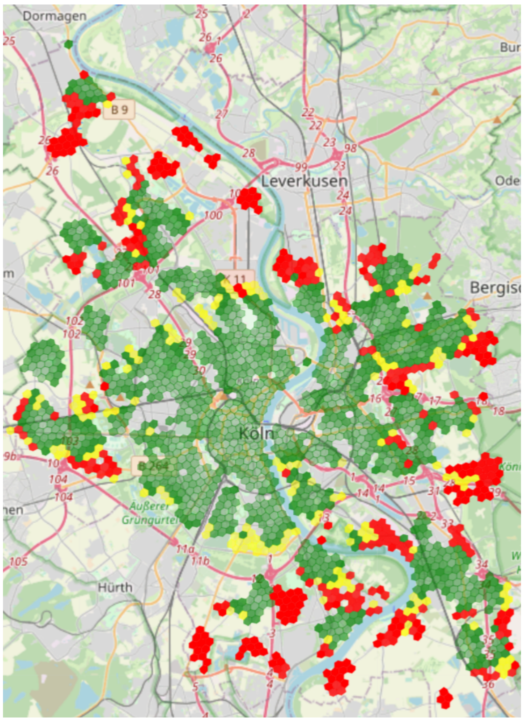


Figure 19: Unfixable, Fixable and Unproblematic Hexagons on a Map

Next, we visualize these problematic areas spatially. Figure 19 displays hexagons in green where necessities can be reached within a 15-minute walk, in yellow where they are only accessible within 15 minutes using any sustainable transport, and in red where necessities are not reachable within this 15-minute timeframe. We see that in the center of Cologne, almost all hexagons qualify as 15-minute city hexagons just by walking alone. At the city's border, we see a ring of hexagons that are only valid 15-minute hexagons through additional modes of transport. Most of the unfixable hexagons lie in the city's suburbs, often appearing in larger groups.

Next, we look at the hexagons previously colored yellow, namely those where bicycles and public transport or a combination of both can decrease the 15-minute city metric below 15 minutes. Figure 20 illustrates hexagons representing areas that qualify as 15-minute cities via public transport in yellow, those that qualify through bicycle sharing in orange, and areas that meet the 15-minute city criteria through either mode in green. The data indicates a modest trend where hexagons that achieve 15-minute city criteria solely through bicycle sharing (marked in orange) tend to be nearer to the city center than those that achieve this criterion solely via public transport.

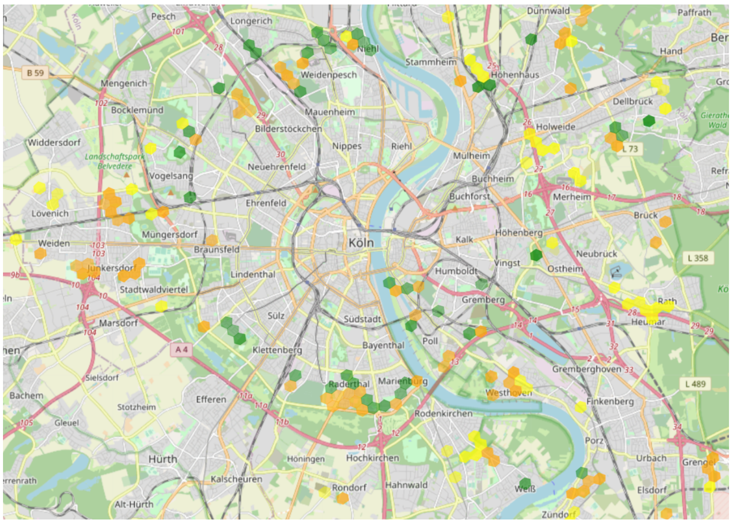


Figure 20: Fixable Hexagons by Mode

The positions of outer clusters of fixable hexagons correlate directly with the locations of bicycles and public transport stops. Figure 21 shows four zoomed-in excerpts from Figure 20, where we've added the location of public transport stops and bicycles. Public Transport stops are visualized as yellow circles, while bicycles are visualized as orange circles. We notice that hexagons fixed by bicycle sharing are always near bicycles. In the same way, hexagons fixed better by public transport are always close to public transport stops. However, being close to bike stations seems to have a more significant effect than being near public transport stops.

Figure 22a shows all hexagons that are not 15-minute hexagons by any sustainable mode of transport. Figure 22b and 22c show the same map but with additional bicycle locations and public transport stop locations, respectively. We can observe that the unfixable hexagons mostly don't contain any bicycles and have a larger distance to the nearest bicycle. The same cannot be said for public transport stops, as public transport stops are often directly inside the unfixable hexagons.

Figure 23 shows all hexagons that only become 15-minute city hexagons in the combined scenario when public transport and bicycle sharing are used simultaneously. As already seen in Table 11, this only concerns less than 2% of all hexagons that are not already 15-minute city hexagons through walking alone. More than half of those (7 out of 10) are located in the southern district of Weiß.

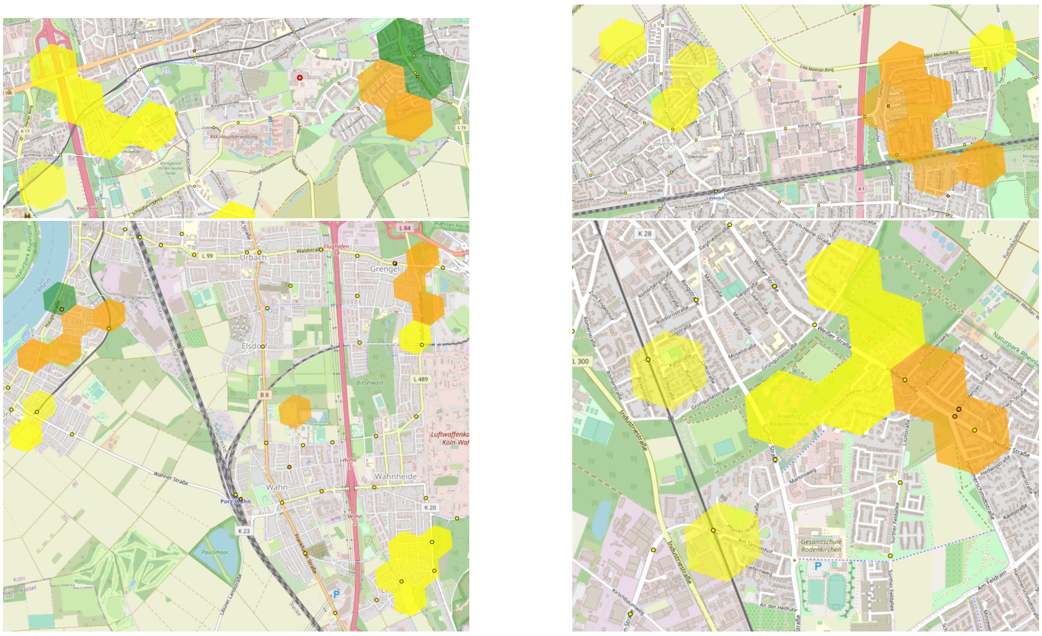
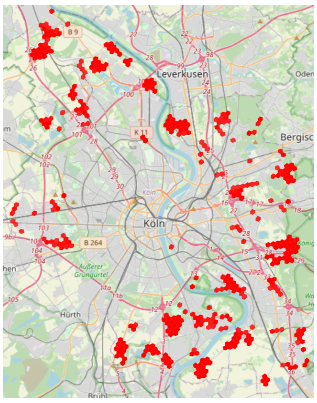
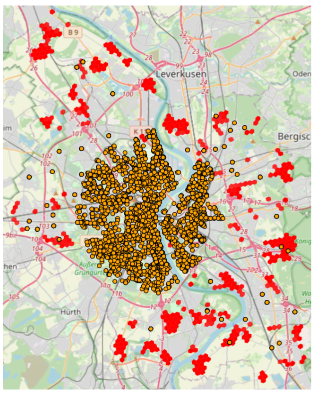


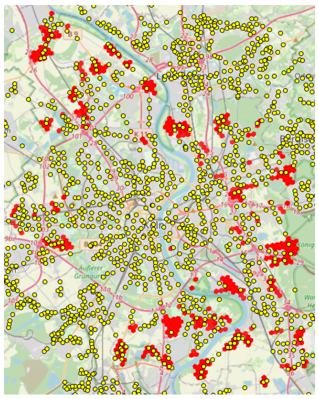
Figure 21: Examples of Fixable Hexagons



(a) Only Unfixable Hexagons



(b) With All Bicycle Locations



(c) With Public Transport Stops

Figure 22: Unfixable Hexagons

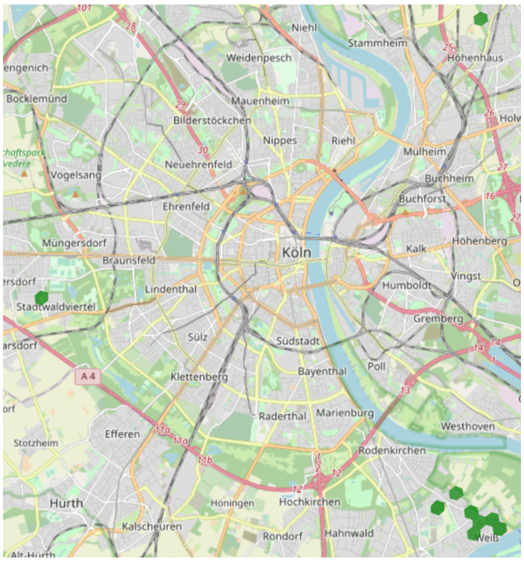


Figure 23: Hexagons Fixable by Combined Mode

5.7 Monthly Costs Per Scenario And Hexagon

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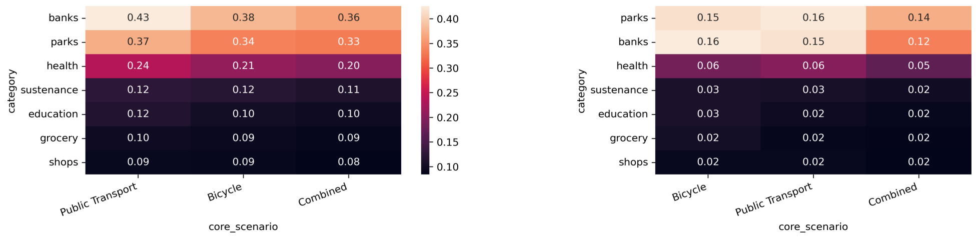
A prevalent measure to incentivize sustainable modes of transport are monthly tickets or subscriptions. To measure whether the costs of these subscriptions are worth it, we will calculate the monthly cost incurred by the trips to all necessities. To do so, we first collected how often people visited each category we defined earlier. Table 12 shows the monthly number of visits per category.

The derivation of these numbers can be found in Appendix E

Table 12: Number of Monthly Visits per Category

category	monthly visits
groceries	12
education	20
health	0.42
banks	9
parks	2.4
sustenance	6.12
shops	4



(a) 10 Minutes (b) 15 Minutes

Figure 24: Impossible Sub-X-Minute Journeys for each Hexagon and Scenario

To understand and compare the usual monthly costs caused by traveling with different modes of transport, we first establish two time-based benchmarks to compare the cost incurred. The first benchmark focuses on the costs incurred when reaching the nearest POI of a given category within a 15-minute timeframe. Conversely, the second benchmark assesses the costs for a similar journey but within a more constrained 10-minute limit. However, to compare these costs, a journey in that time has to be possible, which is not always the case.

Therefore, we show how often a journey is possible within the given timeframe in Figure 24. The combined scenario of bicycle sharing and public transport fails the least, followed by public transport and bicycle sharing. In the 15-minute benchmark, bicycle sharing and public transport perform almost equally well, while in the 10-minute benchmark, bicycle sharing performs better than public transport.

Category-wise, banks seem to be the least accessible category, followed by parks and health. Sustenance, education, grocery, and shops all seem similarly accessible.

As seen in the previous Figure, the number of impossible journeys differs across scenarios. This, again, makes it hard to compare the costs across scenarios. Therefore, we will only look at hexagons and category combinations where a journey is possible within the given timeframe for all scenarios. In addition, we also filter out hexagon category combinations where the cost is zero, i.e. where walking suffices, as those are not interesting for our cost analysis.

Table 13 shows the average monthly costs to reach all categories within 15 minutes for each scenario, and Table 14 shows the same for 10 minutes. As we can see, the total cost averages at €5.80 for the bicycle and combined scenario and €12.90 for the public transport scenario in the 15-minute benchmark. The cost reaches a maximum of €29 for the bicycle and combined scenario and €63.8 for the public transport scenario, while the 25% most expensive

Table 13: Monthly costs per scenario (<15 minutes)

	mean	std	min	25%	50%	75%	max
Scenario							
Bicycle	5.79	5.95	0.42	0.42	4.00	9.00	29.00
Combined	5.79	5.95	0.42	0.42	4.00	9.00	29.00
Public Transport	12.93	13.26	0.93	0.93	8.80	19.80	63.80

Table 14: Monthly costs per scenario (<10 minutes)

	mean	std	min	25%	50%	75%	max
Scenario							
Bicycle	10.49	7.72	0.42	2.42	9.00	20.00	24.54
Combined	10.49	7.72	0.42	2.42	9.00	20.00	24.54
Public Transport	23.08	16.98	0.93	5.32	19.80	44.00	53.98

hexagons require residents to pay 9€ for the bicycle and combined scenario and 19.80 for the public transport scenario. Note that the bicycle and combined scenario always have the same cost. In the 10-minute benchmark, the average cost is €10.5 for the bicycle and combined scenario and €23.1 for the public transport scenario. Here, the cost reaches a maximum of €24.54 for the bicycle and combined scenario and €53.98 for the public transport scenario, while the 25% most expensive hexagons require residents to pay €20 for the bicycle and combined scenario and €44 for the public transport scenario.

Next, we will also look at the monthly costs for the car scenario in the identical hexagons we looked at before in Figure 15. This allows us to compare the cost of cars with other modes of transport. Remember that the cost of 19ct/min tries to capture fuel costs, repair costs, insurance, and tax, but

Table 15: Monthly costs for cars

	mean	std	min	25%	50%	75%	max
Car (15 Minutes)	1.79	1.69	0.00	0.46	1.71	1.79	7.00
Car (10 Minutes)	2.87	2.89	0.00	0.46	1.79	3.91	10.88

not acquisition costs.

6 Discussion

6.1 Interpretation of Results

6.1.1 Runtime Observations

We have shown that our method applies to a large city like Cologne, running in a reasonable amount of time on consumer hardware. While the memory footprints may exceed 32 GB, using swap memory did not degrade the runtime beyond a reasonable amount. We therefore conclude that our method applies to cities of similar size. Also, because our method is parallelizable, we expect it will scale well when using more powerful hardware.

6.1.2 Public Transport Effectiveness

Our findings indicate that public transport effectively enhances accessibility, particularly in remote, low-POI-density suburban areas near high-frequency transport lines. However, it is costlier compared to bicycle sharing. We summarize our findings for public transport effectiveness in the following inferences:

I1. Public transport improves accessibility

I2. Public transport is more effective in remote areas

I3. Public transport is more effective in areas with low accessibility

I4. Public transport is costlier than bicycle sharing

We will reiterate our results and show how they support the above inferences.

In Figure 16, we can see that when users can afford a short public transport trip (cost of 2.20), their accessibility to POIs increases (I1).

The improvement seen by adding public transport mainly comes from areas with low accessibility, as seen in Table 4 and Figure 10 (I3). These areas, or hexagons, are likely far from POIs, and we suspect that public transport helps by covering these longer distances. However, adding public transport might not make a big difference in areas where it is already easy to get to these places. This is because using public transport often involves extra steps: walking to the bus or train stop and waiting for it to arrive. How much this extra time matters depends on the length of the trip. For short trips, getting to and waiting for public transport could be a large part of the travel time, making it less valuable. Nevertheless, for longer trips, especially in the areas that were hard to reach before, this extra time is a smaller part of the journey. This makes public transport more beneficial for these longer trips.

In Figure 10, we see the entire distribution of the optimal X-minute city metric for each scenario. Notably, while public transport is worse than bicycle sharing for the 80% most accessible hexagons, it shows a distinct advantage over bicycle sharing beyond the 80% quantile, facilitating faster access in less accessible areas (I3). The reason for this change in effectiveness between public transport and bicycle sharing is most likely linked to how bicycle sharing is set up in Cologne. With most bicycles available in the city center's "Flex-Zone", suburban areas have fewer bicycles as they can only be found at stations. Consequently, the least accessible hexagons, typically situated in suburban regions, experience low to no availability of bicycles, which explains the superiority of public transport in these areas.

Inferences 3 and 2 are supported by comparing the optimal X-minute city metric spatially between public transport and bicycle sharing, as seen in Figure 12b and 12a. We see the district of Rath/Neumar in the east, which shows low accessibility in general. However, we can see that public transport has an advantage over bicycle sharing in this remote area.

When looking at Table 11 we see that public transport can make 10% of hexagons that are not valid in terms of the 15-minute city by walking alone, valid (1). In addition, when looking at the spatial distribution of those hexagons in Figure 20, we see that the yellow hexagons, which are those that become valid in terms of the 15-minute city only through public transport, are primarily located outside the city in remote areas (I2).

In addition, when investigating the cost and X-minute city metric Pareto fronts in Figure 17, we see that public transport is only able to yield more significant improvements than bicycle sharing when considering only the 10% worst accessible hexagons (I3).

Table 5 and Figure 13 show that public transport's advantage at the least accessible hexagons comes at a cost (I4). As soon as the benefits of public transport manifest, the cost also increases to €2.20, which is obvious as public transport rides are always charged. We can see, however, that it is rarely necessary to travel more than four stops, as the corresponding cost of €3.20 is only reached for the few least accessible hexagons. The different sub-scenarios can explain the three- or four-step increases to the cost of €2.20 and €3.20. In some scenarios, it might be only beneficial to use public transport later.

Looking at Figure 14a also clearly reveals the spatial usage pattern of public transport. As already conjectured previously, we see that public transport is mainly used in remote locations outside the city, which we know have lower accessibility in general (I2 & I3).

The isolated hexagons inside the cities seen in Figure 13 are most likely located very close to a public transport stop, enabling residents to use the public transport system without any loss of time. Inside the city, it seems only beneficial to use the public transport system to reach necessities when living near a stop. However, outside the city, the larger groups of hexagons indicate that using the public transport system is often faster than walking to the necessities, even though walking to the next stop requires some time (I2). This may be because the density of the POIs is lower outside the city.

With the help of the cost and X-minute city metric Pareto fronts, we can evaluate the usefulness and cost-efficiency of short trips (those that travel no more than four stops) and long trips (those that travel more than four stops). Figure 16 and Table 7 show that the improvement caused by the short trip tickets is, on average, 1.28 minutes, compared to the 0.074 minutes of long trip tickets, and therefore almost 20 times larger. Unlike what we previously inferred (I2), the most effective and cost-efficient use of public transport consists of short trips. However, we should note that just because it does not bring as much value to travel more than four stops, this does not mean that trips associated with four stops or fewer are short. Especially in suburban areas, where public transport stops are more sparse than in the city center, it might very well be that trips with four stops or fewer still travel multiple kilometers. When investigating the 25% quantile and 75% quantile Pareto fronts in Figure 17, there is no benefit of long-distance tickets displayed. Only when investigating the 90% quantile Pareto front is the benefit visible. This indicates that long-distance trips are only used for the least accessible hexagons located outside the city 2.

In Figure 12a, we see that while the district of Rath/Neumar shows bad accessibility for all three scenarios, the accessibility in the public transport is better than that of walking and bicycle sharing (I2). Also, we know that the high-frequency city train line 9 runs through this region, which explains the effectiveness of public transport in this region (I3). It also shows us that a high-frequency public transport line from the city center to less accessible areas can significantly improve accessibility.

6.1.3 Bicycle Sharing Effectiveness

Bicycle sharing enhances accessibility in less and well-connected urban areas, offering cost-efficiency over public transport, with its effectiveness highly depending on bicycle allocation. We summarize our findings for bicycle sharing effectiveness in the following inferences:

I1. Bicycle sharing improves accessibility

I2. Bicycle sharing can further improve accessibility in already well-connected areas

I3. Bicycle sharing is only effective in areas, where bicycles are available

I4. Bicycle sharing is more cost-efficient than public transport

We will reiterate our results and show how they support the above inferences.

In Figure 16 we can see that when users can afford a bicycle for 15 minutes (cost of €1), their accessibility to POIs increases drastically (I1).

As detailed in Table 4 and Figure 10, the introduction of bicycle sharing yields benefits across almost all hexagons, offering a more uniform impact compared to public transport (1). Notably, bicycle sharing also yields improvements in already well-accessible areas (I2). We think this is because bicycles have a lower overhead than public transport, which contributes significantly to their practicality in urban settings. Firstly, the higher density of bicycle access points compared to public transport stops inherently reduces the initial distance required to access a mode of transport, facilitating quicker access to the transport system. Secondly, bicycles eliminate the waiting period often associated with public transport schedules, which means that once a user reaches a bicycle, they can immediately start their journey. This immediacy and ease of access render bicycles an effective solution for a more general scope than public transport.

Further, the data in Figure 10 reveals that in more accessible hexagons, combining bicycles with public transport offers greater advantages over using public transport alone (I2). Interestingly, looking at the least accessible hexagons, the disparity between these two scenarios narrows. This observation implies that in areas with very low accessibility, which are most likely remote areas, the addition of bicycles does not significantly enhance accessibility. This trend is likely due to the limited availability of bicycles in these less accessible areas, underscoring the importance of equitable distribution in bicycle-sharing systems (3).

We think the decrease in bicycle effectiveness in areas with low accessibility is linked to the low availability of bicycles in suburban areas, as most bicycles are located in the "Flex-Zone". This hypothesis is supported when looking at the difference between Figures 12b and 12c. Here, an improvement is observed in the bicycle scenario compared to walking, particularly within the "Flex-Zone" as shown in Figure 25, which underscores the impact of bicycle availability on its effectiveness (3).

Figure 19 shows hexagons that are valid in terms of the 15-minute city by walking in green, those that are valid only by the addition of any sus-

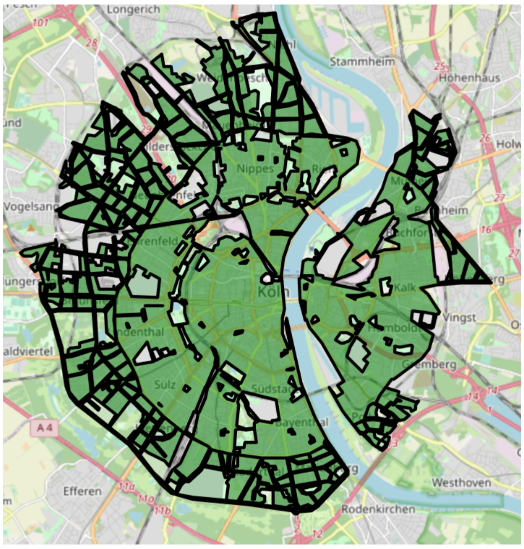


Figure 25: Next Bike's Flex Zones

tainable mode of travel in yellow, and those that are not valid through any sustainable mode of travel in red. We suspect that the very noticeable yellow ring around the city center is in an area with few POIs but still a high availability of bicycles, which can compensate for this sparsity. This spatially shows where sustainable modes of travel are important to compensate for the sparsity of POIs. These areas do not provide a close enough proximity to be considered sub-15-minute city regions by walking alone. However, with bicycle sharing and public transport, they are. In Figure 20, we see that most of the hexagons in the ring are orange or green, meaning they are either fixable by bicycle sharing or public transport. This again underlines that bicycle sharing is more effective if it is present than public transport (I3&I1). In the same Figure, we can see that yellow hexagons, only fixable through public transport, tend to exist in the regions that are further away. Also, the unfixable regions, marked in red, mostly don't have bicycles near them, but they often have public transport stops nearby. This suggests that bicycles are more effective than public transport in helping a region to become a sub 15-minute region (I3&I1).

Investigating the cost and X-minute city metric Pareto fronts in Figures 16 and 17, as well as, the corresponding steps in Tables 7, 8 and 9 shows that using a bicycle for 15 minutes always yields more significant time gains than public transport except for the 10% worst accessible hexagons (I1 & I4). This is a clear indicator of the superiority of bicycle sharing over public transport in terms of accessibility improvements, especially, when considering that the bicycle-sharing infrastructure does not cover all of the considered area.

Table 5 and Figure 13 show that bicycle sharing never costs more than public transport if both are used (4). We can also deduct this from the price of both and the fact that bicycles are never used for more than 15 minutes. We know that bicycles are never used for more than 15 minutes as the maximum cost, as seen in Table 5, is €1, which is the price for a 15-minute ride. Meanwhile, the shortest possible public transport trip costs €2.20, as soon as public transport is used, it always costs more than bicycles. Nevertheless, this shows that bicycle sharing is cheaper than public transport.

In addition, knowing that bicycles are never used for more than 15 minutes tells us that at any location where bicycles are available, Cologne is a 15-minute city. This is a strong indicator that bicycle sharing can make regions 15-minute city regions, improving accessibility (I1).

Table 7 shows the average improvements of the X-minute city metric, at the steps in the Pareto front. We see that bicycle sharing is, on average, more than three times more cost-efficient than public transport (I4). Further, investigating the differences at the 75% and 90% quantile Pareto fronts in Table 8 and 9, shows that bicycle sharing always is more cost-efficient than public transport.

Table 11 shows that bicycle sharing enables 13% of hexagons, which are not sub-15-minute city regions by walking alone, to become accessible within this time frame. This improvement is more significant than that achieved by public transport.

Looking at the spatial distribution of those hexagons in Figure 20, we see that the orange hexagons, which are those that become valid in terms of the 15-minute city only through bicycle sharing, are mostly located at the city's border, where the "Flex-Zone" is still active. This again shows that the effectiveness of bicycle sharing highly depends on the "Flex-zone" (3).

6.1.4 Bicycle Sharing and Public Transport - Substitutes or Complements?

As mentioned, we found clear evidence that bicycle sharing and public transport positively affect accessibility according to the X-minute city metric. It is, however, not clear whether these modes are substitutional to each other, meaning that one mode can compensate for the other or whether they are complements. We could potentially observe two sorts of complementary effects.

Complement 1. Bicycle sharing and public transport are effective under different circumstances and in different areas

Complement 2. Bicycle sharing and public transport used together is necessary to improve accessibility

The presence of complement 1 means that one mode cannot replace the other, and each is necessary under specific circumstances. The presence of complement 2 means that both modes must be used together in a single journey to achieve the highest accessibility. Both effects are not mutually exclusive, meaning we can observe both simultaneously.

Our results show evidence for both effects, yet complement 1 is more pronounced. We will now reiterate our results and show how they support the complements above.

Table 4 shows that the combined scenario on average yields better accessibility than bicycle sharing and public transport alone. This suggests that either complement I or complement II must be present.

We see evidence for complement I in the observation that bicycle sharing is most effective for the 80% more accessible hexagons, while public transport is mostly only effective for the 20% least accessible hexagons.

Table 11 shows how many hexagons in which people are not able to reach all necessities in 15 minutes by walking can reach all necessities in under 15 minutes by public transport or bicycle sharing. We see that bicycle sharing and public transport alone are equally important, as they fix 13% and 11% of hexagons, respectively. In addition, a lot more hexagons are fixed by only one of them (24%) than by either (7%). This again suggests that complement I is present.

Table 11 also shows that the combined scenario only fixes around 2% and is therefore not very impactful. Nevertheless, we prove that the effect of complement II is present.

The presence of complement I should make us aware that the effectiveness of either mode is highly dependent on the spatial circumstances of the region. Some regions might benefit more from bicycle sharing, while others benefit more from public transport. It is, therefore, necessary to analyze each region separately to maximize the positive effect of sustainable modes of travel.

6.1.5 Monetary Considerations

Table 7 shows how a minute of saved time costs for cycling and public transport, respectively. The most cost-efficient variant, bicycle sharing, enables users to save 1.68 minutes per euro, which might not be worth it for most people. The 1.68 minutes per euro spent, in other words, means that to save a minute, people have to spend around 62 cents. Comparing this to the minimum wage in Germany of €12 per hour in 2022 (Germany, n.d.), which is 20 cents per minute, shows that it takes around three minutes to make enough money to save one minute, which is not worth it. This means that, on average, the sustainable modes of travel are currently too expensive.

Even when looking at the least accessible regions (90% quantile) separately in Figure 17c, where we have the most significant improvement possible, the most cost-efficient mode of transport, which is bicycle, only yields an improvement of two minutes per euro, which again does not result in a net positive for people who earn the minimum wage.

With the help of the monthly cost depicted in Table 13 and 14, we can derive recommendations for the price of a monthly ticket or subscription that is appealing to residents, that have to use public transport or bicycle sharing in order to reach certain amenities in under 10 or 15 minutes. We expect that such a monthly ticket would reduce the cost of the trips necessary to reach the amenities to zero. In our experiment in the city of Cologne, this is plausible, as the public transport tickets indeed allow for unlimited travel within the city, while NextBike's subscription makes trips that are under 30 minutes free.

Looking at the tables, we note that the monthly costs for the combined and bicycle scenarios are the same, which shows that only bicycle sharing is used in the combined scenario. In the 15-minute benchmark, we see that in order to appeal to at least 50% of the population, a public transport ticket should cost less than €8.80, while a bicycle sharing subscription should cost less than €4. The 10-minute benchmark shows a similar pattern: the median cost for the bicycle and combined scenario is €9, while the median cost for the public transport scenario is €19.80. Currently, a NextBike subscription costs €10 per month, while the most common public transport ticket, the "Deutschlandticket", costs €49 per month. Both of these prices are significantly higher than the median cost for the bicycle and combined scenario, which means that a monthly ticket is not worth it for most people.

Table 15 shows the monthly car cost, excluding acquisition costs. With the difference between the monthly car cost and the monthly cost of the bicycle, combined and public transport scenario, we can calculate how significant acquisition costs for a car can be, so that it is still cheaper than the sustainable modes of travel. In the case of the 15-minute benchmark, the average car costs are €1.69, while the average cost for the bicycle and combined scenario are €5.79, resulting in a difference of €4.10 per month or €49.20 per year. This difference compared to the usual acquisition cost of a car is so low that it is not monetarily worth it to buy a car if the same journey can be made with bicycle sharing or public transport. In addition, we have to keep in mind that our estimates for the speed of cars are very optimistic, as we assume that there is no traffic and that parking is always available. Obviously, we can only state this for areas where accessibility using sustainable modes of travel suffices. From table 11, we know that 67% of hexagons in which walking alone is not sufficient, only cars can make all amenities accessible in under 15 minutes.

6.1.6 Uncertainty

The standard deviation of the average time it takes to reach all necessities for bicycles is 1 minute and 10 seconds. Relating this to the improvement compared to walking for 1 minute and 38 seconds, we see that the uncertainty is quite significant. This shows us that bicycle placement significantly impacts the bicycle-sharing scenario's effectiveness (I3).

It is interesting to note that bicycles suffer more from uncertainty than public transport, as public transport only has a standard deviation of 16 seconds. Relating the standard deviation to the improvement compared to walking of 1 minute and 28 seconds, it is less impactful than bicycles. However, the standard deviation strongly depends on the choices of our sub-scenarios. For public transport, we tried 08:00, 12:00 and 18:00. We suspect that the variance for public transport would increase more drastically and eventually surpass the one of bicycle sharing if we choose more unusual times like midnight. In addition, the schedule of public transport is often the same for full hours. We could get a more realistic picture by adding more times with non-zero minutes to our sub-scenarios.

We should also note that the comparison of variances should be taken with caution as the method for selecting the sub-scenarios differs per scenario. We employed a clustering method for bicycle sharing while we made a qualitative choice for public transport.

6.2 Implications

From our interpretation of the results, we can derive several implications for the city of Cologne and accessibility in cities in general. We will structure our implications into two sections. First, we will discuss what already works well, and then we will discuss measures that can be taken to improve accessibility.

What already works well is the improvement of accessibility through public transport in remote areas. As long as there are areas with low accessibility caused by low availability of POIs, public transport will be an effective measure. Also, bicycle sharing can improve accessibility everywhere where there are bicycles available. For the most part, at least for Cologne, bicycle sharing is highly effective where the "Flex-Zone" is located. It is essential to understand the relationship between its effectiveness and the location of this zone.

As most of Cologne's central parts are covered by the zone, we can already observe its massive positive effects on accessibility. In addition, approximately 69% of all considered hexagons and with that, 69% of all residential in the administrative district Cologne ("Stadtkreis Köln") are 15-minute city by walking, which shows us that Cologne essentially already has excellent accessibility. Interestingly, this Nicoletti et al. (2023) calculated a vastly higher number.

The observation that approximately 31% of Cologne's area lacks access to essential services within a 15-minute walk highlights the potential for improvements. We hypothesized that introducing bicycle sharing and enhanced public transport could significantly reduce these areas by improving accessibility. However, as indicated in Table 11, a majority (67%) of the hexagons currently not meeting 15-minute city criteria remain to not meet the criteria even with these sustainable modes. Yet, it is important to note the impact of bicycles and public transport in converting 33% of these hexagons into areas meeting the 15-minute city criteria. To further amplify their effectiveness, we propose two strategies. Firstly, expanding the 'flex zone' areas where bicycles are available into inaccessible regions. Given the observed correlation between bicycle availability and enhanced accessibility, this approach will likely yield substantial improvements. Secondly, we recommend establishing high-frequency public transport lines to connect to remote, low-accessible areas. Our findings suggest that public transport effectively improves accessibility in these regions. However, considering the potential impracticality of extending the flex zone to these distant areas, adding or enhancing public transport routes could be a more feasible solution.

We have demonstrated that the success of bicycle-sharing is closely tied to the availability of bicycles. This availability primarily hinges on two factors: the location of the "Flex-zone" and how bicycles are distributed within it. Significantly, our findings reveal that the program's effectiveness varies greatly across different sub-scenarios, highlighting the importance of strategic bicycle distribution. Therefore, carefully managing bicycle placement and timely relocations are crucial for the system's efficiency. To optimize the effectiveness of bicycle sharing, it is essential to conduct regular analyses of system demand and adjust bicycle distribution in response to these insights. He et al. (2020); Lu et al. (2018); Benjaafar et al. (2018) have already researched how to effectively relocate bicycles.

6.3 Limitations

A significant limitation of our analysis is the omission of traffic conditions and parking availability. Urban traffic dynamics can significantly influence the practicality and speed of bicycles, especially car travel, potentially skewing the perceived efficiency. Similarly, the availability of parking plays a crucial role in urban mobility, particularly in cities. By not accounting for these factors, our study may not fully capture the complexities and challenges urban commuters face, possibly overestimating the effectiveness of bicycle-sharing and car travel in congested urban environments.

Another critical limitation is the exclusion of reliability issues such as public transport outages or traffic disruptions due to accidents. These events can drastically affect transportation dynamics in a city. For instance, a public transport outage might temporarily increase the demand for bicycles, while an accident could impede bicycle routes. Not considering these variables limits the scope of our study, particularly in understanding the resilience and adaptability of bicycle-sharing and public transport systems.

The usefulness of the X-minute-city metric employed in our study, which assesses accessibility based on the ability to reach any POI assigned to a category, should also be taken with caution. For example, access to a pet doctor a health POI, is considered equivalent to access to a hospital. While this metric provides a quantifiable measure of accessibility, it may not comprehensively represent the diverse needs of an urban population.

Our analysis also reveals a limitation concerning the scalability of transport modes. While bicycles significantly improve the X-minute city metric in our study, suggesting enhanced accessibility, they inherently lack the scalability of public transport. A bicycle may offer a convenient solution for an individual, but it does not address the mass transit needs of a larger population. This aspect is particularly crucial in dense urban areas where public transport systems are more efficient in moving large numbers of people. Therefore, while bicycles contribute to urban accessibility, they should be considered part of a broader, multi-modal transport strategy rather than a standalone solution.

6.4 Future Work

Building upon the findings of our current study, it is essential to explore new avenues to deepen our understanding of urban mobility and enhance bicycle-sharing systems. This section outlines potential directions for future research that can contribute significantly to this field.

A crucial area of future research is examining the impact of public transport disruptions on accessibility. Disruptions such as strikes, maintenance, or accidents can drastically alter commuting patterns. Investigating these scenarios could involve comparing accessibility between normal and disrupted conditions to determine the impact of outages and to what extent bicycle sharing or other modes can compensate for these outages. This research can provide valuable insights into the role of bicycle-sharing as an alternative mode of transport during public transport failures.

Another promising research direction is to study the effects of modifications to the flex zone. Changing the area where bikes can be borrowed and returned may significantly influence the accessibility improvements caused by bike-sharing. Future studies could experiment with different sizes and placements of flex zones to determine optimal configurations that maximize accessibility and efficiency. These research endeavors should consider or even incorporate the dynamics of bicycle relocations.

Investigating the impact of adding new or improving existing public transport lines on bicycle-sharing systems presents another research opportunity. Such a study could explore how enhancements in public transport affect accessibility in currently inaccessible areas. Understanding these dynamics is crucial for integrated urban transport planning that caters to diverse commuter needs.

A comprehensive study on the usage patterns of roads, bicycles, and public transport is also essential. With the help of our current study, it is possible to find the paths people would take if they tried to get from one specific point to another. This, together with realistic demand data, yields a set of paths that can be analyzed to find potential bottlenecks. The results could inform urban planning and policy decisions, leading to more efficient and responsive urban transport systems.

A Appendix - Overpass Query for Boundary of Cologne

```
[out:json][timeout:50];
area["name"="Köln"]->.searchArea;
relation["boundary"="administrative"]["admin_level"="6"](area.searchArea);
out body;
>;
out skel qt;
```

B Appendix - Pyrosm Network Filter

Pyrosm filters out all ways that have the following tags:

Table 16: Driving Filter

Key	**Values**
area	yes
highway	cycleway, footway, path, pedestrian, steps, track, corridor, elevator, escalator, proposed, construction, bridleway, abandoned, platform, raceway
motor_vehicle	no
motorcar	no
service	parking, parking_aisle, private, emergency_access

Table 17: Walking Filter

Key	**Values**
area	yes
highway	cycleway, motor, proposed, construction, abandoned, platform, raceway, motorway, motorway_link
foot	no
service	private

Table 18: Cycling Filter

Key	**Values**
area	yes
highway	footway, steps, corridor, elevator, escalator, motor, proposed, construction, abandoned, platform, raceway, motorway, motorway_link
bicycle	no
service	private

C Appendix - Categories and Their Corresponding OSM Tags

Table 19: Categories and Their Corresponding OSM Tags

Category	**OSM Key**	**OSM Value**
Grocery	shop	alcohol, bakery, beverages, brewing supplies, butcher, cheese, chocolate, coffee, confectionery, convenience, deli, dairy, farm, frozen food, greengrocer, health food, ice-cream, pasta, pastry, seafood, spices, tea, water, supermarket, department store, general, kiosk, mall
Education	amenity	college, driving school, kindergarten, language school, music school, school, university
Health	amenity	clinic, dentist, doctors, hospital, nursing home, pharmacy, social facility
Banks	amenity	atm, bank, bureau de change, post office
Parks	leisure	park, dog park
Sustenance	amenity	restaurant, pub, bar, cafe, fast-food, food court, ice-cream, biergarten
Shops	shop	department store, general, kiosk, mall, wholesale, baby goods, bag, boutique, clothes, fabric, fashion accessories, jewelry, leather, watches, wool, charity, secondhand, variety store, beauty, chemist, cosmetics, erotic, hairdresser, hairdresser supply, hearing aids, herbalist, massage, medical supply, nutrition supplements, optician, perfumery, tattoo, agrarian, appliance, bathroom furnishing, do-it-yourself, electrical, energy, fireplace, florist, garden centre, garden furniture, fuel, glaziery, groundskeeping, hardware, houseware, locksmith, paint, security, trade, antiques, bed, candles, carpet, curtain, flooring, furniture, household linen, interior decoration, kitchen, lighting, tiles, window blind, computer, electronics, hifi, mobile phone, radio-technics, vacuum cleaner, bicycle, boat, car, car repair, car parts, caravan, fishing, golf, hunting, jet ski, military surplus, motorcycle, outdoor, scuba diving, ski, snowmobile, swimming pool, trailer, tyres, art, collector, craft, frame, games, model, music, musical instrument, photo, camera, trophy, video, videogames, anime, books, gift, lottery, newsagent, stationery, ticket, bookmaker, cannabis, copy shop, dry cleaning, e-cigarette, funeral directors, laundry, moneylender, party, pawnbroker, pet, pet grooming, pest control, pyrotechnics, religion, storage rental, tobacco, toys, travel agency, vacant, weapons, outpost

D Appendix - Experiment Module Matrix Configuration

$$\begin{pmatrix}\text{walking module}\end{pmatrix} \qquad \begin{pmatrix}\end{pmatrix}$$

(a) Initial Matrix (b) Repeating Matrix

Figure 26: Walking Scenario Module Matrices

$$\begin{pmatrix}\text{walking module}\end{pmatrix} \qquad \begin{pmatrix}\text{free-floating vehicle sharing module} & \text{public transport module} \\ \text{walking module} & \end{pmatrix}$$

(a) Initial Matrix (b) Repeating Matrix

Figure 27: Combined scenario module matrices

$$\begin{pmatrix}\end{pmatrix} \qquad \begin{pmatrix}\text{personal car module}\end{pmatrix}$$

(a) Initial Matrix (b) Repeating Matrix

Figure 28: Personal Car Scenario Module Matrices

$$\begin{pmatrix}\text{walking module}\end{pmatrix}$$

(a) Initial Matrix

$$\begin{pmatrix}\text{public transport module}\\ \text{walking module}\end{pmatrix}$$

(b) Repeating Matrix

Figure 29: Public Transport Scenario Module Matrices

$$\begin{pmatrix}\text{walking module}\end{pmatrix}$$

(a) Initial Matrix

$$\begin{pmatrix}\text{free-floating vehicle sharing module}\\ \text{walking module}\end{pmatrix}$$

(b) Repeating Matrix

Figure 30: Bicycle Scenario Module Matrices

E Appendix - Monthly Visits per Category

Grocery 3 times per week according to Nilsson et al. (2015). Resulting in approximately 12 times per month.

Education 5 times per week, as we assume that students visit their school or university 5 times per week.

Health 5.09 per year according to Eurostat (2019). Resulting in approximately 0.42 times per month.

Banks 9 per month according to Optconnect (n.d.).

Parks 29 per year according to National Recreation and Park Association (2016). Resulting in approximately 2.42 times per month.

Sustenance 6.12 per month according to Saprykin et al. (2016).

Shops 4 per month according to Plus (2019).

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