Extending Accessibility Analysis With True Multi-Modality

Master Thesis

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December 2, 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. The Paris Agreement, with its ambitious goals to reduce global warming, serves as a call to action. However, current trends suggest that without immediate action to reduce emissions, achieving these goals 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 key area to reduce emissions.

In order to reduce the amount of car traffic, cities need to be planned in a way that allows people to access everything they need with alternative, more environmentally sustainable modes of transport. Therefore, a recent trend in urban planning is accessibility-based planning (Proffitt, Bartholomew, Ewing, & Miller, 2019) (Geurs & van Wee, 2004). In order for practitioners to be able to plan cities in an accessibility-based way, they need to be able to measure accessibility.

A modern way of measuring accessibility is to use the X-minute city metric, which is inspired by the 15-minute city concept, which recently gained traction during the COVID pandemic (Moreno, Allam, Chabaud, Gall, & Pratlong, 2021).

The concept of the 15-minute city is that all the things a person needs to live a good life should be accessible within 15 minutes of walking or cycling. Traditionally, the modes of transport don't include public transportation or vehicle sharing systems.

However, we argue that in order fully grasp the potential of sustainable transport, it's essential to incorporate all modes, not merely a subset, in the measurement of accessibility

We therefore develop a new tool for accessibility-based planning that incorporates all modes of travel (multi-modal, unrestricted inter-modal). In addition, this tool will use 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 on accessibility via sustainable modes of transport.

We test our tool on the City of Cologne.

The remainder of this paper is structured as follows. In Section 2, we present related work on accessibility-based planning, the 15-minute city concept, and routing algorithms. Next, in Section 3, we describe the specifics of our tool, including the data collection process, the routing algorithm, and the accessibility metric. After that, we introduce our experiment in Section and it's results in Section. Finally, we conclude with a discussion and conclusion in Section and, respectively.

2 Related Work

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2.1 Accessibility Analysis

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 more and more out-of-date, as modern challenges like reducing emissions of greenhouse gases require a more holistic approach. This is where accessibility-based planning comes into play, which focuses planning cities in a way to provide residents with access to important services (Proffitt et al., 2019).

(Geurs & van Wee, 2004) describe four types of accessibility-based planning: (more info here...)

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

The X-minute city metric is a location-based accessibility metric, which is derived from the concept of the 15-minute city.

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 concept of the 15-minute city is that all the things a person needs to live a good life should be accessible within 15 minutes of walking or cycling.

(Willberg, Fink, & Toivonen, 2023) say that it is important to consider elderly people, that are not able to walk as fast as younger people. We could use that as an argument to why public transport needs to be considered.

cultivate stronger social relationsips, because people are more likely to meet (Allam, Moreno, Chabaud, & Pratlong, 2020) a kind of social distancing, because of primarily traveling by walking or cycling (Allam et al., 2020) a more environmentally sustainable mode of transport in cities, which contributes to SDG 11 & 13 (Allam et al., 2020) (Papas, Basbas, & Campisi, 2023)

reduced traffic resulting in economic benefits (Allam et al., 2020) (Papas et al., 2023)

developing cities around the 15-minute city concept reduces social inequalities, as walking is free (Weng et al., 2019) (Gustafson, 2022) therefore, when incorporating other fare-based modes of transport such as bicycle sharing, it is important to consider the fares and their impact (thats why we do multi-objective stuff)

Quantitative studies have developed various ways to measure how well cities match the idea of the 15-minute city concept, by developing metrics that encapsulate this principle. (Olivari, Cipriano, Napolitano, & Giovannini, 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*, n.d.), 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 - 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.

Despite the potential benefits, (Olivari et al., 2023) acknowledge the challenges in realizing the 15-minute city model, notably the substantial investments and strategic planning required.

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 weights are hard for humans to evaluate 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, Sirenko, & Verma, 2023) 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. They discovered that access to urban amenities like healthcare, education, and transportation is not evenly distributed. In particular, communities with more minorities, lower incomes, and fewer university-educated individuals often have less access to these important services.

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 disparities in accessibility are linked to the city's growth. This pattern was consistent even when considering various socio-economic factors.

The framework introduced 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 in access 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) simply 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.

However, 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. The potential benefits of infrastructure such as dedicated bicycle lanes, bicycle sharing systems, and highly available public transport are thus not reflected within the research of (Olivari et al., 2023) and (Nicoletti et al., 2023). To provide a more accurate measure, we propose to enhance the computation of accessibility by integrating a multimodal accessibility metric that accounts for these various transportation methods and their respective infrastructural elements.

(Ferrer-Ortiz, Marquet, Mojica, & Vich, 2022) calculate whether a certain area has access to a certain category within 15 minutes for Barcelona They derive their cateogories from the six 15-minute city "urban social functions" defined by

Moreno. However, they only deal with a subset of four, namely care, education, provisioning and entertainment.

In order to assess the accessibility from a given origin to one or multiple points of interest, a routing algorithm is required. The routing algorithm finds the shortest path from the origin to the destination. Therefore, we investigate different routing algorithms in the following section and find one that is suitable for our use case.

2.2 Routing Algorithms

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:

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

In accessibility contexts, the primary concern frequently revolves around determining the accumulated cost, $d(v_n)$, to reach the destination rather than the actual path.

In more complex real-world scenarios, the problem often encompasses 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 simpler single-objective case with a singular optimal path, the multi-objective scenario 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, there is no other solution that is better in 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 path 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 thought of as 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 $i \in \{1, \ldots, k\}$ and $l'_i < l_i$ for at least one $i \in \{1, \ldots, k\}$. 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. For accessibility analysis routing algorithms are often altered to not find the optimal path(s) 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.

2.2.1 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. In each iteration, the algorithm dequeues the node u with the smallest known distance from the priority queue. 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 either 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 too slow for large graphs.

2.2.2 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 2.2 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 $(0, \dots, 0) \in \mathbb{R}^k$. Each iteration extracts the lexicographically smallest label, as opposed to 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 it isn't dominated by any existing label. 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.

2.2.3 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 different approaches are commonly used, the time-expanded and the time-dependent approach, as explained by (Müller-Hannemann, Schulz, Wagner, & Zaroliagis, 2007). While enabling the use of graph-based algorithms, both approaches still suffer from the previously mentioned runtime problems Dijkstra's algorithm and MLC have.

2.2.4 RAPTOR

To overcome the runtime problems of graph-based approaches, (Delling, Pajor, & Werneck, 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.

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 at 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 to only 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. 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 $\tau^\star(p)$, formally:

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

Here one optimization comes into play. In the case 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 that is the case, we update the earliest arrival times and also mark that stop.

If no stops are marked, then 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 how the transfer graph could look. First, we should note that

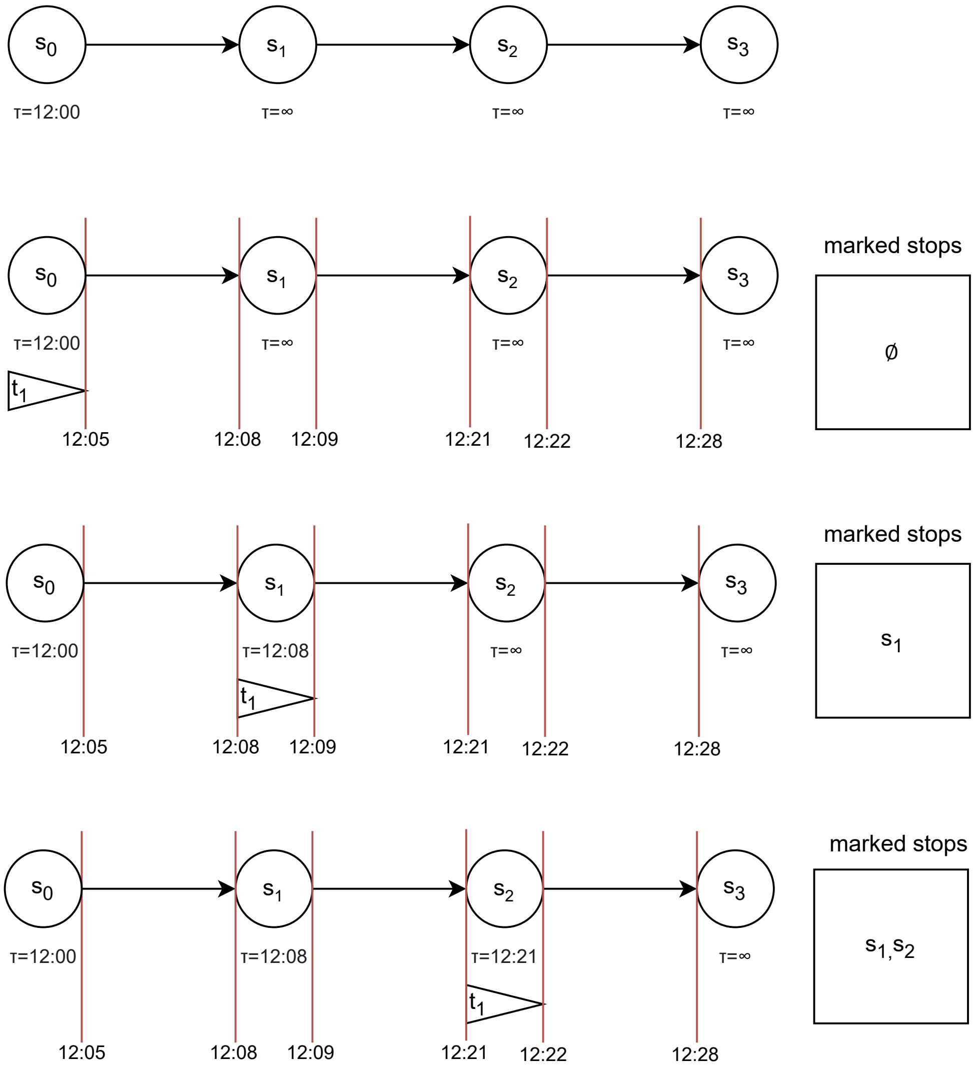


Figure 1: Iterating a route in RAPTOR

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. To keep the transfer graph small, one could limit the maximum walking distance. However, this may remove optimal journeys from the search space. In general, creating the transfer graph requires some amount of preprocessing. 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.

2.2.5 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 $(\tau, 0, 0, \ldots, 0)$, 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 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 labels 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 that are 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 fully depends on the objective and what it represents.

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, namely that the transfer graph is hard to compute.

2.2.6 MCR

To overcome problem of RAPTOR (Delling, Dibbelt, Pajor, Wagner, & Werneck, 2013) introduce Multimodal Multicriteria RAPTOR (MCR). MCR modifies McRAPTOR so that the transfer graph must not be transitively closed. This enables MCR to directly use the street network as an input and therefore no preprocessing is necessary.

This allows us to use the street network as the transfer graph, which has the benefit that during the traversal of the tranfer graph the objectives can be updated. 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 is very similar to RAPTOR. It only replaces the footpath traversal step through MLC.

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.

2.2.7 ULTRA

(Baum, Buchhold, Sauer, Wagner, & Zündorf, 2019) propose another algorithm building on MCR, called UnLimited TRAnsfers for Multi-Modal Route Planning (ULTRA). ULTRA capitalizes on the observation that extensive exploration of the transfer graph 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 that contribute 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, Sanders, Schultes, & Delling, 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.

2.2.8 McTB

(Potthoff & Sauer, 2021)

2.2.9 ULTRA-PHAST

2.3 Public Transport Data

In order to run routing algorithms for public transport networks in practice, a common data format is needed.

The General Transit Feed Specification (GTFS) (?, ?) 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 taken by a particular public transport service, identified by attributes like name, ID, and the mode of transport such as bus or subway. 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.

GTFS data is often distributed in plain text (.txt) files which are bundled together and compressed into a .zip file. This packaging makes it both compact for distribution and straightforward for developers to parse and use.

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

2.4 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) (?, ?).

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 delineate 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 useful in accessibility analysis.

OSM is extensive, regularly updated, and most importantly freely available, which makes it indispensable for projects seeking reproducibility and generalizability.

2.5 Importance of Multimodality & Intermodality

"Results show that bicycles significantly reduce the average transfer times, the average path length of passengers' trips and the Gini coefficient of an urban public transport network" (Yang et al., 2018).

Public transport frequency is significantly positively correlated with the number of bicycle trips, especially short and medium distance trips up to 3 km (Radzimski & Dzięcielski, 2021).

(Murphy & Usher, 2015) conduct a questionnaire, which shows that 39% of bicycle sharing users (in Dublin) use bicycle sharing in conjunction with another mode of transport. Of those, 91.5% use public transport, which indicates that bicycle sharing is synergetic with public transport.

(Fishman, Washington, & Haworth, 2013) perform a literature review on bicycle sharing in general and find that bicycle sharing is synergetic with public transport.

(Ma, Liu, & Erdoğan, 2015) run a linear regression with data ... in which the number of passengers of public transport is regressed on the number of bicycle sharing trips. They find a positive correlation between the two and conclude that bicycle sharing and public transport are complementary. As a possible reason for this, they state that bicycle sharing can be used to solve the first and last mile problem.

"Through an extensive experimental study, it's demonstrated that allowing unrestricted walking considerably reduces travel times compared to scenarios where walking is limited." (Wagner & Zündorf, 2017)

Fact: Computing with unrestricted walking takes way longer to compute. (Wagner & Zündorf, 2017)

3 Method

Our method is split into to two parts, the routing algorithm and the accessibility analysis tool.

3.1 Metric

To evaluate the accessibility in cities, we employ a metric that is an implementation of the 15-minute city concept. The concept measures how fast the access to a variety of important 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. Our categorization is based on the work of (Olivari et al., 2023) with slight modification and can be seen in Table 2.

Each service category encapsulates several POIs. For instance, the "Parks" category may include multiple locations tagged in OSM as "leisure: park" or "leisure: dog park".

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. This approach yields a singular measure that reflects the most significant time distance barrier within an urban area, which effectively captures the least accessible category for any given area. 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 to 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 seven categories, our metric evaluates all categories together. This unified approach makes it more straightforward and easier to understand. In contrast, while NEXI-global also considers all categories in one assessment, it converts the results into a 0-100 score. This percentage system can obscure the real value of the data, making it more difficult to interpret.

Moreover, the NEXI-global's practice of assigning different weights to each

Table 2: 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

category complicates its analysis. Our metric, by focusing on the lowest-performing category across all areas, 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.

Traditionally, the 15-minute city concept is applied to walking and or cycling and ignores other modes of transport. Some researchers, in the context of location-based metrics, even go as far to only calculate the bee-line distance to the nearest amenity and ignore the street network altogether (Gastner & Newman, 2006), while most only consider walking (Olivari et al., 2023; Nicoletti et al., 2023). We, however, believe that to accurately determine the accessibility of a city, all modes of transport must be considered, and the routing needs to be as realistic as possible. We will therefore calculate our metric for various combinations of modes of transport, namely driving with a personal car+walking, free-floating bicycle sharing+walking, public transport+walking, free-floating bicycle sharing+public transport+walking, and walking. The car mode will serve as a baseline metric and show how competitive more sustainable modes of transport are.

Adding potentially fare-based modes of transport poses a challenge, as we need to consider the cost of the trip. Ignoring the cost of the trip could potentially lead to a misrepresentation of accesibility, as a trip with a high cost might be inaccessible to some people. To account for this, we will calculate Pareto sets that balance the minimum travel time and the cost of the trip.

3.2 Routing Algorithm

Our routing algorithm is an applied version of MCR with minor variation to make it more suitable in terms of free-floating vehicle sharing.

3.2.1 Requirements

In order 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**, and **unrestricted inter-modal**, and run in a reasonable time.

Multi-modal means that our routing algorithms 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 where 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 either 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 that 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 needs to consider journeys with bicycle rides between two consecutive public transport trips. **Unrestricted** means that the algorithm fully searches the unscheduled network graphs, and does not pose restrictions like a maximum of 10 minutes walking distance.

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, it requires calculating the walking distance between each node. This computation would yield $125,176^2 = 15,669,030,976$ edges, a number 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 certain 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.

In the following section, we detail the modifications made to MCR to tailor it to our requirements.

3.2.2 Algorithm

As our algorithm should be easily adaptable to different modes of transport and the combination of different modes of transport, 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 to traverse the whole walking graph given the current state of 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 labels, that are Pareto optimal with respect to the objectives. In addition, in our work, a bag is associated with a node some

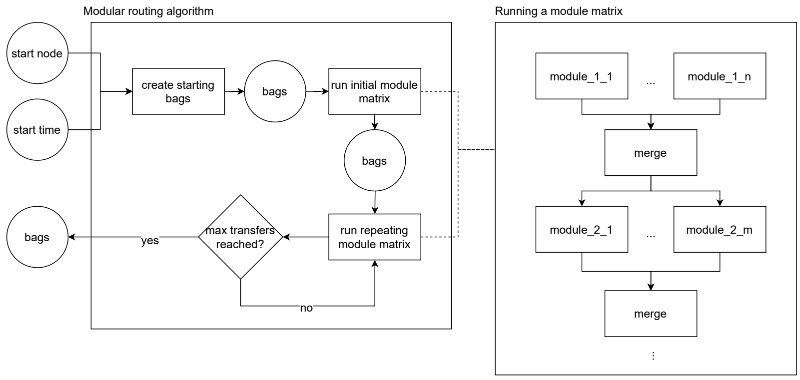


Figure 2: Modular Routing Algorithm

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 in order to merge the bags of different modules. In our work, the common network will be the walking graph. This also has a real-world interpretation, as walking in between different modes of transport is very 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 exactly 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 of the algorithms 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, first the modules of the first row 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 on 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 simplest unscheduled module, it simply 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 a bit more complex. Before running MLC on the respective vehicle graph, the module filters our all bags that are 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 it is allowed to park the vehicle, 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 need to be associated with nodes in the walking graph, as it is the common network. The module may also define any form of monetary cost.

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 that are not located at the starting node. Obviously, this module is only useful 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. TODO: monetary cost

In comparison to the unscheduled modules, the public transport module does not use MLC, but McRAPTOR. As a first step the module filters out all bags that are associated with a node that is not near a stop in the public transport system. Next, the module performs a single iteration of McRAPTOR, which represents a single trip within the public transport system. Last, the resulting bags have to be associated with nodes in the walking network again. To do so, the modules simply use the node that is closest to the coordinates of the public transport stop. Just like the free-floating vehicle module, the public transport module may define any form of monetary cost.

3.2.4 Merging

The merging of bags after running multiple modules in parallel is quite simply. 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 simply 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 that are 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 realistically represent monetary costs.

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 is unable to 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 which is not considered when comparing labels, but that may be used to update cost 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 then additionally allow defining a function that updates while traversing an edge and may use the values and hidden values both 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 already traversed and if that number exceeds four, we can easily 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 used across iterations. 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 it is necessary to change to a different trip. Therefore, if we were to first travel 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 charging 2.20€

two times, which is more realistic.

These enhanced versions of MLC and McRAPTOR are used in our modules, so that we can use the more realistic dynamic pricing schemes.

3.2.6 Example

To illustrate our algorithm, we will now go through an example step by step. The module configuration we use in our example represents travelling by free-floating vehicle sharing, public transport and walking. The initial module matrix just contains the walking module, in order to initially reach the free-floating vehicles, as well as, 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 has some form of cost associated with it. 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 exactly 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 by 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 of 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

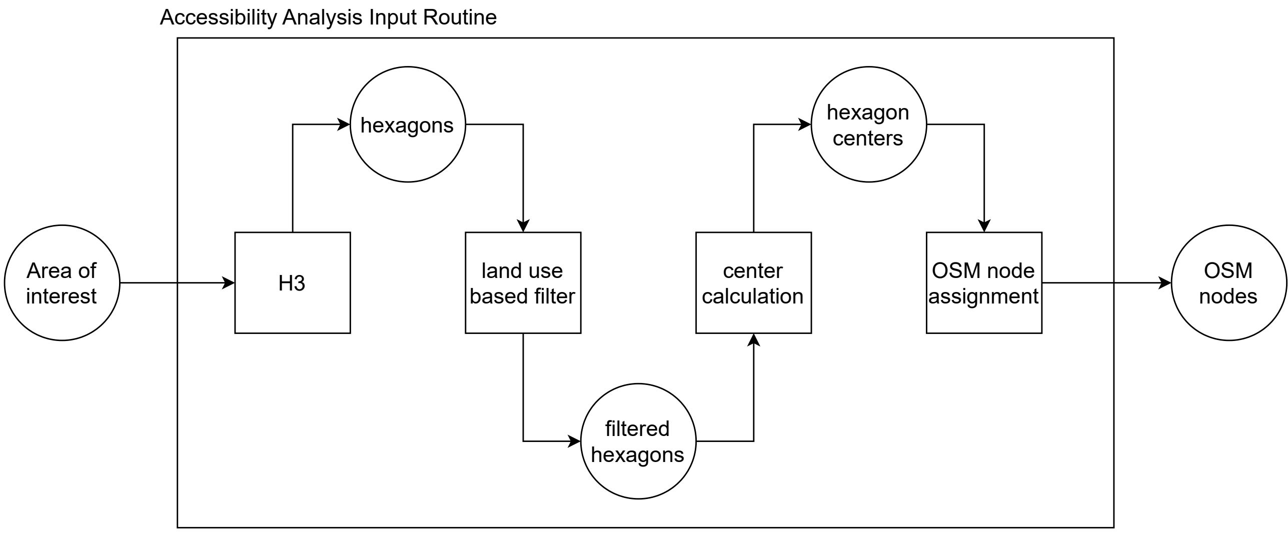


Figure 4: Input Routine

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 important in order to reach nearby POIs after commuting through the public transport system. After that the repeating module matrix is run again, 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 Accessibility Analysis Tool

We embed the routing algorithm described in Section 2.2 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. To create such a grid, we use H3 (*H3 | H3*, n.d.), which uses hexagons to evenly discretize an area. Our goal will be to calculate our metric for each hexagon, so that we 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, which corresponds to a hexagon edge length of roughly 200

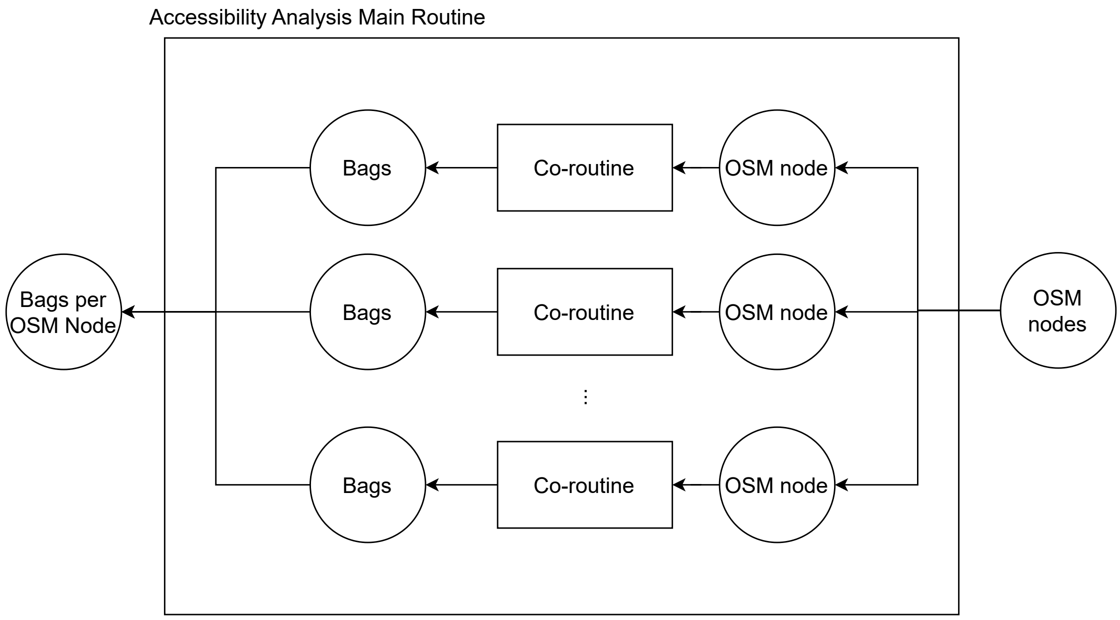


Figure 5: Main Routine

meters, as it is a good compromise between accuracy and computation time.

The underlying street network needs to be larger than the area of interest. Otherwise, border regions will have a lower accessibility than they should, as the street network is incomplete.

The input routine also filters out uninteresting hexagons. For, example we filter out hexagons that don't contain any residential areas, as there are no people living there is no need to access any amenities.

Next the input routine retrieves the centroid of each hexagon and then calculates the Euclidean distance between the centroids and the OSM nodes in order 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 routing algorithm described in Section 2.2 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 of bags.

The co-routine is depicted in Figure 7 and works as follows. We start by collecting all unique cost values in each label in each bag and then sort them in ascending order. For each cost value we then determine the associated X-minute city metric. We do so by checking whether every category is reachable given the

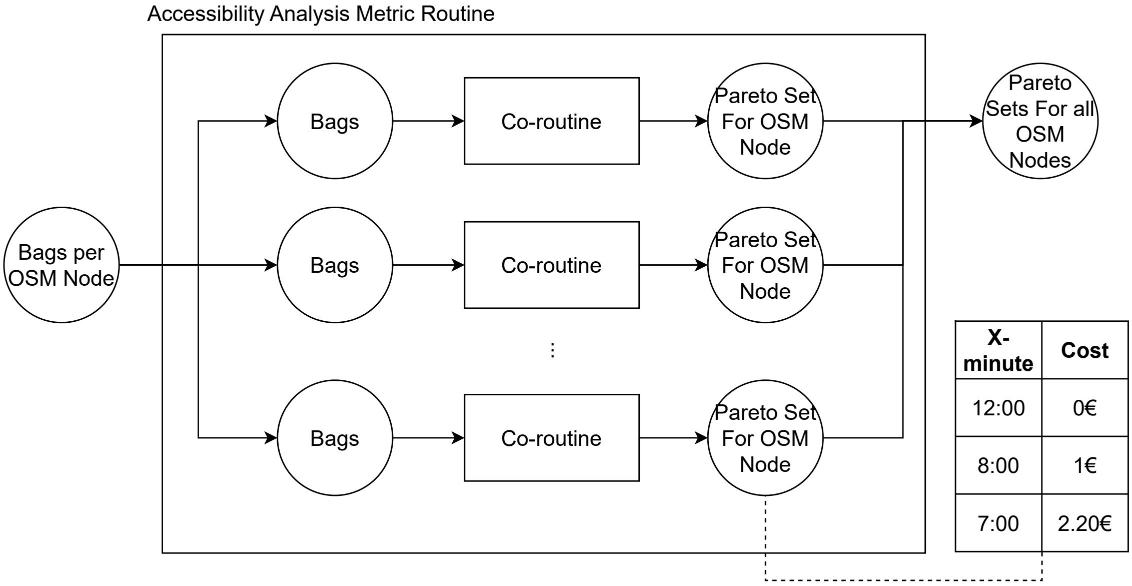


Figure 6: Metric Routine

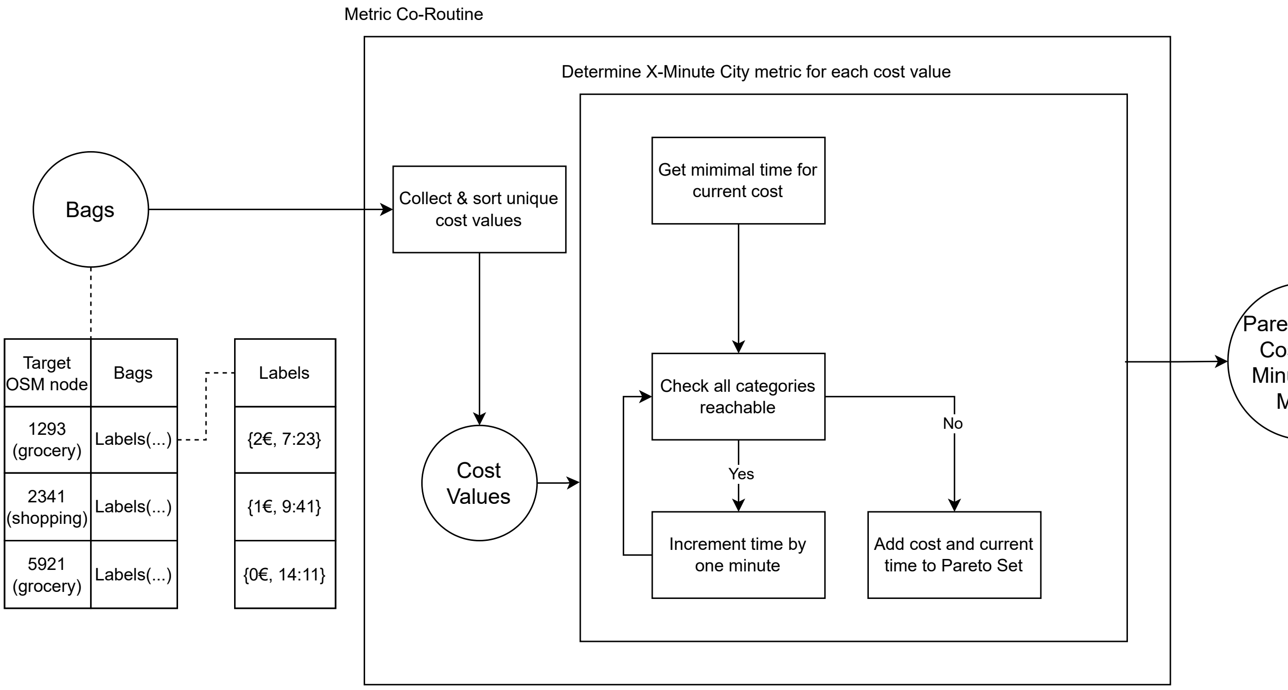


Figure 7: Metric Co-Routine

cost value and an iteratively increasing time value. We start with a time value that is 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.

4 Experiment

To answer the question of how competitive sustainable modes of transport are in comparison to the traditional mode of travel by car, we run an experiment in the city of Cologne. We do so by calculating the X-minute city metric for hexagons all over Cologne.

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, the mode of transport, we always allow for walking, for two reasons. First, walking is the most accessible mode of transport, available to almost everyone and without any additional costs. Second, most other modes of transport require walking at some point, be it to the next bus stop or to the next available bicycle.

The first scenario we consider is our baseline scenario, 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 the scenario of only walking. We consider this scenario as 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 in comparison to the traditional mode of travel by car.

Transitioning from the simplest form of mobility, the third scenario, focused on public transport, becomes 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 in contributing to a more sustainable urban environment. Specifically, it assesses whether public transport is a viable alternative to the personal car and whether it actually offers significant advantages over walking, considering the X-minute city metric.

Next, in the fourth scenario, we shift our focus to the dynamics of bicycle sharing systems. This scenario is important 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. 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 3.

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
Public Transport and Bicycle Sharing	Public Transport, Bicycle Sharing, Walking	Evaluate the effectiveness of sustainable multi-modal transport systems

Table 3: Scenarios for Urban Mobility Analysis

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

4.2 Data

To calculate the Pareto sets of the X-minute city metric for the different scenarios, we use four different datasets. First, we require data that depicts the street network of the city of Cologne. Second, we need to know the locations of the POIs, which we want to reach. Third, we need to know the locations of the public transport stops, as well as, 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, so that we can 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 later trim the datasets to this area. In our case, this area is defined as the area of the administrative district of Cologne, specifically the

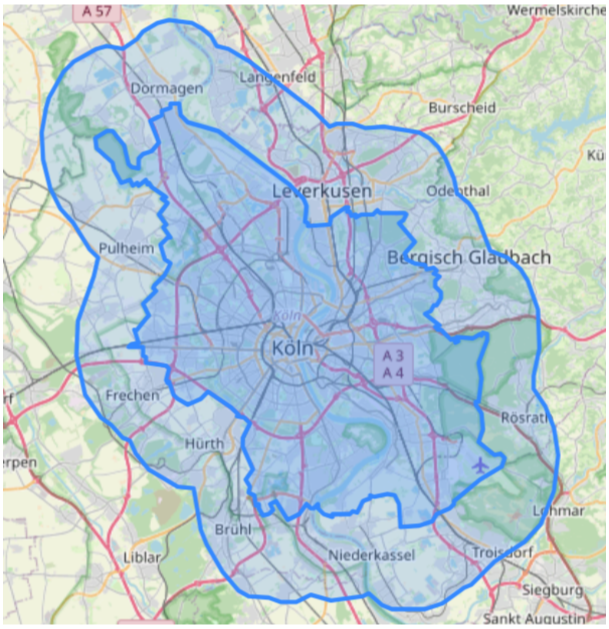


Figure 8: Area of Interest and Buffer Region

"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.

Additionally, the Figure also shows a buffer region around our area of interest. This larger region adds a buffer of approximately 5 km and is used by some in parts of our data processing.

4.2.1 Street Network & POIs

For the street network and the POIs, we use data from OpenStreetMap (OSM) (?, ?). To use OSM data in practice various tools and services have been developed. Among these we use, pyrosm (?, ?) which is 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 (?, ?) and BBBike (?, ?), 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 as well and expand our analysis to other cities.

After retrieving the data, our tool automatically retrieves 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, that are not part of the largest weakly connected component. A weakly connected component is a subgraph in which, if all directed edges were treated as undirected, any two vertices from the subgraph would be connected. 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 important 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.). Our tool will automatically retrieve all POIs that fall into one of our predefined categories specified in Section 3.1 inside of the area of interest plus the buffer mentioned before.

4.2.2 Public Transport

To handle public transport data, we use the General Transit Feed Specification (GTFS) (?, ?). To retrieve it we rely on the Mobility Database (?, ?). This database serves as an open-source repository containing links to publicly available GTFS feeds globally, standing as the subsequent version of TransitFeeds (?, ?).

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 that is more suitable for our algorithm, or more specifically McRAPTOR, which is part of our algorithm.

Specifically, there are two major incompatibilities 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 not possible that a trip skips some stops that another trip of the same route visits, much less use a completely different sequence of routes. In GTFS routes do allow that, as they are much more a group of trips that is presented to the rider under the same name or identifier. Secondly, GTFS trips allow visiting the same stop multiple times, which is not allowed in RAPTOR.

To overcome these difference our tool splits up routes into smaller routes, that follow the same sequence of stops. Additionally, it also removes circular trips, altogether.

4.2.3 Bicycle Sharing

Our bicycle sharing data was retrieved from the NextBike API over a time period of one year. TODO: MORE INFORMATION TO BE ADDED HERE

The data consists of all trips that were made with the NextBike system in the city of 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 is the information 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, that is the most centrally located object in a cluster. Unlike K-means, which uses mean values as cluster centers, K-medoids 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

To identify the residential areas, 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.). The data covers the whole of Europe and is publicly available, which again makes 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 9 that are 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 travelling along an edge on the street network, by walking, cycling or driving, is always proportional to the length of the edge. To

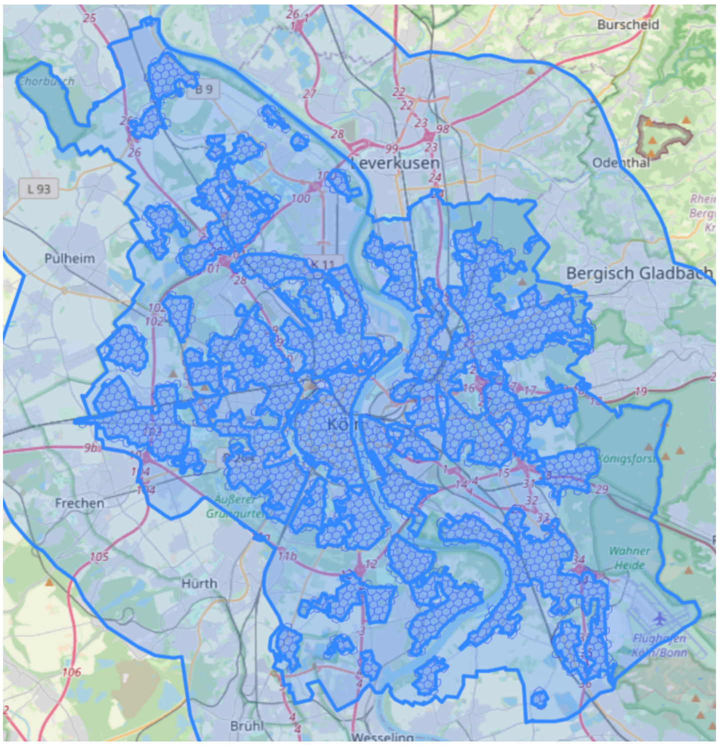


Figure 9: Area of Interest and Buffer Region with Residential Areas and Input Hexagons

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 different modes of transport are listed in Table 4.

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

Table 4: 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 assumption on the transitioning between different modes of transport, as well as, in the case of public transport, the transfer time at the stops. For the transfer time at stops we assume a fixed time of one minute. To transition from any OSM network-based mode of transport to public transport, we assume that the stop is precisely at the location 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. As the OSM network, especially in city is very dense, this assumption is reasonable. We also assume that bicycles and cars can be parked anywhere on their respective network for the sake of simplicity.

4.3.1 Pricing

We try to 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 depicts 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 a hidden values to the labels processed in McRAPTOR that depicts how many stops the traveler already traversed. Because two consecutive trips are considered together, we don't need to nullify the hidden value.

TODO: personal car

Table 5: 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

5 Results

From our experiment, we retrieve the following data: For each (sub)-scenario and hexagon we get the Pareto set of the X-minute city metric and cost. In addition, 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.

5.1 Runtime Observations

5.2 15-Minute City Metric

Table 5 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. 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 therefore be taken with caution.

In contrast, sustainable modes of transport such as bicycles, public transport, a combination of bicycles and public transport, and walking, demonstrate more 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.

The integration of 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.

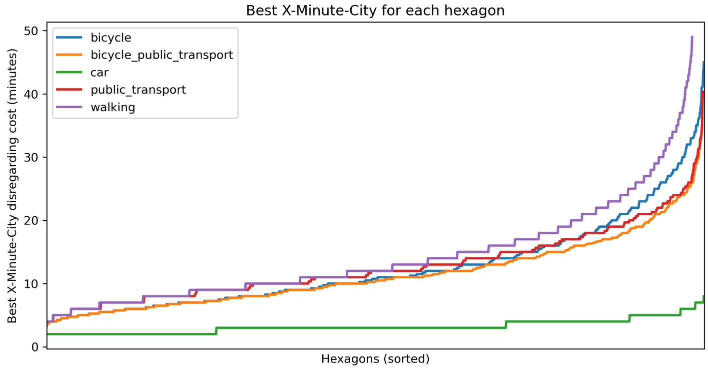


Figure 10: Distribution of optimal x-minute city metric

Similarly, adding public transport to bicycle sharing improves the average optimal time it takes 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 bicycle, this improvement already occurs for the 25% quantile and is therefore more evenly distributed across all hexagons. The addition of bicycles to the walking scenario presents an average time reduction of 1 minutes 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 becomes better. In addition, the public transport scenario is worse than the pure bicycle sharing scenario, but is able to catch up to it 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

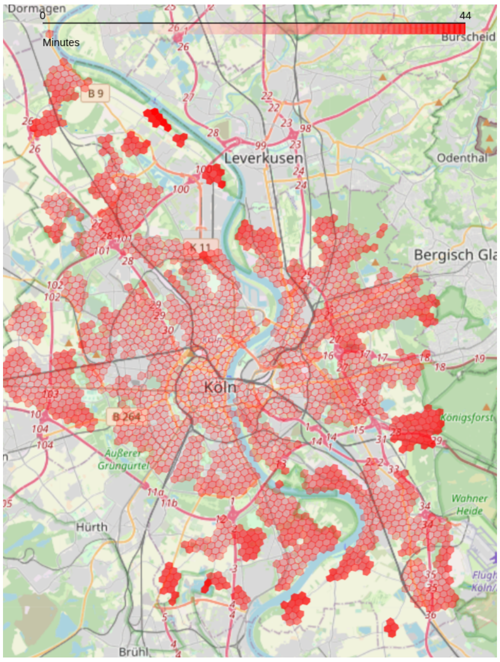
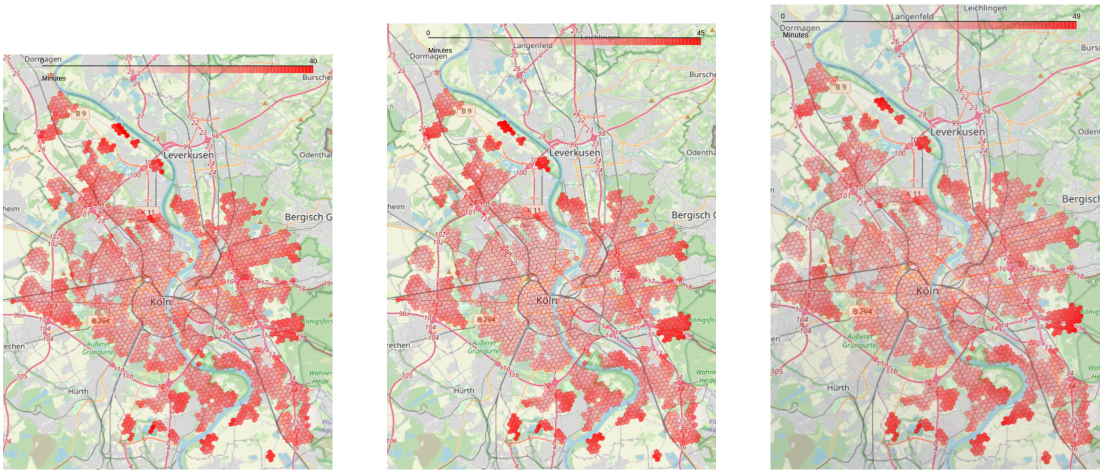


Figure 11: Map Of Optimal X-Minute City Metric

combined scenario provides much better accessibility in the beginning but as we move to the least accessible hexagons both become the same. Generally, we see that adding public transport is able to 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 in the suburban areas in the north and south of Cologne. Especially the region on the left side of the Rhine river next to Leverkusen, which is the district of Merkenenich, is very 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. We see that the areas in and around the city center are more accessible by bicycle sharing than by public transport and walking. At the east of the city, near the forest "Königsforst", we see the district of Rath/Neumar, with a low accessibility for all scenarios. However, one can see that the region is more accessible by public transport than by bicycle sharing and walking.



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

Figure 12: Map Of Optimal X-Minute City Metric Per Scenario

Table 6: Required cost for optimal over all hexagons

scenario	mean	25%	50%	75%	max
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

5.3 Cost Of 15-Minute City

Table 6 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 of the 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 both have zero cost at the 25% quantile, also implying that they are not used for those hexagons.

Looking at the maximum values reach by each sustainable mode of transport tells us that bicycles are used for no more than 15 minutes, as a 15-minute ride costs 1 euro. Next, the long distance ticket of public transport (more than four stops) is used. Also, in the combined scenario, the long distance ticket of public transport is used together with a 15-minute ride of bicycle sharing, in at least one sub scenario, resulting in the maximum price of 3.95€.

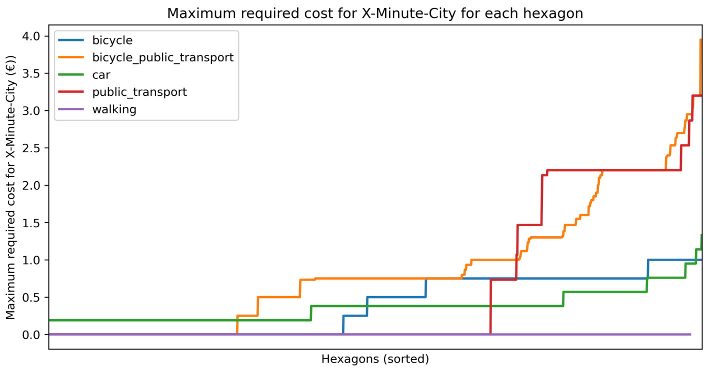
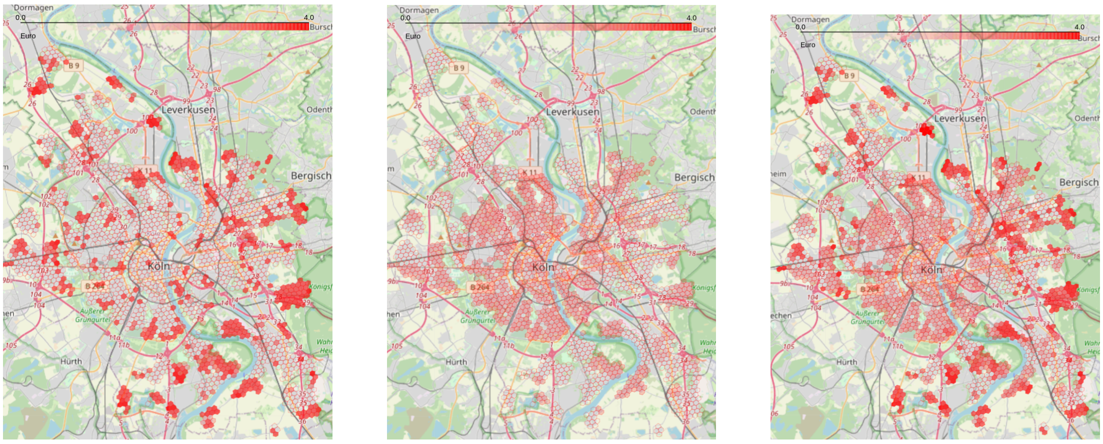


Figure 13: Maximum required cost for optimal x-minute city metric

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 focussing on the comparison between public transport and the combined mode. We see that the combined mode has higher costs earlier, which are then surpassed by public transport, only to be surpassed again by the combined mode. The first price increase in the combined mode can simply be explained by the 1€ cost of 15-minute bicycle sharing. Then public transport surpasses the combined mode. This probably is because bicycle sharing, to some degree is able to compensate public transport, and is more cost-efficient. The fact that the combined mode then surpasses public transport again, most likely stems from the fact that the combined mode is able to achieve faster access than public transport by using bicycle sharing additionally, which is, however, 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 1.00€. This 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 cities center and small groups of hexagons outside the city that have costs have than zero.



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

Figure 14: Map Of Required Cost For Optimal For Each Hexagon

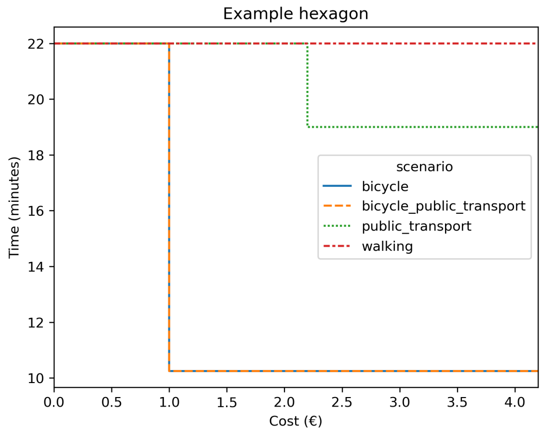


Figure 15: Example Pareto Front

5.4 Interaction Between Cost And 15-Minute City Metric

Next we are going to look at 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 take a look at 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 are able to reach all categories within approximately 10 minutes. Further, increasing the price to 2.20€ yields an improvement for the public transport scenario, where it is now possible to reach all categories within approximately 19 minutes. Further cost

Table 7: Steps in example hexagon

improvement	at cost	minute per euro	scenario
11.75	1.00	11.75	bicycle
11.75	1.00	11.75	bicycle$_{p}ublic_{t}ransport$
3.00	2.20	1.36	public$_{t}ransport$

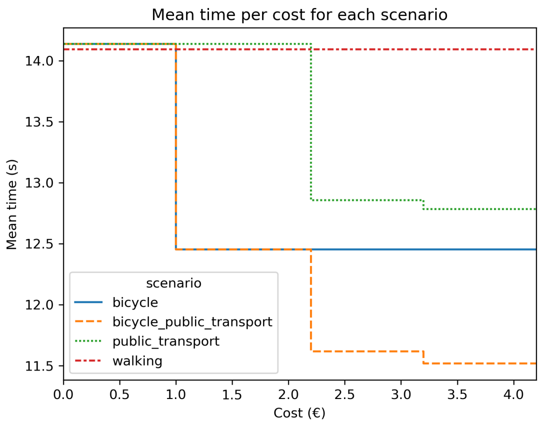


Figure 16: Mean time per cost for all scenarios

increases do not yield any improvements for any scenario.

We can also quantify the value of the improvements as seen in Table 7. This table shows all the steps with their cost position and magnitute that are visible 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 also 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, as well as, the combined scenario at a cost of 1€ of about 1.5 minutes. We can also see the improvements of public transport at a cost of 2.20€. Unlike the example of the single hexagon, we can also see the improvement at a cost of 2.20€ for the combined scenario. Lastly, there is also a slight improvement for the public transport scenario, as well as, the combined scenario at a cost of 3.20€.

To compare these improvements we can again look at the differences in Table 8. Note that we won't be analyzing the differences that occur in the combined scenario, as they may be skewed by prior improvements of other modes and are

Table 8: 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

Table 9: 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

therefore hard to interpret.

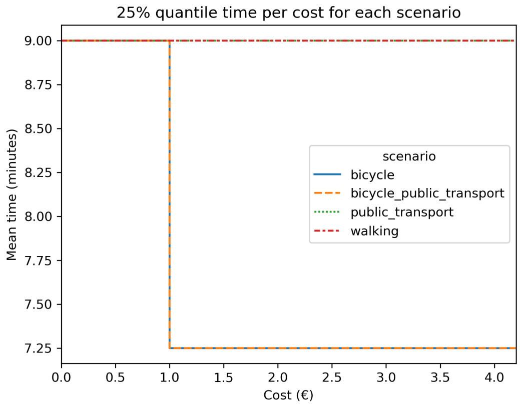
We see that the improvements of the bicycle scenarios at a cost of 1€ are the largest with an improvement of 1.68 minutes and also the most cost-effective with a value of 1.68 minutes per euro. They are followed by the improvements of the public transport scenario at a cost of 2.20€ with an improvement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

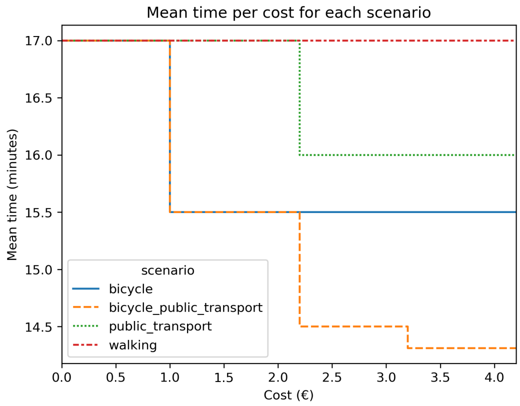
The 25% quantile Pareto front shown in Figure 17a only contains a single improvement at the cost of 1€ for scenarios containing bicycle sharing of 1.75 minutes with a cost-effectiveness of 1.75 minutes per euro.

The 75% quantile Pareto front shown in Figure 17b with its steps shown in Table 9 also has a similar improvement of 1.5 minutes at the cost of 1€ 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€ for bicycle sharing and public transport scenario.

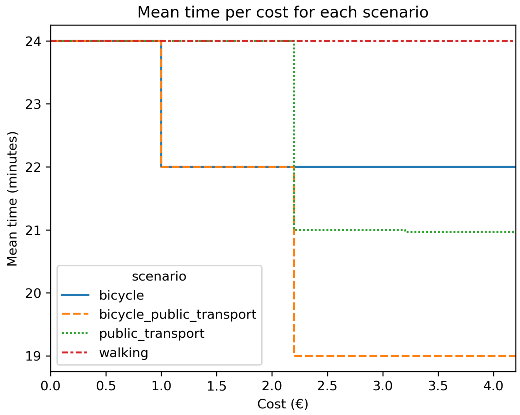
The 90% quantile Pareto Front shown in Figure 17c with its steps shown in Table 10 shows a similar pattern to the 75% quantile Pareto front. The major difference is that the increase at 2.20€ for public transport scenarios is larger than the increase at 1€ for bicycle scenarios. More precisely, while bicycle sharing is more effective in decreasing the 15-minute city metric on average and also for



(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 10: 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

Table 11: 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

the 75% most accessible regions, public transport is more effective than bicycle sharing for the 10% least accessible regions. We should, however, note that even though the improvement in the public transport scenario is larger it is still less cost-effective than the improvement in the bicycle sharing scenario.

5.5 Uncertainty/Subscenarios

As some of our input data is subject to uncertainties, we need to investigate the effects of this uncertainty in order 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 11, which effectively shows the standard deviation of the values in Table 5. Note, that we only display the average standard deviations of the bicycle, public transport and combined scenario as those are the ones with uncertainty.

We see that the mean average standard deviation for bicycle scenarios is around a 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, we see that outliers exist with more than 10 minutes of deviation for the pure bicycle scenario and more than 5 minutes of deviation for the public transport related scenarios. Relating the standard deviation to the mean we also calculated the Coefficient of Variation (CV) to the table, which is calculated as follows:

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

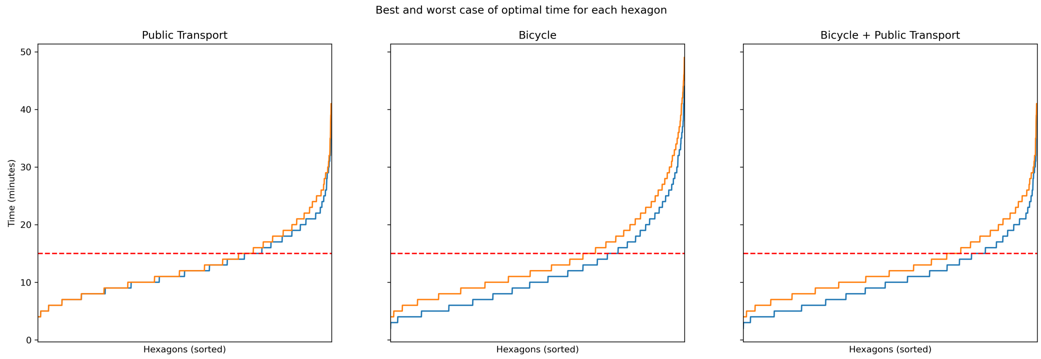


Figure 18: Best and worst case of optimal time for each hexagon

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 context of the 15-minute city. The values best and worst case are calculated by 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 metric is above 15 minutes for the walking mode. We then analyze how the sustainable modes of travel can help to 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 12 presents the distribution of hexagons with a walking time above 15 minutes and how sustainable modes of transport can fix those hexagons. With 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%,

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

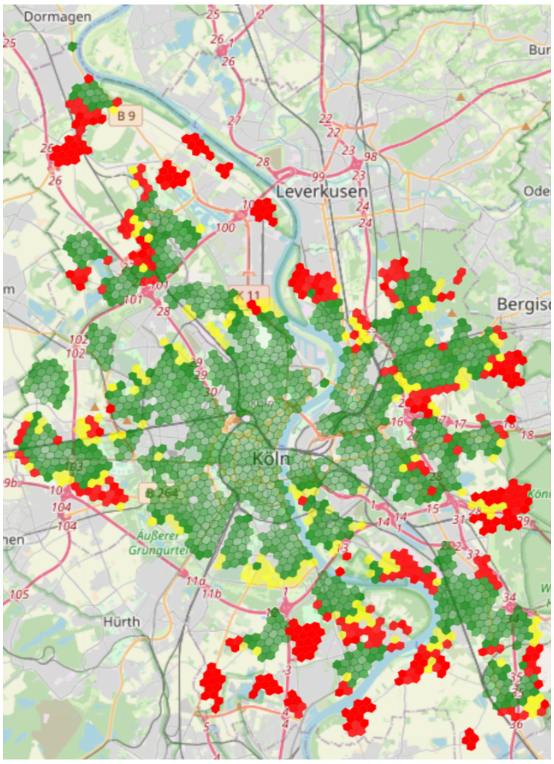


Figure 19: Unfixable, fixable and unproblematic hexagons on a map

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.

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

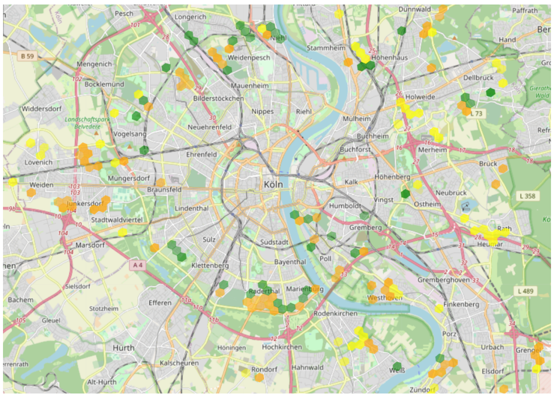


Figure 20: Fixable hexagons by mode

hexagons just by walking alone. At the border of the city, we clearly see a ring of hexagons that are only valid 15-minutes hexagons through additional modes of transport. Most of the unfixable hexagons lie in the cities suburbs, and often they appear in larger groups.

Next we take a 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 compared to those that achieve this criteria solely via public transport.

The outer clusters of fixable hexagons correlates 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 bigger 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 next bicycle. The same cannot be said for public transport stops, as often public transport stops are directly inside the unfixable hexagons.

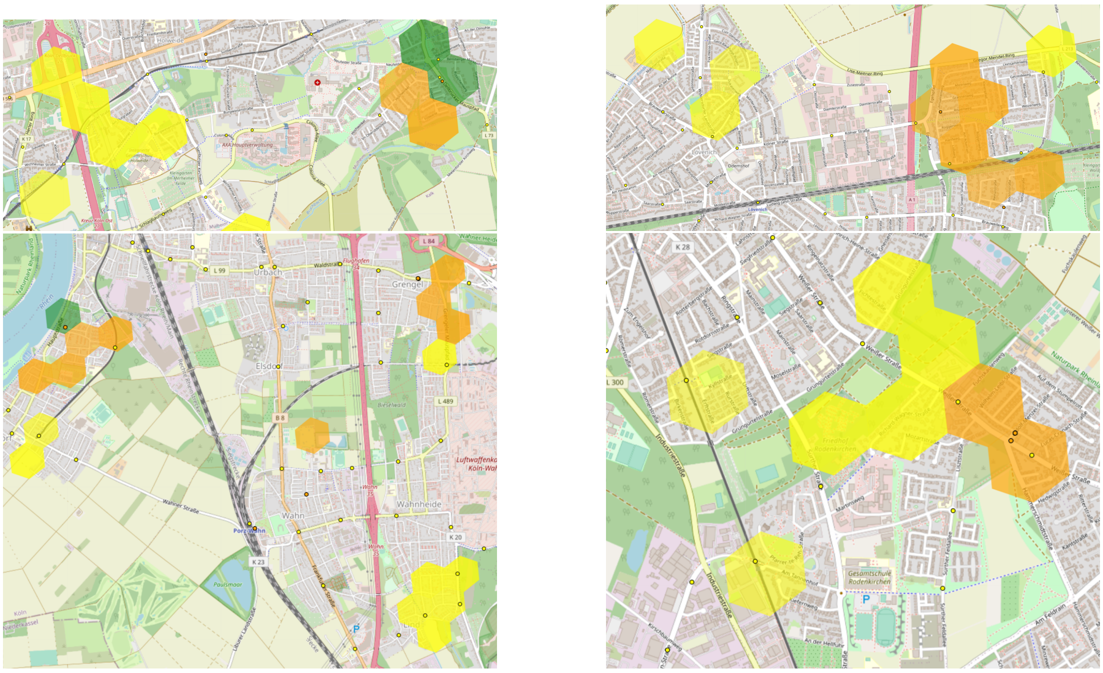
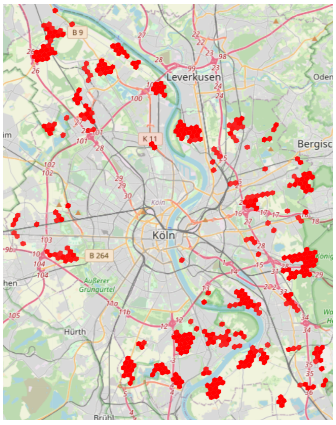
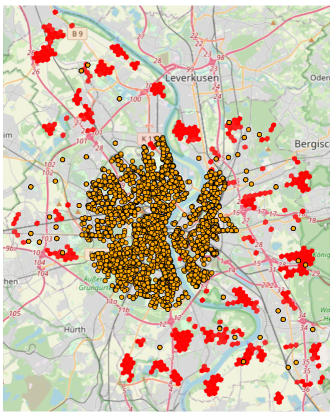


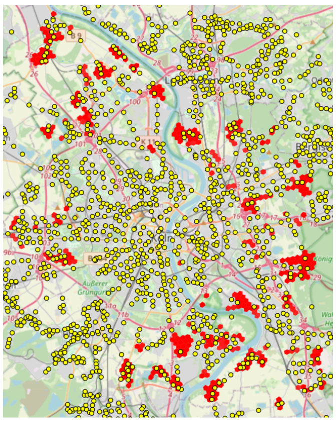
Figure 21: Examples of fixable hexagons



(a) Only Unfixable hexagons



(b) With all bicycle locations



(c) With public transport stops

Figure 22: Unfixable hexagons

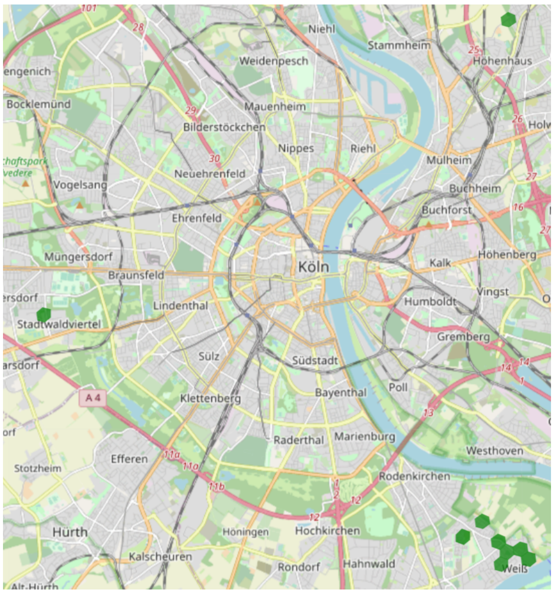


Figure 23: Hexagons fixable by combined mode

Figure 23 shows all hexagons that only become 15-minute city hexagons in the combined scenario, which means when both public transport and bicycle sharing are used at the same time. As already seen in Table 12 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.

5.7 Monthly Costs Per Scenario And Hexagon

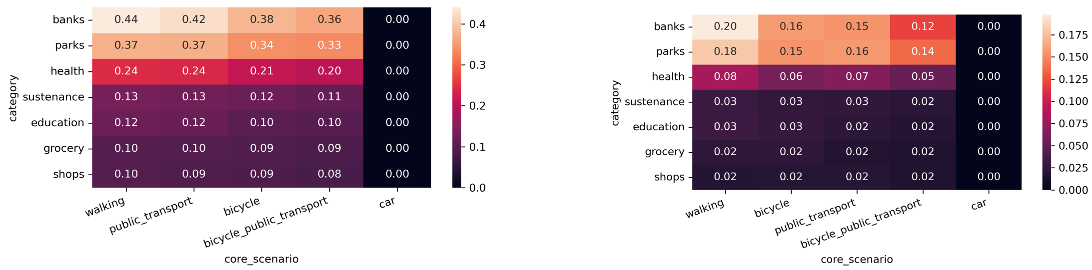
A prevalent measure to incentivize the use of sustainable modes of transport are monthly tickets or subscriptions. To measure whether the costs of these subscriptions are worth it, we will calculate the monthly cost incurred by the trips to all necessities. To do so, we first collected how often people visit each of the categories we defined earlier. The monthly number of visits per category can be seen in Table 13.

The derivation of these numbers can be found in Appendix D

To understand and compare the usual monthly costs caused by travelling with different modes of transport we first establish two time based benchmarks at which we will 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 be able to compare these costs, we have to assume that for each hexagon and each scenario such a journey is possible, which is not always the case.

Table 13: 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

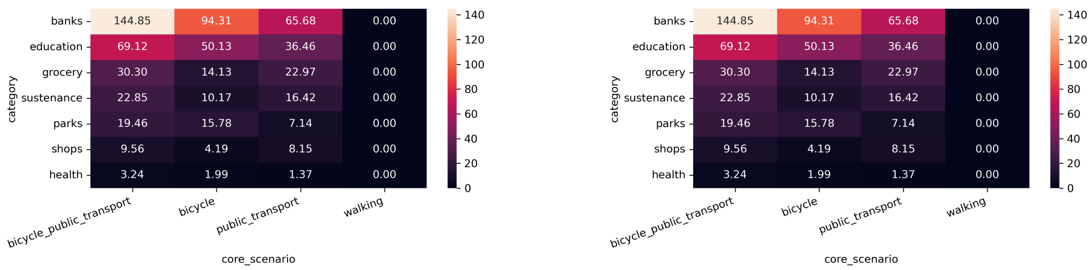
Therefore, we first show how often a journey is possible within the given timeframe in Figure 24.

For both benchmarks we see that walking alone fails the most to accomplish the journeys in the given timeframe and that car never fails to accomplish the journeys. After car 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 to be similarly accessible.

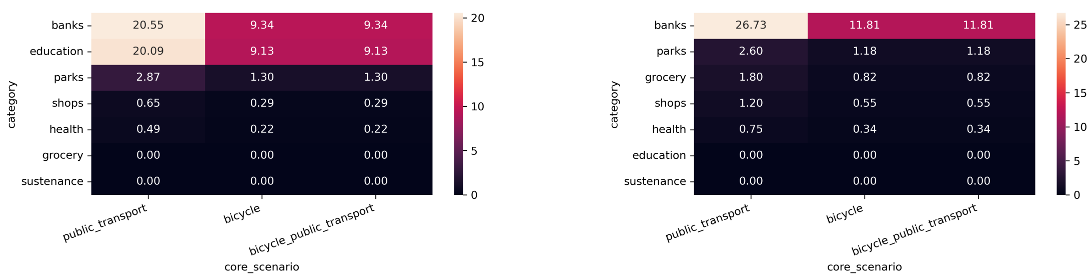
With the impossible journeys filtered out, we can now observe the monthly costs for each hexagon and scenario in Figure 25.

We see that the combined scenario of bicycle sharing and public transport is by far the most expensive scenario for both benchmarks.



(a) 10 Minutes (b) 15 Minutes

Figure 25: Monthly Cost For Sub-X-Minute Journeys For Each Hexagon And Scenario



(a) 10 Minutes (b) 15 Minutes

Figure 26: Monthly Cost For Sub-X-Minute Journeys For Each Hexagon That Is Reachable By Each Mode

6 Discussion

6.1 Interpretation of Results

6.1.1 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 now reiterate our results and show how they support the inferences above.

In Figure 16 we can clearly see that when users are able to 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 5 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, in areas where it's already easy to get to these places, adding public transport might not make a big difference. 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 how long the whole trip is. For short trips, the time spent getting to and waiting for public transport could be a large part of the travel time, making it less useful. But 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 full 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 the majority of 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 clearly see that public transport has an advantage over bicycle sharing in this remote area.

When looking at Table 12 we see that public transport is able to 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 mostly 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 larger improvements than bicycle sharing when considering only the 10% worst accessible hexagons (I3).

Table 6 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 is really rarely necessary to travel more than four stops, as the cost for that (3.20€) is only reached at the very end. The three- or four-step increases to the cost of 2.20€ and 3.20€ can be explained by the different sub-scenarios. In some scenarios it might be only beneficial to use public transport later.

Looking at Figure 13 also clearly reveals the spatial usage pattern of public transport. As already conjectured previously, we see that mostly public transport is used in remote locations outside the city, that we know have lower accessibility in general (I2 & I3).

The single hexagons inside the cities seen in Figure 13 are most likely located very close to a public transport stop, enabling to use the public transport system without any loss of time. Inside the city it seems to only be 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 are able to evaluate the usefulness and cost-efficiency of short trips (those that travel no more than 4 stops) and long trips (those that travel more than 4 stops). Figure 16 and Table 8 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. Different from what we previously inferred (I2), it seems that 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, the benefit is visible. This indicates that long distance trips are only used for the least accessible hexagons, which are located outside the city 2.

In Figure 12a we see that while the district of Rath/Neumar shows bad accessibility for all three scenarios, however, 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 area can significantly improve accessibility.

6.1.2 Bicycle Sharing Effectiveness

Bicycle sharing enhances accessibility in both 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 is able to 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 now reiterate our results and show how they support the inferences above.

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

As detailed in Table 5 and Figure 10, the introduction of bicycle sharing yields benefits across almost all hexagons, offering a more uniform impact compared to public transport (1). It is particularly notable that bicycle sharing also yields improvements in already well-accessible areas (I2). We think that this is due to the fact that bicycles have a lower overhead than public transport which in turn 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, which facilitates 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 that the decrease in bicycle effectiveness in areas with low accessibility is linked to the low availability of bicycles in suburban areas, as the majority of bicycles is 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 27, 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 sustainable 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 where there are fewer POIs, but still a high availability of bicycles, that can compensate this sparsity. This spatially shows where sustainable modes of travel are important to compensate for the sparsity of POIs. These areas don't provide a close enough proximity to be considered valid in terms of the 15-minute city by walking alone. However, with bicycle sharing and public

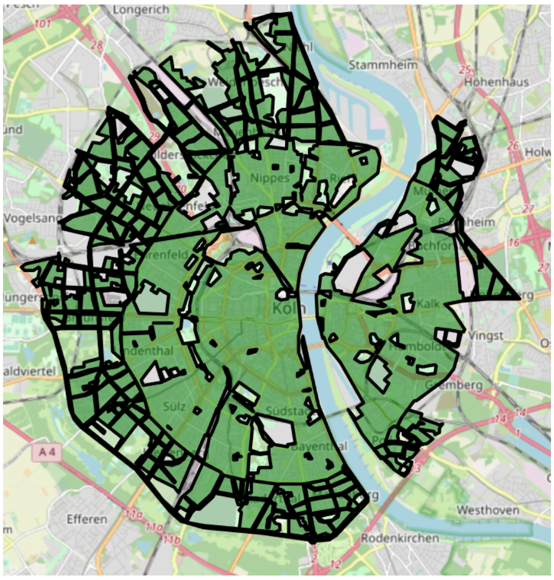


Figure 27: Next Bike's Flex Zones

transport they are. In Figure 20 we see that most of the hexagon in the ring are orange or green, which means that they are either fixable by bicycle sharing or by either 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, those that are only fixable through public transport, tend to exist in the regions that are more far away. Also, the unfixable regions, marked in red, mostly don't have bicycles near them, but they often have public transport nearby. This suggests that bicycles are more effective than public transport to help a region become sub 15-minute (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 8, 9 and 10 shows that using a bicycle for 15 minutes always yields larger time gains than public transport except for the 10% worst accessible hexagons (I1 & I4). This is a clear indicator for 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 6 and Figure 13 shows 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 more than 15 minutes. We now that bicycles are never used for more than 15 minutes as the maximum cost, as seen in Table 6 is 1.00€, which is the price for a 15-minute ride. Meanwhile, the shortest possible public transport trip costs 2.20€, therefore as soon as public transport is used it always costs more than bicycles. Nevertheless, this already shows that bicycle sharing is cheaper than public transport.

In addition, knowing that bicycles never are 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 is able to make regions 15-minute city regions and therefore improves accessibility (I1).

Table 8 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 3 times more cost-efficient than public transport (I4). Further, investigating the differences at the 75% and 90% quantile Pareto fronts in Table 9 and 10, shows that bicycle sharing always is more cost-efficient than public transport.

When looking at Table 12 we see that bicycle sharing is able to make 13% of hexagons that are not valid in terms of the 15-minute city by walking alone, valid, which is more than 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).

6.1.3 Bicycle Sharing and Public Transport - Substitutes or Complements?

As already mentioned we found clear evidence that bicycle sharing and public transport have a positive effect on 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 is able to compensate the other, or whether they are complements. We potentially could observe two sorts of complementary effects.

- Bicycle sharing and public transport are effective under different circumstances and in different areas
- bicycle sharing and public transport used together is necessary to improve accessibility

The presence of complement 6.1.3 means that one mode cannot replace the other, and each is necessary under specific circumstances. The presence of complement 6.1.3 means that both modes need to be used together in a single journey in order to achieve the highest accessibility. Both effects can be described as complementary effects, and they are not mutually exclusive, which means that we can potentially observe both.

In our results we find evidence for both effects, yet complement 6.1.3 is more pronounced. We will now reiterate our results and show how they support the complements above.

Table 5 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 12 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 minute by public transport or bicycle sharing. We see that bicycles sharing, and public transport alone are roughly of equal importance, 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 of them (7%). This again suggests that complement I is present.

Table 12 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.

6.1.4 Monetary Considerations

Table 8 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 of time people have to spend around 62 cents. Comparing this to the minimum wage in Germany of 12 euro 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 obviously is not worth it. This means that currently on average the sustainable modes of travel are too expensive.

Even when looking at the least accessible regions (90% quantile) separately in Figure 17c, where we have the largest 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.

6.1.5 Uncertainty

The standard deviation of the average time it takes to reach all necessities for bicycles is 1 minute and 10 second. Relating this to the improvement compared to walking of 1 minute and 38 seconds, we see that the uncertainty is quite large. This shows us that the placement of bicycles significantly impacts the effectiveness of the bicycle sharing scenario (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 by far not as impactful as with 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, if we would add 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 differ per scenario. For bicycle sharing we employed a clustering method, while for public transport we made a qualitative choice.

6.1.6 Potential of Sustainable Modes To Transform Cities To 15-Minute Cities

copied to implications

6.2 Implications

From our interpretation of the results, we can derive several implications for the city of Cologne and for 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, that is caused by a low availability of POIs, public transport will be an effective measure. Also bicycle sharing is able to improve the accessibility everywhere, where there are bicycles available. For the most part, at least for Cologne, this means that bicycle sharing is highly effective where the "Flez-Zone" is located. It is important to understand the relation between its effectiveness and the location of this zone.

As most of Cologne's central parts are covered by the zone, we already observe it's 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 largely already has an 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 the introduction of bicycle sharing and enhanced public transport could significantly reduce these areas by improving accessibility. However, as indicated in Table 12, 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 regions with currently poor accessibility. Given the observed correlation between bicycle availability and enhanced accessibility, this approach will very 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 a bicycle-sharing is closely tied to the availability of bicycles. This availability primarily hinges on two factors: the location of the 'flex zone' and the manner in which bicycles are distributed within it. Significantly, our findings reveal that the effectiveness of the program varies greatly across different sub-scenarios, highlighting the importance of strategic bicycle distribution. Therefore, the careful management of 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, Hu, & Zhang, 2020; Lu, Chen, & Shen, 2018; Benjaafar, Jiang, Li, & Li, 2018) have already done research in 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 bicycle and 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 faced by urban commuters, 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 that is assigned to a category should be taken with caution as well. For example, the access to a pet doctor, which is a health POI, is considered equivalent to the 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.

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 14: 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 15: Walking Filter

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

Table 16: 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 - Experiment Module Matrix Configuration

TODO: add module matrix configuration for each scenario here

D Appendix - Monthly visits per category

TODO

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