AGILE: GIScience Series, 7, 3, 2026. https://doi.org/10.5194/agile-giss-7-3-2026
Proceedings of the 29th AGILE Conference on Geographic Information Science, 16–19 June 2026.
Eds.: Evelyn Uuemaa, Alexander Kmoch, Holger Virro, and Simon Scheider
This contribution underwent peer review based on a full paper submission.

Inclusive Multimodal Routing: How Behavioral Constraints Shape Accessibility

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Abstract.
Conventional routing algorithms in urban settings typically optimize travel time, assuming that travelers will accept any combination of public and active transport modes to have the fastest route. Empirical evidence, however, shows that people value more than just time: they usually avoid routes with excessive walking or transfers, even if they are technically the fastest. Most existing studies assume an average, healthy population and do not account for travelers who cannot or do not wish to meet typical mobility requirements. This work examines how routing outcomes change when mobility preference thresholds, defined as maximum acceptable walking distance, cycling distance, and number of transfers within a trip, are reduced. Using a synthetic mobility data generation pipeline, we generate thousands of Origin–Destination (OD) pairs and systematically reduce these thresholds by 25%, 50%, and 75% relative to baseline average values. Results from the city of $Vienna$, show that *feasible* routes, namely the routes that satisfy average mobility thresholds, exist for the majority of OD pairs (18,639/20,000), while average travel times for these routes remain relatively stable. However, stricter thresholds lead to major feasibility losses: only 1,506 of 20,000 OD pairs remain feasible, with average travel times increasing by min 5 to max 46% compared to the baseline.

Submission Type. Case Study

BoK Concepts. [TA11-3] Users in infrastructure & transport ; [AM11-7] Accessibility modeling

Keywords. Urban Mobility, Inclusive Mobility, Multimodal Routing, Human Behavior

1 Introduction

People navigate in urban environments on a daily basis, often using mobile navigation systems to find their way and reach their destinations (Eluru et al., 2012; Sun and Wandelt, 2021). These applications rely on routing algorithms that compute an “optimal” route, typically by minimizing travel time, as travel duration is one of the most influential factors in route choice (González Ramírez et al., 2021). Empirical research, however, shows that people do not blindly follow the shortest or fastest path. Instead, they adjust the route based on personal preferences and constraints (Zhu and Levinson, 2015; Huang et al., 2024). The literature commonly reports average stated preferences related to active and multimodal travel, such as acceptable walking and cycling distances and tolerable numbers of transfers between Public Transport (PT) modes. These thresholds typically reflect what an average healthy person is willing to do during a single trip (Larsen et al., 2010; Eluru et al., 2012; Daniels and Mulley, 2013; Zha et al., 2019; Fonseca et al., 2021). Understanding how such average preferences alter routing outcomes compared to fastest path solutions is therefore important, and prior research has begun to incorporate individual constraints, such as maximum walking distance or transfer limits, into routing algorithms (Pereira et al., 2021; Abuaisha et al., 2024). However, existing studies typically treat these constraints in isolation and do not examine their combined effects within a single routing framework.

In the context of European policy agendas that promote inclusivity and “mobility for all”[1], relying solely on average mobility preferences is insufficient. These averages primarily represent healthy individuals who are both willing and able to engage in active and multimodal travel, while many people are either unwilling or unable to meet such average thresholds (Kar et al., 2023; Weiss et al., 2025). This raises critical questions for inclusive mobility planning: How do daily trips change when individuals are unwilling or unable to walk as far as the average traveler? Which destinations become inaccessible under stricter mobility constraints? How do travel times

[1]European Commission’s Sustainable and Smart Mobility Strategy

and modal choices shift, and which transport modes best support these users?

This paper addresses these questions by systematically modeling mobility under varying behavioral thresholds. We employ a multimodal transportation model of the city of $Vienna$ with a well-developed public transport and cycling network to assess how inclusive the current mobility system truly is. The city of $Vienna$ is frequently ranked among the world's best public transport systems, and according to Wiener Linien, the network comprises 5 underground lines, 10 main train lines, 29 tram lines, and 127 bus routes, making it an ideal case study. Starting from average mobility preferences reported in the literature, we progressively modify behavioral thresholds to represent the needs and capabilities of different user groups and evaluate inclusivity in terms of accessibility and trip characteristics—namely, whether destinations remain reachable in a timely manner under increasingly restrictive constraints.

The contribution of this work is manifold:

- **Compares fastest path and average preference-based routes:** The study introduces a constraint-aware routing workflow that incorporates behavioral thresholds into a routing algorithm. In this way, the study evaluates and quantifies how routing results, such as average travel time, distance, and modal share, differ when reported average behavioral thresholds are incorporated compared to the fastest path.

- **Assess inclusiveness through threshold variation**: The study systematically varies reported average behavioral thresholds to represent people whose preferences or physical abilities deviate from this average, and examines how these changes affect routing outcomes. This makes it possible to assess how well one of Europe's best-ranked transport networks serves diverse user groups under different preferences and abilities, thus providing an evidence base for more inclusive urban mobility planning.

- **Reports mode-usage and trip-distances for route changes**: The study focuses on OD pairs whose routes are altered when selected inclusive thresholds are applied, and examines the resulting modal split for these affected OD pairs across distance categories. This reveals at which trip lengths the largest changes from the average thresholds occur and which modes tend to replace others, highlighting where the network becomes less supportive for people with lower willingness or ability to walk and cycle long distances.

2 Related Work

The UN 2030 Agenda and EU strategies highlight the need for better PT networks and the use of active modes, reflecting global concerns over the environmental impacts of transport. PT systems typically produce lower emissions per passenger compared to car travel (Potter, 2003; Rojas-Rueda et al., 2012), and there are various benefits to switching to PT or active modes (Carroll et al., 2019). However, not everyone can or is willing to do so. Work on inclusive urban mobility suggests that transport planning should address inequalities in access to PT and opportunities, particularly for vulnerable groups (Jahangir et al., 2024; Liu et al., 2023). To achieve an inclusive mobility, it is essential to understand human mobility behavior.

Human mobility choices are influenced by multiple factors, some of which have been extensively studied. For example, the built environment is one of many factors that influence how people move around and which transport modes they prefer to use (Tracy et al., 2011; De Vos et al., 2016; Van Wee et al., 2019; Eldeeb et al., 2021). An example study in Beijing using smartphone and route recommendation data finds a strong preference for the first-ranked route, highlighting the importance of routing algorithms to route choices (Sun and Wandelt, 2021).

There has also been extensive research into human mobility habits, preferences, and willingness. For instance, researchers have studied extensively factors such as the **distance individuals are willing to walk or bike** (Larsen et al., 2010; Daniels and Mulley, 2013; Fonseca et al., 2021). Research conducted in the city centers of Bologna and Porto (Fonseca et al., 2021) examines walking as a mode of transport through the use of questionnaires and reported walking distances ranging from 0.8 to 1.6 km. Also, the factors influencing the decision to drive or walk short distances to PT facilities are investigated (Walton and Sunseri, 2010), and the study builds upon existing literature that identifies walkable distances of less than 2 km. Same results are reported from a study in Sydney, Australia, for factors influencing walking distances to access PT, with the results reporting walking distances ranging from 0 to 2 km, with the majority of samples falling within distances up to 1.5 km (Daniels and Mulley, 2013). Across these and related works (Yang and Diez-Roux, 2012; Sarker et al., 2019; Pueboobpaphan et al., 2022), the literature commonly adopts **an average maximum walking threshold of approximately 1,500 meters**. However, systematic reviews of PT accessibility for older adults frequently adopt maximum walking distances around 300–400 meters, reflecting more limited walking capabilities in this group (García-Palomares et al., 2013; Ravensbergen et al., 2022). This further highlights the need to consider such factors and constraints when modeling.

For cycling, empirical studies show that preferred distances are generally longer than for walking but still limited for everyday travel. A study in Montréal, Canada, investigates the distance people walk or bike for various trip purposes, with most work-related cycling trips to be under 5 kilometres (Larsen et al., 2010). In Spain, university students walk an average of 2.6 km and cycle about 5 km to campus (Chillón et al., 2016). Other studies of international cycling surveys indicate that 40-60% of trips are under 2 km, and around 80% are under 5 km, showing that typical cycling distances are generally below 5 km, especially in dense, mixed-use cities (Buehler and Goel, 2022). Based on these studies, **an upper limit of approximately 5 km for a single cycling trip** is commonly assumed in the literature. For both walking and cycling thresholds, it is important to note that these reviewed studies are typically based on participants who are healthy and willing to walk or cycle, and therefore do not fully represent the diversity of mobility capabilities present in populations. For this reason, this study aims to systematically investigate these thresholds, as well as reduced versions of them.

Another factor for urban mobility is people's attitude toward PT modes (Redmond and Mokhtarian, 2001; Páez and Whalen, 2010). Studies show that individuals often prefer longer commutes by car or active modes, due to greater control and interaction with their environment (Negm et al., 2024). In contrast, PT is associated with lower satisfaction due to its limited flexibility, long waiting times, and unpredictability. Transition between modes can also reduce satisfaction, with longer trips with fewer transfers, sometimes preferred over faster options involving multiple transitions across modes (Garcia-Martinez et al., 2018). Following the work of Eluru et al. (2012) and Zha et al. (2019), **an average maximum of four transitions between PT modes** (excluding walking) is considered reasonable by the average community.

Reported averages can provide a useful starting point for modeling human mobility. Especially given that routing algorithms suggest routes that people tend to follow (Eluru et al., 2012; Sun and Wandelt, 2021), including these average thresholds in the routing process can create proxies for average behavior. Previous studies have explored filter inclusion in routing algorithms and assessed their outcomes, such as travel time or path characteristics (Wagner and Zündorf, 2017; Pereira et al., 2021). Our approach varies the average thresholds to explicitly model inclusive scenarios, allowing for the assessment of network performance across different mobility capabilities and willingness.

3 Methodology

In this study, we employ a framework to model and approximate average human mobility behavior and investigate how the network performs under different preferences, willingness, or abilities. The aim is to assess the network's viability when modeling different user groups. We construct a multimodal city graph and select random OD pairs across the entire city to approximate a wide range of trips. Next, we use a Dijkstra-based multimodal routing algorithm and incorporate empirically reported average human mobility behavior preferences to use the resulting routes as an algorithmic proxy for average human mobility behavior, forming a baseline scenario. We then modify these average preferences to represent different user groups. This approach allows us to compare routing outcomes in different scenarios in terms of travel time, distance, modal split, and most importantly, to quantify how many OD pairs become *unfeasible*, in the sense that no path can be found under the specified thresholds (i.e., the destination cannot be reached).

3.1 Data and Software Availability

The proposed framework is designed as a transferable workflow that can be applied to any city where multimodal network data (e.g., OSM and GTFS) is available. In this study, the city of $Vienna$ is used as a demonstration case to highlight the insights produced by the workflow. The street network is extracted from OpenStreetMap (OSM) (OpenStreetMap contributors), while public transport layers are constructed using governmental data, including the General Transit Feed Specification (GTFS). Digital Elevation Models (DEM) are incorporated to provide information on street elevation and steepness, which are particularly relevant for walking and cycling. All data processing, multigraph generation, and routing algorithm implementation are written in Python, with NetworkX as the main library (Hagberg et al., 2008). The data and code for this work are both accessible from our website [2].

3.2 Multigraph generation

The city of $Vienna$ has several transport modes, including cycling, car, buses, trams, trains, and subways that must be represented within a connected multimodal network. This study focuses on inclusivity, so cars are not included since not everyone has access to them, and European Union strategies for inclusive mobility primarily emphasize improving PT and cycling infrastructure. Bike-sharing and e-scooters are also excluded since they are challenging to model. We currently lack publicly available, real-time data on them, and their inclusion falls outside the scope of this study. OSM and GTFS data are used to construct the individual layers for each mode and then connect them to create the multigraph representation of the city. Each layer has nodes and edges, both of which carry attribute information relevant to that mode. All edges include *length* and 'time' values, which are essential inputs for the routing process.

Public Transport Network
For the PT Network, we used GTFS data provided by

[2] https://geoinfo.geo.tuwien.ac.at/resources/

the local authorities[3] to create layers for bus, tram, train, and subway modes that are available in the city. The data come from two different operators, and we utilized the *'shapes.txt'* file of GTFS data, which defines vehicle paths using geographic coordinates. The train network data covered the entire country, and we clipped it to match the spatial extent of our study area. For the analysis, we focused on services running between 07:00 and 19:00, intentionally excluding night-time as we aimed to model the busiest time of day. From the data, we also utilized the PT stations along with their respective geometry, as well as the *length* attribute for the graph edges. The edge attribute 'time' was computed as the average travel time between two consecutive stations for each line (since travel times vary throughout the day).

Each PT station has an additional waiting penalty in the attribute 'time' to represent typical waiting time, calculated as half of the headway (the interval between two consecutive vehicles (Dial, 1967; Sun et al., 2016; Esfeh et al., 2021)). Each transport mode has its own average waiting time calculated from the GTFS data: bus: 6.2 minutes, tram: 4 minutes, train: 5.9 minutes, and subway: 2 minutes.

Walk and Bike Network

Walking and cycling network information is derived from OSM data, which is maintained by the local authorities, so it is considered reliable and up-to-date. We used the Overpass API to download the walking, cycling, and car networks. The car network was only incorporated to comply with the city's Highway Code, which permits bikes to use streets without dedicated cycle lanes.

The edge length values are derived from OSM, and to calculate the edge times, an average speed must be assigned to each edge. The 'time' attribute is then calculated by dividing the segment length by the respective speed. For active modes, these speeds vary with terrain inclination (derived from the DEM provided by local authorities). Table 1 reports speed values (in km/h) for walking and cycling, for slopes ranging from 0 $\pm$ 15% for walking (Weidmann, 1993; Buchmueller and Weidmann, 2006) and a range of 0 to $\pm$ 7% with additional increase or decrease on the average speed for cycling (Table 4, Parkin and Rotheram (2010)). Additionally, a factor of 0.75 (Zilske et al., 2011) is multiplied to the cycling speed to account for acceleration and deceleration. Cycling includes an additional 1-minute transition time accounting for the time required to lock and unlock the bike (Tenkanen and Toivonen, 2020).

Traffic lights used from OSM data are also incorporated into the network and linked to the nearest edge of the walk and bike network. If present, the edge with a signalized junction is marked as 'True' for traffic light presence, and an average waiting penalty of 30 seconds (a commonly used average value (OpenSourceForEver, 2021; Caquot, 2022)) is added to the 'time' edge attribute.

[3] https://www.data.gv.at

Walk Speed	
Slope	**km/h**
-15%	5.1
-10%	5.1
-5%	5.0
0%	4.8
5%	4.6
10%	4.3
15%	4.0
Bike Speed	
Slope	**km/h or Speed Change**
additional 1%	speed increased by 0.86 km/h
-7%	27.6
-6%	26.8
-5%	25.9
-4%	25.1
-3%	24.2
-2%	23.3
-1%	22.5
0%	21.6
1%	20.2
2%	18.8
3%	17.3
4%	15.9
5%	14.4
6%	13.0
7%	11.6
additional 1%	speed reduced by 1.44 km/h

Table 1. Walking and cycling speeds by inclinations based on Weidmann (1993); Buchmueller and Weidmann (2006); Parkin and Rotheram (2010)

The individual aforementioned mode layers are then combined to form the multigraph. Whenever a node is accessible to multiple layers, transitions are possible via that node, with the respective cost. It should be noted that the bike can only be used at the starting node since we do not incorporate bike-sharing facilities.

3.3 Routing Algorithm and Human Behavior Thresholds

To model average human behavior and explore inclusive scenarios, after creating the multimodal graph, we use and modify a routing algorithm to incorporate human mobility preferences using the routes as a proxy. Before the routing process, we select the Origin–Destination (OD) pairs. We defined twenty distance categories from 0–1 km to 19–20 km, which is roughly the maximum cross-city distance, and we randomly selected 1,000 OD pairs in each category, resulting in 20,000 OD pairs. The random selection was based on the assumption that a large sample of OD pairs across different ranges in the whole city can provide an unbiased representation and accurately approximate a variety of trip purposes. While the random sampling does not reflect actual travel demand distributions, it provides a basis for comparing routing outcomes across scenarios.

For the route generation phase, we implemented a custom Dijkstra-based algorithm (Dijkstra, 1959). *Feasibility* constraints identified in the literature (see Section 2) were integrated directly into the search procedure through state augmentation and dynamic pruning. The implementation does not rely on NetworkX's built-in shortest-path, but instead, we extended this standard Dijkstra framework to track additional feasibility attributes during path expansion. Specifically, each node in the search process carries an augmented state vector (w,b,t), representing the cumulative walking distance, cycling distance, and number of mode transitions encountered along the partial path. When an edge is explored, these values are updated according to the edge's modal label (e.g., "walk", "bike", "transition") and length. After each update, the candidate path is immediately evaluated against predefined *feasibility* thresholds. If any constraint is exceeded (walking > 1,500 m; cycling > 5,000 m; transitions > 4), the path is pruned and not further expanded. This ensures that we end up with optimized and feasible paths, and that infeasible paths are excluded during the search itself rather than removed afterward.

Travel time remains a central determinant of route choice and mobility modeling (Ivanov and Lantseva, 2017), so this custom Dijkstra-based algorithm identifies the most time-efficient paths while ensuring that the specified thresholds are satisfied. The *baseline* scenario was created by integrating these average reported thresholds directly into the routing process. If no feasible path satisfying all constraints exists for a given origin–destination pair, that pair is excluded from subsequent analysis.

3.4 Experiments

This study examines inclusivity in a well-planned transport system by modeling whether individuals with various preferences or abilities can reach their destinations and how routing outcomes change under systematically varied behavioral constraints. We use a fixed set of 20,000 OD pairs and generate multiple routing scenarios to enable controlled comparisons. For each OD pair, we first compute the *fastest path* route without any behavioral constraints. This scenario serves as an optimistic best-case reference, establishing the maximum achievable network performance in terms of travel time and connectivity. This allows us to quantify how much behavior-aware routing and mobility limitations alter accessibility outcomes. We then compute a *baseline* scenario by incorporating average human mobility preferences reported in the literature (see Section 2), including limits on walking distance, cycling distance, and the number of mode transitions. Using this baseline as a reference for an average traveler, we systematically vary these thresholds to represent individuals with reduced willingness or ability to engage in active or multimodal travel. Comparing the baseline and restricted scenarios reveals how accessibility changes across different user groups, while contrasting them with the fastest-path reveals the gap between conventional, unconstrained routing and routing that accounts for human behavior.

As Table 2 shows, thresholds are modified in two ways. First, each threshold is reduced independently by 25%, 50%, and 75% (to preserve comparability across thresholds with different units (meters versus number of transitions)), while keeping the remaining thresholds fixed at their baseline values. For example, the walking threshold is reduced from 1,500 m to 1,125 m (–25%), while cycling distance and transition limits remain unchanged. This allows us to isolate the effect of each behavioral constraint. Second, we simultaneously reduce all thresholds by 25%, 50%, and 75% to model increasingly restrictive mobility conditions. The 25-50-75% sequence provides evenly spaced stress levels that approximate mild, moderate, and severe mobility limitations assumptions.

Across all scenarios, we analyze three key aspects: (1) whether a feasible route can be found under the imposed constraints, (2) changes in average travel time and distance relative to the baseline, and (3) shifts in modal usage. For two selected threshold levels, we conduct a more detailed modal split analysis to examine how route changes vary across trip distance categories.

We specifically modeled the following scenarios:

- **Comparing Fastest Paths with Routes Incorporating Average Human Preferences**. We created a *baseline* scenario and incorporated average human behavior preferences derived from literature (see Section 2) as thresholds that might alter the routing outcomes. We then compared the resulting altered routes to the fastest path scenario to evaluate changes to average travel time, distance, and modal split.

- **Exploring Threshold Variations and Their Difference from Average Human Preferences**. We introduce gradual variations in the *baseline* thresholds to formulate inclusive scenarios for individuals that are either unwilling or unable to meet the average thresholds. Table 2 presents the selected values used to systematically represent different levels of willingness or ability. The thresholds for walking and cycling correspond to the maximum allowed distance (in meters) for each mode. The transition thresholds indicate the maximum number of mode changes permitted, excluding walking (e.g., a value of 2 means that only two modes can be used in addition to walking). We then evaluated each condition against the *baseline* scenario.

Reduction Level	Walk Threshold	Bike Threshold	Transition Threshold	Combined Thresholds
-25%	1125 m (WT1125)	3750 m (BT3750)	3 modes (TT3)	TT3–WT1125–BT3750
-50%	750 m (WT750)	2500 m (BT2500)	2 modes (TT2)	TT2–WT750–BT2500
-75%	375 m (WT375)	1250 m (BT1250)	1 mode (TT1)	TT1–WT375–BT1250

Table 2. Table showing the changes applied to the baseline average human behavior threshold. Only one threshold is altered at a time, while the others remain fixed to the average, except for the combined thresholds. The values reported for walking and cycling thresholds are in meters, while the transition thresholds indicate the maximum mode usage on a single trip, excluding walking.

4 Results

This section presents the results of our analyses through pairwise comparisons of scenarios (see Section 3). For each comparison, we first report the number of OD pairs for which a feasible route exists under each scenario, indicating how many destinations remain reachable given the imposed constraints. We then focus on this subset of OD pairs that are feasible in both scenarios and examine how many routes remain unchanged versus how many are altered due to the applied constraints. Finally, for the routes that change, we analyze the resulting differences in travel time, travel distance, and modal share.

The first comparison is between the baseline scenario, i.e., the average thresholds, and the fastest path scenario (see Table 3): the number of feasible routes that appear in both scenarios are 18,639 out of the originally 20,000. These unfeasible routes are mainly from the baseline scenario, as the fastest-path does not include any *feasibility* filters. Then it was found that approximately 40% of baseline routes deviated from the fastest path. In total 11,253 routes were identical in both scenarios. The baseline routes were 15% slower and 16% longer (e.g., a faster path 15-minute route would be 17.25 minutes under the baseline scenario and would cover more distance). We calculated the modes of transport used in each scenario to see which dominated. Figure 1 presents the modal split results between the fastest path and the average thresholds, with the bike dominating, followed by the subway in both cases. The baseline scenario appears to be more multimodal than the fast-path scenario.

Table 4 summarizes the modeled inclusive scenarios, each of which is compared with the baseline. As explained earlier, we first report the number of OD pairs for which the algorithm found routes that satisfy the respective thresholds in both scenarios (i.e., second column of the table). The third table column reports the number of routes that are identical versus those that are altered between the two scenarios, with bike thresholds to be the ones that alter the routes the most, followed by the combined scenarios. Table 4 includes columns for Δ percentage change in average travel time and travel distance, respectively, for the altered routes. When only a single threshold is changed, the Δ time differences to the baseline are small (5-16%), while in the Δ length column, most of the percentage differences are negative. The highest change in Δ time despite a shorter overall distance (Δ length) is reported in scenario when all thresholds are reduced by –75% (TT1–WT375–BT1250). The last three table columns report the walk, bike, and PT share of the altered routes, providing an overall view of the increase or decrease in share compared to the baseline. Some observations are straightforward (e.g., bike threshold restricted, bike share decreases), but there are interesting observations in the combination scenarios (TT1-WT375-BT1250, etc.) where walking and PT shares increase, and in the walking-restriction cases (WT1125, WT750, WT375), where bike share generally decreases, with only one exception.

Based on Table 4, we selected two inclusive scenarios for a detailed modal split investigation, to extract information on the underlying network structure. Trip lengths represent different trip purposes, where shorter trips are assumed to be made by walking or cycling, while medium-long trips are more likely to rely on PT. By analyzing the modal split across distances, we can observe which modes dominate at specific lengths and how this changes when various thresholds are adjusted. Since we initially selected 1,000 OD pairs per distance category (see Section 3), we can now identify the distance ranges in which the largest deviations from the baseline occur. Cycling restricted to 1,250 meters (see Figure 2), and walking restricted to 1,125 meters (see Figure 3) were the two scenarios chosen for detailed modal split analysis because they have the highest and lowest numbers of altered routes, respectively, relative to the baseline. The scenario with the most altered routes is interesting, as it shows how rerouting affects modal split and at which distances, while the least affected scenario is selected to assess its modal split against that of the most affected case. This comparison enables the evaluation of network behavior under both minimal and maximal levels of change. Additionally, the walking restricted scenario (WT1125) is close to the accessibility thresholds often used in the 15-minute city concept (15 minutes of walking corresponds to a catchment distance of 1,200 m, considering an average walking speed of 4.8 km/h (Weidmann, 1993)). Given the growing policy emphasis on the 15-minute city concept, analyzing a walking threshold of 1,125 meters provides a practically meaningful benchmark to assess how reductions in walking tolerance affect route feasibility, accessibility, and travel behavior.

In Figure 2 with the cycling-restricted scenario (BT1250), approximately 43% of the altered routes occur within the first six distance categories (5,347 out of 12,396). In the *baseline* scenario, cycling is heavily used for trips of up

Comparison of Scenarios	*Number of OD pairs that appear in both scenarios*	*Identical / Altered routes (% of the altered routes that appear in both)*	*∆ Time % (fastest path - baseline of the altered routes that appear in both)*	*∆ Length % (fastest path - baseline of the altered routes that appear in both)*
Baseline Thresholds / Fastest Path	18639	11253 / 7386 (39.63%)	-14.70%	-15.94%

Table 3. Average human behavior preferences compared to the fastest path.

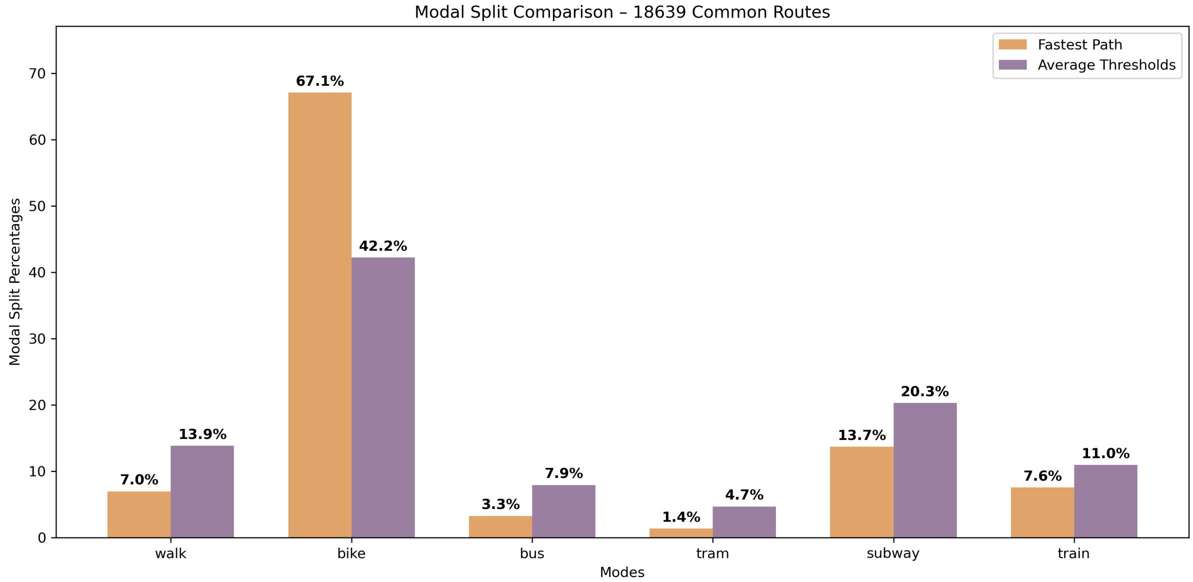

Figure 1. Modal Split comparison of fastest path and average thresholds. The average thresholds make routes more multi-modal compared to the fastest path.

Comparison of Scenarios (modified threshold / baseline thresholds)	*Number of OD pairs that appear in both scenarios*	*Identical / Altered routes (% of the altered routes that appear in both)*	*∆ Time % (modified scenario - baseline of the altered routes that appear in both)*	*∆ Length % (modified scenario - baseline of the altered routes that appear in both)*	*Walk Share compared to the baseline*	*Bike Share compared to the baseline*	*PT Share compared to the baseline*
WT1125 / baseline	18025	17075 / **950 (5.27%)**	**5.35%**	-6.05%	↓	↓	↑
WT750 / baseline	16384	13735 / 2649 (16.17%)	6.55%	-5.38%	↓	↓	↑
WT375 / baseline	10632	7667 / 2965 (27.89%)	10.49%	-5.89%	↓	↑	↑
BT3750 / baseline	**18539**	13738 / 4801 (25.90%)	8.28%	-5.86%	↑	↓	↑
BT2500 / baseline	18392	10080 / 8312 (45.19%)	11.32%	-7.04%	↑	↓	↑
BT1250 / baseline	17948	5552 / **12396 (69.07%)**	14.48%	-6.88%	↑	↓	↑
TT3 / baseline	17826	16039 /1787 (10.02%)	9.28%	-6.09%	↑	↑	↓
TT2 / baseline	13195	9511 / 3684 (27.92%)	13.84%	-3.67%	↑	↑	↓
TT1 / baseline	6244	5477 / 767 (12.28%)	16.33%	**5.27%**	↑	↑	↓
TT3-WT1125-BT3750 / baseline	16332	10539 / 5793 (35.47%)	11.04%	-8.86%	↑	↓	↑
TT2-WT750-BT2500 / baseline	7274	3352 / 3922 (53.92%)	26.31%	-15.85%	↑	↓	↑
TT1-WT375-BT1250 / baseline	**1506**	1077 / 429 (28.49%)	**46.77%**	**-39.44%**	↑	↓	↑

Table 4. Comparison of route changes and modal share changes between the *baseline* human behavior thresholds and the modified thresholds. The highest and lowest values in each column are highlighted in bold. Rows highlighted in yellow indicate the scenarios selected for detailed analysis, corresponding to the maximum and minimum number of altered routes. The bike-restricted scenario has the most altered routes, affecting the resulting routes the most.

to 5–6 km, gradually declining thereafter. Interestingly, cycling restrictions increase the share of buses and trams. Overall, PT share increases, and routes become multimodal under the restrictive scenario. Considering both the results from Figure 2 and the ∆ time data in Table 4, we observe that although the modal split shifts toward PT, the average travel-time difference remains around 14%. The fewest routes compared to the baseline are altered for scenario WT1125 (Figure 3). Among the altered routes, approximately 95% occur after the 6–7 km distance range (907 out of 950). The last bar of Figure 3 with the aggregated modal shares over all length categories, shows a bus share increase by an average of 17%, which is noteworthy considering that the average

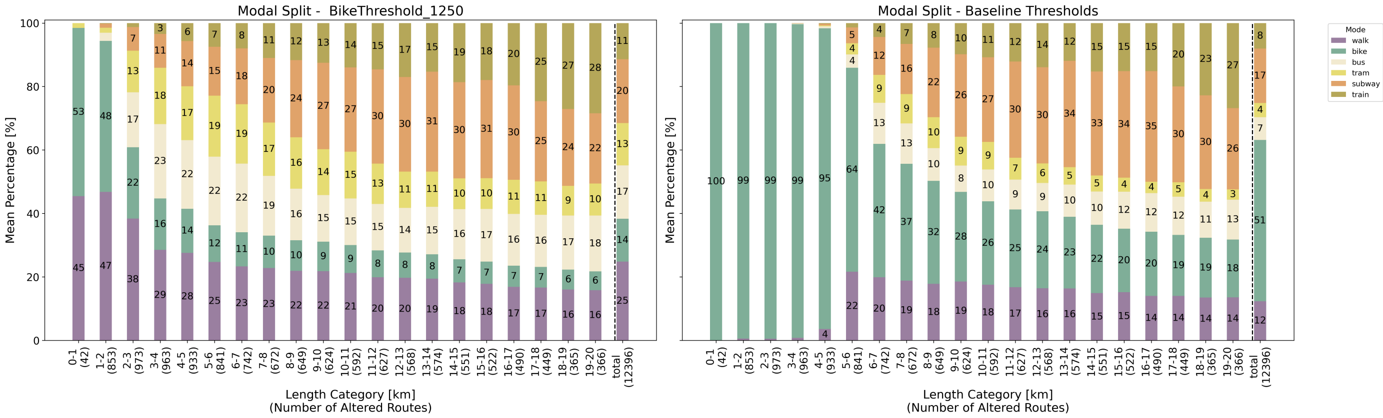

Figure 2. Detailed modal split comparing the **cycling-restricted scenario (BT1250)** with the **baseline scenario**. The X-axis shows distance categories (e.g., 0–1 km, 1–2 km, etc.), with the number of altered routes indicated below each category (total number of routes 12396). The Y-axis presents the modal split, with bars divided by mode of transport usage. The last column shows the aggregated modal split across all distance categories. By restricting bike mode, walk, bus and tram share increase.

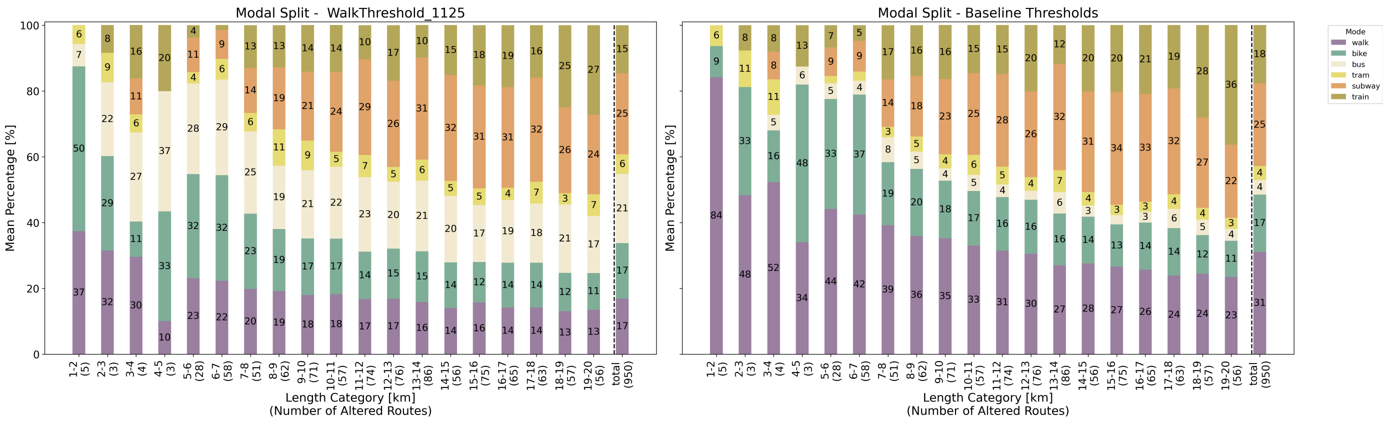

Figure 3. Detailed modal split comparing the **walking-restricted scenario (WT1125)** with the **baseline scenario**. The X-axis shows distance categories (e.g., 0–1 km, 1–2 km, etc.), with the number of altered routes indicated below each category (total number of routes 950). The Y-axis presents the modal split, with bars divided by mode of transport usage. The last column shows the aggregated modal split across all distance categories. Bus share increases, and subway mode dominates among the PT modes.

Δ time between these scenarios remains very small (see Table 4).

The detailed modal-split figures also show how different modes serve trips of varying lengths. Bike mode is time-efficient for trips up to 8-9 km, but usage declines further. Bus share rises in restricted scenarios, especially for short trips, and is important across all distances. Tram is efficient for shorter trips, while subway and train are more important for medium to long-distance trips.

5 Discussion

This section discusses the study's results. We began with the baseline scenario based on average thresholds from the literature, and we further developed scenarios reflecting different willingness and ability levels to understand inclusive mobility (see Sections 2 and 3).

Table 3 and Figure 1 show that when incorporating the average human behavior preferences (*baseline* scenario), the algorithm can find routes that satisfy the average thresholds for 93% of the initially selected 20,000 OD pairs (18,639/20,000) without massively increasing the average travel time or distance (approximately +15%). This indicates that the transport network of the $Vienna$ city provides enough alternatives for reaching the destination that also meet average user preferences. Moreover, the aggregated modal split in Figure 1 shows that in the fastest path, about 70% of all fastest routes rely on cycling, which is optimistic. Depending on the region, cycling is a highly seasonal mode (Tin Tin et al., 2012; Hudde, 2023), and not all individuals choose to bike for commuting even when they own a bike (Sallis et al., 2013). Thus, incorporating average human mobility thresholds not only makes the routes more multimodal but also more representative of actual human behavior. In the fastest path scenario, bus and tram are the two most underutilized modes, and together they account for only about 4% of the total modal split, indicating that they are the slowest options in time-sensitive urban trips. When the average thresholds are applied, these modes gain some additional share, but they remain the least time-efficient overall. This aligns with the literature, which highlights the need for improvements in the speed and performance of these modes (Mason, 2024). However, this result alone only indicates that these modes are not time-efficient, and does not allow us to conclude whether the network itself is sparse or well-connected.

Table 4 outlines the results of simulating inclusive scenarios. The number of *feasible* routes (Table 4, second column) decreases as the thresholds become restrictive, indicating that individuals with lower willingness or ability can reach fewer destinations when they are unable or unwilling to make additional effort. As reported in Section 4, the most restrictive scenario (TT1–WT375–BT1250) has *feasible* routes for only a small number of OD pairs (1,506). The combination of a walking limit of 375 m, a cycling limit of 1.25 km, and allowing only a single transport mode (plus walking) has a substantial influence on route availability. This illustrates how challenging urban movement becomes for individuals with limited active-mode capacity or low tolerance for multimodal transfers. This has direct implications for accessibility measures that often use the fastest path, as it is assumed that all individuals can reach PT stations, but the restrictive threshold scenarios showed that this assumption does not hold for everyone. If a person cannot physically reach a station (Ravensbergen et al., 2022), the computed accessibility can overestimate the accessibility they actually experience. These findings align with existing literature about accessibility for different user groups (Malekzadeh and Chung, 2020). Furthermore, even for the destinations that people with different willingness or abilities can reach, the Δ time differences show that they need, on average, almost twice as much time compared to someone with average willingness or ability (see Table 4). This means that although only a few destinations are reachable without exceeding the preferred thresholds, reaching those places still requires, on average, longer travel times. This result highlights the need for a better understanding of the mobility conditions of these user groups and to consider their needs when planning city infrastructure. From Table 4, across all restricted scenarios, travel time differences relative to the baseline are consistently positive while distance differences are negative. This needs further investigation as it shows that the modified routes tend to be spatially shorter but temporally slower. Probably, stricter behavioral constraints shift routes toward PT options (since the PT share increases in all cases except transfers), reducing total distance but increasing overall travel time due to waiting or transfers. Another observation from Table 4 concerns the combined restricted scenarios (TT1-WT375-BT1250, etc.). As the restrictions increase (-25% to -50% and -75%), the number of routes that the algorithm can find to satisfy these thresholds decreases. However, even with fewer routes, a share of over 30% of these routes still change compared to the baseline. This scenario exhibits the largest negative percentage in Δ length, but it concerns only a small number of routes (1,506 OD pairs, see second column, last row of Table 4). Since the PT share increases in this case, it is likely that for these specific OD pairs, a PT station is located close to the origin or destination, allowing routes to cover less distance on average compared to the baseline. However, this result requires further investigation, as it reflects only a limited subset of the routes and may not generalize to other OD pairs. Additionally, in the combined scenarios, even though walking, biking, and mode transitions are gradually reduced, the PT share increases among the routes that differ from the baseline. This indicates that the PT network remains resilient under stricter thresholds, despite the decreasing number of feasible routes (second column of Table 4), as the increasing PT share highlights the network's ability to serve different user groups, at the cost of increased average travel time.

In Table 4, the third column presents one of the most important results, as it shows how many routes change when comparing each modified threshold scenario with the baseline. This indicates the extent to which the thresholds applied during the routing process affect the resulting outcomes. The strongest effect is observed in the cycling thresholds, which consistently yield the highest number of altered routes. This basically shows, on the one hand, that out of the three thresholds investigated (walking, cycling, and transitions), **the cycling constraints affect routing outcomes the most**. This is useful because it demonstrates that city planners should consider cycling constraints when attempting to predict realistic behavior or when evaluating policy interventions. On the other hand, the fact that reducing the average cycling threshold changes so many routes, while barely increasing travel time (see Δ time in Table 4), shows that although good cycling infrastructure can make bikes one of the fastest modes in the city (Saunier and Chabin, 2020), PT infrastructure is also very crucial for providing fast and flexible alternatives.

As shown in Figure 2, in the baseline scenario, cycling shows a strong dominance for short trips, but may overrepresent bike usage. The modified bike threshold results show walking and PT share increasing for trips up to 7 km, suggesting that **good multimodal network infrastructure not only supports cyclists but also provides time-efficient alternatives through PT modes** when cycling is limited or not preferred. For longer trips (15–20 km), few routes are altered, suggesting that cycling thresholds mainly influence shorter trips. This is noteworthy because it highlights how the multimodal network compensates for limitations in one mode, ensuring that longer-distance travel remains efficient for people with varying levels of willingness or ability.

Finally, Figure 3 shows the scenario with the fewest route changes compared to the baseline. Even a small reduction in walking thresholds can represent a common ability or willingness, and it is essential to explore what the network can offer in this case. Bus mode experiences most of the shift increase, while bike share remains largely unchanged. The affected routes are mostly at longer distances, unlike the previous case, suggesting that shorter trips are only slightly influenced (people with limited mobility or a unwillingness to walk can still reach their destinations). Consistent with Table 4, this scenario also exhibits the lowest Δ time differences, meaning that the resulting routes require little additional travel time compared to baseline preferences. In other words, the network can provide *feasible* alternatives at a small "cost" in terms of travel time.

The results show that incorporating human mobility thresholds into routing is crucial, as it reflects reported average human mobility behaviour. However, threshold choices strongly influence the results, consistent with existing literature (Baum et al., 2023; Abuaisha et al., 2024), meaning that researchers and planners must be cautious when selecting or calibrating such thresholds for simulations. Cycling thresholds influence routing outcomes the most, since restricting cycling alters the largest share of routes and noticeably changes the modal split. Walking restrictions appear to have little effect, as the network provides time-efficient alternatives. Transition thresholds matter, but they become more problematic when combined with other restrictions (combined thresholds). The findings demonstrate that the network can be experienced differently depending on abilities or willingness to use certain modes, and modeling these modified preferences or abilities makes inequalities visible. In many inclusive scenarios, the modified routing algorithm could not identify *feasible* routes for some OD pairs, but the *feasible* routes had only small increases in average travel time. This suggests that alternative modes can offer time-efficient travel options, thereby making the network overall reliable. Further investigation is required for the *unfeasible* OD pairs, as these cases are likely to reveal problematic areas that require targeted interventions to ensure equitable access for all individuals.

6 Conclusion

This study applies an algorithmic routing framework to examine how behavior-based mobility constraints affect travel time and accessibility. Comparing baseline thresholds with fastest-path routes shows minimal changes in average travel time. Progressive restrictions reveal that cycling constraints produce the largest routing changes. The detailed modal split analysis also revealed which modes step in when thresholds become restrictive, with the bus network being a consistently used mode, highlighting its structural importance and strong spatial coverage in the city, though this comes with a moderate increase in average travel time.

Overall, the results are useful for modeling, infrastructure, and mobility planning, as they show that human mobility thresholds influence modeled mobility and that routing algorithms used for accessibility metrics may produce optimistic outcomes when these thresholds are ignored. However, the study has limitations that should be acknowledged. Human mobility behavior is modeled using thresholds from the existing literature; however, users are likely to follow the generated routes, which remain an approximation of their actual behavior. Therefore, the findings should be viewed as a first-step investigation. Additionally, bike-sharing and e-scooter services are not considered in this case study, although the flexible pipeline allows for their inclusion in future work.

Future work could extend this study by integrating additional behavioral components (e.g., weather-dependent mode choices, population-specific constraints) to enhance the model's accuracy. Applying this methodology to cities with different infrastructures could identify potential network gaps and vulnerabilities, as in the present study, the well-connected and high-performing PT network provided sufficient alternatives when thresholds were restricted. However, in other cities, the workflow could highlight areas where interventions could improve accessibility and promote inclusive mobility for all people.

Generative AI Use

Generative AI tools, were used exclusively for grammar refinement and formatting assistance. All conceptual development, analytical procedures, data interpretation, and final argumentation were carried out solely by the authors.

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