

Free as a Bird, but at What Cost? The Impact of Street Networks on the User Experience of As-The-Crow-Flies Navigation for Cyclists

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As-the-crow-flies (ATCF) navigation is an alternative to turn-by-turn navigation for cyclists utilizing the least-angle strategy by providing the beeline to the destination. However, past research found weaknesses (e.g., running into dead ends) affecting the user experience. In this paper, we investigate how the street network attributes to the experience of the navigation method. Using a feature importance analysis and comparison of different city types across 1633 cities, we analyze how ATCF navigation fits different environments. The perfect ATCF-city has long streets, many options to turn at decision points, few dead ends, and a grid-like structure. Cities well suited are primarily found in East Asia and North America. Furthermore, we find that previous ATCF studies were most likely conducted in Western Europe, which features the least suited street networks for the navigation method. We present design implications for future ATCF implementations and argue for diverse study locations in future research.

CCS Concepts: • **Human-centered computing** → **Empirical studies in HCI**; **HCI theory, concepts and models**; *User models*.

Additional Key Words and Phrases: cycling, as-the-crow-flies, navigation, street network, simulation

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1 INTRODUCTION & MOTIVATION

Cycling is an environmentally friendly and carbon-neutral mode of transportation that has increased in popularity throughout the last decades [12, 33, 35]. One reason is the looming climate crisis, as cycling is an essential contributor to the UN sustainable development goals [26]. Thus, more and more people are taking up cycling for environmental but also health benefits [47]. Similar to car drivers and pedestrians, cyclists can choose to use mobile navigation technologies to help them find their way around known and unknown locations. Navigation methods play an essential role in this wayfinding process, with turn-by-turn (TBT) navigation being the most popular method. It has become prevalent due to its ease of use inside the closed cockpit of a car [29, 36]. However, it is not the only option cyclists have to navigate their environment. Especially with the lack of dedicated cycling infrastructure, cyclists can make use of their existing knowledge and local circumstances (e.g. road surface) to make their own navigation decisions. An alternative navigation method less

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focused on strict turn-by-turn instructions that allows for this flexibility has been popularized in the cycling domain: as-the-crow-flies (ATCF) [41]. Instead of following instructions [37], the ATCF navigation method provides a general sense of direction to the traveler at all times. This allows cyclists to better attend to their environment and make navigation decisions as they see fit while still being oriented [41].

Also known as compass-, beeline-, or beacon navigation, ATCF navigation has found its way into commercial products like Beeline [4] and Smarthalo [43] and can be used by people all around the world. Due to its nature, ATCF navigation uses sparse navigation cues and supports exploration [30]; both traits that are believed to improve spatial knowledge acquisition [5, 15]. Furthermore, through the lack of TBT instructions, ATCF navigation could improve learning spatial configurations during active wayfinding [42]. Thus, with most mobile navigation devices for cyclists being only slight adaptations of their car and pedestrian counterparts using visual and audible TBT instructions, ATCF navigation is a promising alternative. Finally, in contrast to ATCF, TBT navigation depends on an underlying routing algorithm [19] and routing criteria interesting for cyclists (e.g., safety [14], beauty [38], or steepness [34]) are only partly accessible in common mobile navigation devices. With ATCF navigation, on the other hand, people can make use of the information accessible in their immediate environment and choose the street with the bike lane instead of the path along the highway, even without dedicated routing.

However, while, in theory, ATCF navigation sounds like an excellent way for cyclists to get around, taking advantage of their ability to freely and quickly move across varying streets and paths, research has shown that people run into three main problems using this method in a real environment:

- Ending up in dead ends [37, 41]
- Going in the "wrong" direction [30, 31, 41]
- Not knowing when to take a turn [1, 41]

Some of these problems originate from human estimation errors (e.g., misinterpreting the angle of deviation [1]) or the lack of feedback in existing implementations [41]. However, maybe these difficulties are also inherent to the environment (i.e., the street network) that cyclists are trying to navigate. In navigation, street networks are represented by an underlying graph consisting of nodes (intersections) and edges (streets). They can be described by a plethora of indicators like count of nodes/edges, mean street segment length, count of physical street intersections, and many more [6, 9]. In this paper, we will use these indicators to get a better understanding of how street networks affect the ATCF navigation by answering the following research question:

RQ How does a city's street network affect the success, performance, and user experience of ATCF navigation?

To investigate how different street networks affect the success and performance of ATCF navigation, we use agent-simulation in combination with a feature importance analysis of 1633 cities to identify street network indicators responsible for the agent's success (whether an agent was able to find a route) and its performance (ratio of the length of the routes compared to the shortest path; the lower the better). Furthermore, we identify geographic differences by categorizing the agent's results based on nine different city types [44].

Our results show that the agent's success is mainly influenced by the average number of in and outgoing streets per intersection and the average length of streets. Straight streets with a low circuitry and overall few dead ends increase the success rate. The performance also benefits from many in and outgoing streets per intersection. In addition, the performance factor decreases as the entropy lowers, meaning the more grid-like a city is, the lower the performance factor and thus the shorter the routes. Furthermore, we find that cities suited for ATCF navigation are mostly found in

East Asia and North America, while the most unsuited cities are in Western Europe. According to the nine city types defined by Thompson et al. [44] the best performing city types are *Irregular*, *Sparse* and *Motor City* cities. So, in summary, the perfect city for ATCF navigation is a grid-like city with long straight streets, many different options to turn at each decision point, and few dead ends.

Based on the related work, it appears that most of the existing studies we examined were conducted in Western Europe (geographically the most unsuited area). Therefore, we propose that it needs more diverse study locations for future navigation experiments. We recommend that, wherever the street network does not favor ATCF navigation, researchers and designers should make sure that they are aware of these impacts and design artifacts and interactions accordingly. This study contributes the necessary context to improve the design of ATCF navigation for these areas and recognizes that different environments need different design approaches.

2 RELATED WORK

While ATCF is a novel navigation method for cyclists, it has been studied in academic research throughout the past 20 years. The navigation method relies on a wayfinding heuristic called the least-angle strategy (LAS), which is also at the core of our agent implementation. In this section, we describe the LAS in detail, including the shortcomings and challenges that come with it. We explain how the ATCF navigation relates to and takes advantage of the LAS. We highlight the problems studies find with ATCF navigation in the field and how these can be explained by human error or experiment circumstances. Lastly, we present how the analysis of street networks is used to learn about different indicators of cities, classify different city types, and show how this knowledge can be used to analyze the success and performance of the ATCF navigation method across cities.

2.1 Least Angle Strategy

The least-angle strategy (LAS), first defined by Hochmair [16], is a heuristic for navigating unknown environments without a map or similar contextual information. The only knowledge they have is the direction to the destination (e.g., seeing a landmark like the top of a building in the distance); they do not have an external map or knowledge about the street network. At each decision point (e.g., an intersection with multiple outgoing streets), the person has to decide which street to take based on the angle deviation between the direction a street is heading into and the direction to the destination. Following the LAS, they choose the option with the least deviation angle [16].

One caveat of the LAS is that a person might see the destination (e.g., a tall building) initially but could lose sight of it throughout the navigation task. This can lead to estimation errors as they have to estimate their position while moving to the destination. In this case, their estimation might get distorted by path-integration errors [16, 20, 23], and their overall estimation of the direction to the destination becomes less precise. This is among the primary reasons why Hochmair describes the LAS as a temporary strategy for shorter distances [16] and evaluated it only for a maximum distance of 500 meters. The longer a person goes without resetting their estimation of the direction to the destination (e.g., by getting a glimpse at the landmark), the less successful the strategy.

To evaluate the LAS, Hochmair [16] conducted a virtual simulation. In order to build an agent that was able to traverse a street network with close to human-like performance, he extended the presented strategy with the memorized least-angle strategy as the basis for his agent. In addition to the above-described behavior, the agent could memorize the last node visited but could not return to this last node in a subsequent step (except when in a dead end) [16]. This, in turn, forms the basis for the implementation of our LAS agent described in Section 3.1.

This section focused on the human wayfinding behavior induced by the LAS and forms the basis of our own implementation of the LAS agent (see Section 3.1). The following section presents

the navigation method built on top of the LAS by providing a sense of direction throughout the navigation task for better orientation and fewer estimation errors.

2.2 As-The-Crow-Flies Navigation

As-the-crow-flies navigation is a navigation method that utilizes the LAS by constantly (or on-demand) providing the direction to the destination. This eliminates the previously mentioned estimation errors described by Hochmair [16, 20, 23] since with a dedicated device, a person knows the exact direction to the destination at each decision point. So ATCF navigation, by providing this direction information, enables people to make use of the LAS to find their way from an origin to a destination. Different consumer products and research studies implement various ways to communicate the direction through multiple modalities like touch, sound, and vision. All of these come with their own benefits and drawbacks. In this section, we present and discuss these different approaches and highlight the overarching navigational problems that have been recorded over multiple studies.

2.2.1 ATCF Navigation Using Vibrotactile Feedback. Vibrotactile feedback for ATCF navigation means that the direction to the destination is encoded in a (spatial) vibration pattern. Robinson et al. [37] for example, used a mobile device to indicate the direction towards the destination for pedestrians. In their study, all participants were able to navigate to a destination within 1500 meters successfully. The ATCF navigation motivated them to explore and take shortcuts which sometimes, however, resulted in walking into dead ends [37]. In a similar study of Pielot et al. [30], pedestrians walked shorter routes (a few hundred meters) but faced problems when there was an obstacle between them and the destination (illustrated in Figure 1 (b)). In these situations, they had to "go the wrong way" for some time until being able to turn towards the destination again [30].

While for pedestrians, the mobile device encoded the direction to the destination in a vibration pattern [30], for cyclists, there was a different approach. In a study, Poppinga et al. [32] used vibrating handlebars to encode the direction to the destination. Depending on the direction, the left and right handle vibrated with different intensities. This design was successful in guiding tourists on cycling trips. However, some participants had problems in understanding the ATCF navigation method, as they expected TBT instructions.

In summary, people were motivated to take shortcuts when using ATCF navigation through vibrotactile feedback since the ATCF navigation let them easily and freely explore their environment. However, this sometimes resulted in people ending up in dead ends [37]. Furthermore, when a path did not allow them to directly follow the indicated direction (caused by an obstacle like a building), people got irritated and unhappy with the lack of specific instructions [30].

2.2.2 ATCF Navigation Using Audio Feedback. One of the first applications of ATCF navigation came in the form of audio feedback. While early research had already picked up this technology for navigation for the blind [22], Holland et al. [17] implemented the first version meant for sighted people. While somewhat sluggish in response (due to latency) for faster travel modes like cars or bicycles, pedestrians could navigate using spatial audio in their study. Fourteen years later, Albrecht et al. [1] saw the benefit of hands- and eyes-free navigation for cyclists and implemented ATCF navigation for pedestrians and cyclists alike. Instead of an artificial sound to indicate the direction, they used music to indicate where to go. They found that people generally considered ATCF navigation suitable for familiar surroundings, but TBT instructions were the preferred choice for unfamiliar surroundings. A problem participants mentioned with the ATCF navigation (in the paper called beacon guidance) was that if a path was not leading straight towards the destination, they were unsure when to take the next turn. The reason being that they did not know how far

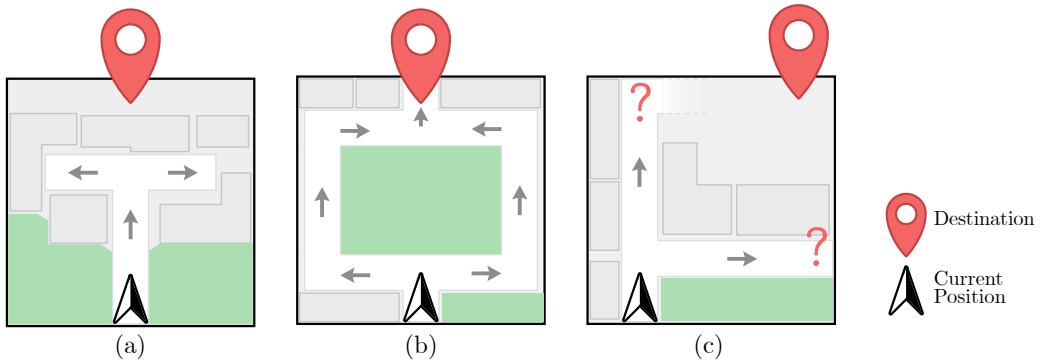


Fig. 1. Situations identified by related work that cause problems with the ATCF navigation: a) Ending up in dead ends; b) Having to go in the "wrong" direction; c) Not knowing when to take a turn.

the next opportunity to turn in the "right" direction would be (illustrated in Figure 1 (c)). This was reflected in participants' confidence with the navigation method [1].

The previous examples show that ATCF navigation can also be conveyed through audio. However, the study by Albrecht et al. [1] introduced an interesting problem. Participants were sometimes unsure when to take a turn, as they did not have a map. Thus, they were unsure whether a turn into the "right" direction would be available if they skipped a current one. This reduced their confidence while riding.

2.2.3 ATCF Navigation Using Visual Feedback. In contrast to the previously presented modalities, the visual communication of ATCF navigation is the most common one used for consumer products [4, 43] despite there being only limited research on it. The reason for this is likely the prevalence of visual interfacing for mobile navigation and, through it, a familiarity that lowers the entry barrier for using these products. Among the existing products which utilize ATCF navigation are the two devices Beeline [4] and SmartHalo [43]. Both function as small devices attached to a bicycle's handlebar and feature ATCF navigation (called compass mode) as an alternative to the also available TBT navigation. Besides the success of the visual ATCF navigation in consumer products, there is limited academic research on it. Among them, a recent study by Savino et al. [41] investigates the advantages and consequences of this modality and the navigation method as a whole for cyclists. Their study compares ATCF navigation (based on the Beeline device) with TBT navigation (Google Maps). The results showcase the superiority of TBT navigation in following the shortest path and highlight the shortcomings of ATCF navigation, confirming results from previous studies. They find that people had problems going into a direction that deviated from the indicated direction to the destination, similar to what Pielot et al. [30] found for pedestrians. Furthermore, participants were unsure when to take a turn due to the lack of a map, similar to the results of Albrecht et al. [1]. Finally, participants ran into dead ends while exploring possible routes to the destination, as also seen in the study of Robinson et al. [37].

2.2.4 ATCF Difficulties Across Modalities. In summary, the related work suggests three major problems, illustrated in Figure 1, that can be observed when people use the ATCF navigation in real-world navigation tasks:

- **Ending up in dead ends:** Exploration can lead to people ending up in dead ends [37, 41].
- **Going in the "wrong" direction:** Not being able to directly follow the indicated direction or following a direction that deviates from the indicated direction leads to confusion [30, 31, 41].

Street Network Indicators	
Indicator	Description
node_count	The number of all the nodes in the graph.
street_segment_count	The number of all (undirected) edges in the graph.
length_mean	Mean (undirected) edge/street length in meters.
length_total	Sum of (undirected) edge lengths in meters.
intersect_count	Count of (undirected) edge/street intersections.
prop_4way	Proportion of nodes that represent 4-way street intersections.
prop_3way	Proportion of nodes that represent 3-way street intersections.
prop_deadend	Proportion of nodes that represent dead-ends.
self_loop_proportion	Proportion of edges that are self-loops.
k_avg	Average node degree (mean number of inbound and outbound edges incident to the nodes).
cc_avg_dir	Average clustering coefficient (extent to which node's neighbourhood forms a complete graph).
circuitry	Average circuitry (ratio of street lengths to straight-line distances).
orientation_entropy	Entropy of street bearings (i.e. how ordered/grid-like the network is).

Table 1. Street network indicators and their meaning based on OSMnx [6] and Boeing [9].

- **Not knowing when to take a turn:** Not knowing when to take a turn, due to the lack of a map and the interpretation of angle deviations [1, 41].

To investigate these problems, we implemented an agent that closely models the behavior observed in the studies above. Furthermore, during the analysis of the above-presented literature, we noticed a similarity between most studies. Through a combination of the author's affiliation, route descriptions, and images published in their works, it appears that most studies have been conducted in Western Europe. As geographic differences are part of our analysis, we will come back to this finding later in the discussion.

2.3 Street Network Analysis

In this paper, we are looking at cities and their street networks from two perspectives: (1) the graph representations of the street networks and their formal network indicators and (2) a high-level classification of nine different city types based on visual representations of their street networks. In this section, we present the related literature for both these perspectives.

2.3.1 Street Network Indicators. A street network is usually represented as a directed multi-graph consisting of nodes and edges. Based on this formalization, many well-established indicators from graph theory are used to describe a street network: e.g., the number of nodes/edges, the total edge length, the proportion of 4-way intersections, among others [9]. We used the street network information available through Open Street Map (OSM) [28] for our study. OSM is an open-sourced global database for graph-based street networks. It features a comprehensive database of cities and

City Types	
City Type	Description
Informal	Sparse, low capacity informal road infrastructure, low railed transport, low formal green space.
Irregular	High green space, mixed formal and informal low and high capacity road networks, low mass transit.
Large Block	Medium density formal low and high capacity road networks, medium railed transport.
Cul de Sac	Very high density, low capacity mixed formal and informal road networks, low mass transit.
High Transit	Medium density, high capacity, formal road networks, high public transport.
Motor City	Medium to low density, high capacity, grid-based, road networks, medium railed transport.
Chequerboard	High density, medium capacity mixed formal and informal road networks, medium public transport.
Intense	Very high density, mixed formal high capacity and informal road networks, high public transport.
Sparse	Low capacity, low density formal and informal road networks, low public transport.

Table 2. City types and their descriptions. The descriptions are direct quotes from Table 1 in the Appendix of Thompson et al. [44].

their street networks and offers an API that researchers and practitioners can use to process and interact with this data.

To extract the indicators from the respective street networks, we used the Python library OSMnx by Boeing [6]. In recent publications, Boeing extracted multiple street network indicators for cities around the globe [6–8] resulting in a dataset of "Street Network Models and Indicators for Every Urban Area in the World" [9]. Based on his research, we chose a subset of street network indicators relevant for the ATCF navigation to be used in our study, which can be seen in Table 1.

2.3.2 City Types. Beyond the individual street network indicators, Thompson et al. [44] came up with a classification of nine different city types. Based on visual representations of the street network of the 1692 largest cities by population from the 2014 UN world urbanization prospects [45], they used a convolutional neural network to cluster them into nine different city types: *Informal*, *Irregular*, *Large Block*, *Cul de Sac*, *High Transit*, *Motor City*, *Chequerboard*, *Intense*, and *Sparse* (see Table 2 for detailed descriptions). While for example *Motor City* cities are mostly located in North America and Australia and feature consistently organized, grid-based networks [44], *High Transit* cities are mainly found in Western Europe and show a more intense network structure compared to most other city types [44].

In this study, we will use street network indicators and the city type to look at cities worldwide in terms of their suitability for applying the LAS. Together, these two ways of looking at street networks result in a comprehensive evaluation of how the environment can affect the performance and success of ATCF navigation. We use the network indicators in a feature importance analysis to determine which ones can affect the performance factor and the success rate. Furthermore, a comparison between the city types can provide information about the geographic differences.

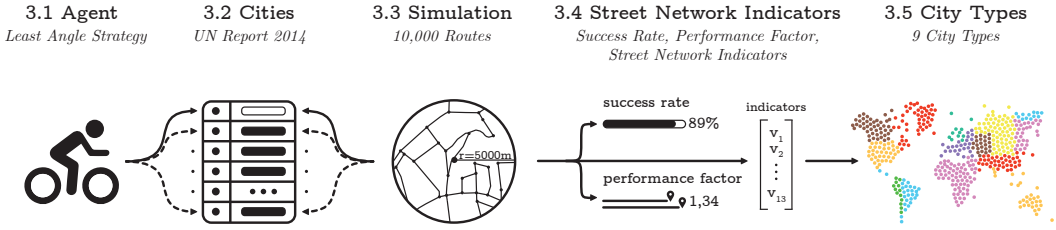


Fig. 2. Description of the simulation framework: For 1692 cities in the 2014 UN world urbanization prospects [45], our agent tried to find 10000 routes based on 10000 random origin and destination pairs between 1-5000m distance. We then computed the success rate, performance factor, and 13 street network indicators for each city and assigned its city type.

3 STUDY

To assess how much the city structures themselves contribute to the success or failure of the ATCF navigation method, we investigated street networks across the 1692 largest cities in the world by population size. Evaluating our research questions on a global scale, required an agent proxying human navigation behavior with ATCF. Therefore, we built an agent implementing the least-angle strategy [16] and a framework to collect the city network data. In this section, we will describe the implementation of the agent and the simulation framework we built using the python library OSMnx [6] (see Figure 2). Throughout this study and our results, we will refer to the success and the performance of the agent in terms of the success rate and performance factor as described by Hochmair [16].

3.1 Agent

We implemented the agent using a modified depth-first search to find a route between an origin and a destination using the least-angle strategy (LAS). Based on the implementation of Hochmair [16] it starts at the origin and always chooses the next unvisited neighbor node with the least angle deviation towards the destination. This behavior continues until the agent has either reached the destination or is caught in a loop. Being caught in a loop is defined by visiting a node V twice from the same previous node with all immediate neighbors of V already visited (this behavior covers both Hochmair’s original cycle and circuit criteria [16]). If the agent, given the stopping criterion, reaches the destination, the run is considered successful. In this study, we use the agent’s success rate as a metric for evaluating how well a city is fit for using the LAS. A human in a similar situation would not stop the navigation altogether but could, for example, resort to asking for directions or use a different navigation method like TBT. Still, such situations result in frustration and loss of confidence [41]. Thus, the agent’s success rate is a proxy for not being confronted with such situations during the navigation, which makes the navigation more pleasant and positively affects the user experience.

Furthermore, the agent calculates the total length of the route (including the parts where it backtracked or walked in circles). These two measures are then used to calculate an overall success rate and performance factor per city as seen in Hochmair [16]. The success rate describes the percentage of successful routes given 10,000 origin-destination pairs. The performance factor describes the average by which the routes found by the agent are longer than the shortest path between the origin and destination (e.g., a performance factor of 1.4 means that the routes found by the agent were on average 40% longer than the respective shortest paths). The following section describes how we collected the city data for the agent to run on.

3.2 Cities

In order to have the agent use its wayfinding algorithm on existing street networks, we collected the necessary data with the OSMnx library [6]. OSMnx is a python library that allows downloading Open Street Map data in a graph format. For our simulation, we chose the 1692 largest cities by population based on the 2014 UN world urbanization prospects [45]. This dataset includes, among other attributes, the coordinates of each city's center (based on OSM) as well as its name and country. Using OSMnx, we downloaded a fixed area comprising all nodes within a 5km radius around the center for each city. When downloading the graph of each street network, OSMnx simplifies and fixes the graph so that the result is a connected graph with a clean periphery. We used the OSM network type "bike" in combination with a custom filter to exclude motor highways, footways, and private streets like driveways to ensure the network consisted of streets where cyclists are allowed to ride.

3.3 The Simulation

For the simulation, we generated 10,000 origin-destination pairs for each of the 1692 cities. The origin-destination pairs were randomly chosen and were between 1 and 5000 meters apart. Additionally to the route the LAS agent generated, we collected the shortest path for each origin-destination pair. This resulted on average in routes that were 4790 meters long for the LAS agent and 3360 for the shortest path, in line with typical average commute lengths for cyclists [10]. With the collected routes, we calculated the success rate and the performance factor for each city. Additionally, we collected the 13 street network indicators shown in Table 1, which are described more closely in the next section.

3.4 Street Network Indicators

From the cities and their corresponding graphs, we collected the inherent street network indicators. As the reader might recall, we analyze all cities' street network indicators using a feature importance analysis to find out which indicators are responsible for the success or failure of the ATCF navigation method in terms of success rate and performance factor. To achieve the former, we identified basic and relevant street network indicators [6, 9]. Table 1 shows all indicators with their descriptions. For our analysis, we divide these indicators into two groups: absolute and relative. Absolute indicators are those which change in absolute numbers with the size of the graph. These include: *node_count*, *street_segment_count*, *length_total*, and *intersect_count*. All other indicators (e.g., *k_avg* or *length_mean*) are relative and thus comparable across cities with different network densities.

3.5 City Types

In addition to the street network indicators, we used the city types identified by Thompson et al. [44] to compare the success and performance of LAS agent across them. In their work, Thompson et al. [44] used the same UN 2014 data set [45] to cluster city types based on their visual street network using a convolutional neural network. This analysis resulted in nine different city types, which can be seen in Table 2. In our analysis, we compare the results of the LAS agent across these city types. Additionally, we use the city type as the 14th feature in our feature importance analysis, adding a visual feature to our otherwise abstract feature set.

After including the city types, we had to exclude 59 cities from our initial dataset due to inconsistencies with the dataset from Thompson et al. [44] and the UN 2014 data set [45] (for a detailed explanation see Section 6) resulting in a total of 1633 cities for the analysis.

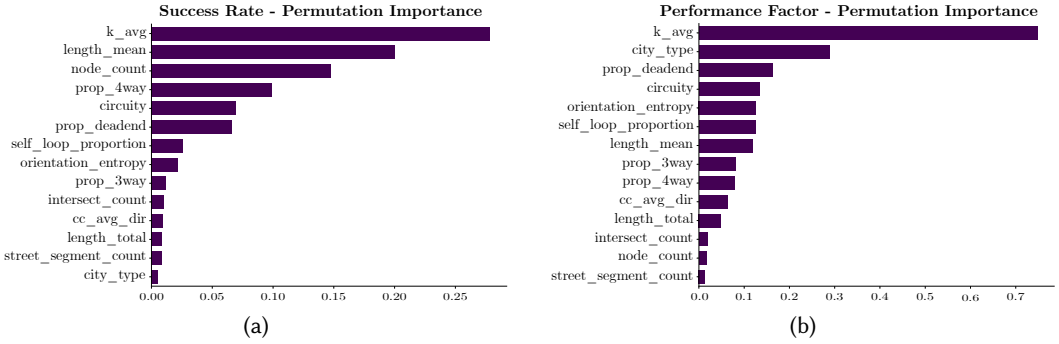


Fig. 3. Permutation feature importance results for the (a) success rate and the (b) performance factor. Note the different scales on the x-axis for both plots.

4 RESULTS

In this section, we present the results of the agent simulation. From the total of 16,330,000 origin destination pairs, the agent was able to successfully find 8,418,141 routes across all 1633 cities. We describe the importance of the different street network indicators for the agent’s success rate and performance factor. Furthermore, we look at the different city types by Thompson et al. [44] and how the results of the agent differ between them.

4.1 Street Network Indicator Importance

To find the most important features responsible for the success and the performance of the agent using the LAS, we used permutation feature importance analysis. We first fit a random forest regressor to our data for the success rate ($R^2 = 0.87$) and the performance factor ($R^2 = 0.37$) respectively. The permutation feature importance i then revealed the most important features of our model (see Figure 3). The overall most important indicators are the average (undirected) node degree (k_avg), the mean (undirected) edge length in meters ($length_mean$), and the city type. Another important feature for the success rate is the $node_count$. However, it is important to keep in mind that the $node_count$ is an absolute feature and thus does not compare well across cities with different network densities. A Spearman correlation showed that it has a high multicollinearity with the remaining absolute features: $length_total$, $intersect_count$, and $street_segment_count$. To indicate the relationship between an indicator and the measured variable, we report the Spearman rank-order correlation coefficient c and its p-value p for each feature.

4.1.1 Success Rate. For the success rate the average (undirected) node degree (k_avg , $i = 0.28$, $c = +0.32$, $p < 0.01$) was the most important indicator. The higher the degree, the higher is the success rate. This is followed by the mean (undirected) edge length ($length_mean$, $i = 0.20$, $c = +0.63$, $p < 0.01$). Here, with increasing length the success rate also increases. The next feature is the $node_count$ ($i = 0.15$, $c = -0.64$, $p < 0.01$). Here we see that with fewer nodes the success rate increases, meaning that smaller graphs (in absolute numbers) result in a higher success rate. The next features by importance are the proportion of 4-way intersections ($prop_4way$, $i = 0.10$, $c = +0.65$, $p < 0.01$), the circuitry ($i = 0.07$, $c = -0.56$, $p < 0.01$), and the proportion of dead ends ($prop_deadend$, $i = 0.05$, $c = -0.62$, $p < 0.01$). All other indicators had a mean feature importance below 0.05. For the full list please see Figure 3a.

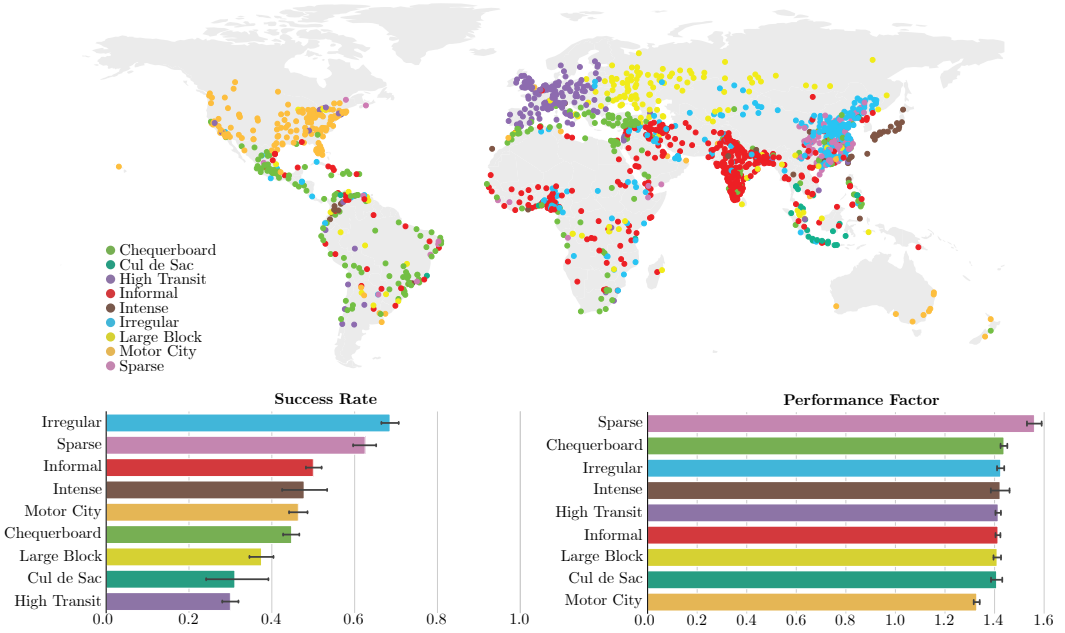


Fig. 4. Success rate and performance factor based on the different city types by Thompson et al [?].

4.1.2 Performance Factor. The most important indicator for the performance factor was the average (undirected) node degree (k_{avg} , $i = 0.75$, $c = -0.42$, $p < 0.01$). With increasing node degree the performance factor gets smaller, meaning the LAS routes become shorter. Second most important was the city type as a feature (0.29). The effect of the city type on the performance factor can be seen in Figure 4 and is discussed in the next section. The third most important feature is the proportion of dead ends ($prop_deadend$, $i = 0.16$, $c = +0.06$, $p < 0.05$). While deemed important by the feature importance analysis, the proportion of dead ends does not seem to have a positive or negative linear relationship with the performance factor. The next important feature is the circuitry ($circuitry$, $i = 0.13$, $c = +0.14$, $p < 0.01$), followed by the orientation entropy ($orientation_entropy$, $i = 0.13$, $c = +0.25$, $p < 0.01$). This shows that the less ordered a street network is and the less straight its streets are, the lower is the performance factor. For the remaining features see Figure 3b.

Overall, we see that the average node degree strongly influences the success rate and performance factor, meaning that a higher number of incoming and outgoing going streets per intersection improves the agent's performance. While for the success rate, the mean edge length, node count, and proportion of 4-way intersections play an essential role, the performance factor is affected by the city type, the circuitry, and the orientation entropy. Furthermore, dead ends affect whether the agent reaches the stopping criterion and thus reduce the success rate. This results in successful routes including fewer dead ends, and therefore, they have little effect on the performance factor.

4.2 City Types

To compare our results based on the city types by Thompson et al. [44] in terms of success and performance of the ATCF navigation method, we recreated their dataset [45] and collected these metrics for each city. Figure 4 shows all cities and their respective type located on a world map. For a visual example of each city type see Figure 6. In the following subsections, we will compare

these city types based on our agent's success rate and performance factor. For all comparisons, we conducted a one-way ANOVA with posthoc t-tests.

4.2.1 Success Rate. We found that overall all city types have a lower success rate than 70%. A one-way ANOVA found significant differences between the city types ($F = 99.71$, $p < 0.001$). *Irregular* (69%) and *Sparse* (63%) cities had the highest success rates with the former being significantly higher than the latter ($p < 0.05$). The next city types by success rate are *Informal* (50%), *Intense* (48%), *Motor City* (46%), and *Chequerboard* (45%) cities with no significant difference between them. However, *Chequerboard* cities (45%) have a significantly higher success rate ($p < 0.01$) than *Large Block* (38%) cities. The lowest success rates were found in the *Cul de Sac* (31%) and *High Transit* (29%) cities, showing no significant difference between both but with *High Transit* (29%) cities having a significantly lower success rate than *Large Block* (38%) cities ($p < 0.001$).

4.2.2 Performance Factor. The performance factor was, on average, very similar between all city types (see Figure 4). A one-way ANOVA found significant differences between the city types ($F = 43.02$, $p < 0.001$). *Sparse* cities had the significantly highest performance factor (1.56), with a p-value of 0.0001 or smaller compared to all other city types. In contrast, *Motor City* cities had the significantly lowest performance factor (1.33), with a p-value of 0.000002 or smaller compared to all other city types. The remaining city types showed a performance factor from 1.41 (*Cul de Sac*) to 1.44 (*Chequerboard*) with no significant differences.

5 DISCUSSION

In this section, we discuss the simulation results and their consequences for the design and application of the ATCF navigation method. As an alternative to TBT navigation, ATCF navigation offers the freedom to explore one's environment. This allows cyclists to attend more to their surroundings and make decisions as they see fit. Still, according to the least-angle strategy (LAS), people will follow the "right" direction as closely as possible. From our results, we learn that some environments make this harder than others, as can be seen in the different success rates and performance factors across cities worldwide (Figure 5). Thus, we should consider these differences when designing for the people who try to navigate these places. Finally, navigation is a part of how people interact with their surrounding city infrastructure. Therefore, we should not only design navigation methods to suit different environments. We should also understand how different city environments developed, what constraints they have, and think about designing them to support more flexible navigation methods that foster exploration and humans' abilities to find their way through them [18].

5.1 Human Error? No, Bad Street Network Design

A central assumption in human-computer interaction (HCI) is that people make mistakes [27]. However, as HCI researchers, we have the tools to ask and understand what causes these mistakes. For ATCF navigation, related work has identified problems people encounter when using it across different modalities. Some of these problems are accounted for by the novelty factor of the method as described in Pielot et al. [31], where participants did not understand the method as they were so used to TBT navigation instructions. Thus, it is only normal that participants would make mistakes using a new technology. However, as our results show, there are differences in how the least-angle strategy works in different cities. As the user experience of the ATCF navigation is dependent on the successful application of the LAS, we need to consider these differences carefully and evaluate their consequences. In the following subsections, we discuss how the street network influences the identified problems.

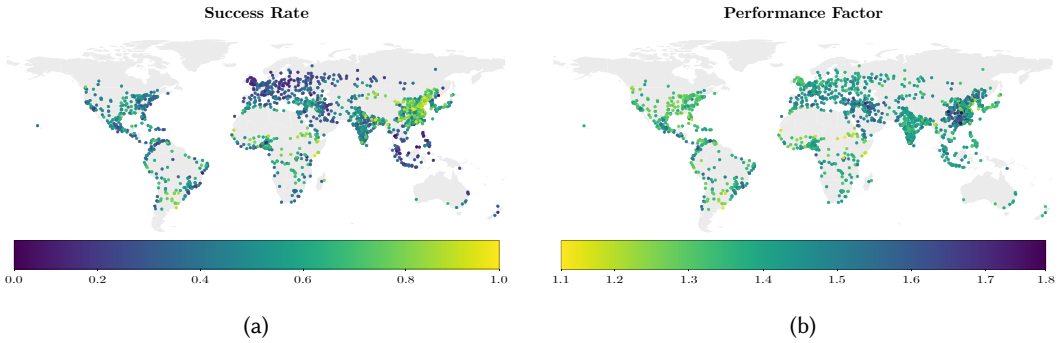


Fig. 5. (a) Success rate and (b) performance factor for all 1633 cities in the dataset. The color map is flipped for the performance factor. For both scales, brighter colors indicate a better result.

5.1.1 Ending Up in Dead Ends. With no map available, participants in the previous studies sometimes ended up running into dead ends [37, 41]. This is frustrating and, in principle, increases the route length and thus the performance factor due to the backtracking necessary to get out of the dead end and resume the navigation. As our data shows, dead ends impact the success rate as well as the performance factor. While for the success rate we see a high negative correlation (the higher the proportion of dead ends, the lower the success rate), we do not see the same for the performance factors. A reason for this could be that routes of the agent reach the stopping criterion in a complex dead end, and thus successful routes only contain limited dead ends. Furthermore, the proportion of dead ends differs between different city types (see appendix A).

It comes as no surprise that the city type featuring the highest proportion of dead ends (24.0%) across all city types is *Cul de Sac*. The city type second to that is *High Transit* with 21.6%. This is also the city type primarily found in Western Europe and appears to be where most of the previously presented studies were conducted. Thus, people driving into dead ends might be a less common problem in other areas like North America (*Motor City*, 14.6%) or China (*Sparse*, 13.1%).

Based on our implementation, a future ATCF navigation system could use our simulation approach to predict the likeliness of running into dead ends on the chosen route and intervene with TBT instructions at critical decision points by, for example, temporarily changing into a map view. Another option would be to alert users that a given area has a high density of dead ends. Thus, they should be looking out for respective road signs more carefully when taking a turn instead of just following the system.

5.1.2 Going in the "Wrong" Direction. The feeling of going in the "wrong" direction or not being able to go where the ATCF navigation points to was a frequently reported issue in previous literature [30, 31, 41] (illustrated in Figure 1 (b)). In terms of street network indicators, this is influenced by the average node degree (k_{avg}) as it describes the average number of options an intersection offers. A higher average node degree thus means that more often, there will be an option that might lead in the "right" direction. When it comes to the average node degree, *Motor City* cities are the leading type with on average 5.27 in and outgoing streets per intersection compared to the lowest average being 4.68 for *High Transit* cities. While more options to turn might offer a higher likelihood of taking a turn in the "right" direction, we still need more information on how people deal with this problem in situ to offer an adequate solution.

Design Implications	
Issue	Design Implication
Ending Up in Dead Ends	Use agent to predict likeliness of running into dead ends; Change to map view at critical decision points; Alert user of high density of dead ends.
Going in the "Wrong" Direction	Include the notion of going in the "wrong" direction into the agent for further investigation.
Not Knowing When to Take a Turn	Indicate whether an upcoming turn is best taken, as the following turn might not lead in the right direction or is too far away.

Table 3. Design implications relating to the three identified difficulties across modalities from Section 2.2.4.

To collect additional information on street networks regarding this problem, a future version of our agent should include the notion of going in the "wrong" direction. In the meanwhile, Savino et al. [41] presented a first approach about giving people feedback on whether they are still on the "right" track, which successfully helped people going "against" the proposed direction.

5.1.3 Not Knowing When to Take a Turn. Not knowing when to take a turn was another of the problems identified to be caused by the ATCF navigation (see Figure 1 (c)). The main reason was that participants did not have a map to consult about when a potential turn would come up [1, 41]. In *High Transit* cities this can mean that a wrong decision can cause a long detour as they have a high orientation entropy ($orientation_entropy = 3.5$), and low average node degree ($k_{avg} = 4.68$). Thus, missing a turn can mean that the current street potentially deviates more and more from the destination and that upcoming turns do not allow a person to turn in the direction of the destination. In that sense, *Motor City* cities are at an advantage through their grid-like structure ($orientation_entropy = 3.1$). As a countermeasure, the ATCF navigation should indicate whether an upcoming turn is best taken, as the following turn might not lead in the right direction or is too far away.

5.1.4 Design Implications for ATCF Navigation. "At the end of the street, turn left"; The extended prevalence of TBT navigation has led to many people getting used to following instructions by navigation systems like Google Maps. This, however, has partly led to an overtrust in navigation systems, sometimes resulting in serious casualties [21]. Due to the popularity of the navigation method, it also became the default for cyclists. Slowly, routing criteria are adapting to account for the needs of specific user groups [19]. Still, ATCF navigation presents the only currently used alternative navigation method that uses peoples' own ability to navigate and takes advantage of their own decision-making.

Current implementations of the ACTF navigation benefit from being simple. A system offering ATCF navigation does not use resource-intensive online calculations and updates as TBT navigation does. However, given a poorly suited environment, this study shows that this lack of flexibility can negatively impact the user experience. In this paper, we propose making ATCF navigation smarter in order to overcome this issue. Using the insights from this section, we can build predictive models that continuously assess the situation during a navigation task and intervene when a person likely runs into a problem. This way, the best of both ATCF and TBT navigation could be combined. Letting people freely navigate whenever possible but prevent them from running into problems.

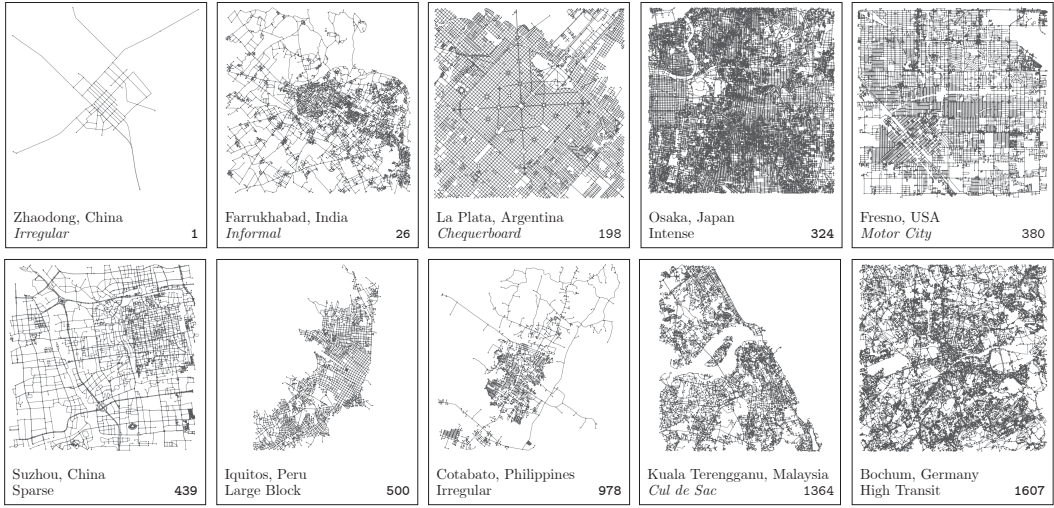


Fig. 6. A selection of ten cities from our dataset. It shows the name of the city, country, the city type and the rank within our data set when sorted by a combined score of performance factor and success rate. Each image shows a map section of 10x10 kilometers.

5.2 Geographic Differences

Different cities come with various sizes, shapes, and, most importantly, street networks. Many cities in Europe grew and developed organically with their street network usually focused on local geography. Inversely, many cities in the USA were planned using geometric grids [13, 24]. Beyond the implications for the ATCF navigation method, our work offers a unique view of geographic differences in urban structures worldwide with implications on future study designs in the domain of navigation. Related work is already acknowledging that different cities come with different environments and proposes increasing comparability between results by identifying similar routes across cities [25]. With this work, we add to this argument by highlighting that geographic differences can influence peoples' navigation tasks which we encourage future studies to report and take into account.

Most of the studies presented in the related works in this paper appear to have been conducted in Western Europe. They, therefore, might have been exposed to the environment of a *High Transit* like street network, which we found to be not very suitable for applying the LAS. *High Transit* cities have the lowest average (undirected) node degree (k_{avg}) with 4.68 in and outgoing streets per node. While these cities feature a large absolute intersection count (due to their intense network structure [44]), their proportions of 3-way (62.8%) and 4-way (14.2%) intersections are at the lower end of the spectrum (for a full comparison, see Appendix A). Together with the high proportion of dead ends (21.6%), these indicators help explain a low success rate for our agent. Figure 6 shows an example of a typical *High Transit* (#1607) from Western Europe. According to Thompson et al. [44], additionally to their intense network structure, these cities also showed a high level of railed massed transit networks.

As described before, European cities developed mostly organically [13, 24]. *High Transit*, being the most prominent city type in this area, they feature the highest orientation entropy (*orientation_entropy*, 3.50) and are thus the least ordered. In contrast, *Motor City* cities are ordered, grid-like networks found in North America and Australia [44]. In our analysis, they stand out,

having the significantly lowest (i.e., best) performance factor, meaning that routes found by the agent were on average the shortest in these types of cities compared to the shortest path. Figure 6 shows a typical North American *Motor City* city (#380). While they had the best performance factor *Motor City* cities featured not the best success rate. Like many other cities, they had a low mean (undirected) edge length (*length_mean*, 83 meters), which, according to our results, is an important feature that correlates with the success rate.

When it comes to the success rate *Irregular* cities had significantly the highest. This had two reasons: (1) some cities featured a very low node count making it almost impossible for the agent to get stuck given the limited possibilities in the street network. A good example of this can be seen in Figure 6 (#1). The feature importance analysis showed that a low number of nodes is advantageous for the success rate, and we believe it is for the previously mentioned reason. That means smaller or lower density graphs should be easier to traverse for the agent. However, examples like Figure 6 (#26) show that the node count itself cannot tell the full story. (2) The second reason we see is the high mean (undirected) edge length, meaning *Irregular* cities often feature long streets with an average length of 210 meters. This is backed up by Thompson et al.'s [44] visual analysis showing that they showed the lowest number of blocks per map tile. Furthermore, they characterize *Irregular* cities being irregular shaped, high level of green space and rectangular blocks of varying sizes [44]. This description fits well to the second example of an *Irregular* city shown in Figure 6 (#978).

Looking at these different examples, we should bear in mind that the influence of the environment can be very noticeable between different city types when evaluating novel navigation methods. Therefore, we need more geographically diverse evaluations when it comes to evaluating them. With this paper, we present the evaluation of a simulation and a way to evaluate the experiment site beforehand and check if the environment could influence the user experience by introducing structural problems like a high density of dead ends or very high orientation entropy.

6 LIMITATIONS & FUTURE WORK

This section presents and discusses the limitations of our approach and presents related and future work that builds upon our results. We discuss the agent's shortcomings and how to make its performance more human-like in the future. Furthermore, we reflect on the data quality of our study and how it affects the quality of our results. Finally, we look at how city size affects our model, what makes a bike-friendly city, and how ATCF navigation applies beyond the bicycle.

6.1 Modeling Human Behavior

Throughout this study, we use our agent as a proxy for human navigation performance. Given that the agent implements the LAS based on Hochmair's work from 2005 [16], we can assume that, in many cases, it will decide similarly to a human given the bearing information they need for a given task. Still, the agent differs in two crucial ways from humans, which are subject to continuous improvement: (1) the agent is too precise, and (2) it gives up too fast. The agent will make a difference even if two possible street angles differ by only 0.1 degree. It will choose the street with the 0.1 better angle over the other one. The notion that humans will not realize such differences builds on research about the perception of angularity during navigation [39]. However, for the specific case of ATCF navigation, we need more fine-grained evidence to add this behavior to our implementation. The second drawback is the stopping criterion. When stuck or caught in a loop, the agent will stop the navigation. A human will continue the task and build up a certain level of frustration with continued errors [41]. Furthermore, humans will use additional information such as road signs to cope with problematic situations. With these limitations, one should be aware that the performance of our LAS agent does not yet perfectly reflect real cyclists' performance. In his paper, Hochmair already suggests possible changes to the original algorithm to make the agent

more human-like (e.g., visiting the node with the least number of past visits first). In addition, we learn from the related work presented in this paper that many different behaviors can be observed when people use the ATCF navigation method [1, 30, 41]. Participants, for example, had problems turning around when riding "against" the proposed direction for too long or not being able to differentiate between minor angular differences. In order to make the agent more human-like, future work should study these behaviors even more closely to be able to formalize them. A recent study by Savino et al. [40] for example, explores the effect of angle perception of humans at intersections and how this behavior can be implemented into an ATCF agent. In their study, they extended the agent of this work with an uncertainty function based on empirical human data. With this uncertainty, the agent can make mistakes if two possible street angles differ only slightly, making its decisions more human-like. The agent was then verified against data from a previous study with human participants using the ATCF navigation method [41] and showed a higher overlap with participant's routes compared to the base agent presented in this work. However, extending the ATCF navigation in such a way makes it more complex. Existing implementations do not need a lot of data or calculations to work. Once a destination is chosen, a system needs to calculate the angle deviation and communicate it to the user via, e.g., a compass bearing. This approach makes ATCF navigation work even without an internet connection but, on the other hand, makes it less flexible. A smarter implementation could pre-calculate routes based on the LAS to predict possible problems in advance and give more concrete instructions where necessary.

6.2 Data Quality

An important aspect of our study design is that the results are only as good as the underlying graph data. Wherever the data collected by Open Street Map (OSM) [28] is incomplete, our model might make wrong assumptions. The results will be accurate given the graph used for the analysis, but the graph might not actually represent the real world. Barrington-Leigh et al. [2] analyzed the completeness of OSM and found an overall completeness of 80% across the world. However, China, a prominent country in our results, was found less than one-third complete. This might be a reason for some of its cities' low node count and thus the high success rate. Furthermore, we had to disregard 59 cities from the total dataset, resulting in 1633 cities. This was due to several mismatches between the 2014 UN world urbanization prospects [45] and the dataset provided by Thompson et al. [44].

6.3 Street Network Radius

We chose a radius of five kilometers for the street networks to achieve route lengths of average commute lengths for cyclists [10]. However, a fixed radius means that the area might include only a portion of the center or some of the outer rural areas for different sized cities. To counter this circumstance, we tried to use an adaptive radius that grows with the size of the population [3, 44]. This approach resulted in the disadvantage that the area of the map was different for each city, as was the graph. This affected street network indicators that work with absolute numbers like *node_count*, *street_segment_count*, *length_total*, and *intersect_count* making them difficult to compare between cities. Thus, we chose to keep the area fixed even though some graphs only feature a smaller part of a city's center region (for very large cities) or include some of the outer rural areas (for smaller cities). Since all cities in our dataset had at least 300,000 inhabitants, very small cities where this effect would have been most severe were excluded, to begin with.

Still, future work should improve the distinction between urban and rural areas even more. In this work, we evaluated the 1633 largest cities by population size. Necessarily, this means that our data set contains mostly urban areas. While these areas are important to investigate how suited

ATCF navigation is for shorter distances and commuting, larger rural areas could yield additional insights which can further our understanding of ATCF navigation for longer cycling trips.

6.4 Bike-Friendly Cities

Our results demonstrate that cities that developed in certain regions seem to be categorically better or worse suited for ATCF navigation. As this result is solely based on the street network, it is important to note that a well-suited street network alone does not necessarily make for a bike-friendly city. To test this assumption, we looked at some of the most bike-friendly cities worldwide and checked how they scored on our combined score of performance factor and success rate. One possible way to measure the bike-friendliness of cities is proposed by the Copenhagenize Index(CI) [11]. Initiated by the Copenhagenize Design Company [11] in 2011, CI is a holistic measure for rating cities on streetscape, biking culture and ambition. This index ranks the 118 most bicycle-friendly cities in the world on 14 parameters, of which one is the bicycle infrastructure. Here, the focus is on the protected and separated infrastructure (like cycling highways) [46], which increases the general bicycle adaptability and convenience but not necessarily ease of navigation. Moreover, it may counter the ease of navigation as the bicycle pathways may be separated from other road infrastructure for safety at the cost of limited intersections. Thus, users may have to take longer or more complicated routes with fewer intersections, resulting in an increased (worse) ATCF performance factor. Looking at the top ten most bike-friendly cities according to the CI, we find that seven out of ten cities rank above 1000 in our metric (see Figure 6 for reference), with Paris ranking the best at rank 721 while at the same time ranking eight on the CI. This means that cities that are particularly unsuited for ATCF navigation, according to our metric, can still feature lots of benefits for cyclists in general. At the time of writing, navigation is not included in the CI. Thus, a high CI does not necessarily mean high navigability. We argue that ease of navigation is a relevant part of any transport modality and the CI and other measures for bike-friendliness should be extended to include navigability especially suited for cyclists, as one of the parameters. Our study finds that some cities are highly ATCF navigation-friendly, but they might lack biking culture or infrastructure limiting its applicability in such places.

While further investigation goes beyond the scope of this paper, this insight shows that bike-friendliness and suitability for ATCF navigation are not necessarily related. Especially dedicated cycling infrastructure could take away from the suitability or usefulness of ATCF navigation as it replaces the flexibility of choosing one's route with safe but dedicated cycle paths. Here a hybrid approach could be a viable solution. ATCF navigation can be used until reaching a dedicated cycling highway. TBT instructions could be then used while riding on it, switching back to ATCF navigation after leaving the cycling highway. However, further research is needed to investigate such scenarios.

6.5 As-The-Crow-Flies Navigation Beyond the Bicycle

Most of the related work on ATCF navigation and current commercial applications [4, 43] are concerned with cycling [1, 30, 41]. For that reason, we also chose to make cycling the focus of our study, and we were able to strengthen that focus by using OSM data specifically for bikes. Thus, our results apply to cyclists only. However, this is not to say that ATCF navigation can solely be used by cyclists. Pedestrians [1] and scooterists are two other groups that would benefit from the same arguments having been made in this and related work for ATCF navigation. To extend the results of this study to those groups, appropriate map data should be used in future work to run the same or similar simulations.

7 CONCLUSION

As-the-crow-flies navigation utilizes cyclists' freedom to move beyond the confines of the dedicated car road network and people's own ability to navigate their environment [18] by providing a sense of orientation [42]. However, related work finds problems with the user experience that hinder its widespread adoption. Improving upon existing ATCF navigation approaches will help make the bicycle an even more attractive way of getting around and promote it further as a sustainable mode of transportation. In this paper, we find that the street network can affect the successful application of the LAS and thus, make the ATCF navigation method more challenging to use in different cities. By acknowledging and understanding these differences, we can consider them when designing new technologies around this method and pick diverse and suitable study locations for future research. These insights will help make the navigation method more usable in all kinds of environments and thus encourage cycling around the world. In turn, making cycling not only a more sustainable mode of transportation in environmental terms but could also have a lasting effect on cyclists' spatial abilities [42], escaping the tyranny of TBT navigation [37].

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A ALL STREET NETWORK INDICATORS ACROSS CITIES

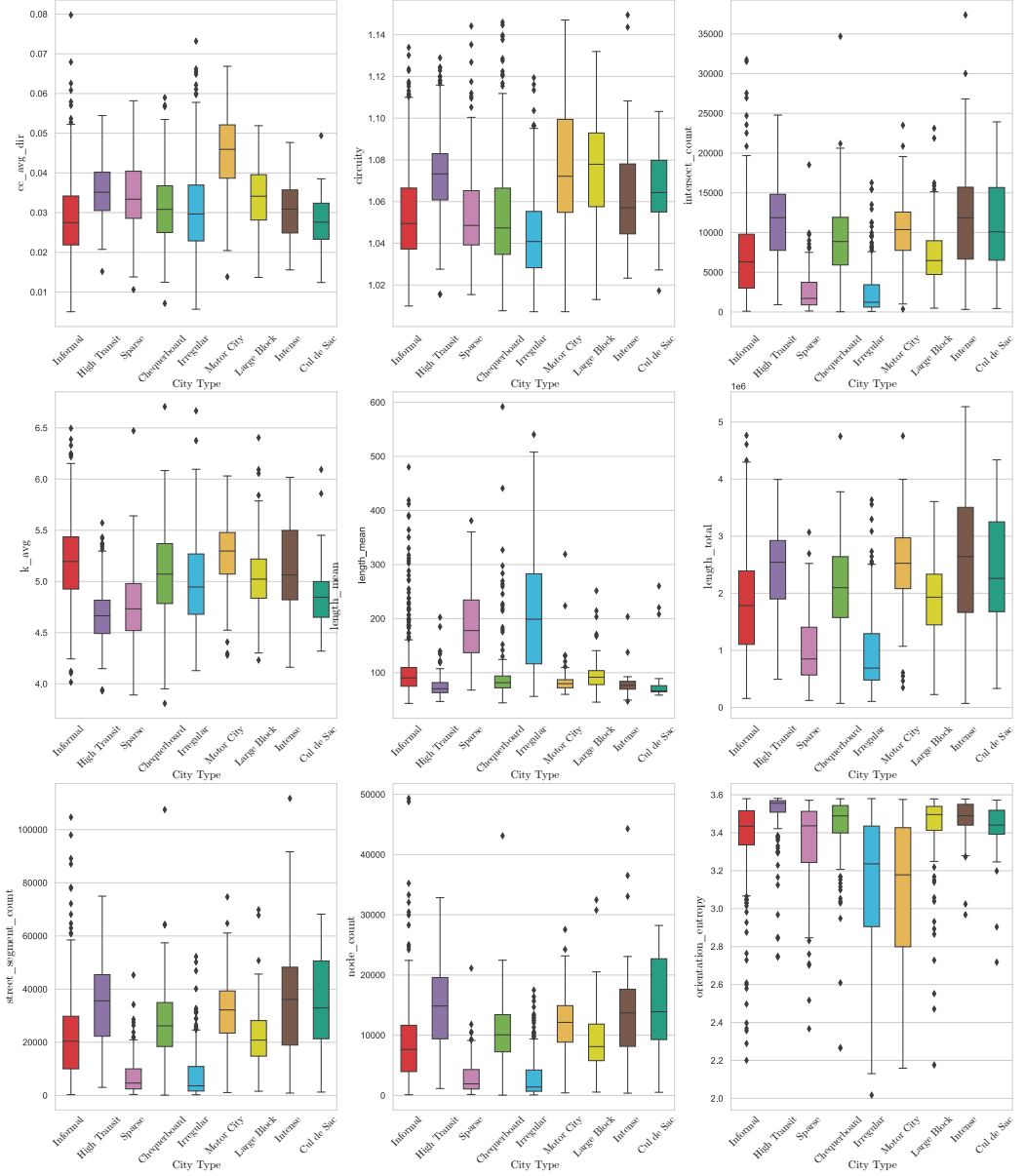


Fig. 7. All street network indicators across city types (1-9).

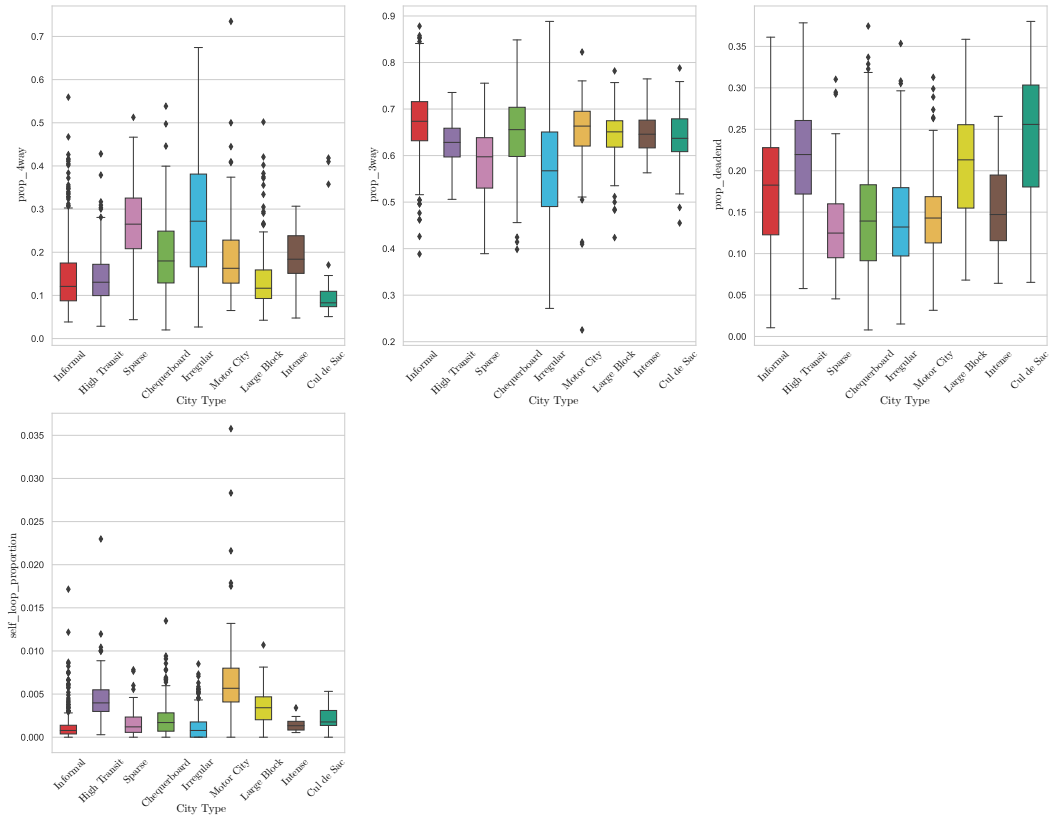


Fig. 8. All street network indicators across city types (10-13).

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