The Path is the Goal: a Study on the Nature and Effects of Shortest-Path Stability Under Perturbation of Destination

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Abstract

This work examines the phenomenon of path variability in urban navigation, where small changes in destination might lead to significantly different suggested routes. Starting from an observation of this variability over the city of Barcelona, we explore whether this is a localized or widespread occurrence and identify factors influencing path variability. We introduce the concept of "path stability", a measure of how robust a suggested route is to minor destination adjustments, define a detailed experimentation process and apply it across multiple cities worldwide. Our analysis shows that path stability is shaped by city-specific factors and trip characteristics, also identifying some common patterns. Results reveal significant heterogeneity in path stability across cities, allowing for categorization into "path-stable" and "path-unstable" cities. These findings offer new insights for urban planning and traffic management, highlighting opportunities for optimizing navigation systems to enhance route consistency and urban mobility.

Keywords: shortest path, path stability, road network, urban structure

1 Introduction

Vehicular traffic is one of the critical factors affecting the efficiency of cities, the quality of life of their citizens, and the environmental impact of transportation. Nowadays, traffic optimization is of particular relevance, especially in the current context where

Fig. 1 Example of two almost identical origin-destination pairs (green and red markers) that lead to different shortest paths (routes generated by OpenStreetMap).

cities continue to expand in population and density, impacting traffic management, pollution, and road safety. Efficient and sustainable road mobility is therefore essential to ensure that cities remain livable, competitive, and able to meet the needs of their residents.

As urban mobility forms a complex phenomenon, it is very important to understand how the travel infrastructures and the city's mobility needs combine, particularly whether the road network provides the correct connections for smooth mass mobility. One recent line of research deals with this aspect by assessing the reachability of city destinations in terms of efficient alternative paths available [1], which is a measure of road network robustness to high traffic loads and resilience to unexpected events (road closures, accidents, extreme traffic for public events, etc.). This work focuses on a related topic that stems from an anecdotal observation: in the city of Barcelona, Spain, mobility navigators often provide very different paths to reach two very close destinations, as shown by the example in Figure 1, where two almost identical destinations are suggested to follow completely different routes.

In this work we develop an analytical framework implementing the concept of path stability – namely, a measure of how much small perturbations to the destination of a trip change the best path to reach it – and then apply it to evaluate empirically the presence and size of the phenomenon in several different cities all around the world, analyzing the results from several perspectives, trying to answer a list of questions that arise:

- **Q1**: Is path stability affected by distance from the city center?
- **Q2**: Which cities are more path-(un)stable?
- **Q3**: Does the magnitude of perturbation affect stability?
- **Q4**: Do features of the road network affect stability?
- **Q5**: Is the shape of the road network relevant?
- **Q6**: Can cities be classified into homogeneous groups?
- **Q7**: Are there spatial patterns of instability?

Our results show that path stability clearly depends both on city factors, in particular the shape of the road network, and on characteristics of the trips analyzed, such as the distance from the city center. Moreover, there exists a significant variability in the overall path stability across the several cities analyzed, allowing us to talk about *path-stable* and *path-unstable* cities.

This work stems from our previous paper [2], which proposed a first formulation of path instability (here revised) and presented some preliminary results (here greatly extended, including a more robust experimental setting and a much deeper exploration of results). The source code to reproduce all experiments is available as open source[1].

In the following sections, we review the relevant literature on the topic (Section 2), describe our approach (Section 3), present the experiments and results (Sections 4 and 5), and finally provide a discussion and conclusive remarks (Sections 6 and 7).

2 Related Work

Road networks form the backbone of modern transportation systems, serving as the circulatory system that facilitates the movement of people and goods within urban landscapes. Understanding and optimizing traffic flow in these networks is a fundamental challenge in transportation research, with significant implications for efficiency, safety, and environmental sustainability. Despite variations in the geographical features (e.g., seas, rivers, mountains, and coastlines), historical contexts, and socio-economic factors that shape urban areas, road networks exhibit universal characteristics and follow scale-invariant patterns [3].

Studying the structure of cities. At their core, cities mostly exhibit a monocentric structure, where urban activities are concentrated around a central area, leading to radial expansion. This expansion is often characterized by a density gradient, where population and socio-economic activities diminish with distance from the center [4]. Crucitti et al. [5] observed that the road networks of self-organized cities exhibit scale-free properties akin to non-spatial networks, whereas planned cities do not. Additional studies have identified various scaling properties of urban and road networks, such as topological and geographical distances and the distribution of betweenness centrality in urban road networks [4, 6–8].

Urban road networks are almost planar [3, 6] and characterized by a narrow range of node degrees [6]. Barthelemy et al. [3] identified a power-law relationship between the total network length and the number of nodes. Lee et al. [4] examined the travel-route efficiency of road networks using the detour index (DI) [9, 10], which measures the ratio between the shortest path distance and the straight-line distance between two locations. Their research revealed universal properties across cities, such as a constant DI regardless of distance from the city center and a negative correlation between DI and road density.

Routing over the road network. The understanding of general road network characteristics has driven extensive research into how to navigate these networks efficiently. While the optimal path (e.g., the shortest or fastest path) represents the most

[1] In case of acceptance, the link to the GitHub repository will be shared here.

intuitive approach for routing from origin to destination [11, 12], relying exclusively on these paths can exacerbate traffic congestion and increase CO2 emissions from a collective standpoint [13–16]. A way to overcome this problem and to distribute the vehicles more evenly on the road network is to go beyond the optimal path assignment using Alternative Routing (AR) algorithms [17] that provide a plurality of alternative paths between an origin and a destination location in a road network. According to Wang et al [18], 98% of roads are underutilized, while 15% of highway-based routes have faster alternatives, demonstrating the potential for more efficient traffic distribution.

Several methods exist for generating alternative routes. Edge-weight-based approaches compute k alternative paths by iteratively recalculating shortest paths while updating the edge weights after each iteration [1, 17, 19]. Plateau-based methods, on the other hand, generate alternatives by identifying common branches between the shortest-path trees of the origin and destination [20]. Other AR algorithms generate k paths that satisfy a dissimilarity constraint and a desired property. For instance, Chondrogiannis et al. [21] introduced the k-Shortest Paths with Limited Overlap (kSPLO), seeking to recommend k-alternative paths that are as short as possible and sufficiently dissimilar. Additionally, Chondrogiannis et al. [22] formalized the k-Dissimilar Paths with Minimum Collective Length (kDPML) providing k paths sufficiently dissimilar while having the lowest collective path length. Hacker et al. [23] proposed the k-Most Diverse Near Shortest Paths (KMD), which recommends k near-shortest paths (based on a user-defined cost threshold) with the highest diversity.

AR solutions are also employed in Traffic assignment (TA), where vehicle trips are allocated across a road network to reduce congestion and travel time [24]. For example, the METIS algorithm [25] integrates AR, specifically the k-Most Diverse Near Shortest Paths algorithm [23], into a one-shot TA process. This method has shown that generating alternative routes can improve traffic distribution and mitigate negative externalities of congestion [25].

Position of our work

Our study focuses on an aspect of mobility over road networks closely related to alternative routing. In contrast to standard approaches, which aim to induce algorithmically some variability of paths over the road network, we study the intrinsic tendency of a network to spontaneously produce diversified routes. Specifically, we introduce the concept of shortest path stability to quantify a road network's propensity to either maintain a consistent path or offer significantly different route options for destinations that are only slightly different.

3 Methods

Path stability refers to the degree to which route alternatives remain similar when the destination location is slightly changed. Our approach to evaluate path stability involves three key stages: *(i)* generating perturbations to simulate variations in trip destinations, *(ii)* calculating the shortest paths for these perturbed destinations, and *(iii)* measuring the similarity between the original and perturbed paths using a weighted Jaccard index.

3.1 Path Perturbations

Given an origin-destination (OD) pair (o, d), namely a trip from a starting location o to an endpoint d, we assess its *shortest path stability* $S_\Delta(o, d)$ by creating variations of the destination d applying small perturbations of magnitude Δ (defined below). These perturbations simulate slight changes in the destination location, offering insights into how consistent the shortest paths remain.

More formally, to perturb the destination location d, we identify candidate alternative nodes in the road network within a ring defined by the radial distance interval $\Delta = [\Delta_{\min}, \Delta_{\max}]$ around the original destination d (as illustrated in Figure 2a). These nodes represent candidate alternative destinations. To ensure even geographic distribution, we divide the ring into k sectors. For each sector, we select a representative node based on the following criteria: if a sector contains no nodes, no point is selected. If a sector has only one node, that node is selected. In sectors with multiple nodes, we choose the node closest to the center of the sector to maintain spatial balance. This approach results in a set of perturbed destinations $D_\Delta(d) = \{d^x\}$, where x denotes the sector and Δ the displacement interval, containing zero to k displaced destinations, depending on node availability.

For an OD pair (o, d), we compute the shortest path $p(o, d)$ from the origin to the destination. We then calculate the shortest path for each of the perturbed destinations forming the set of perturbed shortest paths $P_\Delta(o, d) = \{p(o, d^x) \mid d^x \in D_\Delta(d)\}$, where each d^x is a perturbed destination within the displacement interval Δ.

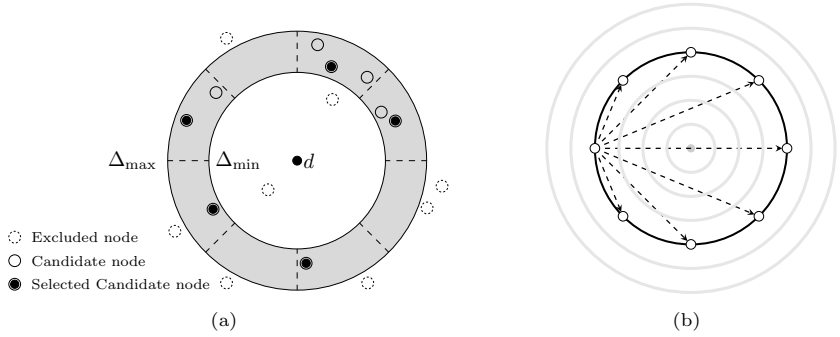

Fig. 2 (a) The destination perturbation process for a given destination d. A ring (shaded in gray) of radial boundaries $\Delta_{\min}$ and $\Delta_{\max}$, representing the displacement interval, is centered around the destination d. Nodes outside the ring (dashed circles) are excluded. The ring is divided into sectors, each containing candidate nodes (empty circles). For each sector, a representative node (filled circle) is selected based on proximity to the sector's center. (b) The radial sampling approach used for generating origin-destination (OD) pairs, featuring multiple concentric circles centered around the city center. In a detailed view of a single circle (in black), each node is connected to all other nodes along the same circumference, thereby forming several origin-destination pairs. For the sake of readability, here we show sample OD pairs relative to a single origin.

To ensure realistic perturbed destinations, we exclude any d^x that would require an impractical detour, such as destinations located on the opposite side of or behind the original destination along a highway. Reaching these points would necessitate a U-turn

or an exit and re-entry on the highway, making them infeasible for realistic analysis. To identify and exclude these outliers, we calculate the ratio between the length of route $p(d, d^x)$ and the maximum displacement distance (Δ_{max}). We then remove any d^x yielding a ratio that falls beyond the 95th percentile of the value distribution.

3.2 Path Stability

We evaluate the shortest path stability $S_\Delta(o, d)$ of an OD pair (o, d) by analyzing how much the original shortest path $p(o, d)$ deviates from its perturbed counterparts $P_\Delta(o, d)$ where small changes are introduced to the destination.

We quantify this variation using the Jaccard Index (also known as Intersection over Union, IoU), a widely recognized metric for measuring the similarity between sets. In this context, each route is represented as the set of road segments it traverses. To account for the relative importance of each road segment, we use a weighted Jaccard Index [26], incorporating road segment lengths as weights. Weighting each segment based on its length ensures that not only the number of shared segments but also their relative significance within the routes is considered. The weighted Jaccard Index is calculated as follows:

$$J(A, B) = \frac{\sum_{i \in A \cap B} w_i}{\sum_{i \in A \cup B} w_i}$$

where A and B are the routes represented as sets of road segments, and w_i is the length of road segment i. A value of $J(A, B) = 1$ indicates that routes A and B are identical, denoting maximum path stability. Conversely, $J(A, B) = 0$ implies that A and B share no common road segments, indicating total path instability. Intermediate values reflect varying degrees of stability, with lower values indicating greater divergence between the routes.

To compute the stability $S_\Delta(o, d)$ for a given OD pair (o, d), we consider the set of perturbed paths $P_\Delta(o, d)$ associated with it. If an OD pair has no perturbed paths, it is excluded from the analysis. When perturbed paths are available, we assess the stability of the shortest path by calculating the Jaccard coefficient between the original shortest path and its perturbed counterparts. This results in a set of Jaccard values $\{J(p(o, d), \hat{p}) \mid \hat{p} \in P_\Delta(o, d)\}$ representing the similarity between the original and perturbed routes. The stability $S_\Delta(o, d)$ of the OD pair (o, d) is then quantified as the average of these Jaccard values:

$$S_\Delta(o, d) = \frac{1}{|P_\Delta(o, d)|} \sum_{\hat{p} \in P_\Delta(o,d)} J(p(o, d), \hat{p})$$

3.3 City-wide Stability Aggregation

To assess the overall stability of the shortest paths across an entire city, it is necessary to analyze the shortest path stability of multiple origin-destination pairs within the road network. Given the impracticality of analyzing every possible OD pair, we generate a representative sample of OD pairs that capture the spatial characteristics of the city's road network using a fixed-radius sampling. Finally, we aggregate the path

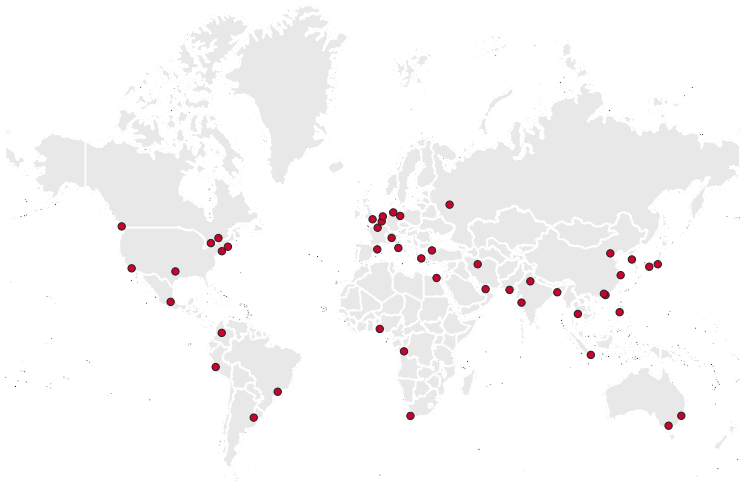

Fig. 3 Cities adopted in this work. The selection covers 46 areas from all continents: 16 in Asia, 12 in Europe, 8 in North America and 4 in South America, 4 in Africa and 2 in Oceania.

stability values $S_\Delta(o, d)$ for all OD pairs either through global measures or through a box-plot distribution.

OD Pairs Generation. To systematically sample OD pairs, we employ a fixed-radius sampling method that scans the network radially outward from the city center. This radial sampling approach, commonly used in urban studies to measure spatial metrics or patterns [4, 10], avoids the biases often associated with traditional origin-destination matrices. As illustrated in Figure 2b, we draw concentric circles from the city center at r_{step}-km intervals, extending from $r_{\min}$ km to $r_{\max}$ km, to represent increasing distances from the urban core to the periphery. For each circle at a given radius, we select n equally spaced points along the circumference. Each point is matched to the nearest road network node within a given distance threshold. If a point has no nearby match (e.g., if it falls in an inaccessible area such as water bodies, forests, or other unconnected terrain), it is excluded from the sample. The nodes lying on the same circle are paired, generating up to $n \cdot (n-1)$ OD pairs per circle. This systematic approach ensures that the selected OD pairs represent diverse trip lengths and geographic areas, from the urban core to more peripheral areas.

4 Experimental Settings

Dataset. We compute the path stability for 46 large-scale cities from diverse regions across the globe, shown in Figure 3. A complete list is also provided in Table 4 on page 21, together with several indicators that will be described in the next sections. The selection includes capital cities, economic hubs, and megacities from all the continents. The road network data for each geographical area of interest was obtained from OpenStreetMap (OSM[2]).

[2] https://www.openstreetmap.org/

OD sampling. Following our experimental strategy, for each urban scenario, we generate OD-pairs using the fixed-radius sampling approach. For each city, we identified the city center based on geographic coordinates sourced from latlong.net, and from there, we defined concentric circles at radii ranging from $r_{\min} = 1$ km to $r_{\max} = 30$ km, with a step size $r_{\text{step}} = 1$ km. This approach ensures that our OD pairs are distributed across varying distances from the urban core to the periphery, capturing both central and outlying areas. Here, adopting a fixed-radius sampling strategy ensures comparability of analyses across cities, regardless of their different sizes. Additionally, we avoided using administrative borders, as they often do not align with the actual extent of the road network. While alternative approaches could adjust the radius based on the structural size of a city's road network, they would introduce a parameter selection phase, potentially making the comparison of results harder.

For each concentric circle, we selected 36 evenly spaced points along the circumference at 10° intervals. These points were matched to the nearest road network node within a distance threshold of 500 meters. This method generated a maximum of 37,800 potential OD pairs per city, assuming all points were accessible.

OD perturbation. For each OD pair (o, d), we systematically displaced the destination within a radial displacement interval $\Delta = [0, 100]$ meters, selecting perturbations in k=8 distinct sectors to ensure even geographic distribution around the original destination. The choice of the displacement interval was driven by the fact that much larger perturbations will naturally lead to completely different destinations, while our objective is to study the (unexpected) effects of small displacements that do not change the meaning of the trip, mostly keeping at walking distance from the original destination. In addition, preliminary tests showed that larger displacement intervals yield very similar results, yet with lower stability levels – as expected.

Shortest path computation. To retrieve the shortest path between an origin location o and a destination location d, we utilize the OSMnx service, which interfaces with OpenStreetMap. Through this service, we obtain a path p representing the shortest route (the one with minimum length) to reach the desired destination d, starting from the specified origin location o.

Filtering abnormal perturbed paths. As discussed in Section 3.1, outlier perturbed destinations are identified by calculating the ratio between the length of route $p(d, d^x)$ and the maximum displacement distance ($\Delta_{max} = 100$ meters). We then remove any d^x yielding a ratio larger than the 95th percentile. In our study, this threshold is approximately 30, meaning we exclude any d^x if the length of $p(d, d^x)$ is greater than 3 km.

5 Results

In this section, we present the results obtained from the analysis over the 46 large-scale cities described above, based on the computation of shortest path stability for several OD pairs and their comparison against perturbations of the destination locations. In particular, we try to answer to the set of research questions introduced in Section 1.

Q1: Is path stability affected by distance from the city center?

Here we study how the perturbation of destinations affects the shortest path across different rings of the radial sampling defined in Section 3. The results are described in terms of the stability $S_\Delta(o,d)$ of OD-pairs sampled at varying distances from the city center, aggregated across all cities.

Figure 4(left) illustrates the relationship between median path stability $S_\Delta(o,d)$ for OD pairs sampled at different distances r from the city center, each gray line representing a different city. The overall trend indicates that path stability increases with distance from the urban core, plateauing at near-complete stability at greater distances. This trend is well-fitted by the exponential function represented by the equation $y = a \cdot e^{-bx} + c$, where the parameter values are $a = -0.26$, $b = -0.43$, and $c = 0.99$, yielding a R^2 value of 0.98. The exponential fit highlights that at shorter distances (0-5 km), the median stability values are relatively low, reflecting greater variability in shortest paths when slight perturbations are applied to the destination. As the distance from the city center increases beyond 5 km, the stability values rise sharply. Beyond 10 km, the stability of the paths converges toward 1, meaning that perturbed paths almost entirely overlap with the original shortest paths. While the general trend is universal across cities, some cities exhibit different levels of stability, as reflected by the slight variations in the individual city curves (see Figure 4(left) and Figures S1-S46 in the Supplementary Material).

Since origins and destinations sampled farther from the city center are on average at a larger distance from each other, it is quite natural to question whether the OD distance is actually the only relevant factor to determine path-stability. In order to explore this, we analyse the distribution of path-stability for different intervals of OD length, as reported in Figure 4(right). As we can see, higher OD distances (red and yellow curves) show a higher path-stability, as expected. However, the dependency of path-stability from radial distance remains very strong, and indeed the general increasing trend found in Figure 4(left) is preserved for each OD distance interval.

Since origins and destinations located farther from the city center tend to be also farther apart, it is natural to ask whether OD distance alone determines path stability. To investigate this, we analyze the distribution of path stability across different OD distance intervals, as shown in Figure 4(right). As expected, longer OD distances (red and yellow curves) correspond to higher path stability. However, the influence of radial distance remains strong. In fact, the overall increasing trend observed in Figure 4(left) persists within each OD distance interval, hence confirming that the radial distance plays an important role by itself.

Q2: Which cities are more path-(un)stable?

Figure 5 presents the distribution of path stability $S_\Delta(o,d)$ among the 46 cities considered in this study through box plots sorted in increasing order of median stability. While the median stability varies only slightly between cities, as expected, the distribution within each city reveals significant heterogeneity. Some cities exhibit a broad range of stability values, while others maintain more consistent stability across their networks. In general, most cities display high median stability, with values approaching

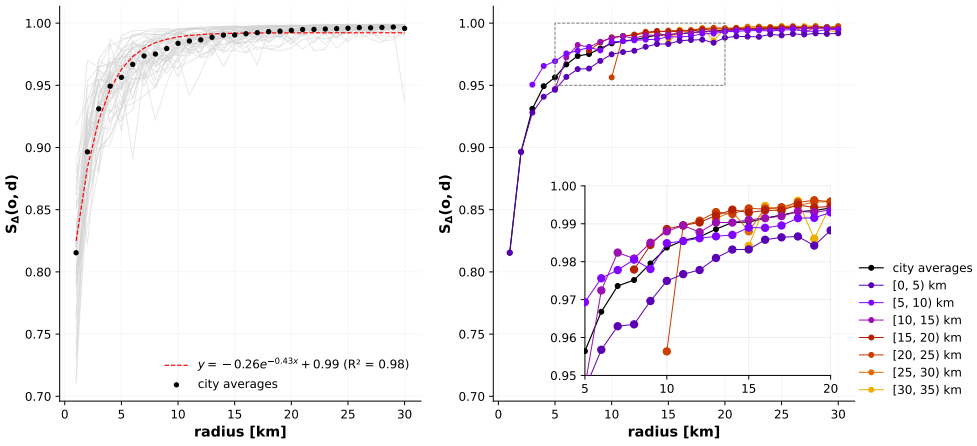

Fig. 4 (left) Median path stability $S_\Delta(o, d)$ for OD pairs at varying radial distance r from the city center. Each gray curve represents the stability of a single city, the black points indicate the city averages, and the red line represents exponential fit $y = a \cdot e^{-bx} + c$. (right) The same plot for different values of OD distance.

1, indicating that small perturbations in destination locations typically have minimal impact on the shortest paths. However, variability still exists, as reflected in the spread of the box plots, where the interquartile range highlights the degree of variation within each city. Some cities, such as Hamburg, Dhaka, and Bruxelles, emerge as "path-stability islands", demonstrating consistently high stability for most of the OD pairs and not just on average. In contrast, cities such as Vancouver, Buenos Aires, and Barcelona—among the least path-stable—exhibit much wider dispersions and significant variability in path stability across different OD pairs. This suggests that certain areas within these cities experience much higher instability than others. Confirming our intuition, Barcelona ranks among the most path-unstable cities, placing 8th globally and 2nd in Europe in terms of median path stability and 2nd globally in terms of interquartile range, surpassed only by Buenos Aires.

Q3: Does the magnitude of perturbation affect stability?

To further understand the factors contributing to low path stability, we analyzed the connectivity between each original destination d and each of its perturbed counterparts $d^x \in D_\Delta(d)$. In particular, we measure the length of the shortest path $p(d, d^x)$ between d and d^x instead of the simple straight line distance, in order to account for the effective travel distance that in some cases can be much larger. This measure can be interpreted as the effort required to reach the new (perturbed) destination while keeping the path followed to reach the original one. Figure 6(left) reveals a strong negative correlation (Pearson's correlation $r = -0.634$, Spearman's correlation $\rho = -0.705$) between the median $p(d, d^x)$ length and path stability, suggesting that cities where perturbed destinations are closely connected (in terms of route length) to the original destination tend to have higher path stability – or, in other terms, the original

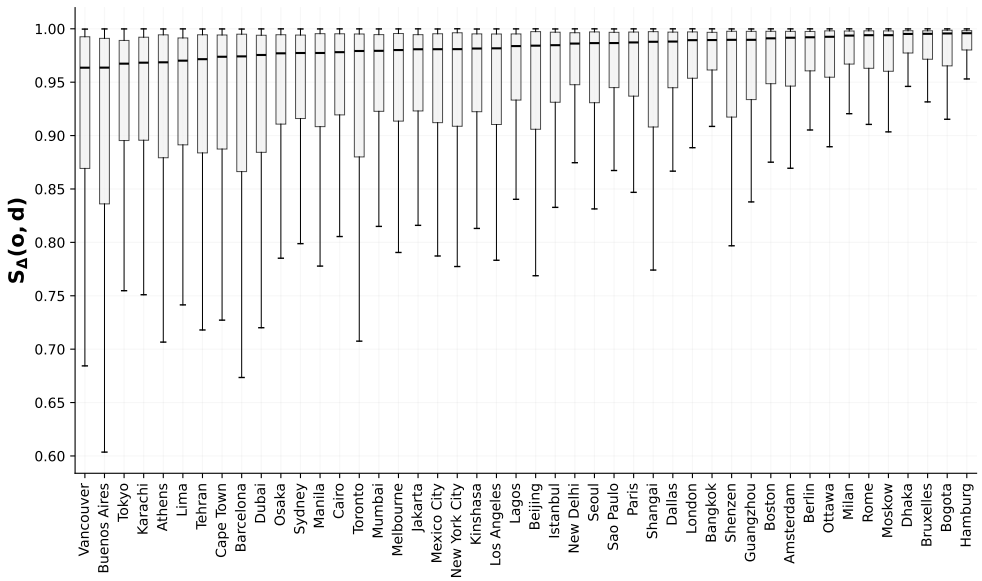

Fig. 5 Distribution of path stability $S\Delta(o,d)$ across 46 cities, represented through box-plots sorted in increasing order of median stability.

shortest path needed only minor corrections to reach the new destination–, while cities with longer $p(d,d^x)$ generally exhibit lower path stability. While this pattern applies to most cities, some outliers deviate from it – highlighted in the figure with their name. For instance, Vancouver and Karachi show relatively low stability (0.964 and 0.968, respectively) despite short $p(d,d^x)$ lengths (105 and 110 meters), indicating notable sensitivity to small destination shifts. Meanwhile, cities like Barcelona and Tehran show both low stability (0.974 and 0.971, respectively) and longer $p(d,d^x)$ paths (242 and 246 meters).

We extend the analysis by normalizing the length of $p(d,d^x)$ w.r.t. the original route length, namely $R = l(p(d,d^x))/l(p(o,d))$, where $l(x)$ denotes the length of path x, in meters. Figure 6(right) illustrates the relationship between route stability and the ratio R. The negative correlation against stability is confirmed and also significantly strengthened ($r = -0.832$, $\rho = -0.912$). We can also observe that the normalization moved some outliers of the previous plot close to the general trend (Karachi and Vancouver in the left part, Tehran on the right part), while Barcelona remained far from it, confirming its outstanding behaviour.

Q4: Do features of the road network affect stability?

The ability of a road network to exhibit path-stable or path-unstable alternative paths is inherently shaped by the underlying network frame. To try to unveil the impact of the road network on stability, we investigated the relationship between path stability

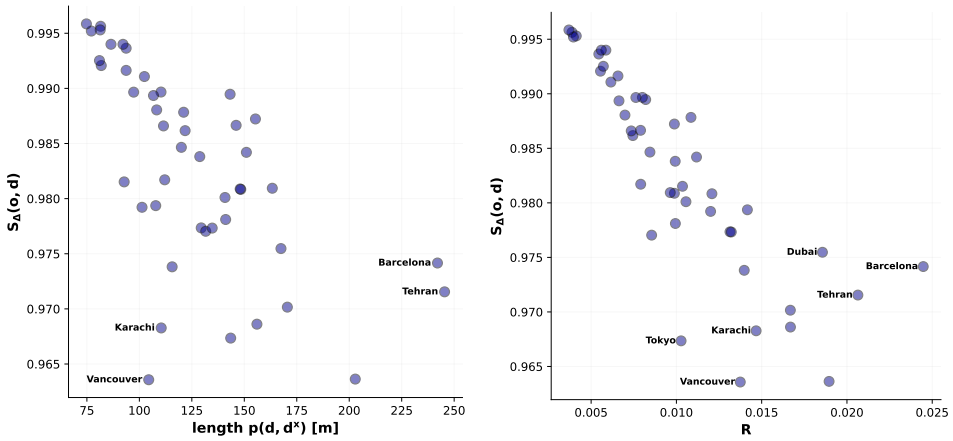

Fig. 6 (Left) Shortest path stability $S_\Delta(o, d)$ (median) vs. distance between original destination d and each of its perturbed counterparts $d^x \in D_\Delta(d)$ (median). (Right) Same plot, but using a distance R normalized over the original path length.

$S_\Delta(o, d)$ and network-based measures. We considered: average street length, its standard deviation, road circuity (defined as ratio between road length and the straight line distance of its endpoints), density of intersections and roads, total road length.

We found a moderate positive correlation ($r = 0.477$, $\rho = 0.540$) between path stability and average street length across cities (see Figure 7(left)), indicating that cities with longer average street segments experience higher path stability. Indeed, longer segments reduce intersections, or "decision points", minimizing route divergence. In contrast to this general trend, Buenos Aires and Vancouver emerge as outliers, displaying lower-than-expected stability despite longer street segments. Moreover, we find a moderate correlation between stability and the standard deviation of edge lengths ($r = 0.593$, $\rho = 0.605$), suggesting that greater variability in edge length enhances stability. Finally, we found a smaller yet significant correlation with the edge-level circuity ($r = 0.401$, $\rho = 0.398$, shown in Figure 7(right)). No meaningful relationships emerged between stability and the other measures.

Q5: Is the shape of the road network relevant?

Beside statistical properties of the road network, also its geometrical configuration might in principle have a strong impact on how shortest paths change. Modern, very regular networks typically allow several alternative paths of similar length to reach the same destination, whereas networks in older or geographically constrained cities provide more limited choices.

We characterize such configurations in two ways:

1. **Entropy of orientation:** we measure how much the road network has a strict grid shape by analyzing the bearing of roads, measuring the entropy of its probability distribution following the methodology outlined in [27]. Grid cities will concentrate bearings along very few directions (for instance four, if all the city grids are aligned),

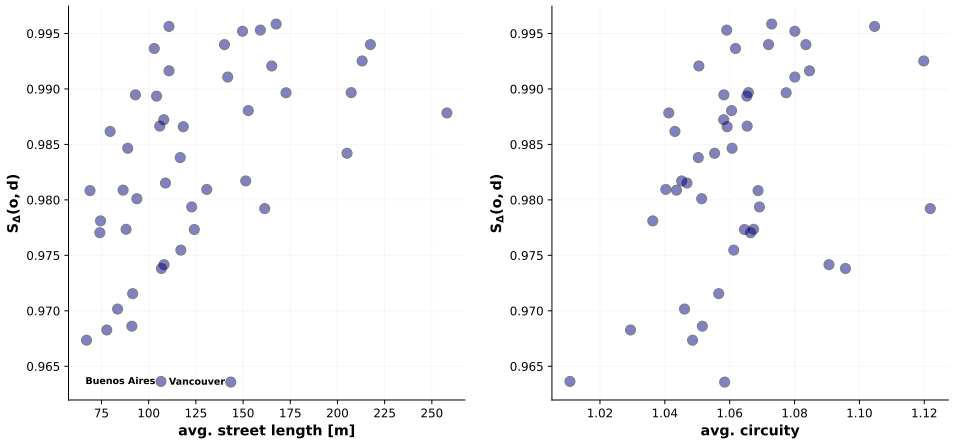

Fig. 7 Shortest path stability $S_\Delta(o,d)$ (median) vs. average street length (Left) and vs. average road circuity (Right). The smaller is the latter, the more straight the roads are.

and will thus be identified by lower entropy values, whereas non-grid ones will be more chaotic, and thus yield a higher entropy;

2. **Urban studies approach:** we refer to the traditional classification adopted in the studies on urban configurations, consisting in three categories: Grid, defined as above; Radial, where roads mainly depart from a center of the city; and Organic, where roads developed around landmarks (hills, rivers, walls, etc.) and/or were added in stratifications without a consistent plan [28]. In this case, our cities were associated to the corresponding class through visual inspection of the road network. Other city classifications have been discussed and proposed in the literature, including some inferred from data through machine learning tools [29], yet exploring them in depth would go beyond the scope of this work, thus we chose to adopt a simple and well established model.

Entropy-based categorization. Here we study the relation between stability and entropy of road bearing, through a plot similar to the previous ones. The results, depicted in Figure 8, show a weak positive correlation between the two values ($r = 0.259$, $\rho = 0.357$). In particular, we can identify a large top-right group of cities with high entropy (most likely having an irregular road network) associated to medium-high stability; and a small group of four cities (Toronto, Vancouver, Melbourne and Beijing) showing a very low entropy and medium-low stability. These results provide a first confirmation of the hypothesis that highly regular (i.e. low entropy) road networks in general lead to lower shortest path stability, although results in the cases of medium and high entropy remain a bit unclear.

Urban studies classification. In Table 1 we associate the road network of the cities under analysis to the three groups mentioned above (Grid, Radial, Organic), also providing, for each city, a thumbnail representation of the road network covering a 6×6 km area around the center. The most common configuration is the Organic one (27 cities), which is predominant in Europe and Asia, followed by Grid (15 cities),

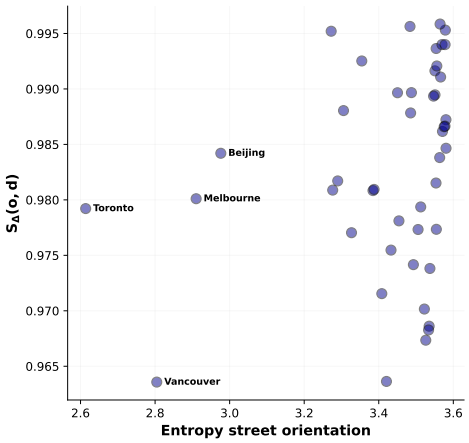

Fig. 8 Shortest path stability $S_\Delta(o,d)$ vs. entropy of road bearing (median). Low entropy values represent cities with a grid-like structure.

predominant in North America, and only a few Radial ones (4 cities), most of them in Europe.

Table 2 shows aggregate stability values grouped by road network shape, together with information on the length of path deviations, streets length and entropy of bearing. As we can see, the cities classified as Grid show a lower stability, followed by Organic cities and, as most path-stable category, Radial. These results generally confirm those obtained through entropy of bearing, and indeed the most path-unstable group of cities (Grid) is also the one with the lowest average entropy. The Organic group arrives rather close to the Grid one along all the measures provided although the entropy of bearing is significantly larger. A closer inspection reveals that the two approaches (entropy vs. shape) simply model the concept of regularity in a different way. In particular, entropy enforces a rather strict requirement that recognizes as regular only quasi-perfectly grid structures (as in the case of the group of four very low-entropy cities highlighted in Figure 8, which indeed are all marked as Grid also in Table 1), whereas cities containing grid-like modules would be confounded with irregular ones, since different modules might be oriented in different directions, thus increasing the entropy of headings. Similarly, Radial shapes – though generally speaking more regular than Organic ones – exhibit an even larger bearing entropy, showing that entropy is not a good criterion to identify them. The study of urban shape, instead, is by definition more flexible, yet also (inevitably) slightly subjective, since human discernment is involved.

A comparison between the path deviations (in particular their normalized length, R) and the stability values show that Grid networks usually lead to longer paths to cover the perturbation introduced, thus suggesting that the lower stability of shortest paths might be related to the difficulty of reaching the new destination by just extending the path that reached the original one – for instance because the new one ends up in a completely different street or because one-way roads make the path "correction" impossible.

City	Shape		City	Shape		City	Shape	
Amsterdam	Radial		Athens	Organic		Bangkok	Organic	
Barcelona	Grid		Beijing	Grid		Berlin	Radial	
Bogota	Grid		Boston	Organic		Bruxelles	Organic	
Buenos Aires	Grid		Cairo	Organic		Cape Town	Organic	
Dallas	Grid		Dhaka	Organic		Dubai	Grid	
Guangzhou	Organic		Hamburg	Organic		Istanbul	Organic	
Jakarta	Organic		Karachi	Organic		Kinshasa	Organic	
Lagos	Organic		Lima	Grid		London	Organic	
Los Angeles	Grid		Manila	Grid		Melbourne	Grid	
Mexico City	Grid		Milan	Radial		Moskow	Radial	
Mumbai	Organic		New Delhi	Organic		New York	Grid	
Osaka	Organic		Ottawa	Grid		Paris	Organic	
Rome	Organic		Sao Paulo	Organic		Seoul	Organic	
Shangai	Organic		Shenzen	Organic		Sydney	Organic	
Tehran	Organic		Tokyo	Organic		Toronto	Grid	
						Vancouver	Grid	

Table 1 City shapes and road network thumbnails.

shape	n.	$\mathbf{S_{\Delta}(o,d)}$	length $\mathbf{p(d,d^x)}$ [m]	R	average street length [m]	entropy bearing
Grid	15	0.979	140.277	0.012	130.149	3.255
Organic	27	0.984	122.864	0.010	119.206	3.511
Radial	4	0.993	88.931	0.006	149.086	3.558

Table 2 Aggregate Shortest path stability $S_{\Delta}(o,d)$, length and normalized length (R) of path deviation $p(d,d^x)$, average street length and the entropy of street orientations vs. overall shape of the road network.

Q6: Can cities be classified into homogeneous groups?

We also investigate whether cities can be grouped into homogeneous clusters based on their routing characteristics and road network features, aiming to reveal shared structural attributes that influence path stability. This clustering approach highlights patterns across diverse urban layouts, creating stability profiles that reflect each cluster's unique structural characteristics. It is important to note that stability was not used as a clustering attribute; rather, it is analyzed post-clustering to understand how stability relates to each group. Our analysis considers several network and routing-related features, including the length of $p(d,d^x)$, the ratio between $p(d,d^x)$ and $p(o,d)$ (R), the average and standard deviation of street lengths, average road circuity, and entropy of street orientations. These values are reported in Table 4. Clustering was performed using the standard K-means clustering algorithm, determining an optimal number of clusters ($k=4$) through the elbow method [30].

Each cluster, represented in Table 3 by mean values of these attributes and overall stability, presents distinctive patterns of stability and network structure across cities. Cities in **Cluster 0** (including Rome, Shanghai and Hamburg) exhibit the highest route stability (0.993), likely due to shorter route length between original and perturbed destinations (89.89 meters) and lower ratio R. These cities have the longest and most varied street lengths, with an average of 172.65 meters and high variability, suggesting a complex layout with both long and short segments. The relatively high road circuity (1.08) indicates winding roads, and the high entropy of street orientations, together with a slight predominance of Organic cities suggests a non-regular road network structure.

Cluster 1 (including Tokyo, New York City and Sao Paulo) is the largest group, including 24 cities with moderately high stability (0.982) and shorter average street lengths. The road circuity is lower than in Cluster 0 (1.06), indicating straighter and more direct roads. These cities are mainly characterized by non-grid layouts, as reflected by their high entropy of street orientations (3.9) and the strong presence of Organic shapes. They also have shorter and less varied street lengths, along with a low R, further supporting stability, as destinations and their displacements are well-connected.

Cluster 2 (including Vancouver, Beijing and Melbourne) exhibits lower stability (0.977) and is associated with the lowest entropy of street orientations (2.83), typical of cities with a regular, grid-like road network – and indeed it contains only Grid

shapes. Although their length of route $p(d, d^x)$, circuity, and the ratio R are similar to those in Cluster 1, the grid-like structure contributes to slightly reduce stability.

Cluster 3 (including Buenos Aires, Barcelona and Lima) has the lowest stability (0.971) due to the highest ratio R and the greatest deviation distance between original and perturbed destinations, which forces substantial detours resulting in high path divergence. This cluster also exhibits the lowest circuity (1.05), suggesting a network with primarily straight roads that lack the flexibility seen in clusters with higher circuity. The cities in this cluster typically feature short and less varied street lengths, containing a mix of Organic and Grid road networks – the latter probably representing borderline cases of their shape category, since the average entropy of orientations if rather high (3.47).

In summary, this clustering analysis identifies key factors for path-stable and path-unstable profiles within urban road networks. Path-stable profiles are associated with cities that have shorter route deviations (length of $p(d, d^x)$), low R, longer, varied street segments, and higher orientation entropy (and indeed, they contain a smaller proportion of Grid shapes). In contrast, path-unstable profiles are found in cities where destination perturbations result in higher deviation distances and greater R values, forcing substantial detours. Path-unstable profiles are often linked to cities with low circuity, short, uniform street lengths, and lower orientation entropy, mainly associated to Grid layouts.

Cluster	$S_\Delta(o,d)$	length $p(d,d^x)$ [m]	R	avg. street length [m]	std street length [m]	average circuity	entropy of bearing	G-R-O
0	0.993	89.889	0.006	172.646	255.944	1.076	3.494	2-3-7
1	0.982	125.693	0.010	103.908	135.172	1.058	3.492	5-1-18
2	0.977	124.384	0.012	150.942	186.241	1.072	2.826	4-0-0
3	0.971	197.395	0.019	99.640	146.042	1.053	3.469	4-0-2

Table 3 Output clusters obtained by K-means over city indicators, including the number of cities in the different shape categories (Grid-Radial-Organic). Notice that *stability* and shape information are only used as explanatory variables, not involved in the clustering.

Q7: Are there spatial patterns of instability?

In order to answer to this question, we first define the stability $S_\Delta(d)$ of a destination location d as the average of the stability values obtained considering all possible origins under the radial sampling used, namely $S_\Delta(d) = avg_o S_\Delta(o, d)$. Then, we study the geographical distribution of $S_\Delta(d)$. We do that through visualization over four highly diversified sample cities, each belonging to a different cluster of the clustering discussed above: Hamburg (Cluster 0), Tokyo (Cluster 1), Vancouver (Cluster 2) and Barcelona (Cluster 3). The results are shown in Figure 9 where destinations up to 10 km from the city center are considered and, for the sake of readability, locations are colored based on their stability value: values below the 20th percentile are shown in red (path-unstable locations); those above the 80th percentile are in blue (path-stable locations); the others are depicted as empty circles. A complete list of plots for all cities is provided in Figures S1-S46 in the Supplementary Material.

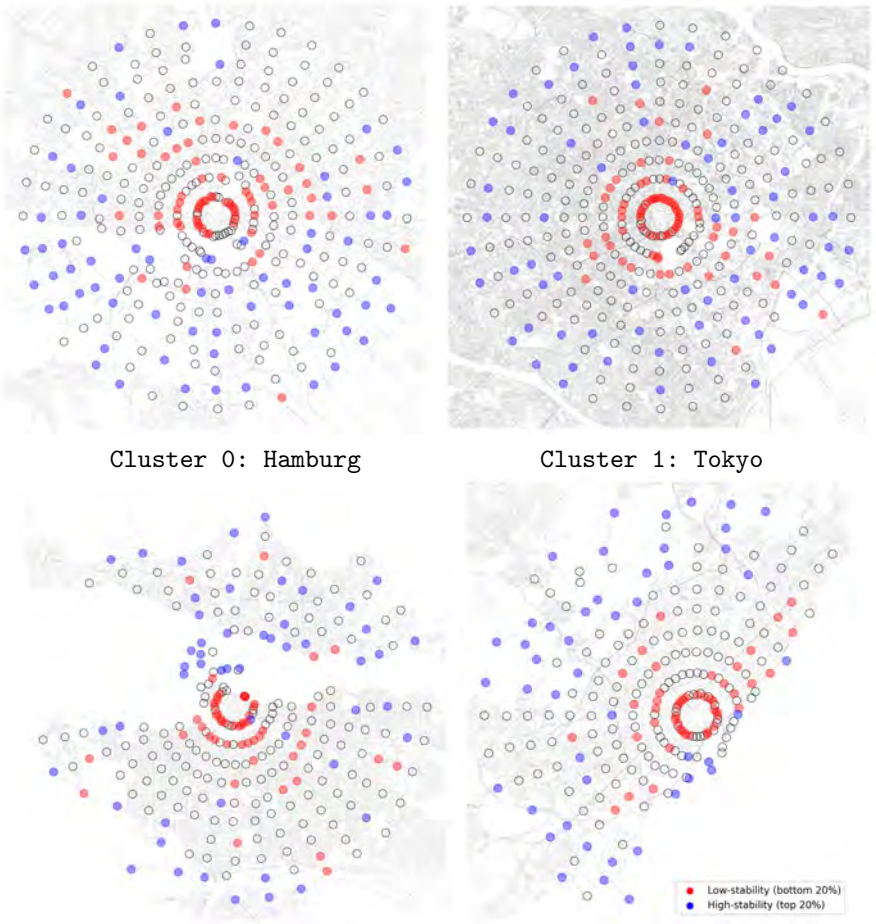

Fig. 9 Spatial distribution of path-stable (blue) and path-unstable (red) destinations in four cities.

We can observe a few common patterns. First, path-unstable destinations are mostly concentrated in the central areas, whereas path-stable ones cover higher distances from the center. This confirms the general trend shown in Figure 4(left). Second, path-stable destinations are more concentrated in areas with a sparse local road network, as it happens in the North-West of Barcelona and the South of Hamburg. Roads in Tokyo are dense everywhere, and indeed the path-stable destinations are distributed more homogeneously. A special case is Vancouver, where the harbor divides the city in two areas, connected by two bridges: this highly constrains paths connecting origins in one part to destinations in the other, reducing the availability of choices – and thus increasing stability, especially of the Northern part, which is smaller and then most of its OD pairs start from the other side and cross the bridge. Third, there is a clear spatial autocorrelation, namely path-unstable destinations tend to cluster together,

rather than disperse randomly, not only in the center (where it is straightforward for their high density) but also in farther layers of the city.

6 Discussion

A universal pattern. The phenomenon of shortest path instability is not limited to our motivating example of Barcelona, which indeed exhibits high instability levels confirming our initial intuition, but instead manifests universally, albeit to varying extents. A consistent trend emerges: as distance from the city center increases, route stability grows and eventually plateaus in peripheral areas. While this stability trend is universal, each city maintains its own baseline level and rate of stability increase, influenced by distinct urban layouts, connectivity, and geographic factors.

Why does distance from the city center impact stability? Figure 4(left) shows that path stability increases with distance from the city center, following an exponential trend that levels off at near-complete stability beyond 10 km. Low stability in the city center (0-5 km) likely results from dense and complex road networks characterized by frequent intersections. Furthermore, short OD distances in these areas mean that $p(d, d^x)$ represents a larger fraction of the original path $p(o, d)$, contributing to lower stability, as demonstrated by the negative relationship between R and stability. Beyond 10 km, trips exhibit greater stability, likely due to their larger (average) length and the consequential transition into road networks that feature long-range, fast routes (such as highways, motorways, etc.). Trips gravitating at this distance from the city center tend to flow into such long-range connections, that represent the main part of the trip and remain unchanged when slightly perturbing the destination.

The role of the local context on perturbed destinations and stability. The relationship between the original destination d and its perturbed counterpart d^x plays a critical role in determining path stability. If the route between d and d^x is lengthy or indirect compared to their displacement (i.e. the straight distance between d and d^x), this suggests poor connectivity between d and d^x, potentially due to geographic or network constraints. In such cases, the shortest route $p(o, d)$ is less likely to align with the shortest route $p(o, d^x)$, as weak connectivity reduces the chance of overlapping shortest paths. Instead, totally different alternative routes from o to d^x might be more efficient compared to simply extending the original route $p(o, d)$ with an extra leg $p(d, d^x)$ to reach d^x. This indicates that path instability is strongly driven by connectivity limitations within the network. Conversely, if d and d^x are well-connected, allowing for a short and direct route, any divergence between routes $p(o, d)$ and $p(o, d^x)$ likely reflects the network's adaptability and the presence of multiple efficient paths rather than structural or connectivity constraints.

Not only the perturbed destination matters. The origin does too. The perturbed destination is essential to path stability, but the position of the origin, particularly the distance separating the origin from the destination, is equally pivotal. When the length of the original route from o to d is short, even a moderate perturbation cost can result in completely disjoint paths, as reaching the perturbed destination d^x may require a new directional approach rather than a simple extension of the original

route. In such cases, characterized by an high value of the ratio R, it is often more efficient for the shortest path algorithm to determine an entirely different route to d^x, resulting in lower stability. However, as the length of the original route $p(o, d)$ increases, R decreases and the influence of the perturbation diminishes.

The role of street length. As highlighted in Figure7a, longer streets tend to be associated with higher stability. This may happen as higher average street length may imply fewer intersections or "decision points" where alternative paths can diverge. In cities with shorter street segments, paths can branch more frequently, increasing the likelihood of different routes being chosen when a destination is slightly perturbed. This could lead to lower stability as multiple potential shortest paths exist. Conversely, in cities with longer streets, fewer choices at intersections may limit route variability, resulting in greater stability.

City path stability: a road network fault or a feature?

At the end of our journey, the natural question that arises is about the connotation we should give to stability. Is it a symptom of an issue, or an evidence of a virtuous city planning? While a definitive answer is far from our current reach, we can shed some light by recalling some of the insights provided along this paper. We do that observing that in terms of the role of the origin and destination in path stability there are primarily two scenarios driven by road network structure and connectivity.

First, in dense, flexible networks, even small displacements in the destination can prompt alternative routes due to abundant intersections and route choices, where the shortest path algorithm might select a new path rather than simply extending the original one. This type of instability reflects the network's adaptability, as alternative routes emerge naturally from minor destination shifts, suggesting a resilient layout and a virtuous road infrastructure plan.

In contrast, a low stability can also be "enforced" when the perturbed destination is poorly connected to the original, as weak connectivity between d and d^x compels the algorithm to determine an entirely different path. Here, path divergence stems not from choice but from the network's structural limitations, where insufficient local connectivity (low density of roads, inefficient one-way streets, etc.) prevents a seamless transition between nearby points.

In summary, path stability appears to be by itself a neutral characteristic of a road network, and instability can either reflect network flexibility with abundant route options or structural limits/constraints that mandate an entirely new route.

In more applicative terms, knowing the stability of an area can help in evaluation and planning tasks. Low stability indicates the presence of diverse alternative routes, which can be advantageous for dispersing traffic, especially in high-density events. For example, if an arena's surroundings exhibit low stability, slight shifts in destination could distribute incoming traffic over multiple routes, easing congestion near the event site. However, in settings where planners have designed high-capacity highways to manage and streamline large volumes of traffic, lower stability might counter these objectives. Stability around highways, where primary, high-efficiency routes are preferred, ensures that traffic is concentrated along these main arteries rather than dispersed across alternative paths. Thus, low stability near highways is not inherently

negative; rather, it reflects a network structure most likely intentionally designed to focus traffic flow through key conduits.

7 Conclusion

In this work, we examine the stability of the shortest path in response to small displacements of the destination location. We analyze path stability across 46 major cities worldwide, focusing on how network structure, local context, and spatial patterns affect path stability. Our findings reveal that path stability is a universal phenomenon, but it varies significantly with the road network's properties and trip characteristics. In particular, we highlighted significant relations between path stability and the trip's position (center vs. periphery), street lengths, the shape of the road network, length of the trips and reachability of the perturbed destinations. In conclusion, path stability provides a valuable lens for evaluating the adaptability and resilience of urban transportation networks. High stability offers predictability, which is particularly beneficial near highways to prevent spillover effects, whereas low stability in specific areas can provide the flexibility needed to alleviate traffic congestion by enabling alternative routes. Recognizing path stability's dual role as an indicator of resilience and flexibility enables city planners and transportation authorities to more effectively manage urban mobility, addressing the diverse needs of an evolving urban landscape.

rank	City	$S_\Delta(o,d)$	IQR	length $p(d,d^x)$ [m]	R	avg. street length [m]	std street length [m]	avg. circuity	entropy of bearing	Cluster
1st	Vancouver	0.964	0.123	104.459	0.014	143.491	187.235	1.058	2.804	2
2nd	Buenos Aires	0.964	0.155	202.879	0.019	106.532	78.974	1.011	3.421	3
3rd	Tokyo	0.967	0.094	143.515	0.010	67.088	71.896	1.049	3.526	1
4th	Karachi	0.968	0.096	110.417	0.015	77.797	102.936	1.029	3.534	1
5th	Athens	0.969	0.115	156.017	0.017	91.089	149.196	1.052	3.535	3
6th	Lima	0.970	0.100	170.522	0.017	83.527	99.988	1.046	3.522	3
7th	Tehran	0.972	0.111	245.429	0.021	91.523	167.629	1.057	3.408	3
8th	Cape Town	0.974	0.107	115.621	0.014	106.741	151.034	1.096	3.537	1
9th	Barcelona	0.974	0.129	242.051	0.024	108.123	194.674	1.091	3.493	3
10th	Dubai	0.975	0.110	167.475	0.019	117.045	185.789	1.061	3.433	3
11th	Osaka	0.977	0.084	131.615	0.009	74.131	102.240	1.066	3.327	1
12th	Sydney	0.977	0.078	134.706	0.013	124.176	157.358	1.065	3.505	1
13th	Manila	0.977	0.087	129.476	0.013	88.026	109.152	1.067	3.555	1
14th	Cairo	0.978	0.076	141.117	0.010	74.485	122.122	1.036	3.454	1
15th	Toronto	0.979	0.115	101.269	0.012	161.453	164.075	1.122	2.614	2
16th	Mumbai	0.979	0.072	107.801	0.014	122.786	170.461	1.069	3.513	1
17th	Melbourne	0.980	0.082	140.807	0.011	93.756	130.105	1.051	2.910	2
18th	Jakarta	0.981	0.071	148.323	0.012	68.916	89.483	1.069	3.385	1
19th	Mexico City	0.981	0.083	148.028	0.010	86.447	119.765	1.044	3.276	1
20th	New York City	0.981	0.088	163.346	0.010	130.767	126.963	1.040	3.387	1
21st	Kinshasa	0.982	0.073	92.759	0.010	108.892	176.730	1.047	3.554	1
22nd	Los Angeles	0.982	0.085	112.080	0.008	151.405	146.615	1.045	3.290	1
23rd	Lagos	0.984	0.062	128.778	0.010	116.709	106.864	1.050	3.563	1
24th	Beijing	0.984	0.091	151.000	0.011	205.068	263.547	1.055	2.976	2
25th	Istanbul	0.985	0.066	120.009	0.008	88.926	140.791	1.061	3.580	1
26th	New Delhi	0.986	0.049	121.806	0.007	79.577	110.559	1.043	3.571	1
27th	Seoul	0.987	0.066	111.498	0.007	118.322	177.761	1.059	3.576	1
28th	Sao Paulo	0.987	0.052	146.110	0.008	105.871	132.631	1.065	3.578	1
29th	Paris	0.987	0.060	155.315	0.010	107.996	150.773	1.058	3.580	1
30th	Shanghai	0.988	0.089	121.100	0.011	257.970	297.162	1.041	3.485	0
31st	Dallas	0.988	0.052	108.245	0.007	152.761	174.535	1.061	3.305	1
32nd	London	0.989	0.043	106.723	0.007	104.174	148.343	1.065	3.547	1
33rd	Bangkok	0.989	0.035	143.232	0.008	92.980	120.363	1.058	3.551	1
34th	Shenzhen	0.990	0.080	97.287	0.008	172.760	281.984	1.077	3.450	0
35th	Guangzhou	0.990	0.064	110.308	0.008	207.269	287.831	1.066	3.488	0
36th	Boston	0.991	0.049	102.397	0.006	141.867	150.132	1.080	3.566	1
37th	Amsterdam	0.992	0.051	93.703	0.007	110.768	232.475	1.085	3.551	0
38th	Berlin	0.992	0.037	81.845	0.006	165.183	219.260	1.050	3.556	0
39th	Ottawa	0.993	0.043	80.980	0.006	213.077	319.846	1.120	3.354	0
40th	Milan	0.994	0.031	93.705	0.005	102.955	184.624	1.062	3.554	1
41st	Rome	0.994	0.035	92.208	0.006	140.145	266.040	1.083	3.578	0
42nd	Moscow	0.994	0.038	86.470	0.006	217.438	268.513	1.072	3.570	0
43rd	Dhaka	0.995	0.021	77.116	0.004	149.710	202.884	1.080	3.272	0
44th	Brussels	0.995	0.027	81.341	0.004	159.164	207.526	1.059	3.579	0
45th	Bogota	0.996	0.033	81.536	0.004	110.761	226.609	1.105	3.484	0
46th	Hamburg	0.996	0.018	74.775	0.004	167.510	261.195	1.073	3.565	0

Table 4 Stability and network metrics for 46 cities, ranked by median stability from least to most path-stable. Metrics include median path stability $S_\Delta(o,d)$, interquartile range (IQR) of stability, average length of $p(d,d^x)$, ratio R, average and standard deviation of street length, average circuity, entropy of road bearing, and assigned cluster.

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