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From Cycling Efficiency to Cycling State: An Exploratory Study Decoupling the Environmental Determinants of Cycling Detour and Trajectory Stability

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Abstract

Evaluating the quality of urban cycling environments is crucial for fostering sustainable non-motorized transportation in high-density metropolitan areas. However, mainstream evaluations rely heavily on efficiency-first, macroscopic metrics—such as detour rates—that fundamentally overlook the dynamic, microscopic spatial friction cyclists experience. Furthermore, traditional linear models fail to capture the non-linear environmental overloads and systemic stressors inherent in complex street networks. To bridge this gap, this study introduces “Trajectory Stability” as a novel geometric proxy derived from crowdsourced GPS data and proposes a “three-in-one” multi-scale analytical framework to decouple macroscopic path efficiency from microscopic process states. The framework first employs Structural Equation Modeling (SEM) to establish global causal transmission chains between multi-scalar spatial variables and cycling behavior. Subsequently, explainable machine learning algorithms (XGBoost and SHAP) and Two-Dimensional Partial Dependence Plots (2D-PDP) are integrated to deconstruct asymmetric long-tail penalty effects and non-linear mutation thresholds. Finally, Hierarchical Cluster Analysis (HCA) translates these continuous non-linear behavioral features into highly operational spatial morphological classifications. Empirical application in Shenzhen reveals that macro-scale network integration strictly dictates path efficiency, whereas micro-scale functional density governs trajectory stability. Specifically, the model uniquely identifies critical non-linear thresholds—such as an office functional mixing degree exceeding 0.63 triggering a “CBD space black hole” effect—demonstrating superior explanatory power over traditional linear assumptions by mapping four distinct spatial intervention typologies. Ultimately, this framework shifts active mobility governance from static spatial allocation to precise, threshold-based parametric interventions, offering a robust paradigm for navigating the complex scale-interface of urban environments.

Keywords: Trajectory stability; Detour rate; Cycling GPS trajectory; Non-linear thresholds; Explainable machine learning

1. Introduction

1.1. Research Background

Urban non-motorized transportation research has long been constrained by an “efficiency-first” macroscopic evaluation paradigm ¹⁻³. Academia predominantly relies on detour rates, such as the Behavioral Detour Ratio (BDR) and Normalized Degree of Deviation (NDD), to quantify physical constraints imposed by the built environment ^{4,5}. This

Origin-Destination (O-D) focused approach fundamentally aligns with a monolithic perspective of “Environmental Determinism”⁶. Specifically, BDR evaluates one-dimensional excess pathlength (Fig. 1)⁷, reflecting rational wayfinding towards dense points of interest^{8,9} (Fig. 2). Complementarily, NDD captures two-dimensional spatial deviations¹⁰, revealing geometric patterns obscured by purely distance-based metrics (Fig. 3 versus Fig. 4).

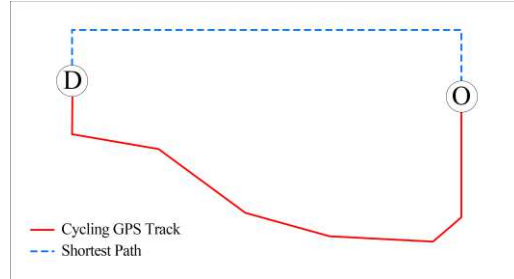


Fig. 1. Trajectory detour rate.

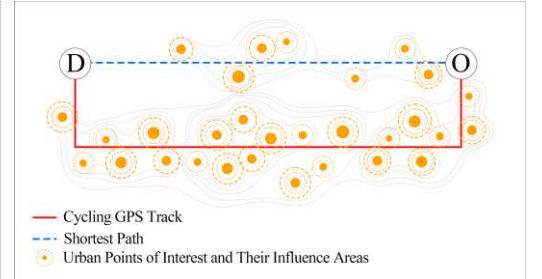


Fig. 2. The Impact of POI.

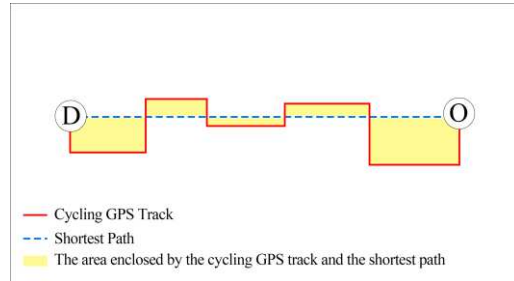


Fig. 3. Low spatial deviation of trajectory.

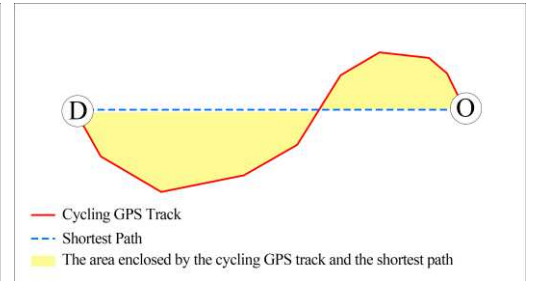


Fig. 4. High spatial deviation of trajectory.

However, traditional detour rates solely measure “outcome efficiency”, focusing heavily on macroscopic destination accessibility. Real-world cycling is a dynamic and high-frequency interactive process between the cyclist and the high-density street environment (Fig. 5), which additionally demands the measurement of “process state”, reflecting microscopic anti-interference ability^{11,12}. Relying solely on detour rates creates a critical evaluation blind spot, failing to capture the anomalous state where a route is macroscopically efficient yet microscopically perturbing. While macroscopic connectivity offers theoretical route choices, real-world riding involves navigating tidal pedestrian-vehicular friction that generates severe micro-scale spatial damping¹³. Conventional linear models struggle to accurately capture this micro-instability and the non-linear spatial penalties inflicted by functional mixing¹⁴, whereas these continuous micro-interactions essentially construct a complex spectrum of riding states¹⁵.



Fig. 5. The cycling environment in cities (owned by author).

Consequently, interpreting trajectory fluctuations is highly scale-dependent: macroscopically, they represent detours around physical barriers; microscopically, they signify

high-frequency stress responses to local environmental interference (Fig. 6)¹⁶. In high-density areas with complex street activities^{17,18}, a trajectory exhibiting high macro-efficiency may still endure continuous microscopic offsets (Fig. 7). To bridge the fundamental disconnect between geometric path efficiency and the actual process state, this study proposes “trajectory stability”. Derived from trajectory offset angles and fluctuating frequencies, this novel metric quantifies the micro-state of real-time cyclist-environment interactions. By decoupling macroscopic path detours from microscopic motion stability, this research aims to shift active mobility evaluation from “efficiency-oriented” to “quality and state-oriented”.

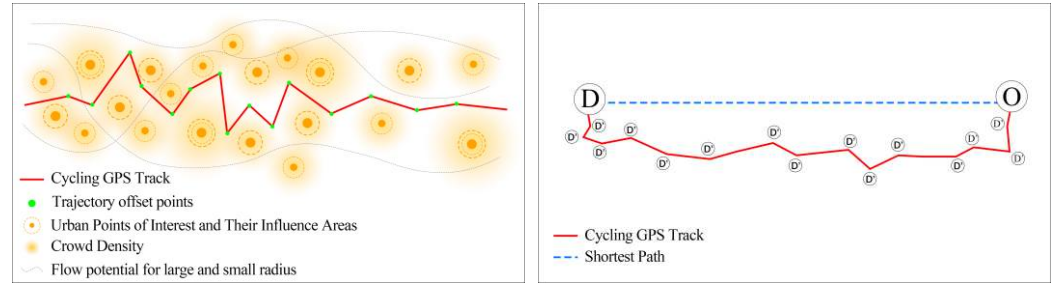


Fig. 6. The “detour” of the trajectory (left).

Fig. 7. Macroscopic and microscopic detour of trajectory (right).

1.2. Research Scale Decoupling: A Paradigm Shift from Macro Circumvention to Micro Fluctuations

In urban spatial behavior, “Environmental Determinism” and “Environmental Possibilism” constitute the dual logical foundation for understanding the cyclist-environment interaction¹⁹. However, traditional non-motorized travel assessments often conflate coercion mechanisms operating at different scales. At the macro-scale, superblocks and enclosed boundaries exert a profound deterministic effect. These physical barriers sever road network connectivity, forcing cyclists to undertake long-distance “physical detours”²⁰. Conversely, at the micro-scale, spatial logic inverts. While highly permeable capillary networks theoretically offer richer destination choices under environmental possibilism, the extreme agglomeration of facilities breeds dynamic obstacles, such as tidal pedestrian flows and mixed-traffic conflicts. This highly heterogeneous micro-environment forces cyclists to constantly perform high-frequency evasions and small-angle deviations, defined here as “behavioral micro-perturbations”²¹. Thus, physical detours reflect the macro-coercion of network boundaries on “where to go”, whereas behavioral micro-perturbations reveal the real-time interference of functional conflicts on “how to proceed”.

To decouple these mechanisms, this study introduces trajectory mileage as a key analytical dimension (Fig. 8). High-mileage routes rely heavily on large-scale networks^{10,22}, where deviations are primarily passive responses to macro-structural constraints²³, typically evaluated by detour rates²⁴. In contrast, low-mileage trips feature short Euclidean distances between origins and destinations. Consequently, trajectory offsets rarely signify network-scale detours. Rather, they arise from real-time interactions with the street micro-environment, such as avoiding non-motorized vehicles, navigating crowds²⁵⁻²⁷, or responding to attractive street interfaces^{28,29}.

These real-time interactions reflect the street as an “environmental possibilism field”, where riding quality fluctuates dynamically based on micro-environmental navigation. Importantly, cyclists travel within a coupled multi-scalar network, where large-radius through-movement potentials overlap with small-radius local accessibility. The superposition of these multi-scalar potentials results in heterogeneous and conflicting traffic flows, generating the primary source of spatial friction. Consequently, the macroscopic

detour ratio cannot adequately capture the micro-scale riding experience. To address this, we focus on the rich microscopic variations inherent in these trips and propose trajectory stability as a novel metric to descriptively capture the dynamic process state of cycling.

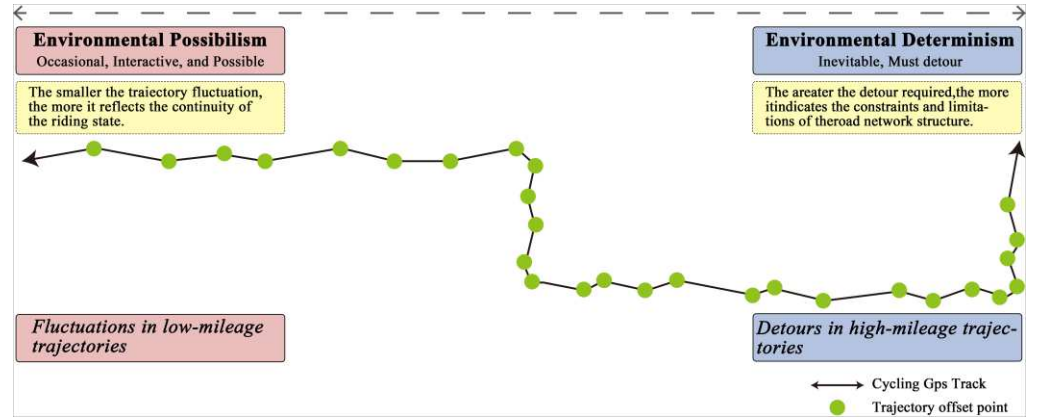


Fig. 8. A conceptual diagram illustrates how trajectory fluctuations may be interpreted differently for high-mileage versus low-mileage trips.

1.3. Research Objectives and Innovative Contributions

This study aims to bridge the measurement gap in existing non-motorized transportation research, which often emphasizes “macro-efficiency while neglecting micro-state”, thereby redefining the constraint mechanisms of multi-scalar built environments on cycling behavior. Theoretically, this study breaks away from the traditional macroscopic detour framework by innovatively proposing “Trajectory Stability”. Derived from the geometric features of crowdsourced GPS trajectories (offset angles and fluctuation frequencies), this novel micro-level metric is not intended as an absolute physical dynamic measurement. Rather, it serves as a “geometric proxy” to map the “instantaneous decision pressure” endured by cyclists navigating complex street friction. This indicator achieves a precise quantitative expression of high-frequency real-time interactive processes between cyclists and high-density street environments, realizing a dimensional leap from evaluating “spatial physical detours” to capturing “real-time behavioral micro-perturbations”.

Methodologically, this study achieves a cutting-edge integration by constructing a “three-in-one” closed-loop analytical framework comprising Structural Equation Modeling (SEM) for causal transmission, Explainable Machine Learning (XGBoost and SHAP) for non-linear threshold capture, and Hierarchical Cluster Analysis (HCA) for spatial morphological classification³⁰. Specifically, SEM establishes the baseline global causal transmission chains of multi-scalar spatial variables on cycling efficiency and micro-states. Subsequently, XGBoost and SHAP algorithms are introduced to transcend linear assumptions, deeply deconstructing the asymmetric long-tail penalty effects and critical mutation thresholds of spatial elements under extreme polarized conditions³¹. Finally, HCA translates the continuous non-linear features identified by machine learning into highly operational physical spatial classifications. This methodological closed-loop not only achieves precise attribution of micro-traffic conflicts but also provides data-driven support for the dual-track governance of “macro-structural replanning” and precise “micro-acupuncture” street interventions in high-density urban areas.

2. Literature Review

Urban cycling research operates across macro, meso, and micro scales. However, research efforts remain unevenly distributed, leaving significant explanatory gaps.

2.1. Macro Scale

Macro-level research evaluates regional transportation geography, cycling network efficiency, and infrastructure impacts. Efficiency is frequently quantified through detour metrics like the Behavioral Detour Ratio (BDR) and the Normalized Degree of Deviation (NDD)^{7,10}, alongside broader spatial network analyses³²⁻³⁴. Macro-studies also encompass policy and social dimensions, assessing gender equality³⁵ or the impact of infrastructure investments on active mode shares³⁶.

The cycling detour rate is typically measured using travel mileage and Origin-Destination (OD) points. Specifically, BDR measures the additional travel distance caused by large-scale road network constraints^{7,37}. Conversely, NDD evaluates the two-dimensional spatial deviation from the shortest path, correlating with environmental factors like bicycle facility coverage, land use types, and street greening rates¹⁰.

While effective for measuring network efficiency, these indices fail to distinguish between active route choices (“environmental possibilism”) and passive spatial deviations (“environmental determinism”). Consequently, macro-studies often implicitly assume that cycling outcomes are solely dictated by large-scale infrastructure. This efficiency-centric model overlooks subtle street-level spatial frictions. By viewing streets merely as single-function networks, existing studies neglect their role as shared carriers of multi-scalar flows (e.g., long-distance traversal versus local access), creating a fundamental explanatory gap between macro-efficiency and micro-experience.

2.2. Meso Scale

Theoretically, the meso-scale navigates the tension between structural constraints and individual choices. Cyclists' path selection represents a trade-off between the physical limits of the built environment and their preferences for accessibility, safety, or amenity³⁸. Using blocks or street segments as analytical units, this scale investigates how built environment features, such as spatial syntax, Point of Interest (POI) density, and bike lane typologies, impact detour preferences and cycling behavior³⁹⁻⁴¹.

However, traditional analyses face methodological limitations in capturing non-linear spatial thresholds and complex causal mechanisms^{14,42,43}. Static path selection analysis alone fails to capture the real-time environmental pressures driving micro-level riding dynamics³³. This reveals a theoretical tension: while deterministic indicators (like detour rates) are easily quantified via network analysis⁴⁴, capturing active experiential choices at the micro-scale is considerably more challenging and traditionally relies on subjective reports or indirect proxies⁴⁵.

To address this gap, the trajectory stability metric proposed in this study aims to quantify street interactions through the geometric properties of GPS data. It operationalizes how the convergence between large-scale network flows and small-scale local activities is reflected in real-time riding states. Therefore, trajectory stability serves as a critical metric to empirically observe the middle ground between deterministic constraints and active choices.

2.3. Micro Scale

Microscopic studies focus on the real-time quantification of individual cycling experiences, including comfort, safety perception, and facility interaction. Current research primarily relies on subjective questionnaires⁴⁶ or indirect quantification using vibration sensors and speed variations⁴⁷⁻⁴⁹. A significant ongoing challenge is the continuous quantification of dynamic states directly from trajectory geometry to evaluate high-quality riding experiences⁵⁰.

However, few objective quantitative indicators currently derive from trajectory geometry, making it difficult to distinguish whether a behavioral change constitutes a passive response or an active choice. Furthermore, existing micro-scale studies confront significant methodological bottlenecks. First, micro-behavioral analyses rely heavily on linear statistical models like Structural Equation Modeling (SEM)⁵¹. These models are mathematically incapable of identifying systemic overloads and abrupt mutation thresholds imposed by micro-street elements. When the density of traffic conflicts surpasses a critical point, cycling comfort experiences a non-linear collapse. Linear models forcibly smooth out these mutations, underestimating the coerciveness of the built environment⁵². Second, while cutting-edge studies adopt non-linear machine learning algorithms (e.g., Random Forest and XGBoost) to predict drops in riding comfort^{52,53}, these data-driven “black-box” models lack causal logic. They fail to explain how spatial pressures from macro-networks cascade to trigger specific micro-perturbations⁵¹.

To address these gaps, we propose “trajectory stability” as a geometrically derived indicator based on GPS data. Crucially, in ultra-high-density cities, the high-frequency small-angle deviations (offset points) observed in GPS trajectories are not random errors. Instead, they reflect acute stress responses to “environmental friction” and “environmental negative feedback”. By shifting the focus from absolute physical properties to a spatial pressure representation, this metric functions as a “Micro-behavioral Perturbation Index”. This approach anchors micro-geometric states and integrates causal transmission with non-linear mutations, differentiating smooth rides from distorted trajectories driven by micro-environmental constraints.

2.4. Research Scale Positioning

The tension between urban functions and road networks, coupled with the methodological dichotomy between “linear causality” and “non-linear mutation”, constitutes a central challenge across cycling research scales. As illustrated in Table 1, current multi-scale frameworks tend to isolate environmental effects. A critical limitation is their failure to account for how macro-level network structures (large-radius integration) and micro-level street activities (small-radius attraction flows) couple to shape real-time cycling experiences. This complexity at the “scale interface” is paramount for understanding how macro-level outcomes transition into micro-level processes.

Furthermore, traditional studies predominantly rely on linear statistical models like Structural Equation Modeling (SEM). These models fundamentally assume constant marginal effects, rendering them mathematically incapable of identifying systemic spatial overloads and abrupt mutation thresholds exerted by the built environment on active travel⁵⁴. Conversely, recent pioneering research shifts towards purely data-driven machine learning algorithms (XGBoost and Random Forest) to capture non-linearities. Despite their superior predictive power, these “black-box” models lack rigorous a priori theoretical frameworks and clear systemic causal transmission chains³⁰. They struggle to elucidate the structural pathways through which multi-scalar environmental elements cross the “scale interface” to induce micro-cycling deviations.

Therefore, the research scale positioning of this study represents a comprehensive methodological synthesis. By proposing a “three-in-one” framework, this paper combines SEM for global causal transmission, XGBoost and SHAP for non-linear threshold capture, and Hierarchical Cluster Analysis for spatial morphological classification. Specifically, by introducing “trajectory stability” as a “geometric proxy”, this study bridges the gap in the continuous dynamic quantification of existing literature. Its primary purpose is to map cross-scale environmental friction and capture real-time “micro-perturbations”. This approach overcomes prevailing methodological limitations and achieves a precise decoupling of macro-efficiency and micro-state in cycling research.

Table 1. Theoretical Research Frameworks and Methodological Limitations at Different Research Scales.

Scale	Main Research Content	Main Research Methods	Limitations	Commonly Implied Causal Perspectives and Analytical Focus
Macro	Network efficiency and total distribution.	GIS Spatial Analysis, Detour Rate Models, Linear Statistical Models (Regression, basic SEM).	1. Static Analysis: Static paths serve as a results-oriented approach. 2. Linear Trap: Linear models assume constant marginal effects, failing to capture systemic overloads and non-linear spatial penalties imposed by macro-environments.	Structurally deterministic and demand driven. Bicycle OD distribution depends on large-scale urban function layout. Detour behavior is often a passive response to network constraints or mandatory destinations.
Meso	Detour route selection preferences and the built environment.	Spatial Syntax, Discrete Choice Models, pure Machine Learning (RF, XGBoost).	1. Behavioral Gap: Ignores real-time individual behavioral differences. 2. Black-box Issue: Pure data-driven machine learning models lack clear a priori causal transmission chains to explain how meso-level features cascade into micro-level pressures.	Preference driven and navigating constraints. Detour route selection reflects both deterministic constraints and agent choice. Cyclists make trade-offs in a given environment.
Micro	Real-time sensations during cycling and riding safety.	Subjective scoring, sensors, speed analysis, micro-behavioral statistical models.	1. Indicator Gap: Lack of objective quantitative indicators derived directly from trajectory geometry to capture dynamic “micro-perturbations”. 2. Threshold Masking: Linear assumptions underestimate abrupt mutation thresholds caused by dense micro-level traffic conflicts.	Environment driven and experiential. Existing studies lack continuous dynamic quantification. “Trajectory stability” is proposed as a “geometric proxy” to map cross-scale environmental friction and real-time states.

2.5. Technical basis for realizing micro-observation: Research on GPS trajectory offset points

At the micro-scale, GPS trajectories consist of offset points rather than smooth lines⁵⁵. These points represent movement deviations caused by turns, obstacles, or sudden changes in motion^{56,57}.

Cycling studies have utilized these points to identify behavioral semantics⁵⁸, such as abrupt stops or deviations caused by bus stops, illegal parking, and vehicle-cyclist conflicts^{37,57}. Critically, these offset points reflect purposeful behavior rather than random noise⁵⁸. This perspective is particularly relevant to low-mileage recreational cycling, where spontaneous environmental interactions are posited to drive micro-scale trajectory offsets.

From the perspectives of behavioral geography and spatial cognition, large-scale crowdsourced GPS trajectory data possess profound scientific validity in capturing and expressing micro-scale active mobility states⁵⁹. These spatiotemporally high-resolution coordinate sequences, spontaneously generated by cyclists during real-world daily trips, effectively eliminate the “Hawthorne effect” inherent in traditional experimental samplings. They provide an objective, high-fidelity log of the collective spatial friction between human behavior and the built environment. Within our geometric measurement framework, the “high-frequency, small-angle deviations” emerging within active mobility trajectories are by no means meaningless random positioning noises or instrumental geometric errors. Rather, they constitute a direct geometric projection in two-dimensional topological space of a cyclist's instantaneous behavioral stress and cognitive control load when encountering real-time physical constraints, high-risk spatial damping, or subtle micro-scale conflicts, such as localized pedestrian-vehicular intertwining, sightline blockages at deformed intersections, or the lack of rigid physical segregations⁶⁰. This geometric projection of instantaneous spatial stress establishes a robust scientific foundation for objectively diagnosing dynamic micro-environmental determinism.

Furthermore, studies have shown that micro-scale trajectory fluctuations are associated with the status of the physical environment. For example, algorithms analyzing physical variations can predict urban road surface conditions⁶¹, suggesting that GPS trajectory shape is intrinsically linked to the physical environment. In summary, GPS trajectory offset points contain rich information signals that support the transition from macroscopic pattern analysis to microscopic behavior and environmental perception. This technical basis supports the construction of our proposed “trajectory stability” index directly from trajectory geometry to quantify previously unobserved micro-cycling states. Importantly, this geometric approach provides a means to explore the distinction between the deterministic “pressure” of the immediate physical environment and the possible “field” of urban context, offering a pathway to examine our dual logic.

2.6. Research Progress on the Driving Mechanism of Active Mobility Space Based on Non-linear Models

To overcome the inherent limitations of traditional linear models in processing multi-scalar spatial elements, an increasing number of quantitative urban spatial studies in recent years have pivoted towards non-linear machine learning algorithms (e.g., XGBoost, Random Forest). These tree-based ensemble algorithms have demonstrated superior predictive performance in handling high-dimensional built environment data and capturing multicollinearity⁶²⁻⁶⁴. Furthermore, beyond these conceptual and scalar limitations, existing macro-scale studies face significant methodological bottlenecks in bridging this explanatory gap. First, the majority of studies rely heavily on traditional statistical models founded on linear assumptions (e.g., multiple regression, basic Structural Equation Modeling)^{65,66}. While these models can establish global causal relationships among macro variables, they typically assume constant marginal effects. Consequently, they are mathematically incapable of identifying the non-linear spatial penalties, systemic overloads, and critical mutation thresholds imposed by the built environment on non-motorized travel, precisely the “subtle environmental determinism” mentioned above^{51,67}. For instance, the polarized long-tail effects caused by extreme high-density urban functions are often forcibly smoothed out by linear fitting. Second, to overcome these linear limitations, some recent pioneering studies have begun to rely purely on tree-based machine learning models (e.g., XGBoost, Random Forest) to capture complex environmental threshold effects⁶⁸. However, despite their robust non-linear fitting capabilities, these “black-box” algorithms lack rigorous a priori theoretical support and clear systemic causal transmission chains. They struggle to explain how environmental elements fundamentally induce trajectory deviations through the cascading, multiscale flows of the street network⁶⁹. Therefore, effectively integrating linear causal inference with non-linear machine learning has become a methodological chasm that current macro-active travel research urgently needs to bridge.

However, as discussed previously, pure machine learning often falls into a “black-box” dilemma, lacking explanatory power for spatial mechanisms. To break this impasse, Explainable Artificial Intelligence (XAI) theories, represented by SHAP (Shapley Additive Explanations) and Partial Dependence Plots (PDP), have been introduced into the fields of urban planning and travel behavior⁷⁰. The core advantage of SHAP theory lies in its ability to precisely quantify the marginal contribution of each built environment feature to the model's output based on game theory, clearly revealing the “asymmetric long-tail effects” of variables under extreme polarized conditions⁷¹. Furthermore, coupled with two-dimensional Partial Dependence Plots (2D-PDP), researchers can visually observe the non-linear interactive gaming between two core spatial dimensions while isolating the interference of other background variables. For instance, by observing the 2D feature space formed by global road network metrics (representing macro-corridor potential) and

specific micro-functional layouts (such as the Office Functional Mixing Degree), it is possible to accurately capture the critical mutation thresholds that trigger a “cliff-like collapse” in active travel experiences⁷². This non-linear analytical framework not only rectifies the flaw of linear models that forcibly smooth out spatial penalties but also enables precise attribution from “macro-holistic patterns” to “micro-extreme spatial friction.” This lays a solid technological foundation for constructing the “causal + non-linear” hybrid methodology in the subsequent chapters of this study.

2.7. Explanation Paths for the Microscopic Cycling Offset Mechanism: Based on the Selection of Core Environmental Variables

As illustrated in Fig. 9a, road network structure and urban function are the core explanatory variables for this study, serving as bridges between “environmental determinism” and “environmental possibilism” across scales^{6,15}. The former represents rigid topological constraints, while the latter reflects cyclists’ active choices. To quantify these impacts, we introduce spatial syntax indicators (e.g., integration, choice) at varying radii to capture street-level structural capacities⁷³. This multi-scalar superposition provides a robust basis for analyzing non-linear spatial friction.

The “information gap” and contradictory interpretations in Fig. 9a arise from the blind statistical aggregation in traditional research. Aggregating micro-behavioral data into macro-patterns leads to causal misinterpretations: we must distinguish whether an offset point represents an active macro-detour toward POIs (possibilism) or a passive micro-perturbation caused by immediate pedestrian-vehicular conflicts (determinism)⁷⁴. This “scale interface” friction implies that active route choices and passive spatial stresses often occur simultaneously at the same location. Therefore, the simplistic binary assumption must be dismantled, which posits that environmental determinism applies only to macro-efficiency while environmental possibilism solely governs micro-experience.

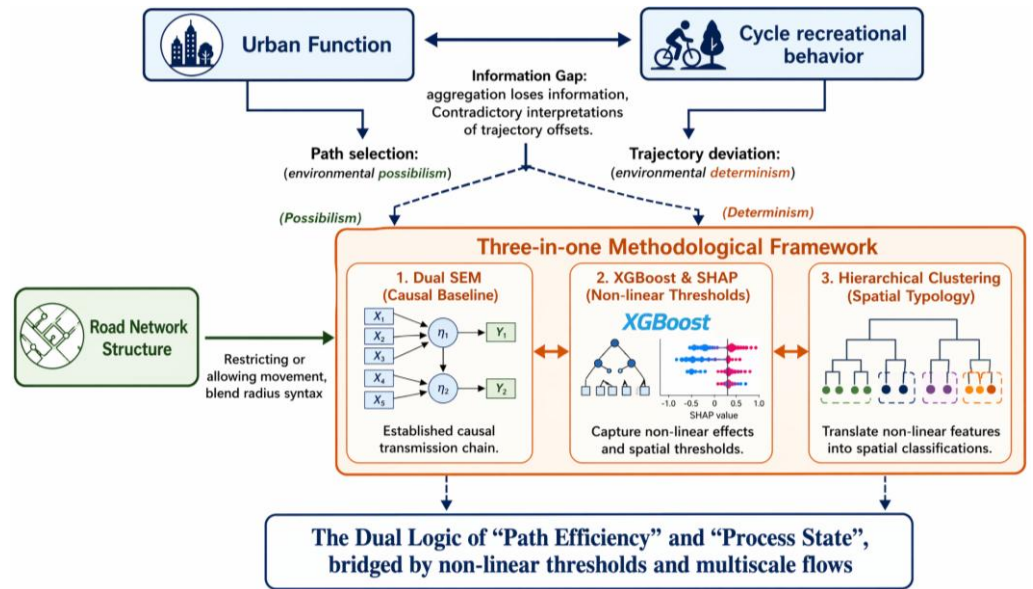


Fig. 9a. Theoretical Research Framework Integrating Non-linear Machine Learning.

To break this theoretical impasse and bridge the information gap, this study formally introduces a “three-in-one methodological framework” in Fig. 9a. This hybrid framework, driven by dual logic detailed in Fig. 9b, seeks to resolve three fundamental empirical inquiries. First, it investigates the driving logic of recreational behavior to determine whether cycling in high-density urban areas is primarily constrained by the deterministic

coercion of the built environment or dominated by individual preferences. Second, it assesses the explanatory blind spots of macro-measurements by evaluating how traditional detour rate indicators, such as BDR and NDD, mask the authentic quality of the micro-cycling state and underestimate the “systemic overload” and non-linear oppression of the built environment. Finally, it explores the emergence of critical mutation thresholds and the subsequent logical reshaping of cycling experiences. By embedding the novel micro-state indicator of “trajectory stability” within a “causal + non-linear” three-in-one closed-loop containing XGBoost and SHAP, this research aims to identify the thresholds that trigger a “cliff-like collapse” in cycling experiences¹⁴. Ultimately, this inquiry reshapes our cognitive understanding of the dual environmental logic regarding “path efficiency (determinism)” and “process state (possibilism)”.

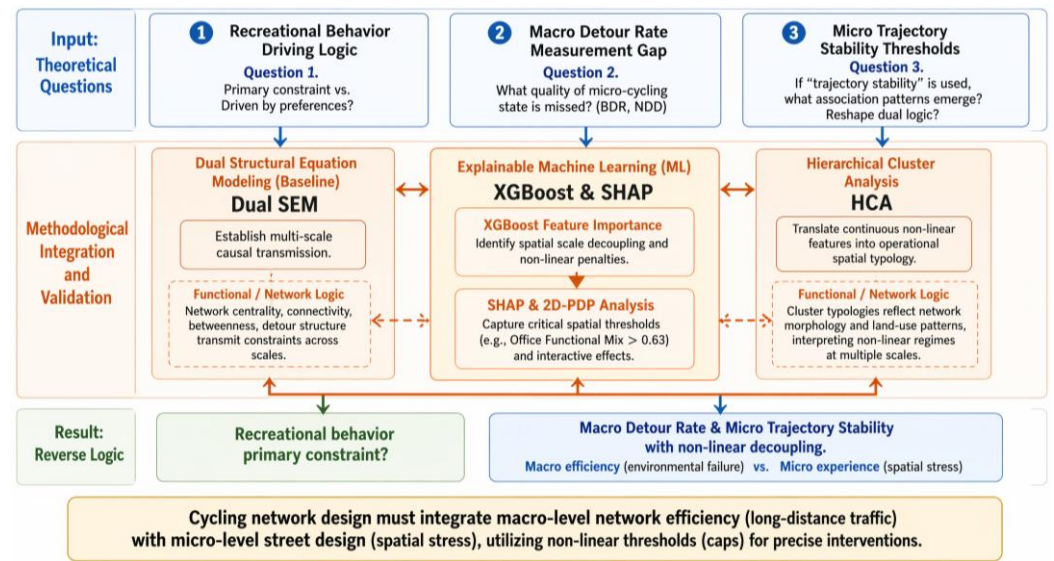


Fig. 9b. Multi-scale & Multi-method Research Flow: Causal Transmission & Non-linear Decoupling.

Fig. 9. A hybrid analytical framework for urban cycling: Integrating multi-scale causal transmission and non-linear machine learning.

3. Research Methods and Data

3.1. Overview of the Study Area

The empirical study area is located in Longhua District, Shenzhen, China (Fig. 10). As a microcosm of rapid urbanization in ultra-high-density metropolitan areas, Longhua District exhibits an extremely complex and heterogeneous spatial texture. The district encompasses large enclosed industrial parks, mega business CBDs, and intricate urban villages densely intertwined with high-tier rail transit hubs⁷⁵. This highly mixed urban morphology constitutes a “spatial superposition and friction field” characterized by intense multi-scalar mobility potentials⁷⁶. Short-distance active travel, primarily oriented towards local access and recreation, frequently overlaps and collides with long-distance cross-district commuting flows within the same street corridors. This interplay makes Longhua District an exceptional empirical baseline for exploring how the physical superposition of multi-scalar movement induces microscopic trajectory offsets and micro-perturbations.

Furthermore, Meituan Bicycle big data indicates a 30% increase in cycling volume within Longhua District during the first half of 2022, establishing it as a key cycling hotspot. Local residents commonly integrate cycling with the high-density public transport network to navigate the constraints of this complex built environment.

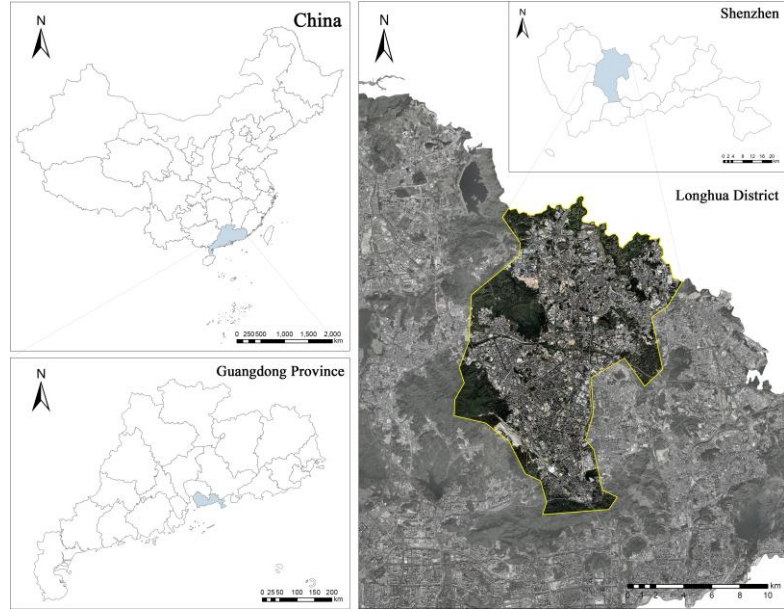


Fig. 10. Study Area: Longhua District, Shenzhen City, Guangdong Province, China.

3.2. Data Sources and Preprocessing

The primary trajectory data were sourced from the Liang Bulu Outdoor Sports platform, which captures outdoor activity records including paths, timestamps, and velocity. These data reflect recreational cycling rather than utilitarian commuting. We extracted KML files pertaining to cycling activities within Longhua District for further analysis.

Raw data were curated by filtering records with irregular timestamps, unrealistic mileage, and invalid speed values. We applied a boxplot method to detect and remove abnormal GPS points characterized by excessive offsets or chaotic trajectories^{57,77}. Cleaned trajectories were imported into Global Mapper, merged, and converted into GIS-compatible Shapefile format. We performed map matching with the OpenStreetMap road network using a Hidden Markov Model, followed by manual topological calibration.

Supplementary data were acquired from additional sources. Baidu Maps provided over 137,000 Points of Interest (POI) across five categories: residential, living services, office, leisure and entertainment, and transportation. Furthermore, we utilized 2025 street map data to generate an axial map of Longhua District via Depthmap software for subsequent road network structure analysis.

3.3. Construction of the dependent variable: Two-dimensional representation of the detour rate and trajectory stability

3.3.1. Measurement index of the cycling process state - Trajectory stability

To quantify the interaction between cyclists and high-density street environments, this study constructs a novel “Trajectory Stability” index based on the micro-geometric properties of crowdsourced GPS trajectories (Fig. 11). Within our data processing pipeline, we extract topological nodal features from each trajectory. Offset points are defined as spatial nodes where the heading angle undergoes significant mutation due to road morphology, physical obstacles, or pedestrian-vehicular conflicts⁷⁸. For any trajectory, the model records the heading deviation angle (θ_i) at each offset point and the total count (n). The index is formalized as the arithmetic mean of all valid offset angles:

$$\text{Trajectory stability} = \frac{\sum_{i=1}^n \theta_i}{n}$$

θ_i : the true heading deviation angle at the i -th offset point

n : the total number of extracted offset points from a single trajectory.

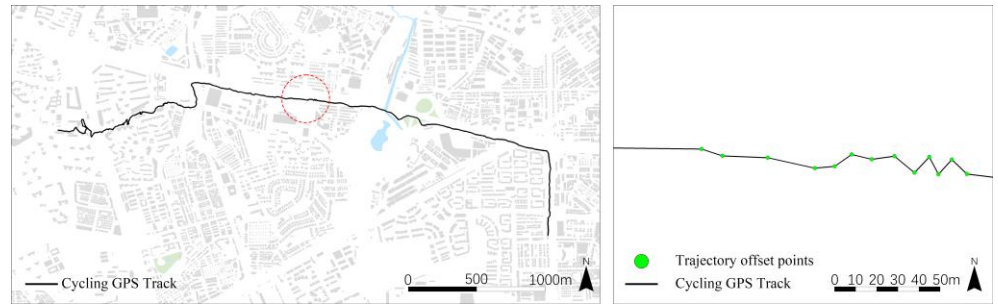


Fig. 11. Example of a Single Cycling GPS Track and Selected Deviation Points in Shenzhen.

Under our “multi-scale dual logic” framework, this geometric index holds significant behavioral mapping power. Higher values characterize a smooth, coherent micro-cycling state, where the cyclist executes fewer, decisive structural turns (e.g., deliberate 90° turns at standard intersections). This represents a frictionless wayfinding process driven by “environmental possibilism”. Conversely, lower values expose a turbulent, stress-reactive riding state. Driven by a high frequency of minor corrective angles, a low index serves as geometric evidence of continuous physical oppression, forcing the cyclist into frequent, small-angle evasions and tremors. This passive “micro-fluctuation” constitutes a direct diagnostic of intense “environmental determinism” and systemic overload within the street space^{79,80}.

3.3.2. Measurement indicator for cycling detour behavior - Detour rate

To quantify macro-scale “path efficiency” and establish a baseline for our dual-logic framework, cycling detour behavior was measured using two complementary indicators: the Behavioral Detour Ratio (BDR) and the Normalized Degree of Deviation (NDD) (Table 2). BDR evaluates one-dimensional distance decay, defined as the ratio of actual cycling distance to the shortest network path. It reflects macroscopic route choices driven by non-mandatory factors, such as safety or amenities⁷. Conversely, NDD captures geometric deviation in two-dimensional topological space by calculating the area enclosed between the actual and shortest paths in GIS, standardized by the shortest path's length^{10,81}. Together, these traditional metrics provide a rigorous assessment of macroscopic network constraints and detour choices⁸².

3.3.3. Comparison of Indicators for Cycling Trajectories

To illustrate the complementarities among BDR, NDD, and trajectory stability, four empirical cycling routes of similar lengths (3–4 km) in Longhua District were compared (Fig. 12).

While trajectories A and B exhibit similar BDR and trajectory stability, their NDD values differ significantly, reflecting diverse two-dimensional spatial geometries despite identical distance efficiency. A crucial comparison arises between paths with nearly identical macro-metrics (BDR and NDD): although they appear similar in macroscopic path selection, their trajectory stability often diverges significantly. This sharp contrast exposes a fundamental limitation of traditional macro-indicators, as identical macro-route choices can conceal vastly different microscopic riding qualities⁸³. This preliminary comparison highlights that path selection results alone cannot fully account for the quality of microscopic cycling experiences. Consequently, trajectory stability is designed to capture microscopic state changes driven by real-time interactions with the street, proving the irreplaceable value of decoupling macro-path efficiency from “micro-process states” for a comprehensive evaluation of the cycling environment.

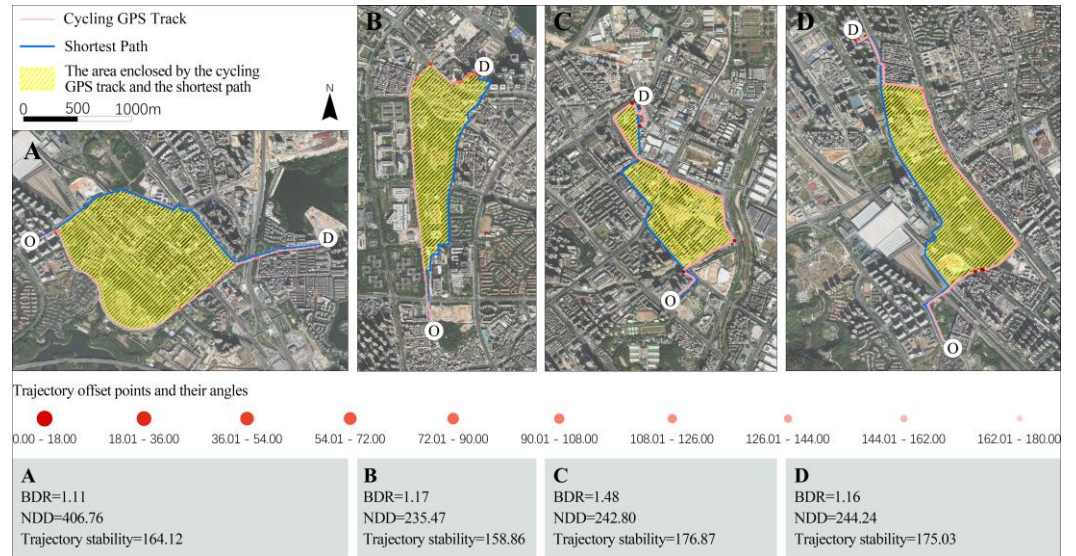


Fig. 12. Examples of cycling routes and the shortest distance paths between four different starting points and destinations in Longhua District, Shenzhen (O: Origin, D: Destination).

3.4. Independent Variable Construction: Road Network Structure and Urban Functions

3.4.1. Road Network Structure

This study utilized multi-scale Space Syntax metrics—Normalized Angular Choice (NACH, indicating global through-movement potential) and Normalized Angular Integration (NAIN, indicating topological local accessibility)—to quantify the urban road network structure⁸⁴. A line segment analysis was conducted at varying radii from 1000m to 5000m to capture traffic flow potentials across different trip distances. Specifically, larger radii (3000m–5000m) represent macro-regional transit corridors, whereas smaller radii (1000m–2000m) map micro-local distribution networks. Notably, a single street segment may simultaneously exhibit high local and global integration. This “spatial superposition” of multi-scale mobility potentials engenders fierce convergence and conflict among heterogeneous traffic flows (fast motorized vs. micro active flows), providing a physical deterministic baseline for micro-trajectory fluctuations.

3.4.2. Urban functional mix

The urban functional mix was utilized to quantify destination attractiveness, mapping active wayfinding choices under environmental possibilism. This study applied the Information Entropy Model, based on a regular 200m × 200m spatial grid, to precisely measure the spatial diversity of POI types within each area⁸⁵. Consequently, specific mixing degrees were calculated for five typical urban functions: Office, Leisure and Entertainment, Transportation, Residential, and Living Services, alongside an overall comprehensive functional mixing degree (Table 2 for descriptions).

3.4.3. Variable Input Guided by Dual Logic

By formulating these independent variables, the study successfully operationalized the two core theoretical dimensions driving cycling behavior: the rigid constraints of “environmental determinism” measured by road network structure, and the elastic choices of “environmental possibilism” measured by urban functional mix. To implement the “Three-in-one Methodological Framework” proposed in Chapter 2, these two sets of variables are not only inputted into Structural Equation Modeling (SEM) to establish baseline linear causal transmission paths; crucially, they are simultaneously fed into explainable machine learning models (XGBoost and SHAP). This enables the precise decoupling of

the “non-linear mutation thresholds” and “long-tail penalty effects” exerted by these heterogeneous spatial elements on both macroscopic detours and microscopic trajectory stability.

Table 2. Variables Used in This Study and Their Descriptions.

Variable Types	Variable Name	Variable Description
Dependent Variables	Behavioral Detour Ratio (BDR)	Mainly Reflects detours influenced by subjective preferences.
	Normalized Degree of Deviation (NDD)	Quantifies the 2D spatial deviation between the actual and shortest path, standardized by the shortest path's length.
	Trajectory Stability	As defined in this study, the state of the cyclist's riding process affected by environmental interaction at the micro – level, calculated as the mean of trajectory offset angles.
Independent Variables		
Road Network Structure	Normalised Angular Choice (NACH)	A space syntax metric measuring a street segment's potential as a through-movement route (a 'shortcut'). Analyzed at radius: 1000m, 2000m, 3000m, 4000m, 5000m.
	Normalised Angular Integration (NAIN)	A space syntax metric measuring a street segment's topological accessibility (closeness to all others). Analyzed at radius: 1000m, 2000m, 3000m, 4000m, 5000m.
Urban Functions	Office Functional Mixing Degree	Information entropy of POIs including companies, enterprises, financial institutions, etc.
	Leisure and Entertainment Functional Mixing Degree	Information entropy of POIs related to leisure, entertainment, shopping, and consumption.
	Transportation Functional Mixing Degree	Information entropy of POIs of transportation facilities (e.g., bus stops, subway stations).
	Residential Functional Mixing Degree	The mixing degree calculated based on the distribution of Information entropy of POIs in residential communities, apartments, urban villages, etc.
	Living Service Functional Mixing Degree	Information entropy of POIs of living services and public facilities (e.g., schools, hospitals).
	Urban Functional Mixing Degree	Comprehensive information entropy based on the distribution of all five categories of POIs.

3.5. Baseline Model Construction: Dual Structural Equation Modeling based on Dual Logic

As the initial step in the “three-in-one” methodological closed-loop of this study, the construction of dual Structural Equation Models (SEMs) aims to establish a rigorous global linear causal baseline for subsequent non-linear machine learning explorations⁸⁶. The robust structural path validation capabilities of SEM enable us to preliminarily disentangle and establish exactly how road network structure (deterministic constraints) and urban functions (possibilistic choices) drive cycling behavior across macro and micro dimensions. Based on an exploratory iteration of the variable pool, this study ultimately established two statistically significant and theoretically interpretable baseline causal skeletons:

3.5.1. Baseline SEM for Detour Rate

This model explores the causal mechanism of route selection at the macro/meso scales.

1. Measurement Model

Road network structure is represented by large-radius choice and local integration (NACH4000, NACH5000, NAIN1000); Urban function is represented by overall, office, and transportation functional mixing degrees; Macro state is reflected by BDR and NDD.

2. Structural Model

Exploratory analysis established a macroscopic causal path: the physical structure of the road network guides the spatial distribution of urban functions, and both synergistically drive the detour choices of cyclists.	513 514 515
<i>3.5.2. Baseline SEM for Trajectory Stability</i>	516
This model explores the causal friction between the dynamic micro-state of cycling and the street environment.	517 518
1. Measurement Model	519
Urban function is represented by overall, office, and living service mixing degrees; Road network structure is represented by local choice/integration (NACH1000, NAIN1000) and global integration (NAIN5000); Micro-state is directly reflected by geometric trajectory stability.	520 521 522 523
2. Structural Model	524
The model reveals a diametrically opposed microscopic causal path: the high-density agglomeration of urban functions attracts the fierce convergence of multi-scalar road network traffic flows, and this compounded physical superposition exerts a significant negative interference (physical coercion) on micro-cycling trajectory stability.	525 526 527 528
These two baseline models successfully delineate the distinctly different linear driving mechanisms of the built environment on “macro-efficiency” and “micro-state.” However, linear models fundamentally smooth out the polarized constraints of spatial variables. Therefore, these causal skeletons will serve as a priori theoretical foundations for feature selection, fully integrated into the subsequent non-linear mutation threshold deconstruction using XGBoost and SHAP ⁸⁷ .	529 530 531 532 533 534
<i>3.6. Non-linear Driving and Interaction Mechanism Model Based on XGBoost and SHAP Theory</i>	535 536
Following the establishment of global linear causal baselines via dual Structural Equation Modeling (SEM), this study introduces the Extreme Gradient Boosting (XGBoost) algorithm to overcome the limitations of linear assumptions. XGBoost efficiently handles multicollinearity in high-dimensional spatial data and precisely captures the non-linear constraints imposed by the built environment on cycling behavior ⁸⁸ . To resolve the “black-box” dilemma, we incorporate game-theory-based SHAP (Shapley Additive Explanations) theory. By computing SHAP Summary Plots, the model quantifies the global marginal contribution of each multi-scale spatial variable, deconstructing the “asymmetric long-tail penalty effects” observed in polarized urban environments.	537 538 539 540 541 542 543 544 545
To reveal the interactive friction of multi-scalar spatial elements, we deploy Two-Dimensional Partial Dependence Plots (2D-PDP). Regarding technical configuration, the axes of the 2D-PDP are rigorously paired based on the Feature Importance outputted by XGBoost and our theoretical dual-logic framework. This strategy assigns global road network metrics to one axis and functional mixing degree metrics to the other, effectively isolating interfering factors within the same feature space. This specific axial configuration allows for a precise comparison of how these “multi-scalar spatial genes” trigger heterogeneous non-linear impacts and critical mutation thresholds when confronting different dimensions of cycling behavior, such as the macro-dimensional “detour rate” and the micro-dimensional “trajectory stability”, within the same two-dimensional feature space ⁸⁹ . This model configuration provides the core algorithmic support for subsequently decoupling the critical conditions between “spatial physical detours” and “micro-state collapse”.	546 547 548 549 550 551 552 553 554 555 556 557
<i>3.7. Hierarchical Cluster Analysis</i>	558
As the final validation and application step of the “three-in-one” methodological closed-loop, this study incorporated data-driven Hierarchical Cluster Analysis (HCA).	559 560

Following the deep decoupling of macro and micro driving mechanisms via Structural Equation Modeling (SEM) and explainable machine learning (XGBoost), HCA was directly applied to the three core behavioral representational metrics: trajectory stability, BDR, and NDD. This step aims to mathematically verify, from a rigorous unsupervised learning perspective, that “micro-trajectory stability” is a heterogeneous measurement dimension completely independent of macro-detour rates. Regarding the algorithmic configuration, the model employed Euclidean distance to measure spatial similarity among samples and utilized Ward's minimum variance method for clustering to effectively minimize intra-cluster variance⁹⁰. This clustering process not only effectively identifies the statistical independence and spatial heterogeneity among multi-dimensional indicators but also translates complex continuous behavioral measures into an intuitive spatial morphological typology. Consequently, it provides highly operational physical classification evidence for the subsequent implementation of “macro-micro dual-track” fine-grained urban governance strategies.

4. Results Analysis: SEM Validation and Indicator Comparison

4.1. Evaluation of Model Goodness of Fit

As the primary validation step of the “three-in-one” methodological closed-loop, a rigorous evaluation of the global goodness-of-fit for the dual Structural Equation Models (SEMs) is indispensable to establish the linear baseline of causal pathways prior to introducing variables into non-linear machine learning algorithms. The fitting results indicate that both theoretical models exhibit an excellent fit with the empirical data.

For the detour rate model: $\chi^2/(df,p)=35.017(14, <0.05)$, GFI (goodness of fit) = 0.984, RMSEA (root mean square error of approximation) = 0.051, TLI (Tucker-Lewis Index) = 0.982, CFI (Comparative Fit Index) = 0.991, normed χ^2 (CMIN/ df) = 2.501. For the trajectory stability model: $\chi^2/(df,p)=14.811(7, <0.05)$, GFI (goodness of fit) = 0.993, RMSEA (root mean square error of approximation) = 0.044, TLI (Tucker-Lewis Index) = 0.981, CFI (Comparative Fit Index) = 0.994, normed χ^2 (CMIN/ df) = 2.116.

All core fit indices significantly surpass the widely accepted statistical threshold criteria for SEMs in travel behavior research (e.g., RMSEA < 0.08, CFI/TLI > 0.90)⁹¹. This outcome demonstrates that the proposed macro-micro dual causal topological skeletons highly correspond with the empirical spatial datasets, thereby providing an impregnable linear causal baseline for the subsequent deconstruction of non-linear spatial coercion thresholds and long-tail penalty effects.

4.2. Model Structure and Path Coefficients: Differential Formation Mechanisms of Detour Rate and Trajectory Stability

Fig. 13 and Fig. 14 illustrate how built environment variables drive macroscopic “path efficiency” and microscopic “process state” through distinct causal chains. Multi-scale spatial syntax metrics reveal the interaction of multi-level traffic flows: the 1000m radius maps local short-distance distributions, whereas the 4000m to 5000m radius represents macro transit corridors for multimodal traffic⁹². Table 3 systematically decouples these heterogeneous causal skeletons.

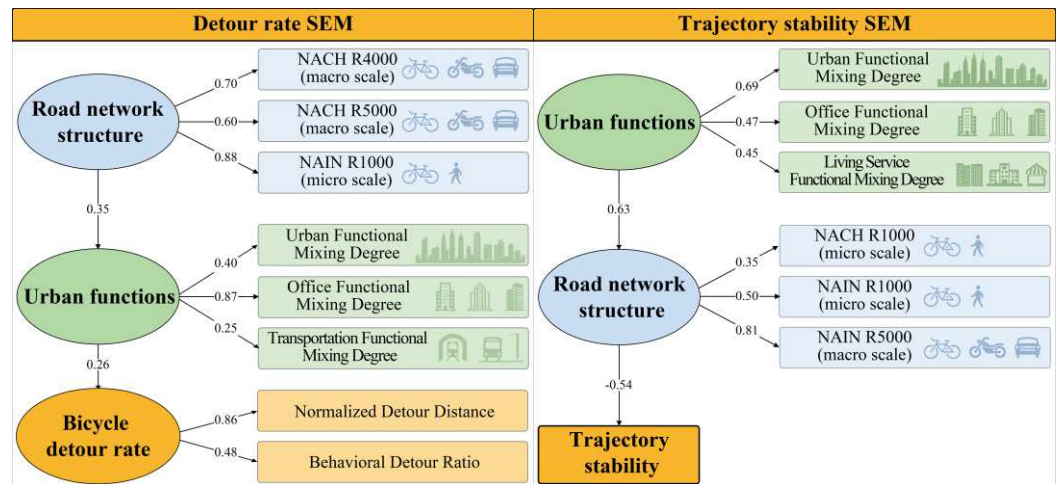


Fig. 13. The results of urban environments affecting detour rate (left).

Fig. 14. The results of urban environments affecting trajectory stability (right).

Table 3. Comparative Analysis of the Associative Patterns Suggested by the Two Exploratory SEMs.

Comparative Dimension	SEM of Detour Rate	SEM of Trajectory Stability
Comprehensive Causal Pattern	Topology guides agglomeration. Macro network physical topology guides the spatial distribution of urban functions, jointly driving cyclists' macroscopic detour choices.	Convergence induces coercion. High density functional agglomeration attracts multi-scalar traffic convergence, exerting physical friction that degrades micro cycling stability and induces "micro-perturbations".
Scale Association	Top down transmission. Large scale transit corridors (e.g., radii from 4000m to 5000m) provide structural constraints for active pathfinding from meso to macro scales.	Bottom up interference. Micro scale street networks (e.g., 1000m radius) overlapping with dense POIs trigger localized real-time stress.
Dominant Factor	Active choice. Primarily driven by the functional attractiveness of destinations to reflect cyclists' active spatial preferences.	Passive constraint. Primarily dominated by physical spatial friction and traffic conflicts to reflect forced behavioral adjustments.
Planning Implication	Macro structural optimization. Enhancing network efficiency by integrating global road network planning with land use diversity.	Micro street intervention. Mitigating "scale interface" conflicts through precise street level right of way (ROW) segregation and micro design.

4.2.1. Core Causal Chain I: Efficiency-Driven and Purpose-Oriented Logic of Macro Detour

As shown in Fig. 13 and Table 4, the structural equation model reveals that global road network metrics representing macro-accessibility significantly drive the agglomeration of transportation-oriented functions, exerting a strong positive effect on macroscopic detour behavior. This confirms that the "detour rate" is an efficiency-driven metric reflecting active route choices. To reach transit hubs, cyclists demonstrate high subjective initiative by enduring longer physical spatial deviations⁸³.

Table 4. Analysis of urban environments affecting detour rate.

Effects between exogenous and endogenous constructs			S.E.	C.R.	P.
Urban function	←	Road network structure	0.274	3.845	***
Bicycle detour rate	←	Urban functions	0.128	3.845	0.11
Effects between indicators and constructs					
NACH R4000	←	Road network structure			
NACH R5000	←	Road network structure	0.018	46.000	***
NAIN R1000	←	Road network structure	0.760	7.255	***
Urban functional mix degree	←	Urban functions			
Office functional mix degree	←	Urban functions	0.291	4.497	***
Transportation functional mix degree	←	Urban functions	0.040	4.792	***
Behavioral Detour Ratio	←	Bicycle detour rate			
Normalized Degree of Deviation	←	Bicycle detour rate	825.989	2.820	0.005

*p < 0.5, **p < 0.01, ***p < 0.001.

4.2.2. Core Causal Chain II: Network-Driven and Experience-Oriented Logic of Micro State

In contrast, the trajectory stability model (Fig. 14 and Table 5) exposes a path of physical coercion. The high-density agglomeration of living service functions strictly constrains local accessibility, inflicting a strong negative penalty on cycling trajectory stability. This establishes “trajectory stability” as a network-driven metric reflecting structural constraints. The pedestrian-vehicular intertwining in high-density areas constitutes intense micro-spatial friction, forcing cyclists into passive high-frequency offsets and “perturbation stress”⁷⁹. This pressure acts as “environmental negative feedback” generated by the environmental system.

Table 5. Analysis of urban environments affecting trajectory stability.

Effects between exogenous and endogenous constructs			S.E.	C.R.	P.
Road network structure	←	Urban functions	0.015	4.572	***
Trajectory stability	←	Road network structure	61.625	-6.385	***
Effects between indicators and constructs					
NACH R1000	←	Road network structure			
NAIN R1000	←	Road network structure	0.485	11.364	***
NAIN R5000	←	Road network structure	1.099	6.364	***
Urban functional mix degree	←	Urban functions			
Office functional mix degree	←	Urban functions	0.065	6.373	***
Service functional mix degree	←	Urban functions	0.137	6.114	***

*p < 0.5, **p < 0.01, ***p < 0.001.

4.2.3. Comparative Analysis: Dual Logical Decoupling of Macro Efficiency and Micro-State

Juxtaposing these two core causal chains corroborates the theoretical necessity of decoupling physical route choice from the cycling process state. Traditional single-scale studies often conflate trajectory offsets. However, this study verifies that the detour rate captures macroscopic decision outcomes based on destination attractiveness, whereas trajectory stability reflects the continuous microscopic stress encountered during the physical superposition of multi-scale traffic flows. This tension at the “scale interface” signifies that the evaluation of cycling environments must transcend simplistic binary assumptions. The successful decoupling of this linear dual logic provides a theoretical foundation for stratified urban governance and lays a solid causal baseline for the subsequent machine learning analysis of non-linear mutation thresholds.

4.3. Feature Importance and Scale/Functional Decoupling Based on SHAP Values

The global feature importance rankings derived from the XGBoost models based on mean absolute SHAP values (Fig. 15) quantify the decisive weights of various built environment elements, revealing two layers of spatial decoupling mechanisms.

First, spatial syntax features exhibit a profound “Scale Decoupling”. In the trajectory stability model (Fig. 15a), global integration (NAIN R5000) representing the macro scale traffic skeleton dominates with a significant advantage (SHAP value ≈ 2.5). Conversely, in detour rate models (Fig. 15b and Fig. 15c), local integration (NAIN R1000) at the micro block scale rules the top rank. This misalignment quantitatively confirms the causal hypothesis: cycling trajectory stability is fundamentally constrained by massive motorized traffic flows and macro signal controls on arterial roads⁹³. Meanwhile, the detour rate directly depends on the permeability of micro capillary road networks within the immediate living circle. In essence, the macro skeleton acts as a “state destroyer”, while the micro network serves as an “efficiency safety net”.

Second, urban functions present a deep “Functional Decoupling”. For metrics based on efficiency (BDR and NDD), a critical misalignment occurs at the second rank of feature

importance. In the behavioral detour ratio (Fig. 15b), transportation functional mixing degree ranks second (SHAP value ≈ 0.035), whereas in the absolute spatial deviation degree (Fig. 15c), office functional mixing degree soars to the second position (SHAP value ≈ 42.5). This exposes two heterogeneous spatial friction mechanisms. Dense crowds and pedestrian vehicular weaving at transit hubs primarily prompt localized “micro-perturbations”. In contrast, high density office islands entail massive closed boundaries that sever micro permeability, compelling cyclists into long distance “physical detours” along peripheral arterial roads ⁹⁴.

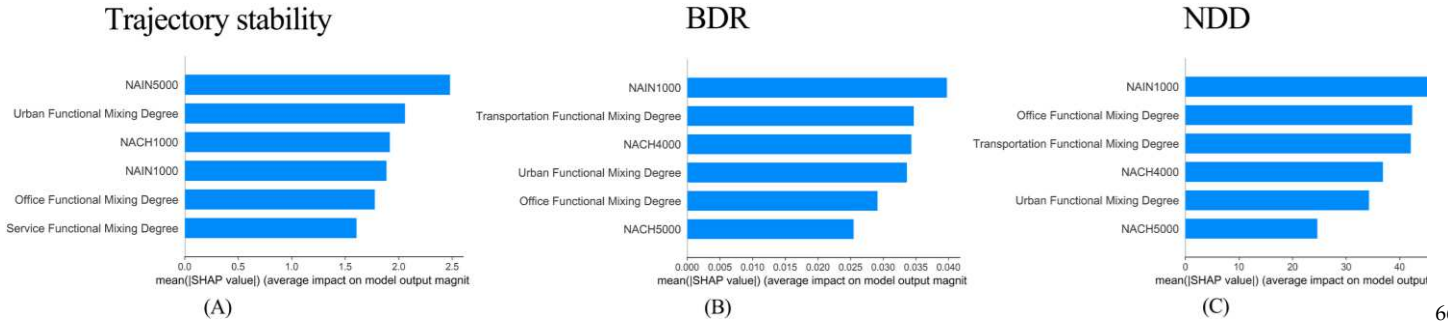


Fig. 15. Global feature importance ranking of the built environment based on mean absolute SHAP values (a: Trajectory stability; b: BDR; c: NDD).

Finally, global choice metrics (NACH R4000 and NACH R5000) representing the probability of a road being traversed as a shortcut consistently occupy the upper middle tiers of the feature weight hierarchy. This supplements a layer of behavioral logic: cyclists actively deviate from the theoretical shortest path to merge into main active travel corridors. This intertwining of subjective and objective wayfinding decisions explains why systematic spatial deviations still occur in high density areas with highly developed micro road networks. In summary, because the micro road network and core functional types exhibit exceptionally high weights, our subsequent 2D PDP analysis focuses on this set of “micro spatial genes” to measure the nonlinear mutation thresholds triggered by their interactive gaming.

4.4. Global Impact Direction and “Long-Tail Penalty Effect” Analysis of Extreme Samples

SHAP Summary Plots (Fig. 16) reveal the nonlinear driving logic of the built environment on micro cycling through feature impact direction and extreme sample distribution. These plots uncover a paradoxical dual nature of urban functional mix: “state suppression” and “efficiency stimulation”. In the trajectory stability model (Fig. 16a), high value samples for functional mixing consistently concentrate in the negative zone. This indicates that increased functional density and POI complexity induce severe pedestrian and vehicular conflicts and psychological stress, exerting a negative suppression on riding smoothness ⁹⁵. Conversely, in the detour rate models (Fig. 16b and Fig. 16c), these same metrics shift to the positive zone. This directional inversion confirms that functional agglomeration creates a micro obstacle network that inevitably increases physical detour costs.

Spatial syntax metrics exhibit “polarized impact directions” in macro and meso efficiency (Fig. 16b and Fig. 16c). Local integration (NAIN R1000) significantly promotes spatial detouring, with high value samples aggregating in the positive zone. In contrast, global choice metrics (NACH R4000 and NACH R5000) show a strong negative correlation, thereby suppressing detours. This reveals physical stratification. Highly integrated micro capillary networks provide redundant space for exploratory lane changes that statistically increase trajectory deviation. Conversely, cycling on large scale transit skeletons

(high NACH) is efficiency dependent, where structured road morphology compels trajectories to remain closer to theoretical shortest paths.

Fig. 16b and Fig. 16c expose a nonlinear characteristic often masked by linear models: the “long tail penalty effect”. The Office Functional Mixing Degree exhibits an exaggerated asymmetric long tail. While attribute fluctuations remain mild in ordinary spaces, the effect emerges explosively beyond polarized high thresholds. In Fig. 16a, ultra-high density office samples form extreme negative outliers, causing trajectory stability to collapse precipitously into passive “micro-perturbation”. In Fig. 16c, the same samples soar to extreme positions with SHAP values exceeding 1,000. This confirms the “CBD Black Hole Effect”. Tidal pedestrian flows, expanded building setbacks, and gated barriers in high density office cores sever micro spatial permeability. Such institutional segregation imposes explosive nonlinear penalties on trajectories, causing detour costs and “micro-perturbations” to deteriorate exponentially⁵³.

The global overview provided by SHAP plots establishes principles for refined active mobility governance. To improve efficiency, emphasis must be placed on reinforcing the direct connectivity of through movement corridors (NACH) to suppress disorderly detours. Conversely, for ultra high density office cores, conventional road adjustments cannot offset the extreme asymmetric long tail resistance, necessitating radical active travel intervention mechanisms in micro spatial regulations.

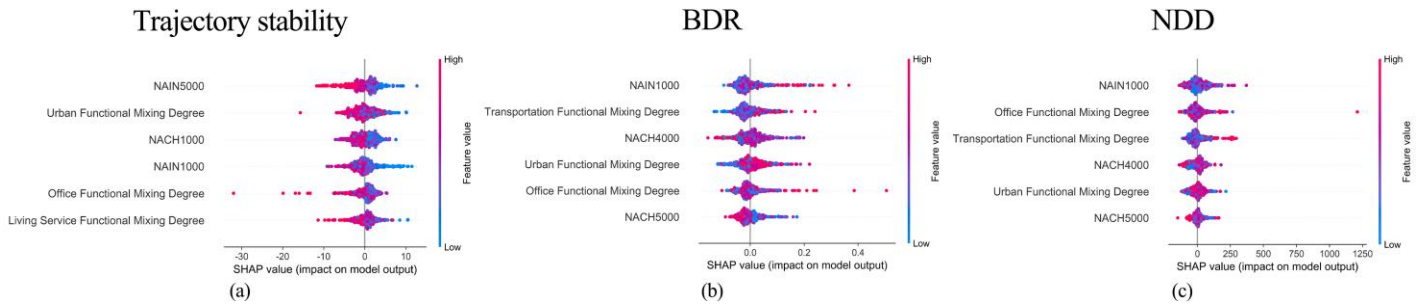


Fig. 16. Non-linear impacts and spatial long-tail effects of the built environment on macro and micro cycling dimensions (Based on SHAP summary plots) (a: Trajectory stability; b: BDR; c: NDD).

4.5. Non-linear Spatial Thresholds and Interactive Gaming of the Built Environment Based on 2D-PDP

To reveal the nonlinear interaction between micro local integration and functional density, this study employs Two Dimensional Partial Dependence Plots (2D PDP). We deliberately pair micro local integration (NAIN R1000) with “Urban Functional Mixing Degree” and “Office Functional Mixing Degree” as the primary feature spaces (Fig. 17). This selection is based on a “cross dimensional control” strategy. As SEM results indicate, these variables are the core environmental factors exerting significant roles simultaneously in both “cycling efficiency” and “trajectory stability”. By locking onto this identical set of micro spatial genes, we can precisely isolate how they trigger nonlinear mutation thresholds across different cycling dimensions within the same feature space. The analysis reveals a “zero sum game” between cycling efficiency and trajectory stability. As Fig. 17c and Fig. 17d demonstrate, when NAIN R1000 falls below the threshold of 1.11, the Behavioral Detour Ratio (BDR) escalates sharply, indicating that physical connectivity acts as the primary resistance to passive detours. Paradoxically, Fig. 17a and Fig. 17b reveal that this low connectivity interval unexpectedly shields cyclists from vehicular interference, creating a high value safety zone for trajectory stability. Furthermore, when the road network is overly connected (> 1.40), the Normalized Degree of Deviation (NDD) exhibits a concentrated “double peak” high value area (Fig. 17e and Fig. 17f). This confirms that while micro connectivity mathematically dilutes the relative sense of detouring, overly

integrated road networks often introduce complex physical segregation, forcing cyclists to pay a harsher deviation penalty on a two dimensional spatial scale^{51,54}.

Regarding the compression of micro cycling space, the “Office Functional Mixing Degree” exhibits a strong “polarized threshold effect”. Our results indicate that as long as this metric remains below 0.63, a “micro active travel safe haven” can be spontaneously formed, balancing low detours and high trajectory stability. However, once the office mixing degree crosses this critical overload point of 0.63, the gated morphology and tidal traffic of the office district trigger a “black hole effect”. This threshold overrides conventional road network optimizations, causing trajectory smoothness to collapse precipitously into passive “micro perturbations”⁵³.

In summary, the influence of high density built environments is a nonlinear game controlled by spatial thresholds. The over accessibility of road networks and the disorderly prosperity of functions lead to a divergence between increased physical detour costs and decreased trajectory anti interference capabilities. Consequently, planning strategies must transition from pursuing global connectivity toward preventing “highly sensitive mutation points”, such as the office mixing degree (0.63) and micro integration (1.11 to 1.27), to maintain the optimal equilibrium between cycling efficiency and riding state.

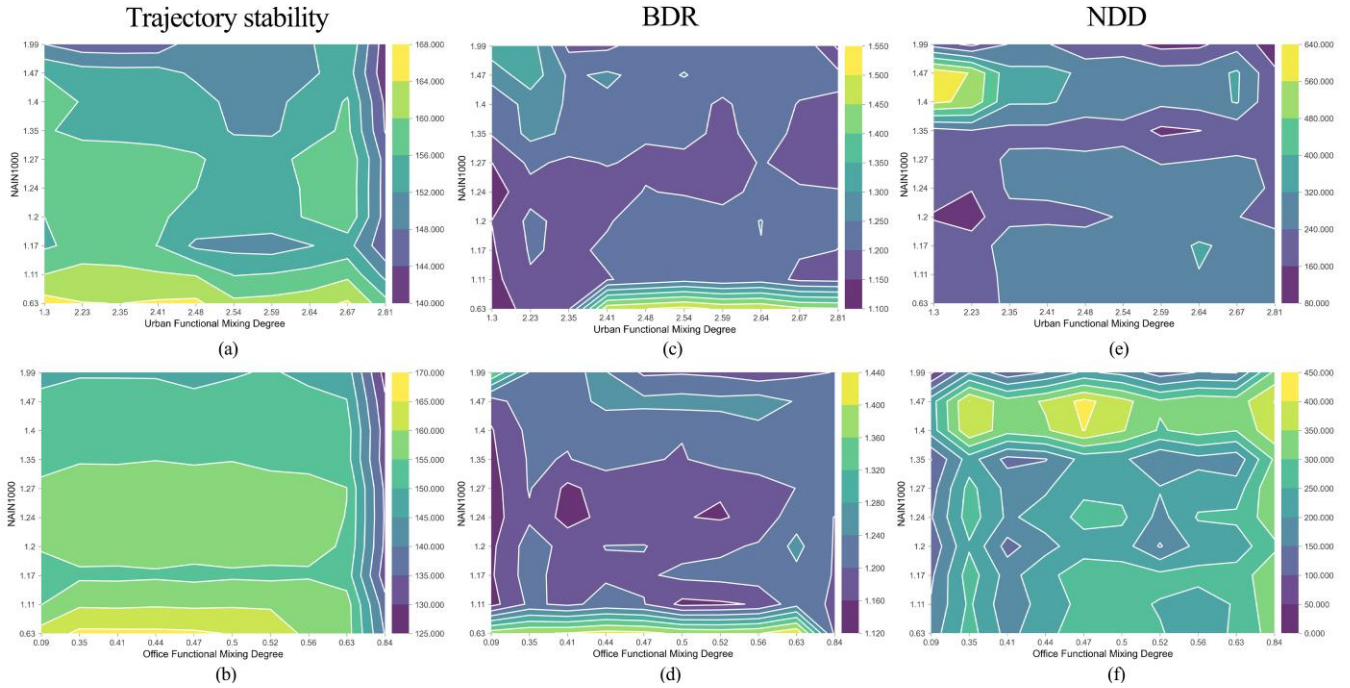


Fig. 17. Non-linear interactive effects of micro-network integration and functional mixing degrees based on Two-Dimensional Partial Dependence Plots (2D-PDP) (a-b: Trajectory stability; c-d: BDR; e-f: NDD).

4.6. Hierarchical Clustering and Morphological Comparison of Cycling Behavior: Visual Mapping of Non-linear Thresholds

To transform abstract machine learning feature spaces into an intuitive urban spatial planning language, this study utilizes R type Hierarchical Clustering Analysis (HCA) and case based micro spatial mapping to conduct a dimensionality reduction and deconstruction of cycling trajectory morphologies.

4.6.1. Three-Dimensional Spatial Reduction of Behavioral Dimensions

The clustering results (Fig. 18a) confirm the causal decoupling logic from an unsupervised perspective. The Behavioral Detour Ratio (BDR) and Normalized Degree of Deviation (NDD) cluster together to characterize the macro and micro efficiency dimension, while trajectory stability emerges as an independent branch representing the micro process state.

Crucially, the clustering analysis successfully extracted an independent spatial category characterized by “low detour, low stability” (e.g., short distances with high frequency large angle deflections). If the proposed indicator were invalid, highly spatially heterogeneous categories (such as the CBD space black hole) could not cluster independently in statistical terms. This inversely proves that by utilizing the average deflection angle as an observer, the trajectory stability metric successfully captures a third dimensional information layer uncovered by detour rates: micro perturbation frequency and the sensation of spatial friction.

To map these statistical patterns onto spatial morphological variations, we project the clustering logic onto a 3D quadrant framework (Fig. 18b) defined by the detour rate, trajectory stability, and total trajectory mileage. The horizontal axis (detour rate) and vertical axis (trajectory stability) isolate core typological features, while the perpendicular axis (total mileage) acts as a metric for spatial exposure to differentiate long distance commuting from short distance transferring. This geometric division breaks through the limitations of efficiency only indicators and provides a morphological reference for precisely sampling and locating typical individual cases from the dataset.

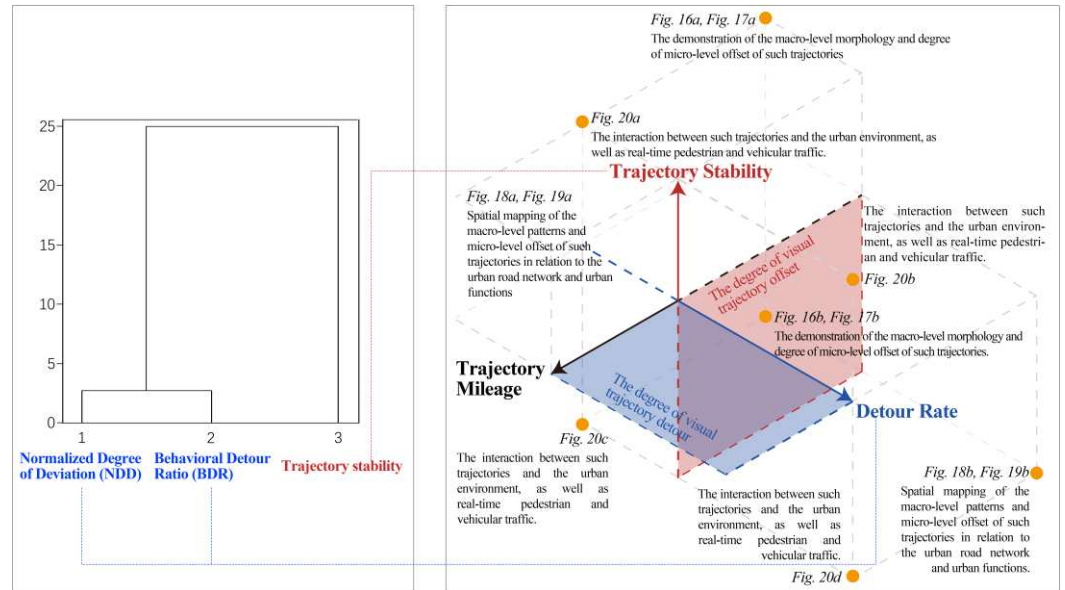


Fig. 18a. Hierarchical clustering results (left).

Fig. 18b. Three-dimensional quadrant of trajectory dimensions (right).

Fig. 18. Toward a Two-Dimensional Analytical Framework: From Statistical Clustering to Spatial Representation.

4.6.2. Visual Verification of Trajectory Micro-Tremors

Under the constraints of this 3D morphological coordinate system and by controlling the shared variable of “high path efficiency” (low BDR and NDD), typical individual cases from different quadrant clusters were extracted for micro visual comparison (Fig. 19-Fig. 22). This visual evidence corroborates the “connectivity backlash” and “safe haven” phenomena revealed by the 2D PDP. High stability trajectories (Fig. 19a, Fig. 20a) feature large angle offset points and highly

coherent morphologies. Superimposing these trajectories onto the empirical urban environment reveals a stark contrast. The high stability trajectories (Fig. 21a, Fig. 22a) primarily navigate through areas with low spatial syntax indicators and medium to low urban functional mixing. This relatively simple environment inadvertently erects a physical barrier that shields cyclists from complex multi scalar traffic interference.

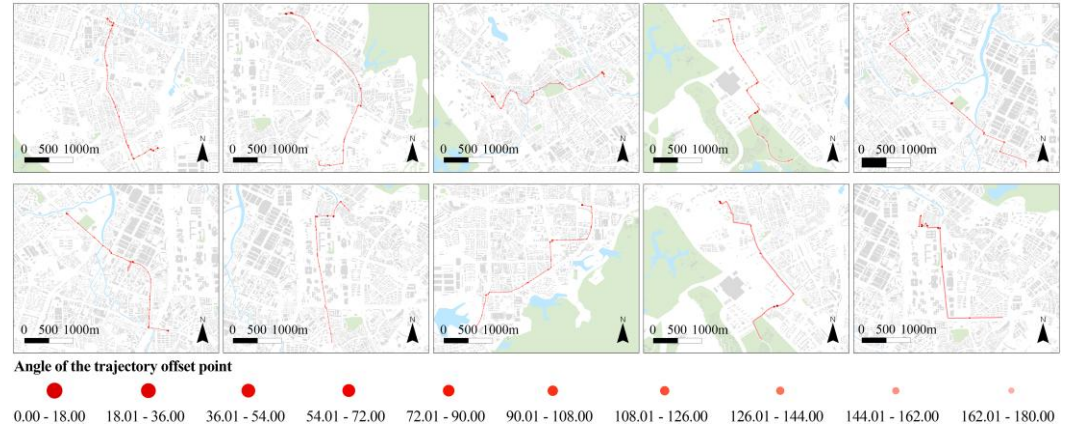


Fig. 19a. Trajectory groups with high trajectory stability, low BDR, low NDD, and low trajectory mileage.

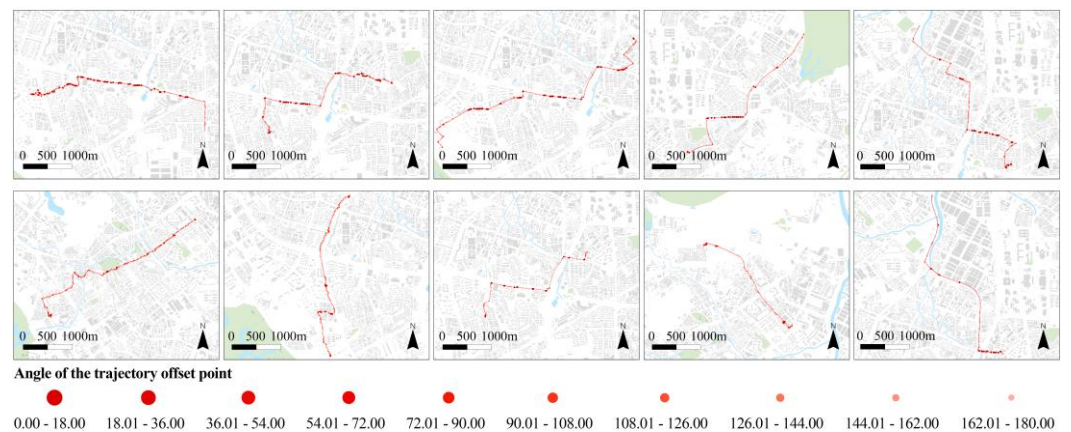


Fig. 19b. Trajectory groups with low trajectory stability, low BDR, low NDD, and low trajectory mileage.

Fig. 19. Trajectory morphology classification in population model.



Fig. 20a. High trajectory stability, low BDR, low NDD, and low trajectory mileage for a single track (left).

Fig. 20b. Low trajectory stability, low BDR, low NDD, and low trajectory mileage for a single track (right).
Fig. 20. Single trajectory cases with high and low stability.

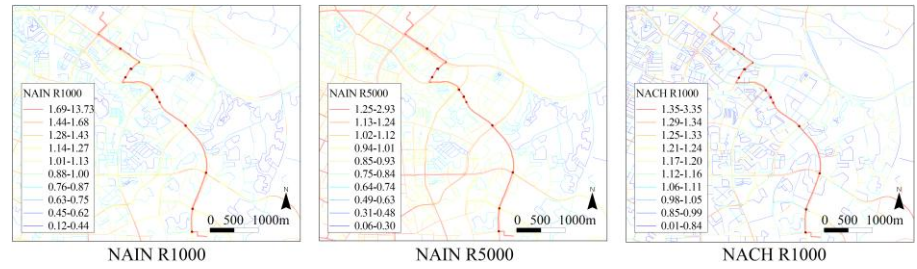


Fig. 21a. Spatial mapping of urban road network structure and trajectories with high trajectory stability and high mileage.

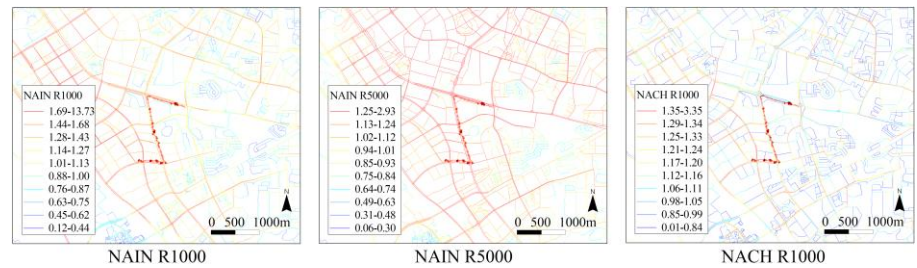


Fig. 21b. Spatial mapping of urban road network structure and trajectories with low trajectory stability and low mileage.

Fig. 21. Mapping between trajectory stability and urban road network.

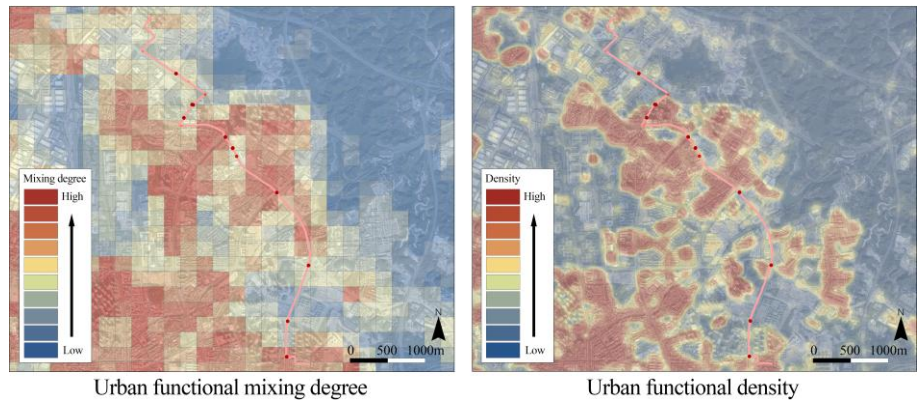


Fig. 22a. Spatial mapping of urban function and trajectories with high trajectory stability and high mileage.

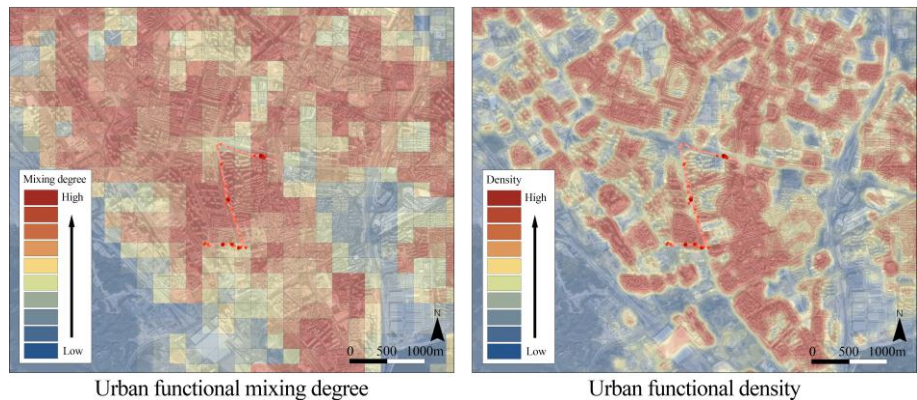


Fig. 22b. Spatial mapping of urban function and trajectories with low trajectory stability and low mileage. 824
825

Fig. 22. Mapping between trajectory stability and urban functions. 826

Conversely, low stability trajectories (Fig. 19b, Fig. 20b) expose dense low angle offsets 827
and “high frequency spatial corrective actions” even on straight segments. Their corresponding 828
spatial mapping (Fig. 21b, Fig. 22b) reveals that this dense environmental perturbation phenome- 829
non occurs precisely within overlapping zones characterized by extremely high micro connectivity 830
(NAIN R1000 > 1.40) and highly complex functional formats. This polarized visual evidence ver- 831
ifies that high grade micro accessibility attracts the physical superposition of multi scalar flows. 832
This intertwining inevitably generates a high pressure “friction field” in the 2D continuous space, 833
forcing cyclists to produce numerous passive “micro perturbations” while moving. 834

4.6.3. A Parametric Threshold-Driven Governance Typology for Active Travel Spaces 835

This study embeds the nonlinear thresholds decoupled via XGBoost and 2D PDP into 836
the four quadrant framework derived from Hierarchical Cluster Analysis (HCA) (Fig. 20). 837
This integration transitions traditional environmental descriptions into a “Parametric Spa- 838
tial Governance Model” underpinned by empirical evidence ⁹⁶. 839

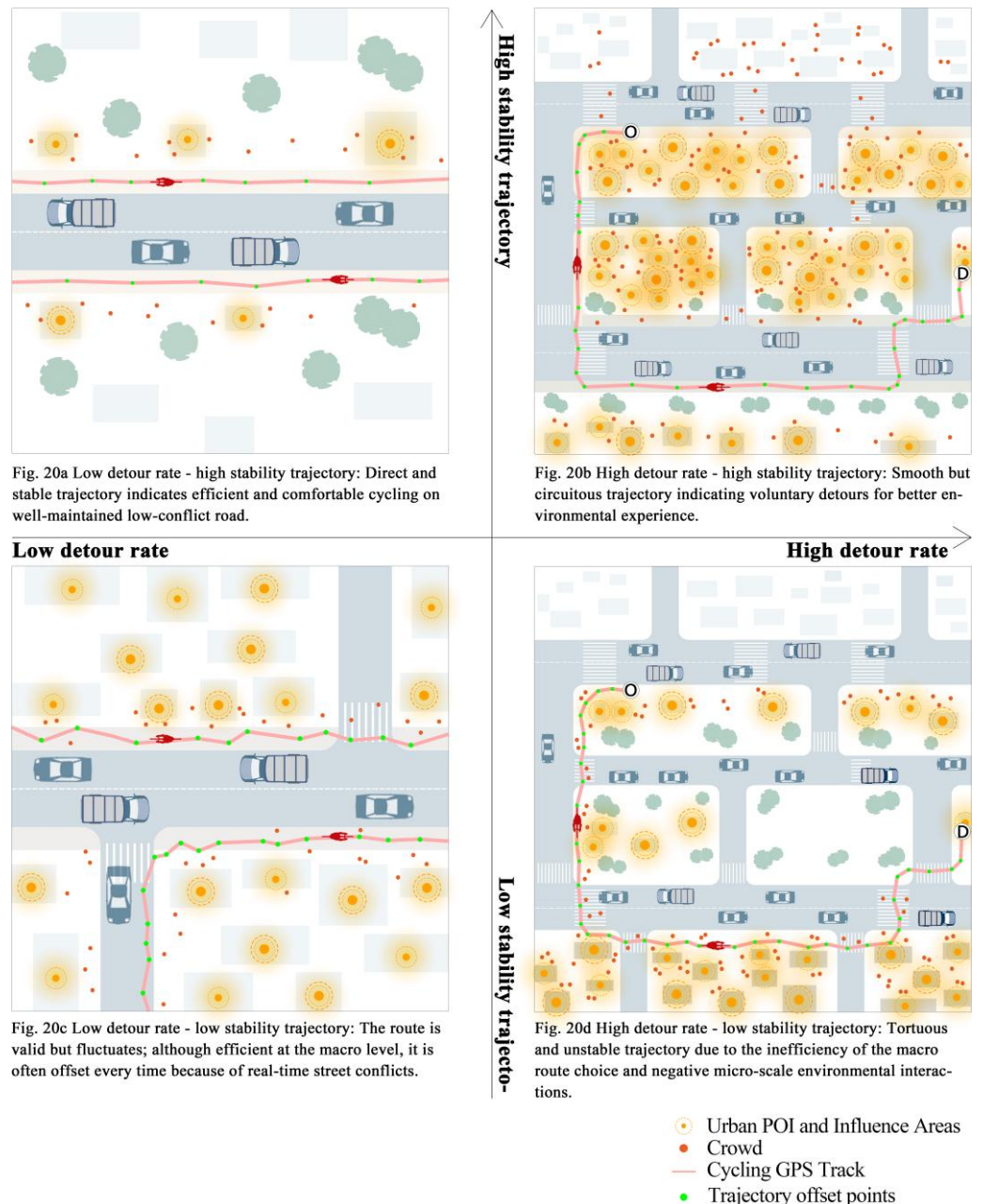


Fig. 23. Typology Framework of Cycling Behavior Based on Detour Rate and Trajectory Stability.

The model identifies four spatial morphologies based on their efficiency and stability performance. The first morphology, defined as a “Micro Active Travel Safe Haven”, achieves equilibrium by precisely controlling spatial redundancy. Its core parametric feature suppresses office functional mixing below the critical 0.63 threshold, while maintaining micro network connectivity (NAIN R1000) within the “Golden Corridor” of 1.11 to 1.27. This ensures permeability while filtering out multi-scale traffic interference. In contrast, the “Multi scalar Topological Overload Zone” exhibits high theoretical accessibility but poor micro experience. This morphology triggers dual backlash thresholds: either micro network over integration ($\text{NAIN R1000} > 1.40$) squeezing active travel right of way, or functional mixing exceeding the “warm water limit” (> 2.67). Both conditions result in continuous passive “micro perturbations” and the deprivation of perceived safety.

Furthermore, the “Oasis of Topological Isolation” offers high stability at the cost of commuting efficiency. Constrained by low micro accessibility ($\text{NAIN R1000} < 1.11$), cyclists are forced into macroscopic detours. However, this “topological isolation” erects a physical barrier that shields them from the friction fields of the primary urban network to

ensure trajectory smoothness. Finally, the “CBD Spatial Black Hole” represents the most severe morphology. Rooted in the polarized overload of office functions, crossing the 0.63 threshold forces massive physical detours and shatters trajectory stability through gated boundaries and tidal crowds, generating severe “micro perturbations”. Conventional road network adjustments fail here, necessitating disruptive interventions like multi-level crossing facilities or absolute right of way segregation.

In summary, this typology shifts active travel governance from “static cross section allocation” to “dynamic nonlinear threshold management”. By locating “highly sensitive mutation points” and “progressive overload zones”, this study provides an evidence based paradigm for refined active mobility design in high density cities.

5. Discussion

5.1. Pathological Analysis of Trajectory Instability and Built Environment Vitality: A Perspective of Friction Deficit

The “micro level trajectory perturbations” observed in cycling trajectories are not stochastic events but manifestations of significant spatial heterogeneity. This phenomenon is not a reflection of individual cycling skills. Rather, it is a manifestation of an “environmental negative feedback variable” imposed on cyclists when the micro street network topology fails to accommodate instantaneous dynamic traffic flows. This reveals a dynamic conflict. When micro network integration exceeds carrying thresholds, cycling trajectories exhibit geometric deviation alongside high frequency “micro perturbations”.

This perturbation pattern represents a stress response within a “spatial friction field”. High frequency “micro perturbations” occur densely at environmental fracture points, such as nodes with multi scalar pedestrian and vehicular conflicts, boundaries of enclosed office zones, and interchange hubs lacking physical segregation. These locations induce an instantaneous superposition of commuting, commercial, and leisure flows, generating a nonlinear “high pressure friction field”⁹⁷. Within such fields, cyclists are forced into continuous passive micro adjustments, leading to an exponential decay in trajectory stability^{98,99}. Consequently, these trajectory perturbations are not accidental occurrences but a structural “friction deficit” exposed when micro urban road networks are subjected to high density interactions from specific functional formats¹⁰⁰. This deficit reflects the topological failure of existing active mobility infrastructure to accommodate instantaneous dynamic loads in high density urban areas¹⁰¹.

5.2. The Critical Load and Cognitive Overload Mechanism of Active Mobility Networks

The nonlinear threshold system revealed by this study exposes three typical “spatial load failure” mechanisms for active mobility in high density urban environments.

First, polarized office loads trigger cognitive collapse. When functional mixing exceeds critical limits, the tidal commuting flows and physical interference of enclosed boundaries confront cyclists with extreme information redundancy⁸⁵. From a behavioral dynamics perspective, this spatial information density exceeds the cyclist's cognitive processing limit and the instantaneous response capacity of the road network. This cognitive overload compels cyclists to shift their strategy from “path execution logic” to “risk avoidance logic”¹⁰². During this transition, the continuous geometric spatial compensations required to overcome the topological lag manifest as passive “micro-perturbations”¹⁰³.

Second, the topological negative feedback loop of micro integration establishes an impedance matching mechanism. Findings indicate that micro network integration does not linearly improve the cycling experience⁵¹. Within the optimal range, the network structure achieves “impedance matching” with high density dynamic flows to effectively

absorb spatial pressure ¹⁰⁴. Deviating from this range induces topological failure. Values below the lower bound lead to closure stress. Conversely, exceeding the upper bound triggers a connectivity backlash where excessive integration introduces uncontrollable transit vehicular flows, resulting in a substantive loss of active mobility right of way ²³.

Finally, the progressive overload of comprehensive functions constitutes flow dynamics saturation ¹⁰⁵. Unlike the “mutation type instability” caused by office formats, comprehensive functional mixing induces a gradual flow dynamics overload by increasing the contact frequency of trajectories. This phenomenon reflects a dilution effect on “behavioral inclusivity” within urban space. As functional complexity increases, high frequency intersections between pedestrian and cycling trajectories force cyclists to continuously sacrifice speed smoothness to maintain equilibrium ¹⁰⁶. This confirms that active mobility governance in high density areas is essentially a nonlinear dynamic game between micro road networks, functional configurations, and interaction flow loads ⁹⁶.

5.3. From Static Allocation to Threshold-based Responsiveness: A Paradigm Shift

This study illuminates the nonlinear logic of active mobility interventions. When the spatial environment operates within “threshold limits”, the cycling experience is sensitive to marginal environmental disturbances. This suggests that planning interventions should focus on high precision micro adjustments. Conversely, when spatial conditions fall into the “Black Hole Effect” of extreme overload, the negative feedback loop of the environment becomes rigid, rendering conventional cross sectional optimization ineffective. This necessitates disruptive interventions involving topological restructuring.

This shift marks a paradigm change in urban planning, moving from a static perspective based on “ideal cross sectional allocation” to a responsive governance path grounded in “mutation dynamics”. Consequently, in future active mobility network design, the role of the practitioner transitions from a “space allocator” to a “regulator of spatial pressure fields”. The core of this paradigm shift lies in acknowledging and leveraging the spatial properties of nonlinear thresholds. By precisely identifying and intervening at “highly sensitive mutation points”, practitioners can facilitate a structural transformation of active mobility systems, transitioning from passive adaptation to active and resilient spatial reconstruction.

6. Conclusion

6.1. Conclusions and Core Contributions

This study identifies that cycling quality in high density urban areas is an emergent property of the micro scale gaming between road network topology and dynamic interaction flows. Our empirical findings establish a “multi scale dual logic” framework that decouples macro efficiency constraints from micro process disturbances ⁹⁸. Macro scale detour rates are primarily driven by destination accessibility, whereas micro scale trajectory perturbations manifest as a passive stress response to structural friction ^{6,50,107}. This decoupling confirms the topological failure of conventional efficiency oriented paradigms in managing multi-scale flow interactions.

The core contribution of this study lies in transforming complex nonlinear behaviors into a “Parametric Threshold Governance Model”. By integrating SEM, XGBoost, and 2D PDP, we identify critical mutation points that dictate cycling quality, most notably the office functional mixing degree (0.63) and micro network local integration (1.11 to 1.27) ¹⁰⁸. These nonlinear thresholds transcend the explanatory limits of traditional linear models, offering a quantitative diagnostic benchmark for identifying “spatial overload zones” ^{52,109}. Ultimately, these results provide a robust theoretical foundation for shifting active

mobility design from “global average design” toward “threshold based precision governance”.

6.2. Paradigm Shift and Governance Framework

The multi scale conduction framework proposed in this study (Fig. 24) shifts active mobility governance from “static space allocation” based on cross sectional widths to “threshold based responsiveness” centered on nonlinear load and topological dynamics¹¹⁰. Our findings redefine cycling quality as an emergent property of the micro scale gaming between road network topology and dynamic interaction flows¹¹¹. We propose two strategic pivots for urban planning.

First, planning must transition from global average standards toward “diagnostic intervention”¹¹². By utilizing parametric thresholds, such as the office functional mixing degree (0.63) and micro network local integration (1.11 to 1.27), planners can identify “Black Hole Effects” of extreme overload. In these zones, practitioners should prioritize structural topological restructuring over superficial lane widening. Second, practitioners must evolve into “regulators of spatial pressure fields”, mitigating multi scalar flow conflicts by precisely intervening at “highly sensitive mutation points”¹¹³. This paradigm shift facilitates the transformation of active mobility systems from passive adaptation to resilient spatial reconstruction, ensuring that networks accommodate urban complexity while effectively preventing passive “micro perturbations”¹¹⁴.

6.3. Limitations and Future Perspectives

Although this study constructs an initial governance framework for active mobility through nonlinear mechanism identification, certain limitations outline directions for future inquiry. By directly addressing these methodological boundaries, we clarify the specific applicability of our findings.

First, regarding data source differences, the crowdsourced trajectories derived from the “2bulu” platform encompass a mix of leisure sports and daily commuting motivations. We acknowledge a certain ambiguity in distinguishing between “active sports deflection” and passive “obstacle avoidance perturbation”. However, given the statistical significance of large samples operating within the same spatial structure, this variance is highly tolerable for discovering macroscopic spatial laws.

Second, we acknowledge that quantifying two dimensional geometric deflection angles using crowdsourced GPS trajectories remains an exploratory endeavor from a macro planning perspective. Current GPS sampling frequencies and accuracies cannot equal the precise measurements of micro engineering. Future research urgently needs to introduce High Frequency Inertial Measurement Units (IMUs) combined with deep learning algorithms to precisely define the kinematic angle thresholds between “active steering” and passive “micro perturbations”. Nevertheless, in the ultra high density urban context of Shenzhen, the current geometric proxy variable based on large samples serves as an effective probabilistic representation. It is statistically sufficient to reveal the compulsory and nonlinear spatial oppression and friction imposed by the physical built environment on the micro cycling state.

Finally, future empirical work should employ longitudinal research designs within urban renewal projects. Tracking trajectory behavior before and after interventions will fully elucidate micro scale human environment interactions and provide robust empirical guidelines for responsive urban governance.

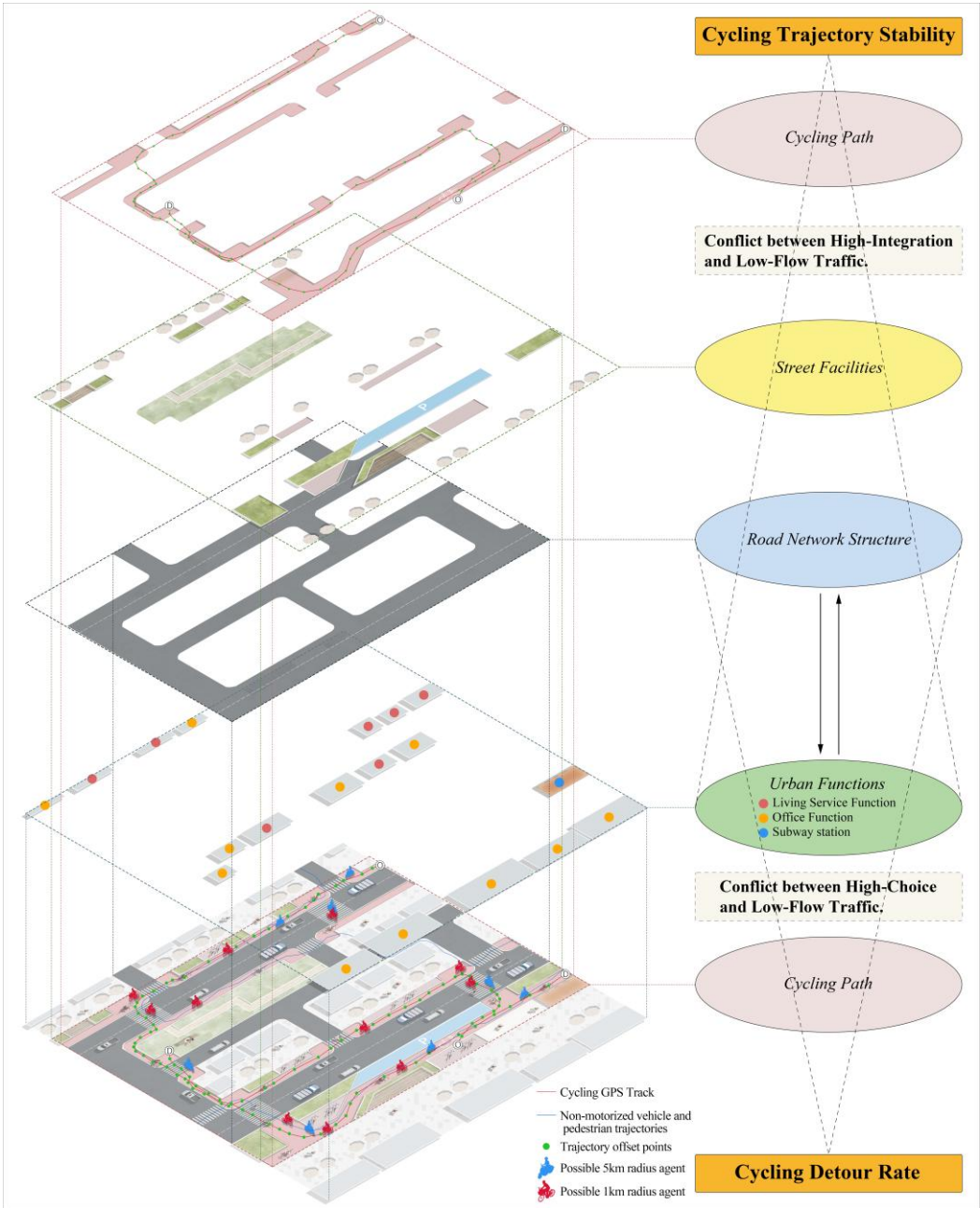


Fig. 24. Bicycle Street design framework based on multi scale screening mechanism.

Data Availability Statement:

The OpenStreetMap data are available at <https://www.openstreetmap.org>. The crowdsourced cycling trajectories are fully anonymized, publicly accessible secondary data from the Liang Bulu platform (<https://www.2bulu.com/>) , accessed in strict compliance with its privacy policy and without involving personally identifiable information. Urban POI and built environment data are available from the corresponding author upon reasonable request. To enhance data transparency, a detailed file retrieval matrix mapping all operationalized variables to their corresponding original shapefiles (.shp) has been provided in the Supplementary Material (Table S1). All relevant spatial data layers provided can be directly imported, visualized, and further examined using standard Geographic Information System (GIS) software, specifically ArcGIS or ArcGIS Pro.

Table S1. Horizontal Matrix of Variable Categories, Analytical Metrics, and Corresponding Source Shapefiles (.shp)

Variable Category	Analytical Metrics / Variables	Corresponding Original Shapefile (.shp)
Dependent Variables	- Macro-efficiency: Detour rate (BDR) - Macro-spatial deviation: (NDD) - Micro-process state: Trajectory Stability	trajectory_data.shp
Road Network Structure(Analysis radii: 1000m, 2000m, 3000m, 4000m, 5000m, and Global)	- Through-movement potential: NACH - Topological accessibility: NAIN	Road_Network_Structure-Space_Syntax.shp
Urban Functions(Specific POI Elements)	- Comprehensive Functional Mix (Entropy) - Office Functional Mixing Degree - Transit functional mix - Residential functional mix - Living Service functional mix - Leisure functional mix	Urban_Functional_Mixing_Degree.shp Subway and Bus Transit.shp Transportation Facilities.shp Business and Residential.shp Science, Education and Culture.shp Living Services.shp Automobile-related Services.shp Healthcare.shp Leisure and Entertainment.shp Shopping and Consumption.shp Food and Dining.shp Sports and Fitness.shp Tourist Attractions.shp Hotels and Accommodation.shp

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1279 **Declarations**

1280 **Competing interests**

The authors declare that they have no known competing financial interests or personal relationships 1281
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