

Article

The Context-Dependent Influence of Eye-Level Motor Traffic on Metro-Integrated Cycling: An AIGC-Enhanced Analysis

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Abstract

This study examines the context-dependent association between eye-level motor traffic and metro-integrated cycling in Shenzhen, China. To address the limitations of static street-view imagery, we constructed a traffic-informed AIGC-enhanced analytical framework to approximate peak-hour visual motor-traffic conditions. The resulting eye-level motor-traffic measure was incorporated into OLS, GWR, and MGWR models together with land-use, road-network, development-intensity, and streetscape variables. The results show that this measure was positively associated with metro-integrated cycling volume primarily during the weekday morning peak, while the association weakened or became statistically insignificant during evening and weekend periods. We describe this pattern as a commuter's paradox-like association: visible motor traffic may co-occur with high first-/last-mile cycling demand in high-intensity commuting environments, rather than necessarily deterring cycling. The analysis further suggests a threshold-like land-use pattern in which residential density may act as a background precondition rather than a linear driver during peak hours. This study illustrates the methodological applicability of Geospatial Artificial Intelligence (GeoAI) for addressing static-data limitations and provides planning implications for evaluating station-area feeder cycling environments.

Keywords: Artificial Intelligence Generated Content (AIGC); GeoAI; spatial heterogeneity; synthetic spatial data; urban mobility; environmental perception; dockless bike-sharing; spatial analysis



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1. Introduction

Rapid urbanization has improved urban economies but has also intensified transportation challenges such as congestion, environmental degradation, and declining quality of urban life. To tackle these issues, cities worldwide have increasingly promoted sustainable transportation solutions—particularly cycling combined with public transit—to achieve more livable urban environments [1]. Dockless Bike-Sharing (DBS) has emerged as an important last-mile solution to bridge transit gaps and promote sustainable urban mobility [2,3].

Recent research underscores the importance of integrating DBS with metro systems, a strategy widely termed the “Bike and Ride” (B + R) model, to extend public transport accessibility and reduce private vehicle dependence [4–6]. Empirical studies have shown that various built environment attributes—including street design, land-use patterns, and visual quality—have been associated with cycling behavior around

metro stations [7,8]. Visual elements captured by street view imagery, such as greenery coverage, street enclosure, and sky openness, have particularly been linked to cycling activities [1,9,10].

However, while existing studies have predominantly analyzed static visual components of urban street environments, dynamic visual factors—particularly the visual proportion of motor vehicles on roadways, which constitutes a substantial part of typical street-level images—remain less examined, especially through dynamic, perception-based metrics. Although the visual presence of motor vehicles may influence cyclists' perceptions and route preferences, this aspect has not been sufficiently examined, partly because of the limitations of traditional data acquisition methods. Conventional metrics, such as macro-level traffic congestion indices or vehicle counts, do not always align well with cyclists' subjective perceptions and experiences at eye level, leaving a gap in understanding how dynamic vehicular visual proportions are associated with cycling preferences and route choices (as illustrated in Figure 1). While other dynamic factors, such as pedestrian or e-bike flows, also contribute to the streetscape, this study specifically focuses on eye-level motor traffic. Motor vehicles are often a major source of perceived safety threats and acoustic stress for cyclists, making them an important dynamic visual factor that shapes route choice and riding comfort in shared-road environments.

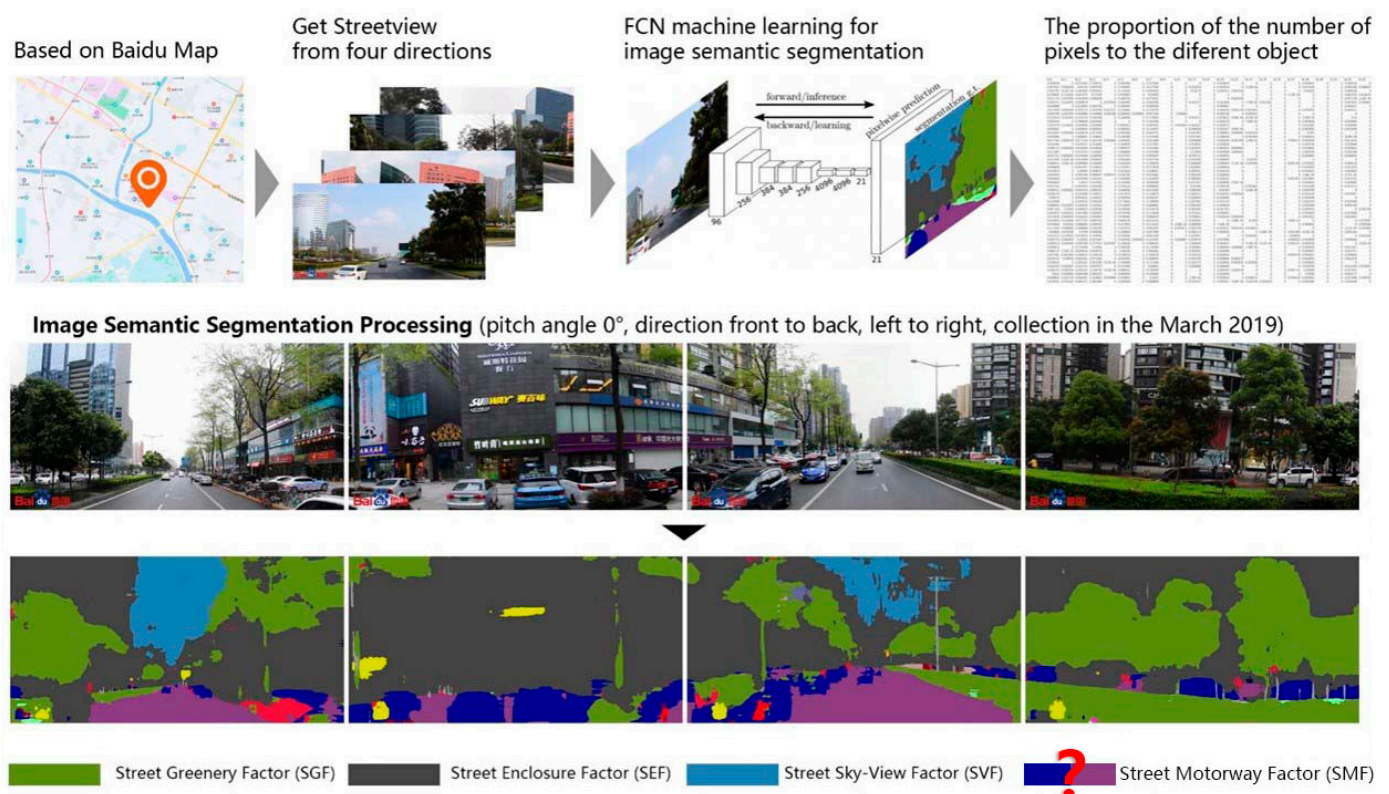


Figure 1. Limitations of traditional semantic segmentation for dynamic traffic analysis. Conventional static street-view semantic segmentation can extract relatively stable streetscape elements, such as greenery, enclosure, and sky-view factors. The question mark indicates that the motor-traffic visual factor cannot be reliably represented by conventional static semantic-segmentation outputs alone, because motor-vehicle presence varies substantially across time and traffic conditions.

To address this gap, this study introduces a traffic-informed AIGC-enhanced analytical framework to approximate dynamic street-level vehicular traffic conditions. Unlike urban or landscape design simulations [11,12] and large multimodal models (LMMs) applied to urban perception studies [13,14], this workflow uses real-time traffic-speed information

and fine-tuned generative models to generate street-level visualizations that approximate peak-hour visual traffic conditions. This approach helps mitigate the limitations of static street-view imagery by using AI-enhanced images as visual proxies for vehicular presence under constrained traffic conditions, thereby providing an exploratory GeoAI-assisted workflow for geospatial visual analytics in urban studies [15,16].

Using detailed DBS data from Shenzhen, we examine the spatial and temporal association between eye-level motor-vehicle proportions—estimated from traffic-informed AIGC-enhanced imagery—and metro-integrated cycling volume. Employing Adaptive Catchment Areas (ACAs) to delineate cycling-influenced zones around metro stations, we address the limitations of traditional buffer or Thiessen polygon methods [17,18]. Furthermore, we apply a Multiscale Geographically Weighted Regression (MGWR) model, incorporating multiple built environment factors—including street-level motor vehicle visual proportions, points of interest (POIs), road hierarchy, and green visibility—to evaluate their spatially and temporally heterogeneous associations with metro-integrated cycling.

This study contributes to the literature in three ways:

1. Methodological contribution: this study develops a traffic-informed, AIGC-enhanced streetscape workflow to derive dynamic visual traffic variables from static street-view imagery under real-time traffic-speed constraints.
2. Empirical contribution: this study examines the time-specific spatial association between eye-level motor traffic and metro-integrated cycling, describes a context-dependent commuter's paradox-like pattern during weekday commuting periods.
3. Planning implication: this study discusses planning implications for high-intensity commuting zones, emphasizing connected separation, continuous cycling infrastructure, and context-sensitive metro-feeder mobility planning.

The subsequent sections of this paper outline the research methodology, analyze cycling behaviors across different spatial-temporal scenarios, present empirical findings based on MGWR modeling, and discuss planning implications for cycling infrastructure and metro-feeder mobility in station areas.

2. Study Area and Data

2.1. Study Area

This study focuses on Shenzhen, a major metropolis in southern China. Shenzhen serves as a suitable empirical setting for this research not only due to its subtropical climate which permits year-round cycling, but for two relevant morphological characteristics. First, as a major Transit-Oriented Development (TOD) city in China, Shenzhen has a mature, high-density metro-integrated cycling network, allowing us to examine whether density-related factors remain differentiating correlates of metro-integrated cycling in already dense station areas. Second, the selected study area—comprising the three core districts of Nanshan, Futian, and Luohu (Figure S1 in Supplementary Material)—presents contrasting urban forms that are relevant to the comparative analysis [10,19].

These three districts represent distinct stages of the city's evolution: Luohu features a traditional, high-density mixed-use fabric with narrow streets; Futian (the CBD) exhibits a dense gridiron network with modern infrastructure; and Nanshan represents a modernist "New City" typology characterized by functional zoning, super-blocks, and wide arterials. Together, these districts provide contrasting urban forms for comparative analysis.

Morphologically, this creates a comparative framework between the "Old City" typology (Luohu and Futian), defined by dense, human-scaled road networks, and the "New City" typology (Nanshan), defined by functional separation and larger block scales. This diversity allows us to examine how different urban structures—and their associated infrastructure patterns—mediate the "last-mile" connection.

Within the selected districts, 102 metro stations were initially identified. However, one station was not in operation during the study period and was therefore excluded from the modeling dataset. The final analysis was conducted using 101 valid station-level ACAs.

2.2. Data Acquisition and Initial Processing

2.2.1. Dockless Bike-Sharing (DBS) Data

DBS data were obtained from the Shenzhen municipal open data platform, covering the week of 1–7 February 2021. This dataset was selected because it represents the most recent high-granularity DBS trajectory dataset officially released by the municipal authority at the time of data acquisition. This period was selected to minimize weather-related bias, as no rainfall occurred during the study week. Using this latest official release supports data validity and compliance with data security regulations, providing a verifiable basis for urban cycling analysis. We acknowledge that the one-week observation window limits temporal generalizability, and this limitation is further discussed in Section 5.

The dataset comprises timestamped geolocation points marking idle parking positions of dockless bicycles, each associated with a unique bike ID. On average, 1.4165 million trips were recorded per weekday and 1.1327 million on weekend days during the study period. Peak usage times were concentrated during the morning (7:00–9:00 a.m.) and evening (5:00–7:00 p.m.) commuting periods (Figure S2), which were therefore used as the main temporal periods for analysis.

Since the raw data only reflect stationary parking points, cycling trajectories were reconstructed by sequentially linking the geolocations of the same bicycle ID according to timestamp. These sequences were then matched to the road network to estimate origin–destination (OD) paths, approximating the movement of dockless bikes across the urban fabric. Abnormal data, such as records indicating prolonged immobility or excessively long cycling distances, were excluded to ensure data quality.

2.2.2. Built Environment Data Sources

Several categories of built environment data were collected.

Points of Interest (POIs): POI data representing land-use diversity were acquired from Amap (Gaode Map), a widely used Chinese online mapping platform. The collected POIs were categorized according to functional types, such as commercial facilities, residential buildings, and workplaces.

Road network data: road network data, including roadway classifications and intersection locations, were derived from OpenStreetMap.

Building data for floor area and height: building footprint and building height data were obtained from Amap.

Street view imagery: static street view imagery for road segments was obtained from Baidu Maps. Some of these images served as the base for AIGC enhancement.

Traffic-speed data for AIGC guidance: To constrain the AIGC enhancement process with observed traffic conditions, real-time traffic speed data were programmatically collected using the Amap navigation service API. For each road segment connecting two intersections within the study area, requests for car navigation times were made repeatedly during the morning (7:00–9:00 a.m.) and evening (5:00–7:00 p.m.) peak commuting periods throughout the study week. The travel speed for each segment at different time intervals was then estimated by dividing the known segment length by the API-retrieved navigation time. Subsequently, this real-time speed was compared to the segment's posted speed limit. Segments were classified as congested if their real-time speed fell below 50% of the speed limit (i.e., speed-to-limit ratio < 0.5). This threshold was used as a pragmatic operational definition to distinguish between free-flowing traffic and the onset of function-

ally impaired, stop-and-go conditions relevant to a cyclist's perceptual experience. This congestion classification was then used as an input to guide the AIGC model in generating or modifying street view imagery to approximate peak-hour traffic density (Figure S3).

3. Methodology

3.1. Defining Metro-Integrated Cycling and Spatial Units of Analysis

This section outlines the methodology used to examine the relationship between the built environment and metro-integrated cycling. The process involves defining the spatial and temporal units of analysis, quantifying a range of independent variables including the AIGC-enhanced eye-level motor-traffic metric, and applying a spatial regression framework to analyze the data. The overall research framework is illustrated in Figure S4.

3.1.1. Identifying Metro-Integrated Trips

To identify metro-integrated cycling trips, we defined a 100 m “landing area” around each metro station using Service Area tool in ArcGIS Pro 3.0.1, which accounts for pedestrian paths and urban barriers. Any reconstructed cycling trip that began or ended within this zone was classified as an integrated trip, indicating that the bicycle was likely used to access or exit a metro station.

3.1.2. Adaptive Catchment Area (ACA) Construction

To capture the behavior-driven service range of each station, we constructed Adaptive Catchment Areas (ACAs) [20] based on the trajectories of integrated trips within a 1500 m threshold (consistent with average trip distances in Shenzhen). The 1500 m distance threshold was selected because it is consistent with the average cycling distance of first-/last-mile metro-transfer trips in Shenzhen, corresponding to approximately 11.7 min of cycling as reported in prior mobility statistics. This threshold was intended to capture the main range of active metro-integrated cycling trajectories while reducing the influence of unusually long-distance or leisure-oriented cycling trips. Based on the valid operating stations, 101 station-level ACAs were constructed for regression modeling. Unlike fixed buffers, ACAs are designed to reflect the directional heterogeneity of cycling flows (see Method S1 and Figure S5 in Supplementary Material).

3.1.3. Dependent Variable Specification

The dependent variable in this study is the volume of metro-integrated DBS trips within each ACA. To capture temporal variations, trip volumes were aggregated for four peak periods: (1) Weekday morning peak (7:00–9:00 a.m.), (2) Weekday evening peak (5:00–7:00 p.m.), (3) Weekend morning peak (7:00–9:00 a.m.), (4) weekend evening peak (5:00–7:00 p.m.).

For each ACA, the trip volume for a given peak period was calculated as the sum of inbound (arriving at the metro station) and outbound (departing from the metro station) DBS trips. Formally, the dependent variable for ACA i during time period t was defined as follows:

$$y_{i,t} = \frac{1}{D_t} \sum_{d=1}^{D_t} (T^{in}i,d,t + T^{out}i,d,t)$$

where $y_{i,t}$ denotes the average metro-integrated cycling volume for ACA i during period t , $T^{in}i,d,t$ and $T^{out}i,d,t$ represent inbound and outbound integrated DBS trips on day d , respectively, and D_t denotes the number of days used for averaging. For weekday periods, $D_t = 5$, and for weekend periods, $D_t = 2$.

Weekday values represent the daily average over the five weekdays, and weekend values represent the daily average over the two weekend days. Descriptive statistics for

the dependent variables across the 101 ACAs (metro stations) are presented in Table S1 in Supplementary Material.

3.2. Independent Variable Quantification

Independent variables were selected based on established literature on cycling behavior and urban design principles, such as the “3Ds” (Density, Diversity, Design) or “5Ds” framework [21]. These variables represent aspects of land use, road infrastructure, eye-level streetscape, and development intensity hypothesized to be associated with metro-integrated cycling.

To appropriately capture the distinct scales at which different built environment characteristics might influence cycling behavior, a dual spatial approach was adopted for quantifying the independent variables:

- **Neighborhood-Level Contextual Factors (1500 m Buffer):** For traditional built environment variables—such as POI densities, road network characteristics, and Floor Area Ratio (FAR)—quantifications were based on a 1500 m circular buffer around each metro station. This radius is commonly used in transportation studies to approximate a localized catchment area accessible by walking or short cycling trips. The rationale is that these variables represent the broader neighborhood character, land use mix, and overall accessibility, which collectively may contribute to the general attractiveness and functional context of a station area for cycling. These factors are treated as contextual factors associated with cycling within the station’s vicinity.
- **Route-Level Perceptual Factors (Adaptive Catchment Area—ACA):** For eye-level streetscape variables—such as the visual proportion of motor vehicles, greenery, and buildings, which directly relate to the cyclist’s immediate visual and perceptual experience along their reconstructed travel paths—quantifications were based on street view images sampled along road segments within each station’s behavior-derived ACA. The resulting metrics (e.g., average vehicle proportion) were then aggregated for the respective ACA. This approach aims to align the measurement of these perceptual variables more closely with the spatial extent of observed cycling activity and the environment experienced by cyclists.

All independent variables, whether initially quantified using the 1500 m buffer or directly within the ACA, were ultimately assigned to the corresponding ACA as the primary unit of analysis for the subsequent regression modeling. Prior to model fitting, all variables were screened for multicollinearity using the Variance Inflation Factor (VIF), and only those with $VIF < 7.5$ were retained for the final analysis to improve model stability.

3.2.1. Traditional Built Environment Variables (Quantified Using 1500 m Buffer)

These variables, representing the broader neighborhood context around each metro station, were quantified within a 1500 m buffer using GIS spatial analysis tools:

We quantified a set of independent variables based on the ‘5Ds’ framework. These include neighborhood-level factors (POIs, road hierarchy, FAR) quantified within 1500 m buffers, and route-level perceptual factors (AIGC-enhanced motor traffic, greenery, building enclosure, and other streetscape indicators) derived from street view imagery. Detailed definitions and calculation methods for all independent variables are listed in Table S2 in the Supplementary Material.

3.2.2. Eye-Level Streetscape Variables (Quantified Within ACAs)

These variables, capturing the eye-level perceptual environment of cyclists, were quantified based on street view imagery analysis within each station’s ACA:

1. **Baseline Image Selection and Congestion Identification:** For each ACA, street view images with 50 m intervals were sampled along its internal road segments from Baidu Maps. As detailed in Section 2.2.2, segments classified as peak-hour congested segments (real-time speed < 50% of speed limit) were identified using Amap real-time traffic data. The speed-to-limit ratio threshold of 0.5 was used as an operational criterion to distinguish near-free-flowing conditions from functionally impaired, slow-moving traffic conditions. This threshold is relevant to cyclist eye-level perception because slow or congested motor traffic tends to remain visually present within the streetscape for longer durations than fast-moving traffic.
2. **AIGC Enhancement for Peak-Hour Traffic Conditions:** A diffusion-based image-generation model, implemented as Flux.1 Kontext with LoRA fine-tuning, was used to process Shenzhen street-view images under congestion-related prompts. For street-view images on identified congested segments, road and vehicle-related regions were localized using Grounding DINO and the Segment Anything Model (SAM). The fine-tuned model then performed context-aware inpainting on road regions to represent denser peak-hour vehicle presence while preserving buildings, greenery, sidewalks, and other non-road elements.
3. **Semantic Segmentation and Metric Calculation:** The AIGC-enhanced (for congested segments) and original (for non-congested segments) street-view images sampled within each ACA were processed using semantic segmentation techniques. This procedure quantified pixel-wise proportions of key environmental components, including vehicles (for weekday_car_morning, weekday_car_evening, weekend_car_morning, weekend_car_evening), greenery (green_index), buildings (building_index), and non-hardened ground (ground_index). These proportions were then averaged across all sampled images for a given ACA to represent its average eye-level streetscape condition during specific periods. The “eye-level motor traffic” variables capture the average visual proportion of vehicles.

Formally, the eye-level motor-traffic ratio for ACA i during period t was calculated as follows:

$$EMT_{i,t} = \frac{1}{n_i} \sum_{j=1}^{n_i} \frac{p_{j,t}^{veh}}{p_{j,t}^{valid}}$$

where $EMT_{i,t}$ denotes the average eye-level motor-traffic ratio in ACA i during period t , n_i is the number of sampled street-view images within ACA i , $p_{j,t}^{veh}$ is the number of pixels classified as vehicles in image j , and $p_{j,t}^{valid}$ is the number of valid classified pixels in the same image. For congested road segments, the AIGC-enhanced image was used; for non-congested segments, the original Baidu street-view image was retained.

We utilized a simulation-based AIGC framework (See Figure 2) to generate approximate peak-hour traffic conditions. A diffusion-based image-generation model, implemented as Flux.1 Kontext with Low-Rank Adaptation (LoRA), was fine-tuned using 2000 expert-verified congestion scenarios to perform context-aware inpainting on identified congested road segments. This ensures that the generated visuals remain consistent with the original perspective and road boundaries (see Method S2).

As a preliminary validation, all generated images were processed through semantic segmentation to programmatically confirm a quantifiable increase in the “vehicle” pixel ratio and a corresponding decrease in the “road” pixel ratio, ensuring prompt effectiveness before perceptual validation.

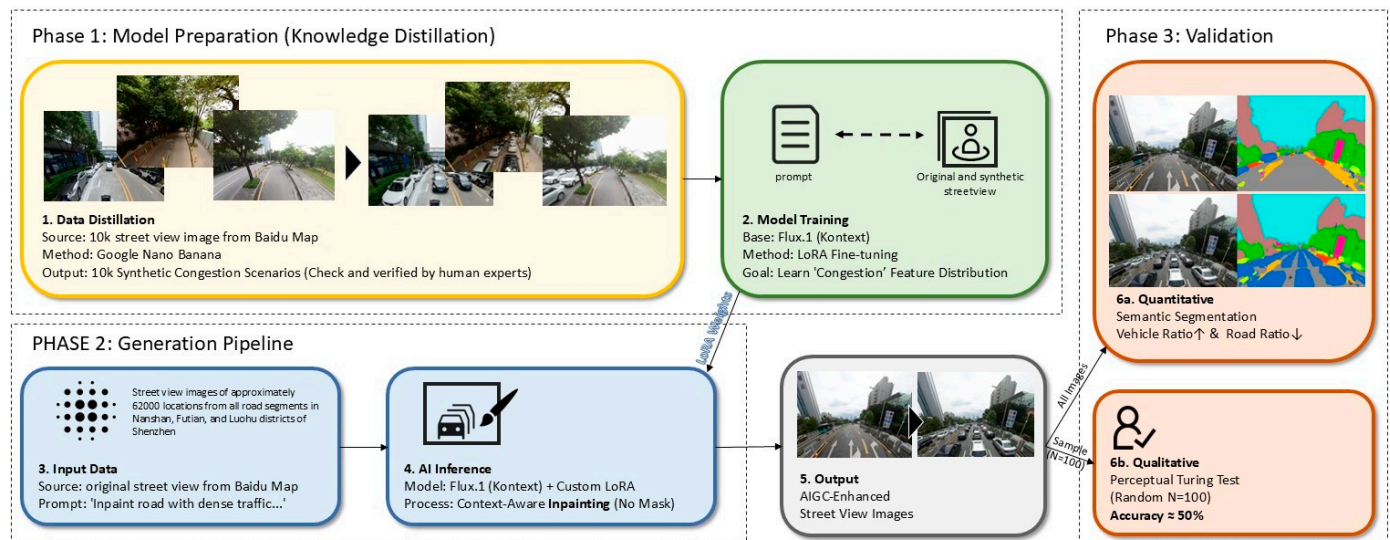


Figure 2. The AIGC-enhanced workflow for generating dynamic traffic scenes. The process involves three phases: (1) distilling congestion features from Google Nano Banana to a Flux.1 LoRA model; (2) prompt-driven, mask-free context-aware inpainting; and (3) a dual-validation protocol comprising quantitative segmentation metrics and a qualitative perceptual Turing test.

3.2.3. Disclosure of AI and AIGC Tools

To improve methodological transparency, we clarify the roles of the AI tools used in this study. Nano Banana was used to generate expert-reviewed rush-hour congestion examples for constructing the training source of the AIGC workflow. Flux.1 Kontext with LoRA fine-tuning was used for context-aware inpainting of selected Baidu street-view images on road segments identified as congested by real-time Amap traffic-speed data. Grounding DINO and the Segment Anything Model (SAM) were used to assist road-region and vehicle-related localization during the image-processing workflow. Semantic segmentation was then applied to both original and AIGC-enhanced images to calculate pixel-level streetscape variables, including the eye-level motor-traffic ratio.

These AI tools were used only for image generation, image editing, segmentation support, and visual-variable extraction. They were not used to determine the statistical results, interpret the regression coefficients, or make causal claims. Language-editing tools were used only for English polishing, and all scientific interpretations, data processing decisions, and conclusions were reviewed and finalized by the authors. Additional implementation details, including prompt design, model configuration, and software/hardware settings, are provided in Method S2 and Table S4 in the Supplementary Material.

3.2.4. AIGC Validation: Perceptual Turing Test

To evaluate the perceptual realism of the AIGC-enhanced imagery, beyond simple manual inspection, we designed and conducted a Perceptual Turing Test. The protocol involved a panel of five domain experts (Master's-level researchers in Urban Planning) who were briefed that they would see a mix of real and AI-edited images. A validation set of 100 images (50 original Baidu Street View images and 50 corresponding AIGC-enhanced images) was randomly shuffled. Each expert was tasked with classifying all 100 images as either "Original" or "AI-enhanced."

The correct identification scores (out of 100) for the five experts were 47, 51, 50, 56, and 55. The overall classification accuracy was 51.8%, with a standard deviation of 3.7 percentage points across evaluators. To formally assess whether the evaluators could distinguish AIGC-enhanced images from original street-view photographs better than random chance, we conducted a one-sample test against the 50% chance level and an exact

binomial test based on all 500 classification judgments. The accuracy was not significantly different from chance level according to either the one-sample test ($t(4) = 1.09$, $p = 0.338$) or the exact binomial test ($p = 0.447$). In addition, Fleiss' kappa was 0.003, indicating near-zero agreement beyond chance among the evaluators.

These results suggest that the AIGC-enhanced images were not perceptually distinguishable from original street-view photographs in this validation task. These findings support the use of the generated images as perceptual visual proxies for peak-hour traffic conditions in the subsequent streetscape measurement. However, perceptual indistinguishability does not by itself establish full scientific validity for quantitative urban analysis; the uncertainty associated with AIGC-generated urban visual data is further discussed in Section 5. Detailed validation statistics are reported in Table S5 in the Supplementary Material.

3.2.5. Final Set of Independent Variables

The final set of independent variables used in the regression models, along with their descriptions and descriptive statistics ($N = 101$), are presented in Table S2. All variables were screened for global multicollinearity using the Variance Inflation Factor (VIF), and only variables with VIF values below 7.5 were retained for the model estimation. The full OLS coefficient estimates and VIF diagnostics are reported in Table S9 in the Supplementary Material.

3.3. Regression Analysis Framework

To examine the spatial associations between built-environment attributes and metro-integrated cycling volume, we used a three-tier regression framework consisting of Ordinary Least Squares (OLS), Geographically Weighted Regression (GWR), and Multiscale Geographically Weighted Regression (MGWR). The three models were used progressively: OLS provided a global non-spatial baseline, GWR allowed for spatially varying coefficients under a single bandwidth, and MGWR further allowed each explanatory variable to be estimated at a variable-specific spatial scale.

First, the OLS model assumes spatial stationarity and is specified as follows:

$$y_i = \beta_0 + \sum_{k=1}^m \beta_k x_{ik} + \epsilon_i$$

where y_i represents the metro-integrated cycling volume of the i -th ACA, x_{ik} denotes the k -th explanatory variable for ACA i , β_0 is the intercept, β_k is the global coefficient of variable k , and ϵ_i is the error term. The final regression dataset included ($i = 1, 2, \dots, 101$) valid ACA observations.

Second, the GWR model relaxes the spatial-stationarity assumption by allowing coefficients to vary across space while using a single bandwidth for all explanatory variables:

$$\left(y_i = \beta_0(u_i, v_i) + \sum_{k=1}^m \beta_k(u_i, v_i) x_{ik} + \epsilon_i \right)$$

where (u_i, v_i) denotes the geographic coordinates of the centroid of ACA i , and $\beta_k(u_i, v_i)$ represents the local coefficient of variable k at that location.

Finally, the MGWR model extends GWR by allowing each explanatory variable to have its own optimized bandwidth:

$$\left(y_i = \beta_{bw0}(u_i, v_i) + \sum_{k=1}^m \beta_{bwk}(u_i, v_i) x_{ik} + \epsilon_i \right)$$

where bw_k denotes the variable-specific bandwidth for the k -th explanatory variable. This structure allows MGWR to represent global, regional, and localized spatial processes, which is particularly relevant because land-use, road-network, and eye-level streetscape variables may operate at different spatial scales.

Model implementation was conducted using ArcGIS Pro 3.0.1. An adaptive bandwidth kernel based on k -nearest neighbors was used rather than a fixed-distance kernel, because metro-station density and road-network density vary substantially across the study area. Bandwidth calibration was performed using a golden-section search with the corrected Akaike Information Criterion (AICc) as the optimization criterion. Model performance was compared using R^2 , adjusted R^2 , and AICc.

To evaluate model diagnostics, we conducted a multi-stage diagnostic procedure. First, global multicollinearity was screened using VIF, with variables exceeding the conventional threshold of 7.5 excluded from the final models. Second, local multicollinearity in the MGWR outputs was assessed using local condition numbers, with values below 30 interpreted as indicating no serious local multicollinearity. Third, Global Moran's I tests were performed on standardized residuals from the final MGWR models to assess whether spatial autocorrelation remained after model fitting. Variable-specific bandwidths and effective numbers of parameters (ENP) were also reported to evaluate the spatial scale and complexity of each MGWR model.

In addition, we conducted an ablation analysis to compare the AIGC-enhanced eye-level motor-traffic variable with the original static vehicle-pixel ratio. The baseline model replaced the AIGC-enhanced motor-traffic measure with the original static Baidu street-view vehicle-pixel ratio, while keeping the remaining covariates and model settings unchanged. The AIGC-enhanced and baseline models were then compared using the same OLS–GWR–MGWR modeling pipeline, with differences in adjusted R^2 and AICc used to evaluate model performance.

4. Results

4.1. Spatio-Temporal Characteristics of Metro-Integrated Cycling

Descriptive analysis shows that metro-integrated cycling is concentrated in the mixed-use “Old City” districts (Futian and Luohu) during weekday morning peaks, exhibiting a short-duration, high-frequency commuting pattern. In contrast, activity in the “New City” (Nanshan) and during off-peak hours is more dispersed (see Figures S2 and S6 in Supplementary Material).

4.2. Model Performance, Diagnostics, and Ablation Analysis

4.2.1. Model Comparison

Table 1 summarizes the performance of the OLS, GWR, and MGWR models across the four temporal periods. The final regression analysis was conducted using 101 valid ACA observations. Overall, model performance improved from OLS to GWR and further to MGWR, indicating that spatially varying models were better able to represent the heterogeneous associations between built-environment attributes and metro-integrated cycling volume.

Table 1. Comparison of Model Performance (OLS, GWR, and MGWR).

Time Period	Model	R^2	Adjusted R^2	AICc
Weekday Morning Peak	OLS	0.494	0.438	1286.562
	GWR	0.734	0.594	236.507
	MGWR	0.818	0.733	213.384

Table 1. *Cont.*

Time Period	Model	R ²	Adjusted R ²	AICc
Weekday Evening Peak	OLS	0.348	0.276	864.794
	GWR	0.566	0.409	262.125
	MGWR	0.596	0.471	260.759
Weekend Morning Peak	OLS	0.441	0.379	1183.462
	GWR	0.646	0.499	249.264
	MGWR	0.681	0.587	234.596
Weekend Evening Peak	OLS	0.376	0.307	977.221
	GWR	0.640	0.491	250.674
	MGWR	0.715	0.597	247.606

During the weekday morning peak, the MGWR model achieved the highest explanatory performance among the three models, with an R² of 0.818 and an adjusted R² of 0.733. This was higher than both the OLS model (R² = 0.494, adjusted R² = 0.438) and the GWR model (R² = 0.734, adjusted R² = 0.594). MGWR also produced the lowest AICc value in all four periods, which supports its use for interpreting spatially heterogeneous associations.

4.2.2. MGWR Diagnostics

Before interpreting the local coefficients, additional diagnostics were conducted to assess the diagnostic performance of the final MGWR models. Global multicollinearity was limited, with the maximum VIF value remaining below 4.55 across all OLS specifications, well below the threshold of 7.5. Local multicollinearity was also not severe: the maximum local condition number in the MGWR outputs was 10.3, below the conventional threshold of 30.

Global Moran's I tests were then applied to the standardized residuals of the final MGWR models. The residual Moran's I statistics were not significant across all four temporal periods, with *p*-values of 0.708, 0.303, 0.741, and 0.465 for the weekday morning, weekday evening, weekend morning, and weekend evening peaks, respectively. These results suggest that the final MGWR models did not show evident residual spatial autocorrelation. In addition, the variable-specific bandwidths indicated that different predictors operated at different spatial scales, which is consistent with the MGWR specification rather than a single-bandwidth GWR model. Detailed diagnostic statistics, bandwidths, effective numbers of parameters, and VIF values are reported in Tables S6, S7 and S9 in the Supplementary Material.

4.2.3. Ablation Analysis

To assess the model contribution of the AIGC-enhanced eye-level motor-traffic variable, we compared the final model with a baseline model using the original static Baidu street-view vehicle-pixel ratio while keeping the remaining covariates and model settings unchanged. The AIGC-enhanced model improved adjusted R² and reduced AICc in the main commuting-period models, especially during the weekday morning peak. For the weekday morning MGWR model, the AIGC-enhanced specification increased adjusted R² by 0.060 and reduced AICc by 7.533 compared with the static-street-view baseline.

The improvement was not uniform across all periods. In particular, the static baseline performed slightly better during the weekend morning peak. This pattern suggests that the AIGC-enhanced measure is more informative for representing temporally specific visual traffic conditions in commuting-oriented contexts, rather than providing a universal improvement across all travel periods. Full ablation results are provided in Table S8 in the Supplementary Material.

4.3. MGWR Model Results

The MGWR models showed spatially varying associations between the built environment and metro-integrated cycling volume (see Figures 3–5 and S7 and Table S3). To maintain a conservative interpretation, the following analysis interprets only those coefficients that demonstrated statistical significance.

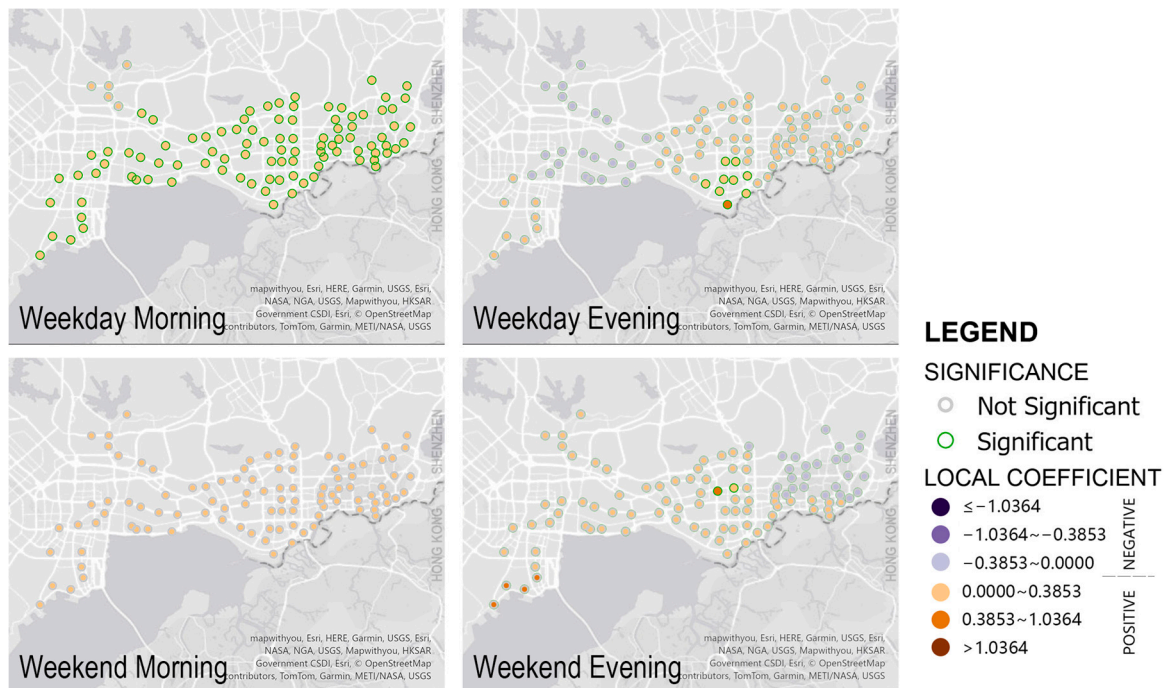


Figure 3. Spatial distribution of MGWR local coefficients for the AIGC-enhanced eye-level motor-traffic variable. Fill color represents the local coefficient value, while the circle outline indicates statistical significance. Green outlines indicate significant local coefficients, and grey outlines indicate non-significant coefficients. Only significant coefficients are interpreted in the text.

4.3.1. The Time-Specific Association of Eye-Level Motor Traffic

The AIGC-enhanced eye-level motor-traffic variable showed temporal variation across the four observation periods (Figure 3). During the weekday morning peak, this variable showed positive local coefficients in the MGWR model, with statistically significant associations appearing in a subset of station areas. This pattern was much weaker during the weekday evening peak and became limited or statistically insignificant during the weekend periods.

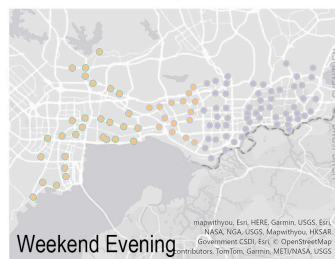
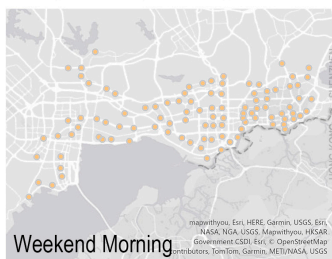
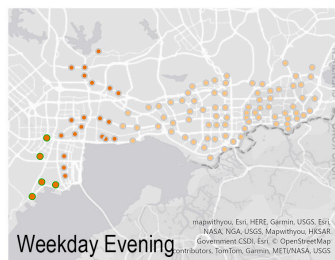
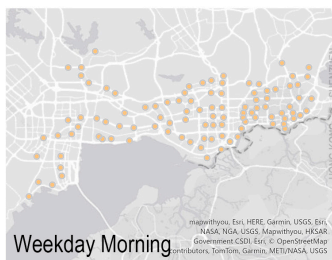
The weekday morning result should be interpreted as a context-dependent spatial association rather than evidence that cyclists prefer or are attracted to motor traffic. In intensive commuting environments, visible motor traffic may co-occur with high metro accessibility, employment concentration, road congestion, and strong first-/last-mile cycling demand. Therefore, the positive association is more appropriately understood as a co-location pattern in time-sensitive commuting contexts. In this sense, eye-level motor traffic can be interpreted as an environmental correlate and visual indicator of high commuting intensity, rather than as an independently verified causal driver of cycling demand.

4.3.2. Temporally Differentiated Land-Use Associations

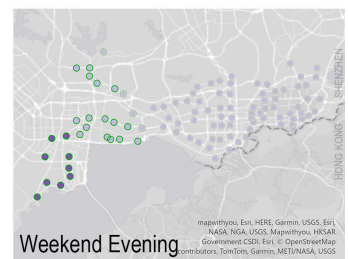
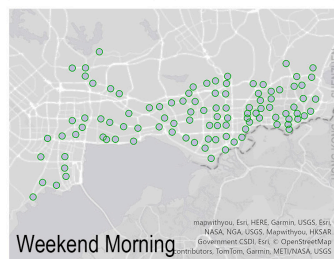
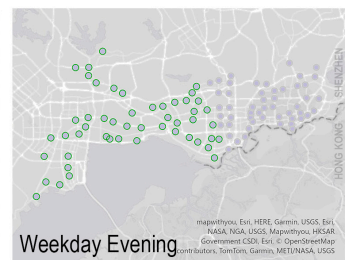
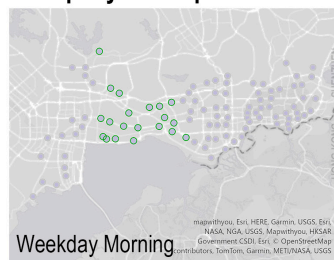
Land-use variables showed temporally differentiated and spatially localized associations with metro-integrated cycling volume (Figure 4). Company Counts were negatively associated with cycling volume in several periods, particularly in central-western station areas during weekday mornings and more broadly during weekend mornings. For Resi-

dent Counts, the MGWR results did not show a significant association during the weekday morning peak. This does not necessarily mean that residential density is irrelevant to metro-integrated cycling. Rather, in already dense station areas, residential density may function as a background precondition rather than a direct differentiating factor explaining spatial variation in cycling volume. Its significant positive association during the weekday evening peak, especially in western districts such as Nanshan, suggests that residential concentration may be more relevant to return-home or evening feeder-cycling contexts. This pattern should therefore be described as threshold-like rather than as a formally identified threshold effect, since no nonlinear threshold model was estimated in this study. Furthermore, the Shop/Entertainment Counts variable showed limited influence, becoming a significant positive predictor only in western districts during the weekend evening peak, which is consistent with leisure-oriented travel patterns.

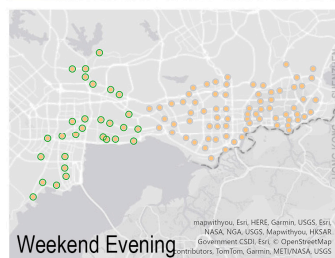
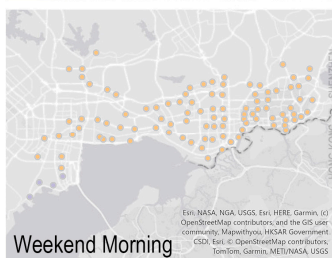
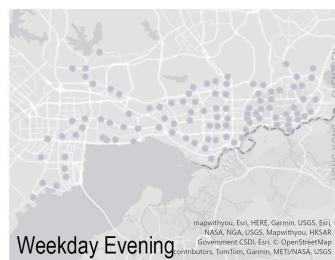
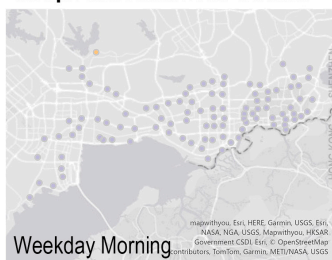
Residential Counts



Company / Workplace Counts



Shop/Entertainment Counts



LEGEND

SIGNIFICANCE

- Not Significant
- Significant

LOCAL COEFFICIENT

- ≤ -1.0364
- -1.0364 ~ -0.3853
- -0.3853 ~ 0.0000
- 0.0000 ~ 0.3853
- 0.3853 ~ 1.0364
- > 1.0364

NEGATIVE
POSITIVE

Figure 4. Spatial distribution of MGWR local coefficients for land-use variables: Residential Counts, Company Counts, and Shop/Entertainment Counts. Fill color represents the local coefficient value, while the circle outline indicates statistical significance. Green outlines indicate significant local coefficients, and grey outlines indicate non-significant coefficients. The maps show coefficient values rather than land-use category distributions.

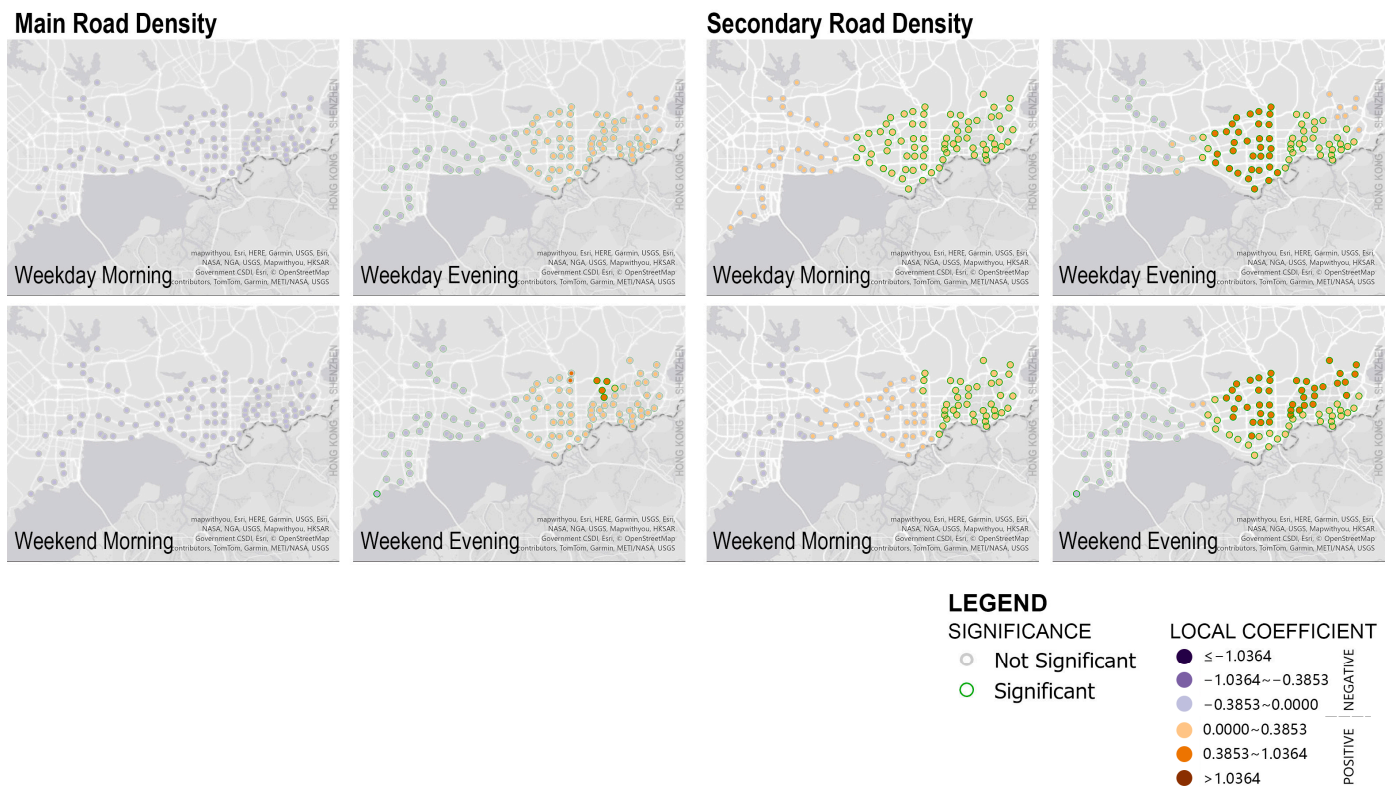


Figure 5. Spatial distribution of MGWR local coefficients for road-network variables: Main Road Density and Secondary Road Density. Fill color represents the local coefficient value, while the circle outline indicates statistical significance. Green outlines indicate significant local coefficients, and grey outlines indicate non-significant coefficients. Only significant coefficients are interpreted in the text.

Furthermore, the Shop/Entertainment Counts variable (representing leisure-oriented POIs) showed limited influence, becoming a significant positive predictor only in the western districts during the weekend evening peak, which is consistent with leisure-oriented travel patterns.

4.3.3. The Contrasting Associations of Road Hierarchy

The analysis of road-network density showed a contrast between main roads and secondary roads (Figure 5). Main Road Density was statistically insignificant in most scenarios, suggesting that high-capacity arterials were not consistently associated with metro-integrated cycling in the present model. Although main roads provide regional connectivity, their large scale and stronger motor-vehicle orientation may reduce their attractiveness for feeder cycling. In contrast, Secondary Road Density showed a more consistent positive association with cycling volume across several periods, especially in the older urban cores of Luohu and Futian. This suggests that dense, human-scaled secondary road networks may be more closely associated with favorable spatial conditions for metro-integrated cycling.

4.3.4. Associations of Streetscape Composition

Regarding control variables, the Eye-Level Non-hardened Ground index was consistently negatively associated with cycling volume across all periods. Conversely, Eye-Level Greenery showed localized positive associations mainly in the older eastern districts, while Floor Area Ratio (FAR) remained statistically insignificant (see Figure S7 in the Supplementary Material).

5. Discussion

This study used a traffic-informed AIGC-enhanced streetscape workflow and an MGWR modeling framework to examine the context-dependent association between eye-level motor traffic and metro-integrated cycling in Shenzhen. The results show that this association varies across time periods and urban contexts. In particular, the positive association between eye-level motor traffic and cycling volume was most evident during the weekday morning peak, while the association weakened or became statistically insignificant during evening and weekend periods. These findings suggest that the role of dynamic visual traffic conditions should be interpreted in relation to commuting intensity, metro accessibility, land-use structure, and local street-network conditions.

5.1. Interpreting the Commuter's Paradox-like Association

One key finding of this study is the time-specific positive association between AIGC-enhanced eye-level motor traffic and metro-integrated cycling during the weekday morning peak. We describe this pattern as a “Commuter's Paradox-like association” rather than as a universal behavioral law. This paradox-like pattern refers to the coexistence of visible motor traffic and high metro-integrated cycling demand in the same intensive commuting environments. This finding differs from the conventional expectation that traffic visibility should generally discourage cycling due to safety concerns and traffic stress [22].

However, this observed spatial association should not be interpreted as direct causal evidence that cyclists prefer, seek, or are attracted to motor traffic. The MGWR model identifies spatially varying associations, but it does not by itself establish the behavioral mechanism behind those associations. During weekday morning peaks, areas with high visual motor traffic are often also areas with high employment concentration, high metro accessibility, road congestion, and considerable first-/last-mile travel demand. Therefore, visible motor traffic may be interpreted as an environmental correlate of high commuting intensity rather than as an independent physical driver of cycling demand.

The notion of a “relative efficiency heuristic” should be treated as a conceptual interpretation of the observed pattern, not as a verified psychological mechanism. In time-sensitive morning commuting contexts, visible congestion may serve as a perceptual marker of localized delay and relative travel-time advantage for cycling. Yet, this interpretation remains suggestive, because the present study does not directly observe individual psychological states, stated preferences, or real-time route-choice reasoning. The weekday morning association may also be partly influenced by co-location effects and omitted urban-activity variables that simultaneously increase motor traffic, metro demand, and DBS usage.

This interpretation may help explain the temporal contrast in the results. When travel purposes are more flexible during evening and weekend periods, the same visual presence of motor traffic no longer shows a strong positive association with cycling volume. Under these conditions, safety, comfort, leisure orientation, or route-environment quality may become more important than time-sensitive efficiency. The “Commuter's Paradox-like association” is therefore better interpreted as a context-dependent empirical pattern in high-intensity commuting environments, rather than as a general claim that motor traffic promotes cycling.

5.2. Interpreting First-/Last-Mile Land-Use Associations

The land-use results also require a cautious interpretation, particularly with regard to residential density. In the weekday morning peak, Resident Counts did not show a statistically significant association with metro-integrated cycling volume. Rather than treating this non-significance as evidence of a formal “threshold effect,” we interpret it as a threshold-like pattern in mature high-density TOD environments. In Shenzhen's

core station areas, residential density may already serve as a background precondition for metro-integrated cycling. Once a baseline level of residential development is widely present around metro stations, additional variation in residential counts may no longer differentiate morning feeder-cycling volumes in a linear manner.

This interpretation differs from a formal threshold model. The present study does not estimate nonlinear turning points, segmented regressions, or interaction thresholds. Therefore, the term “threshold-like pattern” is used only to describe the observed pattern that residential density appears less differentiating during the weekday morning peak than expected under a simple first-mile hypothesis. Other factors, such as street-network connectivity, visual traffic conditions, station accessibility, and commuting intensity, may play a more relevant in explaining local variation once residential density has reached a high background level.

In contrast, Resident Counts showed a clearer positive association during the weekday evening peak, particularly in the western districts such as Nanshan. This pattern may reflect the functional separation between employment hubs and residential super-blocks in the “New City” context [23,24]. Evening metro-integrated cycling in these areas is more often represent a return-home last-mile connection. By comparison, the older central and eastern districts have more mixed-use fabrics, where evening trips may include intermediate activities such as dining, shopping, or walking-based access, thereby weakening the direct spatial link between metro stations and residential density [25,26].

5.3. Context-Dependent Infrastructure Associations

The analysis of road hierarchy indicates the context-dependent role of street-network structure. Secondary Road Density showed a more consistent positive association with metro-integrated cycling than Main Road Density, especially in the eastern and central districts of Luohu and Futian. This pattern is consistent with the morphological differences between the traditional gridiron networks of the “Old City” districts and the modernist super-block structure of the “New City” district [27,28].

In older districts, denser secondary road networks may provide more fine-grained route choices, shorter local connections, and lower-speed alternatives to arterials. These conditions are be associated with metro-feeder cycling by improving local accessibility and reducing dependence on high-capacity roads. In contrast, newer western districts are often characterized by wide arterials and larger block sizes, where secondary road networks may be more discontinuous or less closely associated with short, flexible cycling connections [29,30]. These results suggest that human-scaled secondary road networks are relevant spatial correlates of metro-integrated cycling, although they should not be interpreted as the sole determinant of cycling demand.

5.4. Localized Streetscape Associations

Visual-quality variables also showed differentiated associations with metro-integrated cycling. Eye-Level Greenery showed localized positive associations mainly in older eastern districts, suggesting that greenery may have more relevant in dense and historically developed urban environments where high-quality streetscape amenities are relatively scarce [31]. By contrast, the Eye-Level Non-hardened Ground index showed a consistently negative association across multiple periods. This variable may capture visual cues of incomplete streetscape maintenance, exposed surfaces, or lower environmental quality. These results suggest that positive streetscape amenities and negative environmental cues may show different association patterns: greenery appears to have localized benefits, whereas visually unfinished or poorly maintained ground conditions may be more broadly associated with lower cycling volume.

5.5. Planning and Methodological Considerations

The spatial heterogeneity identified in this study suggests that metro-integrated cycling planning may need to go beyond uniform design standards and consider the specific temporal and morphological context of station areas. The positive association between eye-level motor traffic and cycling during weekday morning peaks does not imply that motor traffic should be encouraged. Rather, it indicates that high-demand cycling corridors often overlap with high-intensity commuting environments where congestion, transit access, and first-/last-mile demand are spatially concentrated.

For primary commuter corridors, the “Connected Separation” principle may provide a relevant planning reference (Figure S8). Cycling infrastructure in such areas should be physically separated enough to reduce traffic risk, while remaining continuous, direct, and well integrated with metro-station access routes [32,33]. The emphasis should be placed on safety, continuity, and travel-time reliability, rather than on preserving exposure to motor traffic itself.

For older central districts such as Luohu and Futian, the results potential relevance of improving fine-grained secondary road networks. Instead of treating arterial roads as the main feeder-cycling corridors, interventions may focus on secondary streets, bicycle-priority links, intersection safety, and short-distance connections to metro entrances [28,34,35]. These measures may strengthen the local “capillary” network that supports short first-/last-mile cycling trips.

For newer districts such as Nanshan, where functional separation between employment hubs and residential super-blocks is more pronounced, planning may prioritize continuous commuter corridors that connect metro stations with major residential and employment areas. The evening association between residential density and cycling suggests that last-mile connections may be particularly relevant in these contexts. However, this should be interpreted as a context-specific association rather than as evidence that residential density alone drives cycling demand [36,37].

Methodologically, the AIGC-enhanced workflow examined in this study provides an exploratory tool for representing dynamic visual traffic conditions when direct peak-hour imagery is unavailable. Planners and DBS operators could use similar traffic-informed visual simulations to compare alternative streetscape scenarios before implementation. However, such applications should be treated as pre-evaluation aids rather than substitutes for field observation, real-time traffic sensing, or post-implementation evaluation.

5.6. Limitations and Future Research

Several limitations should be acknowledged. First, this study is based on observational data and spatial regression models. The MGWR results identify spatially varying associations rather than causal effects [38]. Potential endogeneity remains possible, including simultaneity between commuting intensity, employment concentration, motor-traffic congestion, and DBS demand, as well as omitted urban-activity variables that are difficult to observe fully [39].

Second, the AIGC-enhanced images were validated primarily in terms of perceptual realism. Although the perceptual Turing test showed that evaluators could not distinguish AIGC-enhanced images from original street-view photographs better than chance, perceptual indistinguishability does not fully establish validity for quantitative urban analysis. Future research should compare AIGC-enhanced imagery with real peak-hour street-view images, traffic-camera data, or observed traffic-volume measurements.

Third, the DBS dataset covers one week in 2021. Although this dataset represents the most recent high-granularity DBS trajectory dataset officially released by the municipal authority at the time of data acquisition and was selected to minimize weather-related bias,

the one-week observation window limits temporal generalizability. Future studies should evaluate the framework using multi-week, multi-season, and more recent mobility data when such data become available.

Finally, the analysis is based on 101 station-level ACAs in Shenzhen's high-density urban context. The findings may not directly generalize to cities with different cycling cultures, street-network structures, transit systems, or traffic conditions. Future research should also examine exposure uncertainty and the sensitivity of visual-environment measurements to spatial-unit definitions [40]. Comparative studies across multiple cities would help further assess the generalizability of the "Commuter's Paradox-like association," the threshold-like land-use pattern, and the infrastructure-related findings.

6. Conclusions

This study developed a traffic-informed AIGC-enhanced streetscape workflow to examine the context-dependent association between eye-level motor traffic and metro-integrated cycling in Shenzhen. By combining dockless bike-sharing trajectories, station-level Adaptive Catchment Areas, AIGC-enhanced street-view imagery, and OLS/GWR/MGWR modeling, this study presents an exploratory approach to incorporating dynamic visual traffic conditions into metro-feeder cycling analysis.

The empirical results show that the AIGC-enhanced eye-level motor-traffic variable was positively associated with metro-integrated cycling volume primarily during the weekday morning peak. This association weakened or became statistically insignificant during evening and weekend periods, indicating that the association between visible motor traffic and cycling demand is temporally specific rather than universal. We describe this pattern as a "Commuter's Paradox-like association": in high-intensity commuting environments, visible motor traffic may co-occur with high first-/last-mile cycling demand, metro accessibility, and employment concentration. This finding should be interpreted as a spatial association rather than as evidence of a direct causal mechanism.

The land-use and infrastructure results further suggest that residential density may serve as a background precondition in mature high-density station areas, suggesting a threshold-like pattern rather than a formally identified threshold effect. Secondary road density showed a more consistent positive association with metro-integrated cycling than main road density, indicating the potential relevance of fine-grained, human-scaled street networks for feeder cycling. These findings suggest context-sensitive planning considerations, including connected separation, continuous cycling routes, and safer station-area access in high-demand commuting corridors.

Methodologically, this study illustrates the potential use of traffic-informed GeoAI imagery as an exploratory tool for representing dynamic streetscape conditions when direct peak-hour imagery is unavailable. The additional MGWR diagnostics and ablation analysis provide further support for the revised analysis, particularly for weekday commuting periods. Future research should further validate AIGC-enhanced visual measures using real peak-hour imagery, multi-period mobility data, and research designs better suited to causal inference.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/ijgi15070289/s1>, Method S1: Detailed Construction of Adaptive Catchment Areas; Method S2: AIGC Model Architecture, Prompt Engineering, and Implementation Details; Figure S1: Location of the study area, showing the boundaries of the three selected districts: Nanshan, Futian, and Luohu; Figure S2: Temporal distribution of DBS usage during the study week (1–7 February 2021); Figure S3: Spatial distribution of congested road segments (speed-to-limit ratio < 0.5) identified for AIGC enhancement; Figure S4: The overall research framework of this study; Figure S5: The construction and superiority of the Adaptive Catchment Area (ACA); Figure S6:

Kernel density map of metro-integrated cycling activity; Figure S7: Spatial distribution of MGWR local coefficients for the Green View, Building and Non-hardened Ground Index variable; Figure S8: Illustration of the “Connected Separation” design principle for cycling infrastructure; Table S1: Descriptive Statistics of Dependent Variables (Metro-Integrated Cycling Volume, $N = 101$); Table S2: Definition and Descriptive Statistics of Independent Variables ($N = 101$); Table S3: Summary of MGWR Coefficient Statistics for Independent Variables; Table S4: AIGC Implementation Details and Tool Disclosure; Table S5: Statistical Validation of AIGC-Enhanced Images; Table S6: MGWR Model Diagnostics; Table S7: MGWR Bandwidth and Effective Number of Parameters; Table S8: Ablation Analysis Comparing Static and AIGC-Enhanced Vehicle-Pixel Measures; Table S9: OLS Coefficient Estimates and Global VIF Diagnostics. References cited in the Supplementary Material are included in the main reference list [41–45].

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Data Availability Statement: The Dockless Bike-Sharing (DBS) data supporting the findings of this study are openly available from the Shenzhen Municipal Government Open Data Platform at https://opendata.sz.gov.cn/data/api/toApiDetails/29200_00403627 (accessed on 10 March 2024). The street view imagery analyzed during the current study was retrieved from Baidu Maps Open Platform (<https://lbsyun.baidu.com/>). The AIGC-generated datasets and derived variables are available from the corresponding author on reasonable request.

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Abbreviations

The following abbreviations are used in this manuscript:

AIGC	Artificial Intelligence Generated Content
DBS	Dockless Bike-Sharing
MGWR	Multiscale Geographically Weighted Regression

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