

Article

Time-Varying Characteristics and Reliability of Urban Travel Impedance Based on High-Frequency Navigation OD Data

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Abstract

With the advancement of urbanization and motorization, urban traffic conditions increasingly affect both travel efficiency and system stability, yet existing studies based on high-frequency OD data mainly focus on single aspects such as congestion patterns or travel time variability, lacking a unified analytical framework that jointly captures time-varying travel impedance, reliability, and anomaly risks under comparable conditions, especially in cross-city contexts. This study constructs a standardized analytical framework with a novel integration based on a “city × weekday × 5 min interval” structure, using high-frequency navigation OD data from eight major cities in China over four consecutive weeks, totaling approximately 560,000 valid samples. Travel Time per Unit Distance (TTUD) is employed as the core metric, and a distance-stratified weighting approach is adopted to improve cross-city comparability. Reliability is characterized by variability, dispersion, and tail risk, and anomalous events are identified using a dynamic baseline. The results reveal clear intra-week temporal regularity and significant inter-city heterogeneity, with weekday evening peaks generally lasting longer than those on weekends, reflecting sustained commuting pressure and slower dissipation of travel demand. A total of 249 anomaly events are detected, with higher frequency and persistence on weekdays, highlighting the increased vulnerability of traffic systems during peak commuting periods and indicating that commuting periods are more prone to sustained deviations due to higher system load and demand instability. Overall, the proposed framework provides a unified and comparable basis for cross-city traffic performance evaluation and supports practical applications such as peak-period traffic management, congestion mitigation, and traffic risk monitoring.

Keywords: high-frequency navigation OD data; travel impedance; travel time reliability; time-slice analysis; anomalous event detection



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1. Introduction

With the rapid advancement of global urbanization and motorization, the efficiency and reliability of urban transportation systems have become critical constraints on sustainable urban development [1]. As a fundamental infrastructure supporting urban spatial organization and functional operations, road transportation networks not only determine travel efficiency [2] but also directly influence energy consumption and environmental quality [3,4]. The growing imbalance between rising vehicle ownership and limited road infrastructure has led to widespread congestion, delays, and associated externalities, such

as energy waste and emissions, in cities worldwide [4], with these problems showing a persistent upward trend [3]. Existing studies indicate that congestion not only undermines traffic mobility [3] but also exerts profound impacts on economic performance, environmental health, and quality of life [5], thereby motivating extensive research on intelligent transportation systems and network optimization [6].

Against this backdrop, the scientific assessment of urban transportation performance—reflected in travel impedance, which represents travel efficiency—and system stability—captured by travel time reliability, which reflects variability and predictability—has evolved from coarse statistical descriptions to fine-grained, dynamic diagnostics. Together, these two dimensions provide a comprehensive understanding of traffic system performance [7,8]. Traditional studies relying on fixed sensors or survey-based data suffer from limited spatial coverage and high costs [8,9], making it difficult to capture complete origin–destination (OD) travel experiences and their temporal dynamics [10]. In recent years, emerging data sources, including mobile phone signaling, probe vehicle GPS, and navigation platform data, have provided new opportunities for traffic analysis due to their wide coverage, high temporal resolution, and ability to directly reflect OD-based travel time [11–14]. Nevertheless, key challenges remain in constructing a comparable cross-city analytical framework using high-frequency data, while simultaneously accounting for efficiency, routine variability, and abnormal risks within a unified perspective.

From the perspective of theoretical development and indicator innovation, the measurement of travel impedance and reliability has shifted from static and single-dimensional metrics toward dynamic, multidimensional, and user-oriented evaluation systems [15]. Early studies often approximated travel impedance using geometric distance or free-flow travel time [16]. However, it is now widely recognized that perceived impedance is a composite function of travel time, cost, reliability, and comfort, and its decay characteristics vary significantly with travel purpose, individual attributes, and urban spatial structure [17]. For instance, Verma and Ukkusuri demonstrated that relying on a single generalized cost function may lead to substantial bias in evaluating accessibility across different social groups [18]. Meanwhile, research on travel time reliability has progressed beyond traditional measures of variability (e.g., coefficient of variation) toward metrics more closely linked to user decision-making and system resilience [1]. Indicators such as the buffer time index and planning time index quantify the additional time required to ensure on-time arrival and thus directly capture traveler experience [19,20]. More recently, concepts such as tail risk ratio and conditional value-at-risk have been introduced to assess system vulnerability under extreme conditions [21,22]. Building on this, Gore et al. proposed an integrated framework combining congestion intensity, duration, and reliability, marking a convergence between reliability management and proactive congestion control [23].

At the methodological level of high-frequency data applications and cross-city comparisons, the increasing availability of data has not eliminated the challenge of ensuring fair and meaningful comparisons, with the core issue lying in the standardization of inter-city heterogeneity [24]. Navigation platform data (e.g., Amap, Baidu) provide minute-level updates and full-network OD travel time estimates, and have been widely used in fine-scale congestion pattern identification, dynamic travel behavior analysis, and policy evaluation [25]. However, most existing studies remain confined to within-city analyses [26]. When extending to multiple cities, substantial differences in population size, urban form, network density, travel distance distributions, and commuting culture render direct comparisons based on aggregate indicators (e.g., average speed or congestion duration) unreliable [27]. Travel distance is widely recognized as a primary factor requiring normalization [28]. Previous studies have attempted to address this by applying distance thresholds or constructing decay functions [29]. However, these approaches often rely on

simple linear adjustments or coarse stratification, failing to capture the nonlinear variations in impedance and reliability across distance intervals, and rarely integrate distance structures with temporal segmentation (e.g., weekday peak periods) to establish dynamic standardized baselines [17].

In spatiotemporal anomaly detection, identifying systematic risks through dynamic baselines has emerged as a key approach to enhancing transportation system resilience [30]. Traditional approaches typically rely on fixed thresholds or historical averages to detect short-term congestion anomalies caused by events, adverse weather, or stochastic fluctuations [31]. However, from a system management perspective, greater value lies in identifying anomalies that exceed routine fluctuations and exhibit specific temporal patterns or sustained impacts (e.g., recurrent Friday evening peaks) [32]. This requires constructing high-resolution dynamic baseline states and quantifying deviations from these baselines [33]. Such approaches not only enable anomaly detection but also reveal periodic vulnerabilities and recovery capacities of urban transportation systems [34]. For example, long-term analysis can distinguish differences in anomaly frequency and intensity between Monday morning peaks and Friday evening peaks, providing a basis for differentiated management strategies [33]. Integrating anomaly detection with tail-risk-based reliability metrics further promotes a shift from risk identification to comprehensive risk assessment [35].

Despite these advances, several key limitations remain in existing studies. First, most studies based on high-frequency OD data focus on single aspects, such as congestion patterns, travel time variability, or anomaly detection, without integrating these dimensions into a unified analytical framework. As a result, the joint understanding of efficiency, reliability, and system risk remains fragmented. Second, cross-city comparative studies remain limited by the lack of standardized approaches to effectively control for inter-city heterogeneity, particularly differences in travel distance structures, urban form, and demand patterns. This often leads to biased or non-comparable results when using aggregate indicators. Third, existing anomaly detection methods are typically based on static thresholds or historical averages, which are insufficient to capture systematic deviations under dynamic temporal contexts. To address these gaps, this study proposes a standardized time-slice analytical framework and adopts travel time per unit distance as the core efficiency indicator. A distance-stratified weighting approach is introduced to mitigate the influence of heterogeneous travel distance structures, enabling fair comparisons across cities within a unified city $\times$ weekday $\times$ time-slice framework.

Furthermore, a multidimensional reliability indicator system integrating the coefficient of variation, percentile spread, and tail risk ratio is developed to characterize variability, distributional dispersion, and extreme risk. Finally, a dynamic baseline anomaly detection method based on weekday–time matching is employed to jointly identify regular patterns and abnormal risks within a unified framework. Using high-frequency OD data covering eight major Chinese cities over four consecutive weeks, this study not only reveals the spatiotemporal heterogeneity of urban traffic operations but also contributes a replicable and extensible analytical paradigm for cross-city traffic diagnosis and risk assessment.

2. Materials and Methods

2.1. Overall Framework

The overall analytical framework of this study is shown in Figure 1 and consists of four main stages: data acquisition, data preprocessing, indicator construction, and result presentation. High-frequency navigation OD samples spanning four consecutive weeks are first collected using the Amap API, and key attributes such as city, date, and timestamp are standardized. The raw data are then cleaned, temporally normalized, and stratified by travel

distance, based on which a time-slice analytical framework of “city $\times$ weekday $\times$ 5 min interval” is constructed to ensure comparability across cities under consistent temporal conditions. Within this unified framework, travel time per unit distance, impedance percentiles, peak-period windows, reliability indicators, and anomalous events are calculated, and explanatory correlation analysis is conducted in combination with road network density. Finally, the temporal characteristics, stability differences, and anomaly risks of urban travel impedance across cities are comprehensively illustrated and compared using heatmaps, peak-period comparison charts, anomaly statistics, and correlation scatter plots.

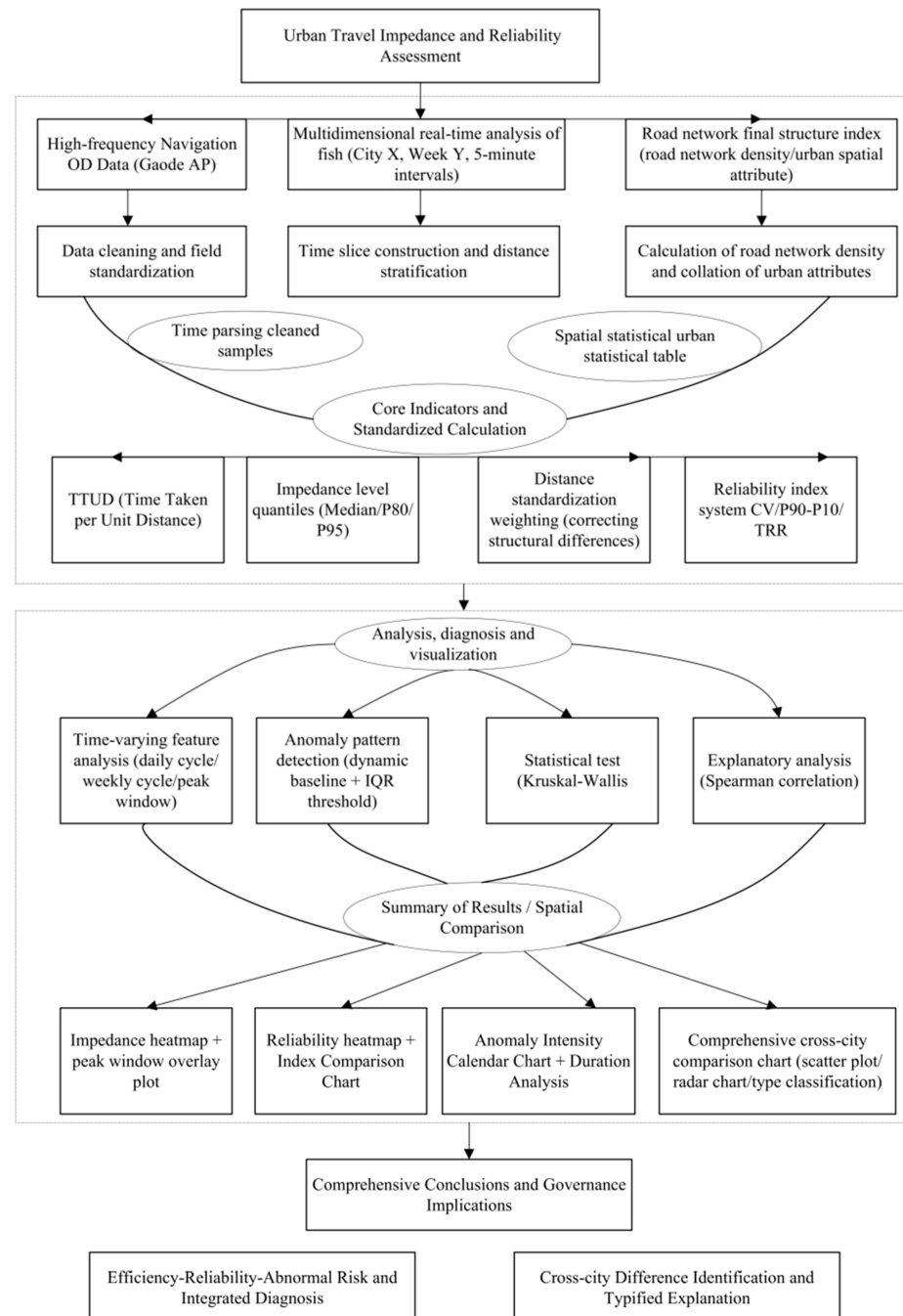


Figure 1. Overall analytical workflow of this study.

2.2. Study Area and Data Source

This study selects eight representative cities in China, as shown in Figure 2, namely Beijing, Shanghai, Guangzhou, Shenzhen, Chengdu, Wuhan, Xi'an, and Lanzhou. These

cities cover major regions including North China, East China, South China, Central China, Southwest China, and Northwest China, and include both metropolitan cities and national central cities as well as regional central cities, thereby effectively reflecting differences in travel operations under varying city sizes, spatial structures, and traffic organization conditions. By combining regional distribution and city types, the study can identify both common patterns and heterogeneous characteristics of urban travel impedance across a more diverse geographical context (the spatial coverage of OD samples in each city is provided in Appendix A).



Figure 2. Spatial distribution pattern of the eight selected cities across China.

The research data are derived from high-frequency navigation OD samples obtained via the Amap API, spanning 3 September to 30 September 2024, covering four consecutive weeks. Each record includes a city identifier, timestamp, origin and destination coordinates, travel distance, and travel time. Compared with traditional survey data or fixed-location monitoring data, such high-frequency OD samples offer advantages, including high temporal resolution, wide spatial coverage, and the ability to directly reflect travel experience at the OD level, making them more suitable for cross-city and continuous temporal impedance-comparison analyses. Based on the raw data, this study performs systematic data cleaning and structured processing.

The high-frequency OD samples are summarized from four aspects: data scale, sampling intensity, data quality, and travel characteristics. The total sample size represents the number of valid OD samples collected over the four-week (28-day) period, with similar magnitudes across cities (approximately 70,000 samples each), indicating good data balance for cross-city comparison, and ensuring comparability across cities under consistent sampling conditions; the average daily sample size is approximately 2800, reflecting a high sampling frequency that supports high-resolution spatiotemporal analysis; all statistics in the table are based on cleaned valid samples, and therefore the valid sample rate is 100%; the average travel distance and average travel time are used to characterize urban travel chain features and differences in traffic operation efficiency. It should be noted that the data used in this study are limited to September, and potential seasonal variations in travel patterns are not explicitly considered, which may introduce certain temporal biases and limit the generalizability of the findings to other seasons or holiday periods.

2.3. Data Preprocessing and Temporal Slicing

To ensure consistency in comparisons and robust results, the study uses the Python 3.9 datetime module to standardize dates, maps each record to its corresponding weekday, and then selects samples that fully cover the four weeks. In the data cleaning process, obviously unreasonable travel records are removed, including samples with distances ≤ 100 m or travel times ≤ 10 s, which account for a small proportion of the total dataset and are removed to reduce the influence of noise and abnormal records, in order to reduce the influence of noise and outliers on statistical distributions and reliability indicators. In addition, to avoid systematic bias caused by differences in travel distance structures among cities, a distance stratification approach is adopted to classify travel distances into four categories: short-distance (0–3 km), short-to-medium distance (3–8 km), medium-distance (8–15 km), and long-distance (above 15 km). This classification is based on the distributional characteristics of urban travel distances and on findings from studies on the average travel distances of urban residents in China, providing a foundation for subsequent stratified comparisons and standardized analyses. The data scale and basic travel characteristics of OD samples are demonstrated in Table 1.

Table 1. Data scale and basic travel characteristics of OD samples for each study city.

City	Total Sample Size	Average Daily Sample Size	Valid Sample Ratio	Average Distance (km)	Average Travel Time (min)
Chengdu	69,988	2880	1	14.03	21.71
Shenzhen	69,982	2878	1	12.37	21.39
Guangzhou	69,997	2879	1	12.97	25.85
Wuhan	69,988	2880	1	26.62	38.20
Beijing	70,020	2879	1	19.65	33.22
Shanghai	70,008	2880	1	17.82	32.22
Lanzhou	69,988	2879	1	21.29	34.86
Xi'an	69,992	2880	1	18.23	30.16
Total	559,963	23,035	1	17.87	29.70

3. Method

3.1. Indicators and Analytical Methods

Based on the overall analytical framework described above, the methodological system of this study is developed along five key components: the characterization of travel efficiency using travel time per unit distance (TTUD) as the core metric; the description of impedance levels based on percentile measures; the identification of peak-period windows using a robust and adaptive threshold approach; the construction of reliability indicators focusing on variability and tail risk; and a distance-standardized weighting method designed to mitigate inter-city differences in travel distance structures. These methods operate synergistically within a unified “city $\times$ weekday $\times$ 5 min time-slice” framework, collectively supporting a systematic analysis of the time-varying characteristics of urban travel impedance and its reliability.

3.1.1. Travel Time per Unit Distance (TTUD)

Travel Time per Unit Distance (TTUD) is adopted as the core indicator for measuring travel efficiency and serves as the primary metric in this study. It represents the travel time required per unit distance. By normalizing total travel time relative to travel distance, this

indicator effectively eliminates the influence of trip length, enabling comparability across trips of different distances.

$$TTUDi = \frac{Ti}{Di} (\text{Second} / \text{Meter}) \quad (1)$$

where Ti denotes the travel time (in seconds) of the i -th trip, and Di represents the travel distance (in meters). For ease of interpretation, the indicator is converted into minutes per kilometer in the subsequent analysis.

3.1.2. Impedance Level Indicators

Impedance level indicators are used to characterize the travel efficiency state of a city within a specific time slice. In this study, the basic unit of analysis is defined as city $\times$ weekday $\times$ 5 min interval, and TTUD percentiles are employed to represent different levels of travel impedance. The median reflects the typical travel experience at a given time, higher percentiles capture travel costs under congested conditions, and upper-tail percentiles are used to identify extreme impedance scenarios. Compared with a single mean-based measure, percentile-based indicators better preserve the asymmetry and heavy-tail characteristics of traffic distributions, making them more suitable for describing variations in urban traffic conditions under normal, congested, and extreme states, and are widely adopted in traffic performance evaluation to represent different operational regimes. Table 2 illustrates the impedance level indicators.

Table 2. Impedance level indicators are stratified based on TTUD percentiles.

Level (TTUD)	Impedance Level
$TTUD \leq Q_{25}(c, t)$	Free-flow
$Q_{25}(c, t) < TTUD \leq Q_{50}(c, t)$	Typical
$Q_{50}(c, t) < TTUD \leq Q_{80}(c, t)$	Congested
$TTUD > Q_{80}(c, t)$	Extreme congestion

3.1.3. Peak-Period Window Identification Based on a Robust Adaptive Threshold

To quantitatively compare differences in the temporal position and duration characteristics of morning and evening peak periods across cities, this study identifies peak-period windows from the 5 min impedance time series aggregated by city and day type. The procedure begins with robust smoothing of the series to reduce short-term fluctuations and fragmented variations. Subsequently, adaptive thresholds are constructed separately within predefined morning and evening time windows, and consecutive time intervals exceeding the threshold are merged into candidate peak segments. Finally, the principal peak segment is selected based on the maximum exceedance area, and key indicators—including peak start time, end time, duration, and intensity—are derived. This approach enables consistent and quantitative identification of peak periods while accounting for inter-city differences in peak patterns.

Formally, let the 5 min impedance time series for city c under day type g (weekday or weekend) be denoted as $x_{c,g}(t)$. Peak identification is conducted within predefined time windows (morning peak: 05:00–12:00; evening peak: 12:00–24:00). The original series is first smoothed to obtain $\tilde{x}_{c,g}(t)$, reducing fragmentation caused by short-term variability. Within each window W , a robust adaptive threshold $\theta_{c,g}^{(W)}$ is constructed using the median as the central tendency and the interquartile range (IQR) to characterize dispersion. Time intervals that satisfy the threshold condition $\tilde{x}_{c,g}(t) > \theta_{c,g}^{(W)}$ are merged into candidate peak segments $\{S_j\}$, with a minimum duration constraint to exclude isolated fluctuations. The principal peak segment S^* is then determined using the maximum exceedance area

criterion, ensuring both stable boundary detection and a representative peak intensity. The final outputs include peak start and end times, duration, and intensity metrics.

(1) Robust threshold within window:

$$\theta_{c,g}^{(W)} = \text{median}(\tilde{x}_{c,g} \in W) + \lambda \cdot IQR(\tilde{x}_{c,g} \in W), IQR = Q_{75} - Q_{25} \quad (2)$$

(2) Principal peak segment selection (maximum exceedance area):

$$S^{\setminus*} = \underset{S_j}{\operatorname{argmax}} A(S_j), A(S_j) = \sum_{t \in S_j} \max(0, \tilde{x}_{c,g}(t) - \theta_{c,g}^{(W)}) \cdot 5 \quad (3)$$

(3) Peak-period indicators:

$$Start = \min S^{\setminus*}, End = \max S^{\setminus*}, Duration = 5 \cdot |S^{\setminus*}| \quad (4)$$

$$Intensity = \frac{1}{|S^{\setminus*}|} \sum_{t \in S^{\setminus*}} \max(0, \tilde{x}_{c,g}(t) - \theta_{c,g}^{(W)}) \quad (5)$$

Note: λ denotes the threshold coefficient, and $|S^{\setminus*}|$ represents the number of 5 min intervals contained in the principal peak segment.

3.1.4. Reliability Indicators

Reliability indicators quantify the stability and variability of travel time, thereby reflecting the predictability of transportation system performance. In this study, travel time reliability is evaluated using three complementary metrics: the coefficient of variation (CV), the percentile range (P90–P10), and the tail risk ratio (TRR).

(1) Coefficient of Variation (CV):

$$CV(C, T) = \frac{\sigma(c, t)}{\mu(c, t)} \quad (6)$$

The coefficient of variation is used to characterize the relative dispersion of travel time, where $\sigma(c, t)$ denotes the standard deviation and $\mu(c, t)$ represents the mean. A higher CV indicates greater variability in travel time and thus lower stability of the transportation system.

(2) Percentile Range (P90–P10):

$$PR(c, t) = Q_{90}(c, t) - Q_{10}(c, t) \quad (7)$$

The percentile range reflects the spread of the travel time distribution. Larger values indicate greater differences among travel samples, implying stronger inequality in travel experiences.

(3) Tail Risk Ratio (TRR):

$$TRR(c, t) = \frac{Q_{95}(c, t)}{Q_{50}(c, t)} \quad (8)$$

The tail risk ratio measures the relative impact of extreme congestion events compared with typical travel conditions. A higher TRR indicates that the system is more sensitive to extreme events and more vulnerable under high-stress conditions.

3.1.5. Distance-Standardized Weighting

Due to the differences in travel distance structures across cities, directly comparing impedance or reliability metrics may introduce bias. To reduce the influence of

distance structure differences on the comparison results, this study introduces distance-standardization weights to reweight samples across different distance strata.

$$\omega_d = \frac{\sum_c n_{c,d}}{\sum_c \sum_d n_{c,d}} \quad (9)$$

where $n_{c,d}$ denotes the number of samples of city c in distance stratum d , and $\sum_c$ represents the total number of samples in city c . Based on this unified weighting scheme, the stratified impedance indicators of each city are aggregated through weighted integration:

The standardized metric is then calculated as:

$$TTUD_{c,t}^{std} = \sum_{d=1}^4 \omega_{c,d} \cdot TTUD_{c,t,d} \quad (10)$$

This method, by introducing a unified distance structure benchmark, effectively reduces the influence of differences in travel distance distributions among cities on comparison results, thereby improving the fairness and consistency of cross-city analysis.

3.2. Analytical Methods

To systematically reveal the spatiotemporal evolution patterns of urban travel impedance and their underlying inter-city differences, this study develops a comprehensive analytical framework building upon the aforementioned data preprocessing procedures and indicator system. The analysis is conducted from multiple dimensions, including temporal structuring, anomaly detection, statistical testing, peak-period characterization, and structural interpretation. These components are sequentially integrated to form a coherent methodological pipeline that supports a refined characterization of urban traffic dynamics and a robust cross-city comparative analysis.

3.2.1. Time-Slice Analysis

Based on the characteristics of the sample data, the temporal dimension is decomposed into two components: the weekday dimension and the intra-day time dimension. The weekday dimension consists of seven categories from Monday to Sunday. The intra-day dimension spans from 00:00 to 23:55, with a temporal resolution of 5 min from 06:00 to 24:00 and 10 min from 00:00 to 06:00, reflecting the data acquisition frequency.

Based on this temporal structure, a three-dimensional analytical framework is constructed: city $\times$ weekday $\times$ time slice. This framework enables consistent alignment of traffic states across cities under comparable temporal conditions and provides the foundation for subsequent analysis of temporal patterns, peak dynamics, and anomaly detection.

3.2.2. Anomaly Detection Method

In this study, anomalies are defined as significant increases in travel impedance after controlling for intra-week temporal regularity. Specifically, an observation is considered anomalous when the Travel Time per Unit Distance (TTUD) exhibits a pronounced positive deviation from the dynamic baseline corresponding to the same weekday $\times$ time slice, rather than merely reflecting routine peak-period congestion.

Formally, the dynamic baseline is constructed using four-week samples for each (c,d,t) combination (city, weekday, and time slice), defined as:

$$B(c,d,t) = \text{Median}(TTUD_{c,d,t}) \quad (11)$$

The deviation from the baseline is then calculated as:

$$\Delta(c, d, t) = TTUD_{c,d,t} - B(c, d, t) \quad (12)$$

An adaptive anomaly threshold is determined based on the interquartile range (IQR) of the deviation distribution:

$$T(c, d, t) = Q_3(\Delta) + \lambda \cdot IQR(\Delta) \quad (13)$$

where λ is a scaling parameter used to control the sensitivity of anomaly detection, determined based on the interquartile range (IQR) to balance robustness against noise and sensitivity to significant deviations. Observations satisfying $\Delta(c, d, t) > T(c, d, t)$ are identified as anomalous points.

To avoid fragmented interpretation, consecutive anomalous points across adjacent 5 min intervals are merged into anomalous events. Event-level metrics—including frequency, peak intensity, and duration—are subsequently derived, providing a unified basis for quantitative comparison and statistical testing of anomaly patterns across cities.

3.2.3. Statistical Testing

Within the city $\times$ weekday $\times$ 5 min time-slice analytical framework, statistical testing aims to advance the analysis from descriptive visualization to statistically verifiable differences. Specifically, deviation values relative to the dynamic baseline are computed for each time slice, and anomalous events are identified using the IQR-based adaptive threshold. By aggregating consecutive anomalous intervals, event-level indicators—such as frequency, peak intensity, and duration—are derived, forming a set of comparable, testable metrics for cross-city analysis.

To assess whether these indicators differ significantly across cities, the Kruskal–Wallis nonparametric test is used at the $\alpha = 0.05$ significance level. This method is chosen to avoid strong assumptions regarding normality and homoscedasticity, making it more suitable for high-frequency OD data characterized by skewness, heavy tails, and heteroscedasticity.

When the test results are statistically significant, it indicates that at least one city exhibits a distribution of the corresponding indicator (e.g., anomaly frequency, intensity, duration, or impedance/reliability metrics across time slices) that differs from the others. This provides robust statistical support for subsequent cross-city comparisons and interpretations.

3.2.4. City-Level Correlation Method for Road Network Density and Peak-Period Impedance

To provide structural explanatory insights into cross-city differences in peak-period characteristics without introducing a complex causal framework, this study adopts road network density—defined as total road length per unit urban area—as a coarse proxy for network supply, and conducts an explanatory correlation analysis at the city scale between road network density and peak-period indicators, including peak intensity and duration for both morning and evening peaks; given the relatively small sample size and the potential for nonlinear or monotonic relationships, the Spearman rank correlation test is employed to report correlation coefficients and significance levels, and the relationships are visualized using city-level scatter plots with an overlaid strongly constrained nonparametric smoothing curve to depict overall trends while avoiding overfitting; this analysis is intended as an exploratory investigation of potential structural mechanisms, serving only to support the discussion of possible associations between network supply and peak-period patterns, rather than to establish causal inference, and interpretations are made with due caution regarding potential confounding factors.

4. Results and Analysis

4.1. Travel Impedance Heatmaps and Peak-Period Analysis

The travel impedance heatmaps provide a continuous representation of traffic conditions across the three-dimensional framework of city–weekday–time of day. Overall, all eight cities exhibit pronounced intra-week regularity and intra-day variability, indicating that traffic pressure follows a structured temporal pattern rather than random fluctuations. The dataset is well balanced across cities (approximately 70,000 OD samples per city, totaling 559,963 records), ensuring comparability. Substantial inter-city differences are observed in average travel distance and time: Wuhan shows the highest values (26.62 km and 38.20 min), whereas Shenzhen records the lowest (12.37 km and 21.39 min), reflecting variations in spatial scale and trip chain length.

Figure 3 clearly represents the travel impedance heatmaps of eight metropolitan cities in China. In the heatmaps, the orange lines denote the start and end times of the morning peak period, whereas the blue lines denote the start and end times of the evening peak period. From the heatmap patterns and 5 min profiles, high-impedance periods are consistently more pronounced on weekdays than on weekends, with evening congestion bands exhibiting stronger continuity, which may be attributed to the accumulation of commuting demand, more dispersed departure times after work, and slower dissipation of traffic pressure during evening periods compared to the more synchronized and shorter morning peaks. In terms of peak values, Guangzhou reaches the highest weekday median impedance (3.322 at 18:25), while Shanghai and Beijing show prominent morning peaks at 07:45 (3.022) and 07:50 (2.752), respectively. This indicates a clear temporal differentiation: Beijing and Shanghai exhibit concentrated morning commuting peaks, whereas cities such as Guangzhou and Shenzhen display more pronounced evening accumulation effects. Weekend peaks are generally lower and more temporally dispersed, indicating that traffic demand during weekends is less structured and more evenly distributed across time, primarily driven by flexible leisure activities rather than synchronized commuting behavior (e.g., Shanghai shifts to 14:25), suggesting that traffic pressure is driven more by leisure and non-commuting activities rather than structured commuting demand.

4.2. Peak-Period Identification and Cross-City Comparison

As Figure 4 clearly illustrates, the identified peak windows further quantify inter-city differences in peak structure. On average, weekday morning and evening peaks last 56.25 min and 73.00 min, respectively, both exceeding weekend values (50.63 min and 40.94 min). Corresponding peak intensities are 1.242 and 2.536 on weekdays, compared to only 0.539 and 0.371 on weekends, indicating that weekday evening peak intensity is approximately 6–7 times higher than that on weekends, indicating that traffic systems operate under substantially higher load during commuting periods, where demand concentration leads to stronger congestion accumulation, making it the dominant period of traffic pressure.

At the city level, Guangzhou and Shanghai exhibit the most pronounced evening peaks (90 min/4.602 and 84 min/4.029, respectively). At the same time, Beijing and Lanzhou also exhibit prolonged evening peaks lasting up to 90 min, reflecting a clear “delayed dissipation” pattern. In contrast, Shenzhen and Chengdu have shorter evening peak durations (52 min and 49 min), indicating weaker persistence. For morning peaks, Wuhan (72 min) and Guangzhou (68 min) have the longest durations. In contrast, Beijing, despite a shorter duration (46 min), exhibits a more concentrated, sharper peak, suggesting greater synchronization of commuting activities. Although weekend peaks are generally weaker, some cities, such as Xi’an (72.5 min) and Chengdu (67.5 min), still exhibit relatively long morning peak durations, suggesting that temporal clustering of activities persists

even in non-commuting contexts. Overall, cities can be broadly categorized into “morning-concentrated” and “evening-extended” peak types, reflecting differences in job–housing spatial separation, commuting distance distributions, and daily activity scheduling patterns across cities, which together shape substantial intercity heterogeneity in traffic organization and daily mobility rhythms. Furthermore, differences in peak duration and intensity across cities are statistically significant ($p < 0.05$) according to the Kruskal–Wallis test, indicating that the observed inter-city heterogeneity is not due to random variation but reflects systematic structural differences.

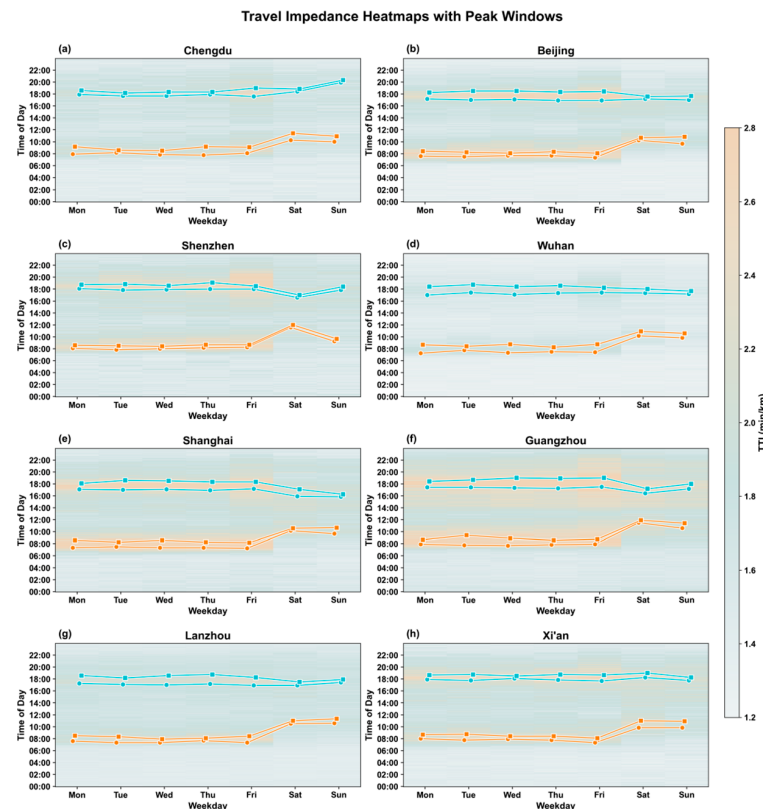


Figure 3. Travel impedance heatmaps and identified peak-period windows for the eight cities (color scales are standardized across cities and legends are enlarged for improved readability).

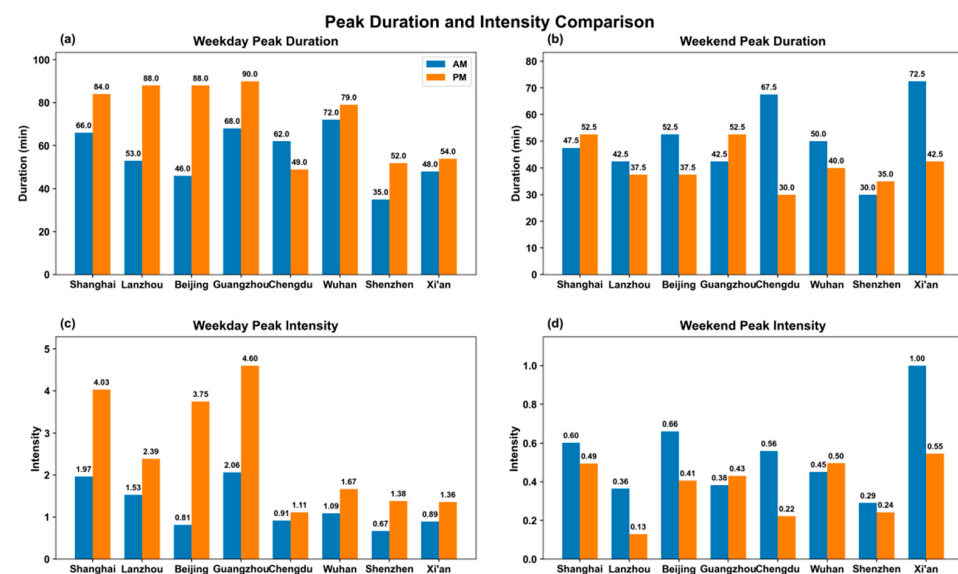


Figure 4. Comparison of peak-period duration and peak intensity across cities.

4.3. Explanatory Correlation Analysis Between Road Network Density and Peak-Period Impedance

Figure 5 clearly illustrates that road network density varies considerably across cities (24.63–41.30 km/km²), with Shanghai (41.30), Chengdu (40.39), and Guangzhou (39.81) at the higher end, and Wuhan (24.63) and Lanzhou (27.19) at the lower end. Notably, higher road density does not correspond to lower peak pressure. On the contrary, Shanghai and Guangzhou, despite their dense networks, still exhibit long evening peak durations (84–90 min) and high intensities (4.029–4.602).

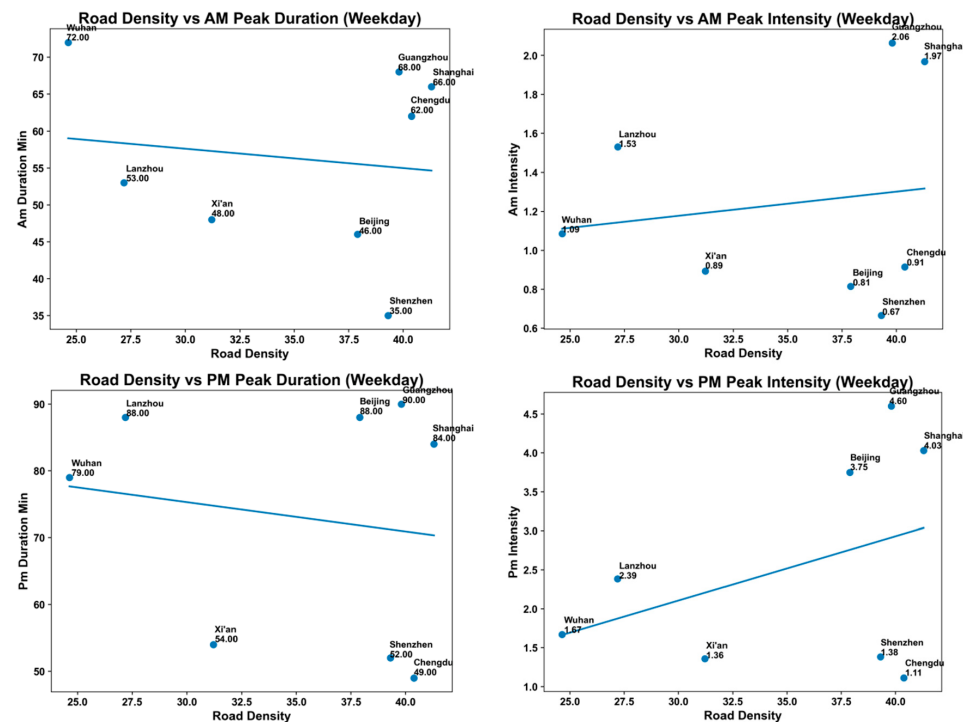


Figure 5. Explanatory correlation analysis between road network density and peak-period impedance.

Correlation analysis (Spearman's $\rho \approx 0.81$) indicates a strong positive association between road network density and weekday evening peak intensity. This suggests that road supply is often accompanied by higher levels of population agglomeration and land development intensity, which in turn generate greater travel demand, implying that increasing infrastructure capacity alone may not effectively alleviate congestion without demand-side management. Under such conditions, increased infrastructure capacity does not necessarily alleviate congestion; instead, it may support higher traffic volumes, resulting in more intense yet organized peak conditions. Therefore, road density should be interpreted as a proxy for the coupled effect of infrastructure provision and demand concentration, rather than a direct determinant of congestion mitigation, and the observed relationship should be interpreted as an association rather than evidence of causality.

4.4. Anomaly Pattern Analysis

A total of 249 anomaly events were identified during the study period, as shown in Figure 6, corresponding to an average of approximately 1.11 events per city per day. The average duration of anomaly events is 24.96 min (median: 20 min), with an average intensity of 1.445 (median: 0.886), indicating that anomalies typically manifest as moderate disturbances lasting 20–30 min rather than extreme long-duration disruptions. Notably, 85.9% of anomalies occur on weekdays, with slightly higher intensity compared to weekends, suggesting that traffic systems operate closer to capacity during commuting periods, making them more sensitive to demand fluctuations and external disturbances. This pattern reflects

instability in peak demand and system saturation under high-load conditions, where small perturbations can lead to sustained deviations from normal traffic states, highlighting the reduced resilience of traffic systems during peak commuting periods.

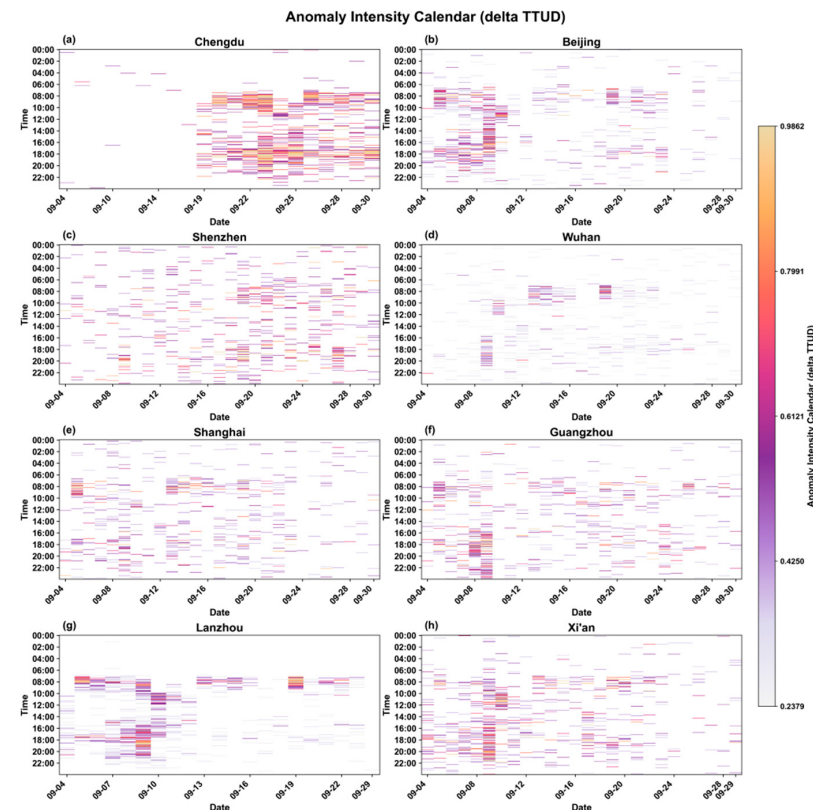


Figure 6. Calendar visualization of anomaly intensity distribution.

Substantial inter-city variation is observed. Lanzhou, Chengdu, and Beijing record the highest number of anomaly events (56, 49, and 45, respectively), whereas Shenzhen and Shanghai exhibit fewer events (11 and 17). In terms of intensity, Chengdu shows the highest value (2.054) and the longest duration (28.98 min), indicating a “low-frequency, high-impact” pattern. Xi’an and Lanzhou also display relatively high intensities, while Wuhan and Shanghai exhibit lower values (around 1.0), suggesting milder deviations. These findings reveal that anomaly characteristics differ significantly across cities: some are characterized by frequent fluctuations, while others experience less frequent but more severe disruptions. This highlights structural differences in traffic system stability and recovery capacity that cannot be captured by average impedance measures alone.

5. Discussion

The findings of this study provide important insights into the spatiotemporal dynamics and underlying mechanisms of urban traffic systems, particularly regarding peak-period evolution, cross-city heterogeneity, and the formation of anomaly risk. The longer duration and greater persistence of weekday evening peaks observed in most cities may be partly explained by cumulative commuting demand, more dispersed departure times after work, and slower dissipation of traffic pressure compared to morning peaks [36,37]. The observed inter-city heterogeneity reflects differences in urban spatial structure, job-housing separation, travel distance distributions, and daily activity organization, which jointly shape the temporal patterns of traffic impedance [38]. The concentration of anomaly events on weekdays further indicates that traffic systems tend to operate closer to capacity during commuting periods, where demand instability and system saturation increase vulnera-

bility to disturbances. These findings are consistent with existing studies that emphasize the interaction among transportation supply, demand concentration, and urban spatial organization in shaping congestion dynamics and system performance [1,39].

From an empirical perspective, the study provides comparative evidence on the temporal regularity, peak-period dynamics, and anomaly characteristics of urban traffic systems across multiple cities. From a practical perspective, the findings have implications for peak-period traffic management, suggesting the need for demand-side regulation, adaptive signal control, and targeted congestion mitigation strategies during the evening peak. In addition, the identification of anomaly patterns supports the development of traffic risk monitoring and early-warning systems, enabling more proactive and resilient transportation management [40].

Although this study provides a systematic framework for cross-city comparison, peak-period identification, and anomaly analysis based on high-frequency navigation OD data, several limitations should be acknowledged.

First, the data used in this study are derived from navigation platform route planning results, which reflect platform-generated travel information based on algorithmic routing rather than directly observed traffic flows. While such data offer advantages in terms of high temporal resolution, wide spatial coverage, and the ability to capture OD-level travel time variations, they remain fundamentally platform-based observations rather than direct measurements of real-world traffic conditions [36]. As such, they may be influenced by multiple platform-specific factors, including user behavior, variations in platform penetration across cities, and routing algorithms that optimize recommended paths rather than actual traffic conditions, and therefore cannot be considered a complete representation of overall urban travel behavior. In addition, user groups that rely on navigation services may not fully represent the entire traveling population, potentially introducing biases toward specific travel purposes or behavioral patterns. Consequently, the findings of this study are more appropriate for characterizing relative operational patterns and inter-city differences under consistent analytical conditions, rather than for directly generalizing as absolute measures of population-wide travel behavior.

Second, the analysis is based on a four-week observation period confined to September. Although this duration is sufficient to capture intra-week regularity and short-term anomalies under relatively stable conditions, it remains limited in revealing longer-term dynamics, such as seasonal variations, holiday effects, and structural evolution of urban traffic systems, which may lead to substantially different traffic patterns under varying temporal contexts. Given the strong temporal heterogeneity in traffic conditions, impedance patterns may vary significantly across seasons, holiday types, and special events. Therefore, caution should be exercised when generalizing the findings of this study to other seasons, holiday periods, or special events characterized by significantly different travel demand patterns.

Third, the explanatory analysis of peak-period differences primarily relies on road network density as a proxy for transportation supply at the city level. However, the formation mechanisms of urban traffic dynamics are inherently multifaceted. Factors such as land-use intensity, spatial distribution of employment and residence, public transport provision, weather conditions, traffic incidents, and large-scale events may all play important roles in shaping impedance evolution and anomaly formation [41]. Accordingly, the correlation analysis in this study should be interpreted as providing structural insights rather than a comprehensive explanation of underlying mechanisms. Future research could incorporate multi-source data, including built environment characteristics, human activity patterns, and event-related disturbances, to develop a more detailed explanatory framework.

Finally, the current analysis is conducted at the aggregate city level and does not explicitly account for intra-urban heterogeneity, which may obscure substantial spatial

variations within cities. In practice, spatial variations within a city—across functional zones, travel corridors, and different types of OD trips—are often driven by heterogeneous land-use patterns, job–housing distributions, and travel demand concentrations, and may be substantially greater than those captured by city-level averages, indicating that city-level aggregation may mask critical localized congestion patterns and anomaly risks. The mechanisms governing impedance may differ across spatial units, distance ranges, and travel purposes. Future work could extend the proposed time-slice framework to finer spatial scales, such as intra-city zones, key corridors, or specific OD categories, and integrate regression analysis, spatiotemporal clustering, or predictive modeling approaches to further investigate system resilience and the propagation of traffic risks.

6. Conclusions

This study develops a standardized analytical framework based on high-frequency navigation OD data, structured as “city $\times$ weekday $\times$ 5 min interval”, contributing methodologically, analytically, and empirically to cross-city traffic analysis. The framework integrates distance-stratified standardization, peak-period identification, reliability measurement, and anomaly detection to jointly characterize the temporal dynamics of travel impedance. The findings demonstrate that conventional single indicators, such as average travel time, are insufficient to capture the multidimensional nature of traffic performance in cross-city comparisons. Instead, an analytical framework centered on travel time per unit distance under consistent temporal and distance constraints provides a more robust and comparable basis for cross-city analysis.

Empirically, the study reveals pronounced intra-week regularity and significant inter-city heterogeneity in travel impedance patterns, peak period patterns, and anomaly risk. In most cities, weekday evening peaks are longer and more persistent, reflecting higher demand accumulation during commuting periods. In contrast, Beijing exhibits a dual characteristic: highly concentrated morning peaks and prolonged evening peaks. Anomaly events are more frequent and sustained on weekdays than on weekends, indicating that commuting-dominated periods are more prone to sustained deviations beyond normal temporal patterns. A positive relationship between road network density and peak intensity highlights the interaction between infrastructure supply, spatial structure, and demand concentration, suggesting that the formation of urban traffic pressure is closely related to the complex interplay among road network supply, spatial agglomeration, and activity organization.

Overall, this study contributes a unified analytical framework for jointly characterizing travel efficiency, operational stability, and anomaly risks in urban traffic systems. The proposed approach offers a more comparable quantitative basis for cross-city traffic performance evaluation and offers practical implications for peak-period management and anomaly risk identification, while also laying a foundation for future research across longer time spans and finer spatial scales.

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Abbreviations

The following abbreviations are used in this manuscript:

OD	Origin–Destination
TTUD	Travel Time per Unit Distance
CV	Coefficient of Variation
TTR	Tail Risk Ratio
IQR	Interquartile Range
API	Application Programming Interface

Appendix A. Spatial Extent and Sampling Ranges of OD Samples

Given differences among cities in urban morphology, built-up area structure, and core urban scale, this study did not use the full administrative boundary as the sampling boundary for OD samples. Instead, based on the actual spatial structure of each city's main urban area, core urban spaces within ring roads, expressways, or continuous built-up areas were selected as the OD sample generation areas. For example, the sampling areas in Beijing, Chengdu, Wuhan, and Xi'an were mainly determined by their ring roads. In contrast, those of Shanghai, Shenzhen, and Guangzhou were defined by coastal urban morphology, continuous built-up areas, and urban expressway structures. For Lanzhou, two core urban sampling sections were established based on its elongated urban spatial structure. This approach helps avoid weakening the validity of inter-city comparison due to large differences in administrative area size. It enables the OD samples to better reflect travel impedance characteristics within the core urban areas of each city.

The longitude and latitude ranges listed in Table A1 further clarify the spatial coverage of OD samples in each city, providing a basis for understanding sample spatial distribution, urban-scale differences, and the comparability of cross-city analyses.

Table A1. Longitude and latitude ranges of OD samples in the eight study cities.

City	Longitude Range of OD Samples	Latitude Range of OD Samples	Study Area
Beijing	116.21–116.53° E	39.78–40.01° N	Main urban area within the Fifth Ring Road
Shanghai	121.37–121.60° E	31.13–31.37° N	Main urban area within the Outer Ring Expressway
Shenzhen	113.90–114.12° E	22.53–22.58° N	Main urban area of Bao'an, Futian, and Nanshan districts
Guangzhou	113.21–113.39° E	23.06–23.16° N	Main urban area within the Ring Expressway
Chengdu	103.96–104.17° E	30.57–30.72° N	Main urban area within the Ring Expressway
Wuhan	114.16–114.52° E	30.44–30.72° N	Main urban area within the Fourth Ring Road
Xi'an	108.81–109.10° E	34.20–34.36° N	Main urban area within the Third Ring Road
Lanzhou	103.67–103.75° E; 103.82–103.93° E	36.08–36.12° N; 36.04–36.08° N	Two core sections in the elongated main urban area

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