A Study on the Travel Characteristics of Rail Transit Passengers in Township Areas of Wuxi City

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Abstract
With China's new urbanization driving integrated urban-rural transport, this study examines the Wuxi–Jiangyin S1 township rail line serving over 30,000 daily riders. Using high-precision LBS data from October 2024, we identified township passengers via spatio-temporal filters, inferred trip purposes through a white-box model combining spatial and temporal rules, and classified last-mile modes with fuzzy membership functions. Ridership is dominated by middle-aged, multi-generational households; leisure trips comprise over 50%; medium-distance (8–29 km) travel prevails; and bicycles/motorcycles lead access/egress. More than 60% of travelers make no station-area stops, indicating weak station-city integration. Findings offer guidance for service optimization, TOD planning, and policies to enhance sustainable township rail development.

Keywords: Rail Transit; Township Areas; Wuxi City; Travel Characteristics

1 Introduction
National strategies for new urbanization and integrated urban-rural development are driving the evolution of intercity railways, which are reshaping urban-rural spatial links. The "Yangtze River Delta Regional Integration Development Plan Outline" aims to establish a "one-hour commuter circle," fostering composite transportation systems that merge urban rail transit (metro) with intercity railway functions. Township rail transit, through technical standard compatibility (e.g., platform spacing, vehicle types) and innovative operational modes (e.g., bus-like scheduling, through-line operations), creates high-frequency, efficient connections between core metropolitan cities and outlying townships (Li Fengjun et al., 2020; Yang Shaohui et al., 2022; Zhang Pei et al., 2017). By 2023, the Yangtze River Delta's intercity railway network surpassed 1500 km, projected to exceed 3000 km by 2025, deeply serving low-urbanization areas (2000-5000 people/km²), signifying a new "rail transit extending to townships" phase.

The Wuxi-Jiangyin S1 Line in Wuxi exemplifies such systems, pioneering through-operation between an intercity railway and an urban metro in China. It connects Jiangyin's urban area, township nodes like Zhouzhuang and Qingyang, and Wuxi's main urban area via a "one-train direct access" model, serving over 30,000 daily bidirectional urban-rural commuters. Its data reveal unique spatio-temporal distribution, travel purposes, and behavioral preferences of township rail passengers. While current research focuses on urban rail transit, a gap exists regarding township rail passengers with both intercity and metro characteristics. Analyzing these patterns is vital for optimizing transportation in urban-rural integration and addressing dilemmas like the "urban siphon effect" versus "township transportation deserts". This study analyzes the S1 Line's township passenger travel characteristics to inform operational optimization, station-area land use planning, and broader urban-rural transport policies.

2 Literature Review
Rail transit, as a pivotal component of urban public transportation systems, demands systematic investigation of passenger travel characteristics to optimize operational strategies, enhance service quality, and inform future infrastructure planning. With accelerating urbanization and shifting socio-economic structures, usage patterns among distinct passenger cohorts have become markedly heterogeneous. Accordingly, segmenting passengers by individual attributes—such as age, gender, and occupation—or by behavioral characteristics—such as trip purpose and frequency—is a critical step in understanding and addressing diverse needs. Through such segmentation, the unique travel patterns of specific groups can be identified, furnishing a basis for designing personalized services that elevate overall passenger satisfaction and system efficiency. Furthermore, targeted research on special populations (e.g., the elderly, children, and persons with disabilities) facilitates the development of more inclusive policies, ensuring that all members of society enjoy equitable access to effective rail transit services.

Travel characteristics differ significantly across passenger groups. Research categorizes groups by individual attributes, travel features, or combined factors. Some studies focus on age and gender impacts. Xiong Meicheng et al. (2022) found that older elderly (≥70) in Kunming have reduced mobility but increased public transport reliance compared to younger elderly (60-69). Yang Hong et al. (2023) noted Wuhan's elderly avoid peak hours and prefer shorter distances. Xiaohan Liu et al. (2024) found travel distance, time, and space variations among different gender and age groups.

Other studies examine travel purposes and frequencies to identify patterns and drivers. Cheng Xiaoyun et al. (2020) proposed a classification framework based on travel days, daily trips, concentration, time consumption, and line utilization entropy. Comprehensive approaches consider multiple simultaneous factors. Rezwana Rafiq et al. (2021) used Latent Class Analysis (LCA) for user classification, identifying five activity-travel patterns, such as employed white males on simple transit-based work trips and employed white females on complex work trips. Some research classifies passengers by activity within hub station areas, finding differences in activity range and travel time distribution (Cheng L et al., 2024).

Travel characteristics are often described by time, space, and intensity (Zou Qingru et al., 2024). Spatial attributes include origin (LE M K et al., 2015), path, stations (MA X et al., 2013), and commuting distance (JI Y J et al., 2019; and Kang Hehe et al., 2018). Temporal attributes include average travel time (Long Ying et al., 2015), departure time (LE M K et al., 2015), journey time (MA X et al., 2013), and first departure time (JI Y J et al., 2019). Rail usage intensity is measured by trip counts over periods (El MAHRSI M K et al., 2017) or average trips and travel days (Liu Ying et al., 2019).

Effective classification algorithms are critical(Cheng Xiaoyun et al., 2020). Studies have used DBSCAN, GMM, OPTICS (VENUGOPAL S et al., 2016), LCA, k-means++ (Xu Xiaowei et al., 2017), and hierarchical clustering with k-means (ZHAO J J et al., 2014; Pang L et al., 2023) for urban rail user segmentation, providing rich methods for understanding travel diversity.

Existing research offers robust perspectives and methods for urban rail optimization. However, township rail stations and passengers remain understudied. Townships differ from urban centers in population density, land use, economic activities, and lifestyles, leading to unique passenger flow and demands at their rail stations. Lines like the Wuxi-Jiangyin S1, connecting cities with townships and integrating with urban metros, may serve complex demands (commuting, services, leisure) and exhibit distinct travel behaviors (purpose, duration, access/egress modes) compared to traditional urban or suburban rail users. This disparity is this study's focus, as specialized research on such hybrid-feature township rail transit is scarce.

This research aims to fill this gap by studying Wuxi-Jiangyin S1 Line's township passengers, detailing their attributes and behaviors for a comprehensive understanding of their composition and needs. This supports S1 Line's operational optimization and service improvement, offering empirical references and theoretical insights for non-urban rail service models and station-area integrated development.

3 Research Content and Methods

3.1 Research Scope and Data

This study focuses on the Wuxi-Jiangyin S1 Line, stretching 30.4 km (10.5 km underground, 0.2 km transitional, 19.7 km elevated) with 10 stations (5 underground, 5 elevated) and a design speed of 120 km/h, operating through-service with Wuxi Metro Line 1. The Jiangyin urban section is underground; the Xuxiake Avenue section is elevated. Qingyang, Xuxiake, and Science City stations are elevated. The selected suburban section includes Nanzha, Qiaoqi, Qingyang, Xiake Bay Science City, and Mazhen Stations (Figure 1).

The study uses LBS data from Wuxi City (October 14-20, 2024), providing high-precision user spatio-temporal trajectories, enabling capture of travel chains, stay point identification, and travel purpose inference.

3.2 Research Methods

3.2.1Identification of Rail Transit Passengers in Township Areas

LBS data provide certain spatial identification of metro stations, allowing high-precision matching via hard thresholds. The study first anchors metro travel to maintain base passenger group purity, adopting a phased identification: first, identify township rail passengers, then use fuzzy theory for access/egress modes, balancing data traits and research goals.

A framework for identifying township rail passengers uses multi-source data fusion and spatio-temporal analysis. High-precision LBS data (error ≤ 50m) and geofencing match user stay points with metro station coordinates, filtering records within a 100m station buffer with stay duration ≥3 minutes. Travel chain continuity rules extract records of continuous visits to different metro stations consistent with prior knowledge, identifying metro users. To target township rail passengers, travel chains through township stations (Mazhen, Qingyang, Science City, Qiaoqi defined as township functional stations) are extracted, identifying those with at least one township station stop.

3.2.2 Stay Point Identification Based on Density

Trajectory stay point identification is key for mining travel activity semantics and characterizing crowd demands. Existing methods include cluster-based, probability-based, and discrimination-based strategies (Lu Jianfeng et al., 2020). Cluster-based density algorithms are common but spatially limited. Probability-based methods (Bayesian, Gaussian mixture models) infer frequent locations but ignore trajectory temporal sequences. Discrimination-based methods focus on stay/representative points, missing spatio-temporal aggregation (Zhang Xun, 2022). To address these, Li Yuru et al. (2018) proposed SPID (Stay Point Identification based on Density), which considers temporal continuity, directionality, and spatio-temporal aggregation.

This study uses SPID for Wuxi's LBS data. Steps: Identify trajectory points; calculate distances to other points chronologically (forward/backward); add points within distance thresholds to a set; stop when distances exceed thresholds. Stay points are determined by point set density (He Guofeng, 2022). Following literature (Jin Tanhua, 2019), spatial threshold is 100m, time threshold is 15min.

3.2.3 Travel Purpose Inference

To ensure effective semantic identification of passenger activities and precise crowd feature characterization, this study builds on identifying daily township rail users and stay points. It uses LBS travel chain data and stay point spatio-temporal attributes (period, duration) for activity chain semantic recognition for each passenger's daily stay points. Rail station spatio-temporal matching rules extract metro travel segments for precise analysis of purposes and patterns.

Traditional activity chain data from surveys are costly and not timely (Hartgen et al., 2009; Collia et al., 2003; McDonald et al., 2008). Mobile phone data are now used. Methods include: 1) Regression models, like Diao et al. (2016) using multinomial logit for semantic labels from activity time, weather, etc.; 2) Hidden Markov Network (HMN) sequence models, e.g., Widhalm et al. (2015) on Boston/Vienna data, and Yin et al. (2018) with HMN optimized by activity transfer patterns; 3) Machine learning (e.g., random forests), like Zhao Pengjun et al. (2020) using RF for metro trip purpose classification. However, these methods have limitations: 1) "Black-box" models lack interpretability (HMNs, ML). 2) Data dependency versus universality: require proprietary survey data for transition probabilities or fine-grained land use/large training sets, creating researcher barriers. 3) Massive data processing challenges (Cao, J. et al., 2019; Deville, P. et al., 2014).

This study, referencing Yin L et al. (2021), uses a transparent, rule-based inference algorithm considering spatial/temporal features for activity purpose, with Monte Carlo for final determination. This ensures interpretability and uses open-source geographic data, offering an operable tool.

• Stay Point Type Classification. This study classifies travel activity purposes into five categories: living, working, schooling, leisure, and other. Since the attributes of activities (start time, end time, location) are long-term choices made by individuals and authorities in the case of fixed activities, while the characteristics of flexible activities vary greatly among different people and on different days for the same person. Therefore, this study, based on the dual dimensions of activity priority and spatio-temporal decision-making freedom, divides activities into fixed and flexible. According to activity priority from high to low, they are special, fixed, semi-flexible, and flexible activities (Figure not provided).

• Calculating Activity Purpose Probability Based on Spatial Features. People's daily activities are closely related to the spatial features (such as land use type and building type) around their activity locations (Yang et al., 2019). The relationship between daily activities and geographical attributes can be used to support the inference of one attribute given the other (Yin L et al., 2021). To infer activity patterns from geographical attributes, the research by Widhalm et al. (2015) and this study both use the basic assumption: the activity a person engages in is closely related to the corresponding spatial features. Therefore, a link must be established between spatial features and activity purposes. Spatial features are usually described as enumerated types. Combined with POI service capacity (Li S et al., 2021; Liu J et al., 2023), different weights are assigned to each POI type to assess the probability that a specific activity category is dominant at each location.

• Calculating Activity Purpose Probability Based on Temporal Features. Residents' daily activity arrangements are often constrained by prevailing social norms and life rhythms, thus forming daily behavioral patterns with a certain cadence. The transition patterns between different types of activity purposes (e.g., departing from "home" for "work" in the morning, returning from "work" to "home" in the evening, or engaging in "leisure" activities on weekends) can effectively characterize this regularity. These transition patterns can be extracted from auxiliary data, such as historical resident travel surveys, social network check-in data, or through statistical analysis of large-scale LBS data (Yin L et al., 2021). This study will set corresponding temporal transition probability matrices based on different demographic attributes (e.g., age groups) and date types (weekdays/weekends) to reflect the likelihood of different activities occurring at specific times.

• Inferring Activity Purpose Based on the Combination of Spatial and Temporal Features. To integrate spatial and temporal features and clearly demonstrate their impact on activity purpose inference, this study adopts a concise model that linearly combines these two features. Specifically, a weighting parameter[0,1] is used to flexibly combine the activity purpose results inferred from spatial and temporal features. We denote by the combined probability that an individual performs an activity of type k during a certain stay. A straightforward intuitive method, defined by the formula, is used to combine the probabilities derived from the two types of features.

A Monte Carlo simulation method is employed to determine the specific activity purpose for each stop based on the activity purpose probability distribution .

• Model Validation

Due to the unavailability of ground truth for activity chains derived from mobile phone location data, this study employs methods such as manual comparison with attribute information inherent in LBS data and small-sample questionnaire survey data to validate the reasonableness and effectiveness of the model inference results.

3.3 Research Content

This study's core content involves: 1) Focusing on the Wuxi-Jiangyin S1 Line, a typical township-serving rail line. 2) Using LBS travel chain data and multi-stage screening to identify core township rail passengers. 3) Applying SPID to LBS trajectories for stay point identification, extracting spatio-temporal stay point data. 4) Using a transparent, rule-based "white-box" model integrating spatio-temporal features to infer activity types (travel purposes) of stay points. 5) Extracting complete metro travel segments (origin/destination stations, related stay points). 6) Using fuzzy theory (prior knowledge, membership functions) to infer last-mile access/egress modes.

After data processing, a structured township rail travel dataset with rich attributes will be analyzed for passengers' ontological (socio-demographics, residence) and behavioral (purpose, spatio-temporal patterns, access/egress choices) characteristics. Findings aim to provide evidence for optimizing township rail operations, guiding station-area development (TOD models), and enhancing urban-rural transport integration.

4 Analysis of Travel Characteristics

4.1 Indicator Construction

To comprehensively and systematically characterize the features of township rail transit passenger groups, this study has constructed an indicator system comprising two main categories: ontological attributes and behavioral attributes. The selection of these indicators aims to capture key factors influencing travel behavior and the multidimensional manifestations of travel behavior itself.

Ontological attributes primarily reflect the relatively stable demographic, socio-economic, and spatial locational characteristics of the passenger group (Table 2). These indicators are chosen because an individual's natural attributes (e.g., age, gender), social attributes (e.g., education level, income, family structure), and the geographical location of their residence profoundly influence their travel demand, travel capability, choice of travel mode, and expectations for transportation services. For example, "age" is closely related to travel activity levels and the composition of travel purposes; "household size" in township areas may be more associated with joint travel as a family unit; "income level" directly affects sensitivity to travel costs and demand for travel comfort; and "residential location" directly reflects the service coverage and attractiveness of rail transit to different areas (Jiangyin townships, Jiangyin sub-districts, Wuxi townships, Wuxi sub-districts, and other areas).

Table 2. Ontological Attributes

Ontological attributes	Attribute category	Quantitative indicators	Label extraction
Natural attribute	Gender	Male	Male
		Female	Female
	Age group	20-29 years old	Youth
		30-49 years old	Middle-aged
		Above 50 years old	Elderly
	Education level	Junior high school and below	Low education
		High school or junior college	Medium education
		Bachelor's degree or above	High education
	Household size	1 person	Single
		2 people	Small family
		3 people and above	Big family
Social attribute	Income level	Monthly income of 4.5K and below	Low income
		Monthly income: 4.5K-10K	Medium income
		Monthly income of more than 10K	High income
Regional attribute	Residential location	Whether it belongs to a township area of Jiangyin City	Jiangyin Township
		Whether it belongs to a sub-district of Jiangyin City	Jiangyin Sub-district
		Whether it belongs to a township area other than Jiangyin in Wuxi City	Wuxi Township
		Whether it belongs to a street in Wuxi City other than Jiangyin	Wuxi Sub-district
		It doesn't belong to the heart of Wuxi City	Other places

Behavioral attributes focus on the dynamic manifestations of the passenger group while using rail transit (Table 3). These indicators are selected because they can directly reflect the passenger group's travel purposes, spatio-temporal preferences, travel efficiency, degree of reliance on rail transit, and solutions for the "last mile." "Travel semantics" reveals what kinds of needs rail transit meets; "temporal characteristics" describe the timing, duration, and frequency of travel, where labels like "happy commuting" for "travel duration" provide a preliminary assessment of the travel experience; "spatial characteristics" focus on the spatial span of travel and the utilization of station areas, with "number of activities at station" being an important indirect indicator of station-city integration; "subway connection method" within "travel diversity" is particularly crucial for township areas with inconvenient transportation.

Table 3. Behavioral Attributes

Behavioral attributes	Attribute category	Quantitative indicators	Label extraction
Temporal characteristics	Day of travel	10.14.-18.	Weekday
		10.19.-20.	Weekend
	Working/non-working travel time	6:00-10:00	Morning rush hour
		10:00-15:00	Noon
		15:00-19:00	Evening rush hour
		19:00-6:00	Night
	Travel duration	None	None
		Within 45min	Happy commuting
		Within 45-60min	Normal commuting
		Above 60min	Extremely long commuting
	Frequency	Once a day	Low frequency
		Twice a day	Intermediate frequency
		3 times a day	High frequency
		4 times a day or more	Ultra-high frequency
Spatial characteristics	Subway travel distance	Within 8km	Short-distance travel
		8-29km	Medium-distance travel
		Above 29km	Long-distance travel
	Number of arrival activities	0 times	No arrival activities
		1 time	Arrival activities included
		2 times or more	Rely on rail transit to connect activities

4.2 Analysis of Ontological Dimensions

Based on a multi-dimensional analysis of natural, social, and regional attributes, the township rail transit passenger group exhibits significant structural characteristics (Table 4). In terms of natural attributes, the core of the passenger group is middle-aged individuals (30-49 years old, 80.61%), with family structures predominantly being large, multi-generational households (71.51%). Education levels are concentrated at medium (high school or junior college, 52.89%), reflecting the typical characteristic of the middle-aged labor force in township areas shouldering dual family and economic responsibilities. The travel demands of this group often revolve around fixed activities such as work commutes and children's education, and are significantly influenced by family cooperation patterns. In terms of social attributes, income distribution shows a "spindle-shaped" structure, with the medium-income group (monthly income 4.5K-10K, 51.29%) accounting for the highest proportion. High-income (17.09%) and low-income (31.62%) groups form two poles, suggesting that rail transit services need to balance fare affordability with comfort upgrades to meet differentiated needs. Regional attribute analysis further reveals the spatial distribution characteristics of the passenger group: a clear trend of localization and agglomeration is evident, with local residents from Jiangyin and Wuxi collectively accounting for 84.3% (Jiangyin Township 28.62%, Wuxi Sub-district 21.41%, etc.), while users from other areas only account for 15.7%. This indicates that rail transit primarily serves the medium and short-distance travel of permanent residents. Significant differences exist in urban-rural distribution: township users (Jiangyin Township 28.62%, Wuxi Township 7.29%) rely on rail transit to address issues of inadequate access and egress facilities, while urban users (e.g., Wuxi Sub-district 21.41%) are more inclined towards multimodal travel combinations.

Overall, the passenger group's behavior patterns are driven by both demographic structure and socio-economic attributes: the middle-aged and family-oriented characteristics reinforce the priority of fixed activities such as commuting and medical care; the predominance of the medium-income bracket requires a balance between efficiency and cost in service design; and differences in urban-rural distribution necessitate targeted optimization of access/egress networks (e.g., adding dedicated bus lines in townships, improving transfer efficiency in urban areas). The portrait system constructed in this study provides data support for the precise matching of "demand-service" for township rail transit. In the future, dynamic spatio-temporal behavior data can be incorporated to further deepen the analysis of causal mechanisms.

Table 4. Profile of Township Rail Transit Passengers

Variable	Percentage/%
Natural attribute	
Gender	
Male	52.62
Female	47.38
Age group	
Youth	9.70
Middle-aged	80.61
Elderly	9.68
Household size	
Single	24.65
Small family	3.85
Big family	71.51
Education level	
Low education	32.69
Medium education	52.89
High education	17.22
Social attribute	
Income level	
Low income	31.62
Medium income	51.29
High income	17.09
Regional attribute	
Residential location	
Jiangyin Township	28.62
Jiangyin Sub-district	26.98
Wuxi Township	7.29
Wuxi Sub-district	21.41
Other places	15.70

4.3 Analysis of Behavioral Dimensions

(1) Temporal Characteristics

Travel time characteristics are a crucial dimension for understanding passenger travel patterns and evaluating the efficiency of transportation services. This section will analyze the distribution of travel on weekdays/weekends, the temporal distribution of different travel purposes throughout the day, travel duration, and the frequency of metro usage.

According to data analysis (Table 6), work-related travel during the morning rush hour (6:00-10:00) accounts for 13.60%, which is the main period for work travel, consistent with basic commuting patterns. It is noteworthy that work-related travel during the midday period (10:00-15:00) also reached 14.10%, while the evening rush hour (15:00-19:00) accounted for 11.00%, and the night period (19:00-6:00) was lower at 4.39%. The higher proportion of work travel during midday may reflect that some township residents are engaged in non-standard work hours (such as in the service industry or freelance work), or that there are instances of round trips between work and home (or other activity points) during midday. The 56.91% of "None" for work travel time corresponds to the previously mentioned proportion of passengers whose trips do not include work.

Non-work-related travel, however, exhibits different temporal distribution characteristics. The midday period (10:00-15:00) and the evening rush hour period (15:00-19:00) are the two peaks for non-work travel, accounting for 27.26% and 28.08% respectively. This aligns closely with the occurrence times of activities such as leisure and shopping. Non-work travel during the morning rush hour (6:00-10:00) accounts for 17.13%, and non-work travel during the night period (19:00-6:00) also constitutes a certain proportion (14.35%), indicating the broad timing of leisure activities for township residents. The 13.18% of "None" for non-work travel time corresponds to passengers with no non-work activities or only work activities in their travel purposes.

Table 6. Proportion of temporal characteristics

Variable	Percentage/%
Temporal characteristics	
Working travel time	
Morning rush hour (6:00-10:00)	13.60
Noon (10:00-15:00)	14.10
Evening rush hour (15:00-19:00)	11.00
Night (19:00-6:00)	4.39
None	56.91
Non-working travel time	
Morning rush hour (6:00-10:00)	17.13
Noon (10:00-15:00)	27.26
Evening rush hour (15:00-19:00)	28.08
Night (19:00-6:00)	14.35
None	13.18
Day of travel	
Weekday	67.28
Weekend	32.72
Travel duration	
Within 45min	42.93
Within 45-60min	10.16
Above 60min	46.90
Frequency	
Once a day	45.67
Twice a day	32.83
3 times a day	13.20
4 times a day or more	8.31

Weekday travel (Oct 14-18, 2024) is 67.28%; weekend (Oct 19-20) is 32.72%. Higher weekday volume links to commuting regularity and some weekday leisure (e.g., post-work).

Travel duration: 42.93% are "happy commutes" (≤45 min); 10.16% "normal" (45-60 min); 46.90% "extremely long" (>60 min). The S1 line, connecting Jiangyin townships to Wuxi, serves long distances, causing many long trips, likely cross-regional work/leisure commutes.
Daily metro frequency: 45.67% once (one-way/one leg of round trip); 32.83% twice (typical round trip); 13.20% thrice; 8.31% ≥4 times (ultra-high). Most use it 1-2 times daily (low/medium frequency).

In sum, township rail users travel mainly on weekdays; non-work travel peaks midday/evening. High "extremely long commuting" is notable. If for high-value leisure (to Wuxi centers), tolerance for long travel may be high, suggesting S1 expands activity space and life choices, justifying longer travel for higher needs.

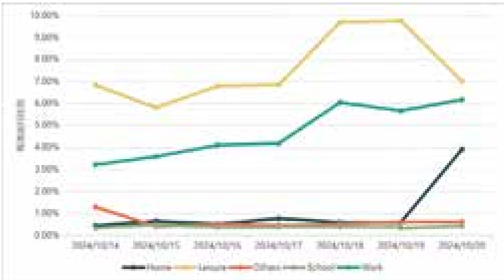


Fig 1. Statistics of the number of various types of trips every day within a week

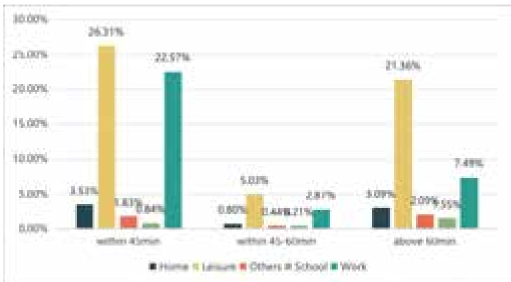


Fig 2. The distribution of travel duration for various types of trips

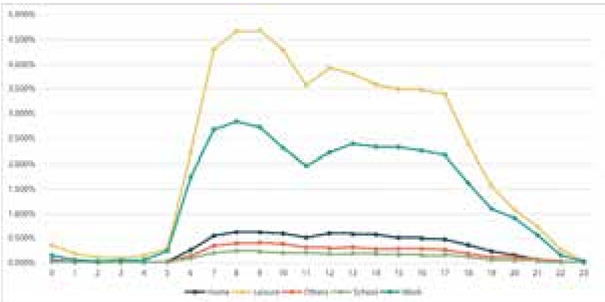


Fig 3. The distribution of travel start times for various types of trips

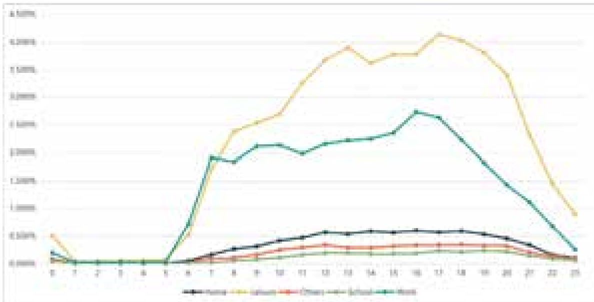
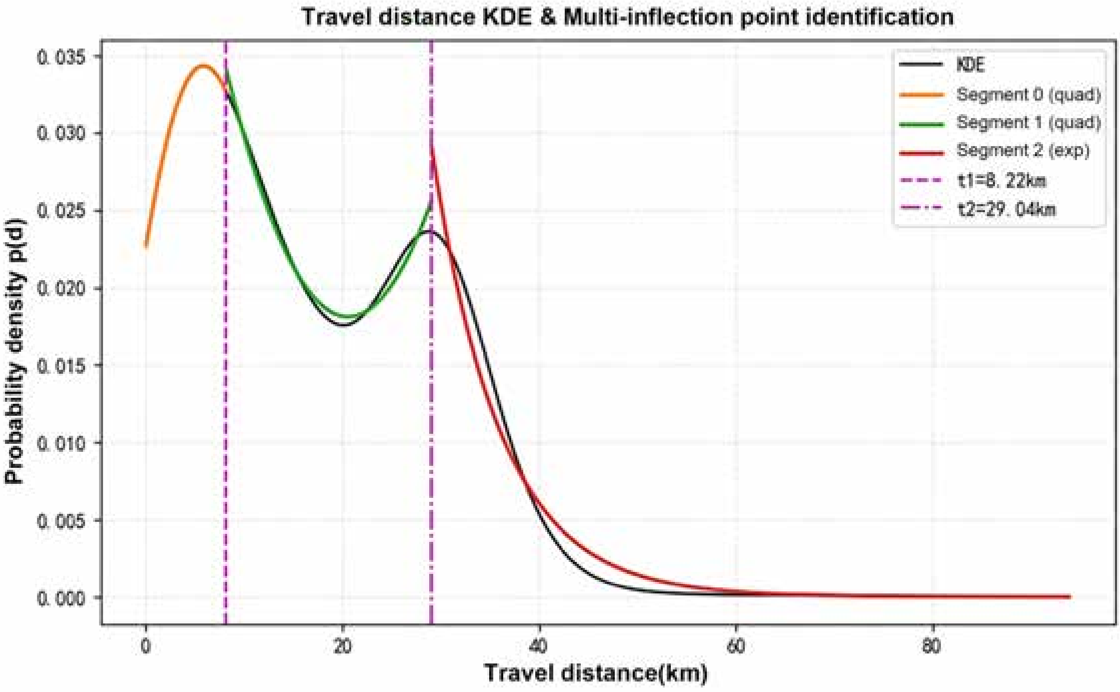


Fig 4. The distribution of travel end times for various types of trips

(2) Spatial Characteristics
This study mainly refers to the research of Qiao et al. (2019), Raja et al. (2015), and Shi Ruizheng et al. (2022). It employs the Euclidean distance between the origin and destination of passengers' metro trips, i.e., the shortest straight-line distance between the two points, as the travel distance for each metro trip. Using travel distance as the fitting object, a probability distribution function for travel distance is fitted, with different distributions at its two ends. By comparing the coefficient of determination R^2 for different distances, the corresponding travel distance cutoff thresholds are determined (Qiao Mengling et al., 2019). The specific method uses Kernel Density Estimation (KDE) to divide travel distances by thresholds, with the optimal fit shown in the figure.



Remark: The first segment is fitted with a quadratic function, model , ; the second segment is fitted with a quadratic function, model , ; the third segment is fitted with an exponential function, model ,

Fig 5. The optimal fitting situation of the probability distribution graph of travel distance

The travel distance for passengers using township area rail transit follows a quadratic function when less than 8.22km (Model 1, yellow line); it follows a quadratic function distribution when the distance is between 8.22-29.04km (Model 2, green line); and it follows an exponential function when the distance is greater than 29.04km (Model 3, red line). For statistical convenience, thresholds are rounded to integers, determining cutoff values of 8km and 29km.

Based on this, a statistical analysis of travel distance was conducted (Table 7). It can be seen that medium-distance travel (64.77%) is mainstream for township rail transit passengers, followed by short-distance travel (22.91%), with long-distance travel being the least common (12.32%). Looking at different travel purposes, medium-distance leisure travel has the highest proportion (23.94%), indicating that cross-city leisure trips from Jiangyin residents to Wuxi commercial districts, scenic spots, etc., are numerous. Although short-distance work travel accounts for over 40%, considering the "2024 China Major Cities Commute Monitoring Report" released by the China Academy of Urban Planning and Design, the average one-way commute distance in Wuxi is 7.4km, with 55% of commutes being "happy commutes" within 5km. Work travel on the Wuxi-Jiangyin S1 Line is still dominated by medium to long-distance commutes. As a cross-city rail line, its passengers' travel characteristics are significantly different from those of Wuxi's main urban metro. Residential and school-related travel are mainly medium-distance, reflecting that some families may choose a "dual-city life" model of living in Jiangyin and schooling in Wuxi. For other (medical) travel, short-distance travel has the highest proportion, but at the same time, the proportion of long-distance travel is the highest among the five categories, indicating a prominent rigid demand for long-distance medical treatment.

Further analysis of the coverage of township rail transit stations (Table 7) reveals that over 60% of passengers have no additional activities after arriving at the station, indicating a lack of commercial and service facilities around the stations, with passengers merely using rail transit as a "point-to-point" commuting tool. Cross-analysis (Figure 6 and Figure 7) shows that leisure travel accounts for the highest proportion within the station coverage area, indicating that the rail coverage area primarily serves leisure demand, but activity frequency is still low, mainly single instances. Work-related travel covered by stations is relatively small, only half of that for non-station-based work activities. According to the "2024 China Major Cities Commute Monitoring Report," the proportion of commutes covered by rail transit in Wuxi is only 9%, meaning the proportion of the commuting population whose residences and workplaces are both within 800 meters of a rail station is far below the national average of 20%. This indicates that Wuxi's rail transit provides weak support for residential and employment spaces, and the Wuxi-Jiangyin S1 Line shares this problem. In addition, school-related travel within station coverage areas is much lower than non-station-based travel, possibly because schools are often located in areas not covered by rail, exacerbating the pressure of "cross-district schooling." The low frequency of activities at S1 Line stations and Wuxi's weak rail coverage for commuting jointly point to the core contradiction of "rail construction being disconnected from urban functions." It is necessary to promote the new urbanization process in township areas through "comprehensive station development + equalization of public services," rationally allocate public service facilities, and upgrade rail transit from a "commuting corridor" to a "vitality link."

Table 7. Spatial Characteristics of Township Rail Transit Passengers

Variable	Percentage/%
Spatial Characteristics	
Subway travel distance	
Short-distance travel	22.91
Medium-distance travel	64.77
Long-distance travel	12.32
Number of arrival activities	
0 times	61.60
1 time	26.39
2 times or more	12.01

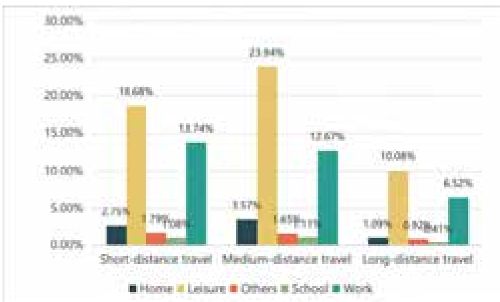


Fig 6. The distribution of travel distances for various types of trips

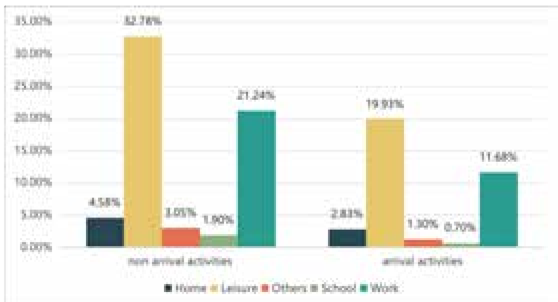


Fig 7. The distribution of arrival activities for various types of travel

5 Conclusion

This study of Wuxi-Jiangyin S1 Line using LBS data analyzed township rail passenger attributes and behaviors, revealing unique traits and offering insights for service optimization and regional development.

- Distinct Passenger Profile: Core users are middle-aged (30-49), from larger local families, with medium/low education and income, differing from urban metro users; their needs may be more complex/pragmatic.
- Leisure Travel Dominance: Over 50% of trips are for leisure, far exceeding work travel, unlike traditional commute-focused rail. S1 is a "lifeline" expanding lifestyle options and activating cross-regional leisure consumption.
- Medium-Long Cross-District Travel: Medium (8-29km) and longer trips are common for leisure, work, and medical needs, reflecting S1's role as an intercity urban-rural connector. Some "extremely long commutes" (>60min) exist.
- Severe Lack of "Station-City Integration": >60% of passengers have no activities around township stations. Stations are mere transfer points, poorly integrated with urban functions; "rail-city disconnect" is prominent, failing TOD potential.

Optimize services for passenger traits. Address family needs (middle-aged, large families) with off-peak/weekend family tickets, better in-carriage facilities (storage), and improved station accessibility (barrier-free, maternal-child facilities). Empower leisure/lifestyle travel by linking S1 with attractions/commercial centers, enhancing station-city integration for vitality. Implement locally adapted TOD: treat station areas as township renewal nodes, introducing mixed uses (retail, community services, entertainment, offices) matching resident needs and local resources to create vibrant micro-centers, requiring planning/transport/land development synergy.

LBS data may have representation bias (e.g., underrepresenting elderly, non-smartphone users). Stay point/purpose inference accuracy is limited by data granularity and algorithm universality. The study is mainly quantitative, lacking qualitative depth on motivations/perceptions. It's a cross-sectional study, not capturing dynamic evolution; characteristics may change with township development and S1 operation time.

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