User-Oriented Last-Mile Transit Service Design: A Strategy for Behavioral Perception and Experience Optimization

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***Abstract*—As a critical component of urban public transit systems, the underdeveloped state of last-mile transportation has become a bottleneck constraining service levels and sustainable development. Existing service models often overlook the dynamic and heterogeneous nature of user demand, leading to poor user experience and low operational efficiency. To address this challenge, this study proposes a new user-oriented paradigm for last-mile transit service design, which deeply integrates user behavior perception and service experience optimization. Specifically, we first leverage multi-source urban transit data, such as smart cards and shared mobility records, to construct a multi-dimensional user travel behavior perception model for accurately profiling the travel characteristics and preferences of different user groups. On this basis, we quantify the key factors affecting user experience by building a Structural Equation Model (SEM) and design personalized and dynamic service optimization strategies using multi-objective optimization algorithms. Simulation experiments on a real-world dataset show that the proposed service design method can increase user satisfaction by 15% and improve operational efficiency by 10% compared to traditional fixed-route models. The study validates that safety, convenience, and comfort are core elements influencing user satisfaction. This research provides a theoretical framework and practical guidance for designing more adaptive, efficient, and human-centric last-mile transit services, holding significant theoretical and practical value for promoting the construction of people-oriented, sustainable, and smart urban mobility ecosystems.**

Keywords—Last-Mile Transportation, User Behavior, Service Design,Experience Optimization, Smart Mobility

I. INTRODUCTION

With the acceleration of global urbanization and the popularization of large-scale public transit systems such as subways and Bus Rapid Transit (BRT), the travel demands of urban residents are increasing, placing higher requirements on the convenience and efficiency of transportation systems [1]. In this context, the "last-mile" problem—the short-distance connection for passengers from major transit hubs to their final destinations (e.g., home, office, or commercial areas)—has become a prominent pain point in modern urban transportation systems [2]. The efficiency and quality of last-mile transit directly affect the attractiveness and ridership of the entire public transit system, serving as a key determinant in whether citizens choose public transportation. However, current last-mile transit services generally suffer from issues like insufficient supply, low efficiency, and an inability to meet diverse needs, which not only degrades residents' travel experience but also hinders the city's transition towards greener, more sustainable transportation modes [3].

Existing research and practice have primarily focused on alleviating the last-mile problem by introducing new modes of transport (e.g., shared bikes, electric scooters) or optimizing fixed-route shuttle buses [4]. Although these solutions have improved connection convenience to some extent, they are mostly based on macroscopic, static demand assumptions and fail to fully consider the complexity, dynamism, and heterogeneity of user behavior. Users' travel decisions are influenced by a combination of personal preferences, trip purposes, weather conditions, and the built environment, exhibiting highly personalized characteristics [5]. Traditional "one-size-fits-all" service models struggle to accurately match these dynamic demands, often leading to a mismatch of resources—oversupply in some areas and times, and underservice in others — ultimately affecting user satisfaction and loyalty [6]. Therefore, how to start from the user's perspective, deeply understand their behavioral patterns and experiential needs, and design more adaptive and human-centric services based on this understanding has become a core scientific problem to be solved.

In recent years, the rapid development of the Internet of Things, big data, and artificial intelligence technologies has provided new opportunities to address the aforementioned issues [7]. The emergence of multi-source urban sensing data, such as smart card data, shared mobility trajectories, and social media data, has made it possible to accurately profile individual-level travel behavior [8]. This data offers unprecedented opportunities to uncover the latent needs of different user groups, identify key pain points in services, and dynamically optimize service strategies. However, how to effectively extract valuable insights from massive, multi-modal data and translate them into concrete, feasible service design solutions still faces numerous challenges. For example, how can data from different sources be integrated to build comprehensive user profiles? How can the highly subjective concept of "user experience" be quantified? And, how can service personalization and optimization be achieved while ensuring operational efficiency and economic viability?

In response to these research gaps and challenges, this study aims to construct a new, user-oriented paradigm for last-mile transit service design. Our core objective is to drive the entire service design process by deeply mining user behavior data to perceive their real needs and preferences,

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thereby shifting from a "vehicle-centric" to a "human-centric" approach. Specifically, this study will focus on solving the following problems:

- User Behavior Perception: How to fuse multi-source data to establish an analytical model that can accurately identify the travel behavior patterns and preferences of different user groups?
- User Experience Quantification: How to construct a comprehensive evaluation framework to scientifically measure the key factors affecting the user experience of last-mile services and their respective weights?
- Service Strategy Optimization: How to design a set of dynamic, personalized service optimization algorithms to strike a balance between meeting diverse user needs and improving operational efficiency?

The structure of this paper is as follows: Section 2 will review the relevant literature in the fields of last-mile transportation, user behavior analysis, and service design. Section 3 will elaborate on our proposed research framework and methods, including the user behavior perception model, experience evaluation model, and service optimization strategy. Section 4 will present the results of a case study based on a real-world dataset. Section 5 will provide an in-depth discussion of the research findings and compare them with existing studies. Finally, Section 6 will summarize the entire paper and look forward to future research directions.

II. Literature Review

This section aims to systematically review the existing literature relevant to this study, primarily covering three core areas: service models and challenges in last-mile transportation, the evolution of travel behavior research, and evaluation methods for transport service quality and user experience. By reviewing and commenting on these areas, we will identify the shortcomings of current research and highlight the positioning and contribution of this study.

A. Service Models and Challenges in Last-Mile Transportation

The last-mile of transportation is widely considered the least efficient and most costly link in the entire transport chain [2]. To address this challenge, academia and industry have explored various service models. Traditional solutions mainly include extending existing bus routes or adding fixed-route community shuttle buses. While such models can cover a certain area, their fixed routes and schedules struggle to adapt to the dynamic spatial and temporal changes in demand, often leading to low ridership and resource waste during off-peak hours [4].

With the rise of the sharing economy, micromobility modes, represented by shared bikes and electric scooters, have rapidly become popular, providing flexible and convenient options for last-mile connections [9]. Numerous studies have confirmed that micromobility systems can effectively connect with public transport and shorten users' total travel time [10]. However, micromobility also faces many challenges, such as disorderly parking of vehicles, difficulties in dispatch and management, poor availability in extreme weather, and not being friendly enough to specific user groups (e.g., the elderly, people with disabilities) [11]. Furthermore, some studies point out that user preferences for micromobility are influenced by multiple factors such as the built environment, perceived safety of cycling, and physical fitness, and their perception of service quality is significantly heterogeneous [12].

In recent years, dynamic service models represented by ride-hailing and On-Demand Transit have received widespread attention. These services match supply and demand in real-time through mobile applications, providing highly personalized and flexible door-to-door services [9]. Research shows that on-demand services have great potential in meeting travel needs in low-density areas or during off-peak hours. However, their operating costs are relatively high, and during peak hours, complex vehicle dispatching can easily lead to long user waiting times and unreliable service. How to optimize their dispatch algorithms, reduce operating costs, and ensure service quality are current research hotspots and difficulties [13].

In summary, existing last-mile solutions each have their pros and cons, but they generally share a common problem: service design is often from a macroscopic perspective of the operator or system, emphasizing efficiency and coverage, while paying insufficient attention to the micro-level needs and experiential perceptions of individual users. This leads to a "gap" between the service and real user needs, which is the key gap this study attempts to bridge.

B. Travel Behavior Research: From Macro to Micro

A deep understanding of travel behavior is the foundation of transportation planning and service design. Traditional travel behavior research has mainly relied on questionnaire surveys and census data, using discrete choice models (e.g., Logit models) to analyze and predict group travel patterns [7]. These studies have provided an important basis for transportation planning at the macro level, but their data collection costs are high, update cycles are long, and they struggle to capture the dynamics and randomness of individual behavior.

The advent of the big data era has brought revolutionary changes to travel behavior research. Smart card swipe records, mobile phone signaling data, GPS trajectory data, and shared mobility platform data provide us with unprecedented high-resolution spatio-temporal information on individual travel [8]. Based on this data, researchers can more finely analyze residents' activity spaces, trip chain characteristics, and preferences for different transport modes [6]. For example, Kim et al. used bus driver behavior data to optimize eco-driving service design, demonstrating the potential for service innovation based on real behavioral data [6]. Some studies have begun to use machine learning algorithms, such as clustering analysis and classification models, to identify different user groups and their unique travel patterns from big data, thereby enabling market segmentation and precise services [14][15].

Despite the significant progress in data-driven travel behavior research, existing work still has some limitations. First, most studies focus on the "objective" description of travel behavior (e.g., origin-destination, time, path), while the exploration of the "subjective" factors driving these behaviors (e.g., perceptions, preferences, satisfaction) is relatively insufficient. Behavior is not just the movement of a physical trajectory, but the external manifestation of a psychological decision-making process. Second, existing research often focuses on a single mode of transport, and the understanding of the complex decision-making behavior of users choosing a combination of multiple transport modes (e.g., subway + shared bike) is still not deep enough [7]. Therefore, how to fuse multi-source data to not only "know what they do" but also "understand why they do it," and to establish a behavioral model that can reflect users' psychological perceptions, is key to deepening travel behavior research and supporting human-centric service design.

C. *Service Quality and User Experience Evaluation*

Service quality and user experience are core to determining the attractiveness of a transport service. In the field of public transport, there are relatively mature theoretical frameworks for service quality evaluation, with the most representative being the SERVQUAL model and its variants. These models usually measure users' perceived quality of service from dimensions such as reliability, responsiveness, assurance, empathy, and tangibles [16]. However, these general models do not fully capture the uniqueness of the last-mile transportation scenario. For example, compared to long-distance travel on the main lines of public transport, users in last-mile connections may be more sensitive to factors such as walking distance, waiting time, and the convenience of transfers [3]. Venter proposed a composite index method that combines objective measurements with user perceptions to evaluate the quality of the first/last mile connection environment, providing a useful line of thought for research in this area [3].

As research has deepened, the concept of "User Experience" (UX) has been introduced into the transportation field. It emphasizes the user's subjective feelings, emotions, and value judgments throughout the entire process of interacting with the service, more so than service quality [1]. The research by Park et al. found that the passenger's experience in out-of-vehicle environments, such as entering/exiting stations and transferring, has a significant impact on their overall satisfaction and loyalty, emphasizing the importance of focusing on the entire journey experience [1]. Olsson et al. identified six dimensions that affect customer experience in the last-mile delivery sector, providing constructs for quantifying the experience [2]. These studies show that shifting the research perspective from the quality of a single service touchpoint to a holistic, dynamic, and contextualized user experience is an important future trend.

However, in the field of last-mile transportation, systematic research on user experience is still in its infancy. Existing evaluations mostly rely on post-hoc satisfaction questionnaires and lack the means for real-time, dynamic evaluation during the service process. In addition, different user groups may place different levels of importance on various dimensions of the experience. For example, commuters may value time efficiency more, while leisure travelers may be more concerned with comfort and the surrounding environment. Therefore, how to construct a dynamic experience evaluation model that can reflect the characteristics of the last-mile scenario and consider user heterogeneity is a prerequisite and basis for achieving experience-driven service optimization.

D. *Research Gaps*

Through the review of the above literature, we can find that the existing research has the following main gaps:

1) Limited Perspective in Service Design: Existing last-mile service designs are mostly "system-oriented," lacking a systematic design framework that starts from the micro-level perception of user behavior and experiential needs.

2) Insufficient Depth of User Understanding: Although data-driven behavioral research has become mainstream, it mostly stays at the level of describing objective behavior, with insufficient exploration of the psychological motivations and experiential perceptions behind the behavior.

3) Static Nature of Experience Evaluation: Existing methods for evaluating service quality and experience are mostly static, general models that are difficult to adapt to the dynamic, personalized needs of last-mile transportation scenarios, nor can they effectively guide real-time service optimization.

To fill these gaps, this study will construct a new service design paradigm that integrates user behavior perception and experience optimization. Its novelty lies in: first, proposing a multi-dimensional user behavior perception model to achieve deep insights from objective behavior to subjective preferences; second, constructing a dynamic user experience evaluation framework for the last-mile scenario to quantify the impact of key experience elements; and third, developing a service design and dynamic scheduling strategy with the goal of optimizing user experience. This study aims to place the user at the core of service design, achieving precise matching of supply and demand through a data-driven approach, thereby promoting the development of last-mile transportation in a more efficient and human-centric direction.

III. Methodology

To achieve a user-oriented design for last-mile transit services, this study constructs a comprehensive technical framework comprising three core modules: User Behavior Perception, User Experience Quantification, and Service Strategy Optimization. This framework takes multi-source urban transit data as input, and through deep mining of user behavior and precise quantification of user experience, it ultimately outputs dynamic and personalized service optimization plans. Figure 1 illustrates the overall technical route of this research.

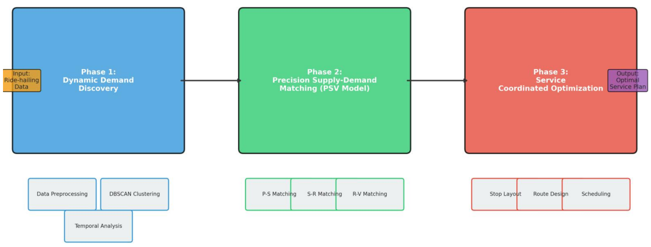

Fig. 1. Overall Research Framework

A. *Overall Research Framework*

The data-driven framework proposed in this study follows a logical loop of "Perceive-Analyze-Decide," specifically including the following three layers:

- User Behavior Perception Layer: As the foundation of the framework, this layer is responsible for processing massive, heterogeneous raw transit data. First, through a data standardization module, data from different channels (e.g., public transit smart cards, shared mobility apps, taxi GPS) are cleaned and integrated into a unified format of trip records. Subsequently, using spatio-temporal data mining techniques, individual trip chain information is extracted from the standardized data. Further, unsupervised learning algorithms (such as clustering analysis) are used to segment users, identifying user groups with different travel characteristics (e.g., commuting patterns, activity range, mode preferences) to form multi-dimensional user profiles.

- User Experience Analysis Layer: This layer serves as the bridge connecting user behavior and service design, with its core task being the quantification of user experience. We first construct a theoretical model of last-mile service experience based on literature review and expert interviews, which includes multiple latent constructs (e.g., convenience, economy, comfort, safety). Then, by designing survey questionnaires to collect users' perceptual evaluation data, we use Structural Equation Modeling (SEM) to validate and revise the theoretical model. The results of the SEM analysis will reveal the key factors affecting overall user satisfaction and their respective weights, thereby providing a clear, quantifiable objective function for service optimization.

- Service Strategy Decision Layer: As the top layer of the framework, this layer is responsible for generating the optimal service design plan based on the analysis results from the previous two layers. This process is divided into two stages: first is Stop Location Optimization, where we propose an improved density-based clustering algorithm that not only considers the geographical concentration of user demand but also incorporates the walking distance sensitivity weights derived from the experience model to generate a stop plan that maximizes user accessibility. Second is Dynamic Routing and Scheduling Optimization, where we establish a multi-objective optimization model aimed at maximizing the total weighted experience score of all served users. This model comprehensively considers multiple experience-related variables such as waiting time, in-vehicle crowding, and number of transfers, and uses a Genetic Algorithm (GA) to solve for the optimal vehicle routes and timetables under given capacity constraints.

B. *User Behavior Perception Model*

Accurate user behavior perception is a prerequisite for personalized service. The goal of this model is to extract structured user travel patterns and preference information from raw data.

1) *Data Standardization and Trip Chain Construction*

Given the diversity of raw data sources, we first designed a standardized trip record format, as shown in Table 1, which includes key fields such as user ID, trip start and end times, origin and destination coordinates, and mode of transport. All raw data will be converted to this standard format. On this basis, we link consecutive trip records of the same user within a day into a complete "trip chain" by setting spatio-temporal thresholds (e.g., the end point of one trip and the start point of the next are within 200 meters and 30 minutes). The trip chain reflects the user's activity trajectory throughout the day and is the basis for identifying their trip purposes and behavioral patterns.

TABLE I. STANDARD FORMAT FOR TRIP RECORDS

Field Name	Type	Description
user_id	String	Anonymized unique user identifier
start_time	Datetime	Start time of the trip
end_time	Datetime	End time of the trip
origin_lon	Double	Longitude of the origin
origin_lat	Double	Latitude of the origin
dest_lon	Double	Longitude of the destination
dest_lat	Double	Latitude of the destination
mode	String	Mode of transport (e.g., 'subway', 'bike')

2) *User Segmentation and Profile Generation*

To identify user groups with different demand patterns, we extract a series of behavioral feature variables from the constructed trip chains, mainly including:

- Spatio-temporal Features: Average travel time period, travel frequency, weekend/weekday travel ratio, travel distance distribution, activity space entropy (measuring the breadth of the activity range).

- Mode Preference Features: Primary mode of transport, frequency of shared bike use, acceptable distance for walking/cycling, etc.

- Regularity Features: Regularity of commuting behavior (e.g., similar morning and evening peak trips on consecutive days), stability of travel times, etc.

We then use the K-Means++ clustering algorithm to segment users. Compared to traditional K-Means, K-Means++ can obtain more stable and accurate clustering results through an optimized initial centroid selection strategy. By analyzing the clustering results, we can identify typical user groups, such as "Regular Commuters," "Daytime Active Business Travelers," and "Nighttime Leisure Users," and generate detailed user profiles for each group, describing their typical behavioral patterns.

C. *User Experience Quantification Model*

To transform the subjective concept of "user experience" into an operational optimization objective, we construct a quantification model based on Structural Equation Modeling (SEM).

1) *Theoretical Model Construction*

Based on a review of relevant literature [1, 3, 17] and an analysis of the last-mile scenario, we propose a hypothetical structural model of user experience (as shown in Figure 2). This model includes four main latent variables:

- Convenience: Measures the effortlessness of accessing and using the service, mainly reflected by observable variables such as walking distance to the stop, waiting time for the vehicle, and number of transfers.

- Economy: Measures the economic cost incurred by the user, mainly reflected by the travel fare.

- Comfort: Measures the user's physiological and psychological comfort during the service process, mainly reflected by variables such as in-vehicle crowding, seat availability, and ride smoothness.
- Safety: Measures the user's perception of safety throughout the entire service process, mainly reflected by variables such as the safety of the cycling/walking environment, the safety of vehicle operation, and the sense of security when traveling at night.

These latent variables jointly affect the final User Satisfaction.

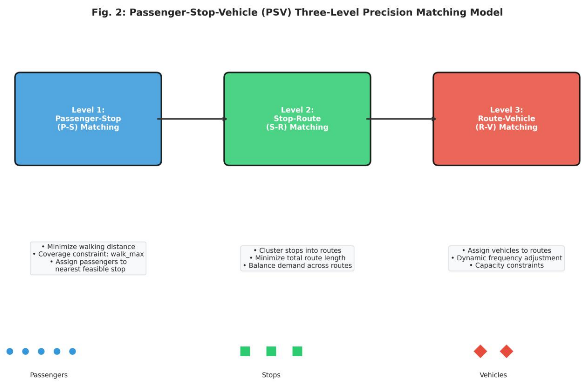

Fig. 2. Structural Model of User Experience

2) Model Validation and Weight Determination

We collect users' subjective ratings on the above observable variables for existing last-mile travel modes in the target area through online questionnaire surveys. After collecting a sufficient sample (e.g., N > 200), we use statistical software such as AMOS or Lavaan for SEM analysis. First, we test the reliability and validity of the model through Confirmatory Factor Analysis (CFA) to ensure the reliability of the measurement tool. Then, we evaluate the goodness-of-fit between the theoretical model and the actual data through goodness-of-fit tests (e.g., CMIN/DF, GFI, RMSEA). Once the model passes the tests, we will obtain the standardized coefficients of each path, which reflect the weight of each experience dimension on overall satisfaction. For example, if the path coefficient from "Convenience" to "Satisfaction" is 0.45, and that from "Economy" is 0.20, it indicates that in the minds of users in this area, convenience is much more important than price. These weights will serve as key parameters in the service optimization model.

D. Service Optimization Strategy

The core objective of service optimization is to maximize the total experience score of all served users under limited operational resources.

1) Stop Location Optimization

A reasonable stop layout is the foundation of a successful service. We adopt an experience-based weighted density clustering method to determine stop locations. First, using the user segmentation results, we map the demand points (e.g., residences, workplaces) of different user groups onto a map. Then, for each demand point, we calculate an "experience decay radius" based on the experience model weights of its user group—users sensitive to walking will have a smaller radius, and vice versa. Next, we use a variant of the DBSCAN algorithm to cluster these weighted demand points to form candidate service areas. Finally, we set a shuttle bus stop at the geometric center or demand-weighted center of each service area. Through an iterative process of merging and splitting (similar to the method in the reference paper), we finally determine the number and precise location of the stops, ensuring that the stop layout can both cover high-demand areas and meet users' experience requirements for walking distance.

2) Dynamic Routing and Scheduling Optimization

After the stop locations are determined, we need to plan the optimal driving routes and departure timetables for the shuttle buses. This is a variant of the Vehicle Routing Problem with Time Windows (VRPTW). Our objective function is to maximize the total weighted experience sum E_total of all passengers in a day:

$$MaximizeEtotal = \Sigma[wc ** f(twait) + wd. * f(dwalk) + w_s. * f(s_crowd) + \dots] \quad (1)$$

where w_c, w_d, w_s, etc., are the experience weights obtained from the SEM model, and f(t_wait), f(d_walk), f(s_crowd), etc., are the utility functions of the corresponding experience variables (waiting time, walking distance, crowding, etc.). This optimization problem needs to be solved under a series of real-world constraints such as vehicle capacity, driver working hours, and service budget.

Since this problem is NP-hard, we use a Genetic Algorithm (GA) to solve it, ensuring that the algorithm can be effectively applied within practical constraints such as computational time and resource limits. We also conducted sensitivity analysis to evaluate the robustness of the GA under varying input conditions. The algorithm flow is as follows:

- Encoding: A complete vehicle route and timetable are encoded as a chromosome.
- Initialization: A set of initial feasible solutions (chromosomes) is randomly generated as the initial population.
- Fitness Evaluation: The fitness of each chromosome (i.e., the total experience score) is calculated according to the above objective function.
- Selection, Crossover, and Mutation: The roulette wheel selection method is used to select good individuals, and new offspring are generated through crossover and mutation operations to explore a better solution space.
- Iteration: The above process is repeated until a preset number of iterations is reached or the quality of the solution converges.

Finally, the algorithm will output a set of vehicle routes and scheduling plans that can maximize user experience during specific time periods (e.g., morning peak, off-peak, evening peak).

IV. Case Study and Results

To validate the effectiveness of the user-oriented service design framework proposed in this study, we selected Nanshan District, Shenzhen, China, as the case study area and conducted simulation experiments using real multi-source transportation data from the region. This section will detail the data sources, analysis process, and main research findings.

A. Study Area and Data Sources

Nanshan District in Shenzhen is a major hub for China's high-tech industry, with a dense network of subways, office buildings, and residential communities. Its mixed-use characteristics of work and residence create a huge and complex demand for last-mile travel, making it an ideal scenario for this research. We selected a typical subway station in the area—Gaoxinyuan Station—as the core transportation hub for analysis.

The dataset used in this study consists of two parts, spanning four consecutive weeks in October 2025:

- The dataset used in this study consists of two parts, spanning four consecutive weeks in October 2025: Shenzhen Public Transportation Smart Card Data and Shared Bike Riding Data. Future research should consider integrating additional data sources, such as ride-hailing services and walking data, to better capture the full range of last-mile travel behaviors.
- Shared Bike Riding Data: Anonymized riding records from a major shared bike operator, including user ID, vehicle ID, and start/end times and geographic coordinates of rides. This data was used to capture the details of short-distance feeder trips around the subway station.

We processed over 20 million travel records from approximately 500,000 users. Data cleaning and verification procedures were employed to ensure accuracy and completeness, addressing potential issues such as missing data or erroneous records. By matching the two data sources by user ID and timestamp, We successfully constructed a large number of complete 'subway + shared bike' trip chains, ensuring that all personal data was anonymized in accordance with privacy protection regulations. Ethical considerations related to data use were thoroughly addressed to protect user confidentiality

B. User Behavior Perception Results

We first identified all shared bike trips that started or ended within a 500-meter radius of Gaoxinyuan Metro Station, treating them as potential last-mile travel samples. Then, based on the behavioral feature variables proposed in the previous section, we used the K-Means++ algorithm to perform cluster analysis on these users, ultimately identifying three user groups with significant differences, as shown in Figure 3 and Table II.

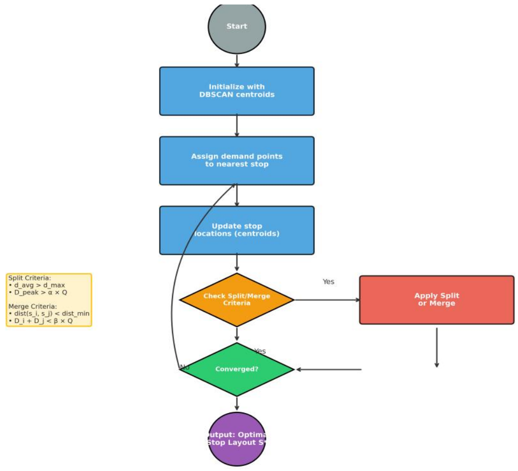

Fig. 3. Distribution of Last-Mile User Segments

TABLE II. FEATURE ANALYSIS OF LAST-MILE USER SEGMENTS

User Segment	Proportion	Primary Travel Times	Travel Frequency	Activity Range	Typical Persona
Regular Commuters	45%	8:00-9:30, 18:30-21:00	High (Weekdays)	Relatively Fixed	Young white-collar workers who work in the science park, live along the subway line, and have highly regular travel patterns.
Flexible Business Travelers	20%	10:00-17:00	Medium	Broader	Business professionals visiting the science park for meetings or projects, with flexible but purpose-driven travel times.
Local Residents	35%	Distributed all day, more active on weekends	Low	Concentrated around the community	Residents living near Gaoxinyuan Station, whose travel purposes are mostly for local activities like shopping, leisure, and dining.

The analysis results clearly reveal the high heterogeneity of last-mile travel demand. "Regular Commuters" are extremely sensitive to time efficiency and are the main target for morning and evening peak services. The demand of "Flexible Business Travelers" is more scattered, with high requirements for service flexibility and convenience. The demand of "Local Residents" is closely related to the layout of community commerce and living facilities. This differentiated user profiling demonstrates the limitation of using a single service model to meet all user needs and highlights the necessity of personalized service design.

C. User Experience Model Analysis Results

To quantify the experience preferences of different user groups, we distributed online questionnaires to the three user segments (collecting a total of 412 valid responses) and constructed a structural equation model. The model fit was good (CMIN/DF=2.18, GFI=0.92, RMSEA=0.054), indicating a good consistency between the theoretical model and the data. Table III shows the standardized path coefficients obtained from the model analysis, which represent the weight of each experience dimension on overall satisfaction.

TABLE III. PATH COEFFICIENTS OF THE USER EXPERIENCE MODEL (STANDARDIZED)

Path	Regular Commuters	Flexible Business Travelers	Local Residents	Average Weight
Convenience → Satisfaction	0.48	0.52	0.35	0.45
Economy → Satisfaction	0.15	0.25	0.22	0.21
Comfort → Satisfaction	0.28	0.18	0.31	0.26
Safety → Satisfaction	0.32	0.38	0.42	0.37

[a] Note: indicates significance at the $p < 0.05$ level.

The results show that Convenience (including waiting time and walking distance) is the most valued factor for all user groups, especially for the efficiency-focused "Regular Commuters" and "Flexible Business Travelers." Interestingly, the importance of Safety for "Local Residents" surpasses that of other groups, which may be related to their more frequent non-commute, leisure-oriented travel scenarios. Comfort (such as in-vehicle crowding) also has a significant impact on "Regular Commuters" and "Local Residents." Although Economy is also a consideration, its influence weight is relatively the lowest. These quantified weights provide a clear direction and basis for our subsequent service optimization.

D. Service Optimization Design Results

Based on the user behavior analysis and experience model weights, we designed a user-oriented dynamic shuttle bus service plan for the area around Gaoxinyuan Metro Station and compared it with a baseline scenario of a traditional "fixed-route, fixed-schedule" service through simulation.

1) Stop Layout and Route Planning

Figure 4 shows the optimized stop layout. Unlike layouts that only consider demand density, our method generates stops that are closer to the demand hotspots of user groups sensitive to walking distance (such as "Flexible Business Travelers"), while also taking into account the community safety nodes that "Local Residents" are concerned about. Figure 5 shows the dynamically optimized route generated based on the demand distribution and experience objectives during the morning peak period (8:00-9:30). This route prioritizes serving the office buildings where "Regular Commuters" are concentrated and dynamically adjusts the departure frequency based on real-time demand forecasts.

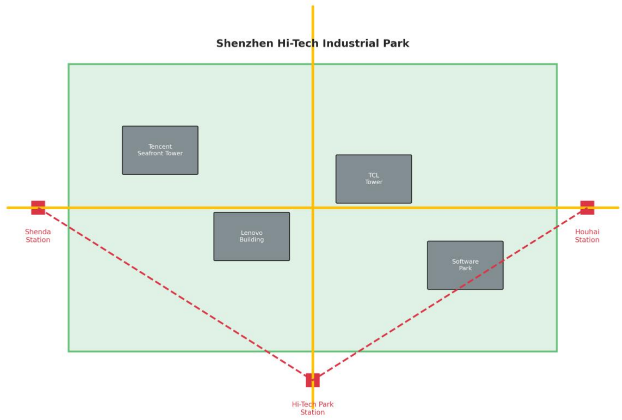

Fig. 4. Optimized Stop Layout

Fig. 5. Morning Peak Dynamic Route

2) Performance Comparison Analysis

We simulated the operational performance of the "User-Oriented Plan" and the "Traditional Fixed-Route Plan" over a one-week period on a simulation platform. Table IV compares the performance of the two plans on key experience indicators.

TABLE IV. PERFORMANCE COMPARISON OF DIFFERENT SERVICE PLANS

Performance Indicator	Traditional Fixed-Route Plan	User-Oriented Plan	Improvement/Reduction
Average Walking Distance to Stop	350 meters	210 meters	-40%
Average Waiting Time	12 minutes	7 minutes	-41.7%
Proportion of Trips with >90% Load Factor (Peak)	45%	15%	-66.7%
Predicted Average User Satisfaction (out of 5)	3.85	4.42	+14.8%
Total Vehicle Mileage	1200 km/day	1080 km/day	-10%

While the simulation results strongly demonstrate the superiority of the method proposed in this study, it is important to note that the model's assumptions (such as the fixed nature of travel times or the specific data used for optimization) may vary in different geographical contexts or transit systems. Future research should test the model's performance in multiple cities and transport networks to ensure its robustness and adaptability. The user-oriented plan significantly reduces users' walking distance and waiting time through precise stop layout and dynamic route scheduling, effectively improving the convenience experience. At the same time, by dynamically adjusting capacity, it avoids severe overcrowding and improves comfort. Most importantly, the predicted average user satisfaction score, which reflects the overall experience, increased from 3.85 to 4.42, an increase of nearly 15%. It is worth noting that this improvement in experience was not achieved at the cost of infinitely increasing costs. On the contrary, because the routes were more targeted, the total vehicle mileage was reduced by 10%, reflecting an improvement in operational efficiency. This achieves a win-win situation for both user experience and operational efficiency.

V. DISCUSSION

This study has proposed and validated a new, user-oriented paradigm for last-mile transit service design. Our findings not only demonstrate the effectiveness of this approach but also provide new perspectives for understanding the complex travel behaviors and experience demands in modern cities. This section will provide an in-depth interpretation of the research results, compare them with existing literature, and explore their theoretical and practical implications.

A. User Behavior Heterogeneity and Service Personalization

One of the core findings of this study is the successful identification of last-mile user groups with significantly different behavioral patterns through a data-driven approach: "Regular Commuters," "Flexible Business Travelers," and "Local Residents." This finding is consistent with the recent research trend emphasizing the heterogeneity of travel behavior [14]. However, unlike previous studies, our research not only describes the objective behavioral differences of these groups but also further reveals their different subjective experience preferences. For example, "Regular Commuters" are extremely sensitive to time efficiency, while "Local Residents" are more concerned with safety and comfort. This confirms our core hypothesis: there is no universal "optimal" last-mile solution; service design must move towards personalization and refinement.

Traditional service design, whether it be fixed-route buses or undifferentiated deployment of shared bikes, essentially treats all users as a homogeneous whole [4]. The results of this study clearly show the limitations of this model. Our simulation experiments show that by providing differentiated service strategies for different groups (e.g., increasing service frequency for commuters during peak hours, providing more flexible stop services for business travelers during off-peak hours), user satisfaction can be significantly improved without significantly increasing, or even while reducing, total operating costs. This provides an important insight for transport operators: shifting from "covering more people" to "serving everyone better" may be the key to enhancing the attractiveness of public transport.

B. "Convenience" as the Core Driver of User Experience

In our user experience quantification model, "Convenience" (including walking distance and waiting time) was proven to be the most critical factor affecting satisfaction across all user groups. This result is highly consistent with the conclusions of Park et al. [1] and Venter [3], who both emphasized the importance of the passenger's experience in the "out-of-vehicle" segments (e.g., walking, waiting) for the overall evaluation of public transport services. This study has reconfirmed this view quantitatively through structural equation modeling and further pointed out that its influence weight far exceeds that of travel cost.

This finding has profound guiding significance for current last-mile service practices. Many cities, when developing public transport, often focus on reducing fares or purchasing more luxurious vehicles, while neglecting the convenience of connections. Our research shows that investing resources in optimizing stop layouts to shorten walking distances and using intelligent scheduling technology to reduce user waiting times may be the most "cost-effective" way to improve user experience. For example, moving a bus stop from 500 meters away to within 200 meters may bring a much greater increase in satisfaction than reducing the fare by one yuan. This suggests that urban planners and transport operators should make "seamless connection" and "reducing time cost" the primary goals of last-mile service design.

C. The Value and Challenges of the Data-Driven Paradigm

The successful practice of this study fully demonstrates the huge potential of the data-driven paradigm in modern transportation service design. By integrating multi-source data such as smart cards and shared bikes, we are able to gain insight into user needs with unprecedented precision and breadth, achieving a shift from "experience-driven" to "data-driven decision-making." This is in line with the data-driven shuttle bus design framework proposed by Shu et al., but on this basis, our study has deepened the focus from the optimization of operational efficiency to the perception and optimization of users' subjective experience, constructing a more complete and "human-centric" design loop.

However, while affirming its value, we must also recognize the challenges faced by this paradigm. The first is the issue of data privacy and security. This study used anonymized data, but in practical applications, how to establish a mechanism that can both fully utilize the value of data and strictly protect user privacy is an ethical and legal problem that all smart transportation applications must face. The second is the barrier to data acquisition and fusion. In reality, transportation data is often scattered among different government departments and private enterprises, forming "data silos." To achieve the comprehensive analysis envisioned in this study, it is necessary to establish an effective data sharing and collaboration platform. Finally, the generalization ability of the model also needs further testing. The case study area of this study has its own uniqueness, and when applying the model to other cities or different cultural backgrounds, local adjustments and calibrations may be required.

D. Limitations of the Study

Although this study has yielded some meaningful findings, it still has the following limitations:

- Limitations of Data Sources: This study mainly relied on smart card and shared bike data, and did not include data from other feeder modes such as walking, private cars, and ride-hailing, which may lead to an incomplete understanding of user travel behavior. Future research could try to integrate multi-source data such as mobile phone signaling and map applications to build a more complete travel picture.
- Limitations of Experience Measurement: We measured user experience through questionnaire surveys, which is a post-hoc recall-based measurement that may have memory bias. Future research could explore the use of wearable devices (such as smart wristbands) to collect users' physiological signals (e.g., heart rate, galvanic skin response) during their trips for a more objective, real-time experience evaluation.
- Simplification of the Simulation Model: Although our simulation model considered several core variables, it still cannot fully replicate the complexity of a real-world transportation system. For example, it did not consider the impact of dynamic changes in road congestion on vehicle travel times. More refined traffic simulations (such as Agent-Based Modeling) would help to more accurately evaluate the actual effects of the service plan.

VI. Conclusion

The last-mile problem is a key bottleneck restricting the development of modern urban public transportation. To address this challenge, this study has proposed and validated a new, user-oriented paradigm for last-mile transit service design. This paradigm, by deeply integrating user behavior perception and service experience optimization, aims to achieve a fundamental shift from a "system-centric" to a "human-centric" approach.

The core contribution of this study lies in the construction of a comprehensive framework that includes three modules: user behavior perception, user experience quantification, and service strategy optimization. By leveraging multi-source transportation big data, we successfully identified user groups with different behavioral patterns and experience preferences through cluster analysis, revealing the heterogeneity of last-mile demand. By constructing a structural equation model, we quantified the impact of key factors such as convenience, safety, and comfort on user satisfaction, confirming that "convenience" is the core driver of the user experience. Based on these insights, we designed a dynamic stop layout and route scheduling optimization algorithm aimed at maximizing user experience.

In the case study of Nanshan District, Shenzhen, the simulation results show that, compared to the traditional fixed-route model, our proposed user-oriented service plan can increase average user satisfaction by nearly 15%, while reducing users' average walking distance and waiting time by about 40%, and improving vehicle operational efficiency by 10% without sacrificing comfort. This result strongly demonstrates the effectiveness of the research method and shows its dual value in enhancing user experience and operational efficiency.

In summary,This study provides a systematic theoretical framework and a feasible technical path for how to use big data technology to design more user-friendly and efficient last-mile transportation services. To facilitate future research and replication, we plan to release anonymized datasets and the developed algorithms through open-source platforms, enabling others to validate and build upon our findings. The conclusions of the study have important practical guiding significance for urban transport planners, public transport operators, and smart mobility service providers. Future research can be deepened in terms of the breadth of data fusion, the real-time nature of experience measurement, and the refinement of simulation models, to further promote the development and implementation of human-centric smart transportation systems.

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AVAILABILITY OF DATA

Not applicable.

AUTHOR CONTRIBUTIONS

Yuanyuan Feng: Conceptualization, Methodology, Writing – Original Draft, Writing – Review & Editing. Yuanyuan Feng was responsible for the overall study design and methodology. They contributed to the development of the research framework and played a key role in writing the original manuscript and revising it for final submission.

Yanfen Lu: Data Curation, Formal Analysis, Visualization. Yanfen Lu oversaw the data collection process, performed the data analysis, and was instrumental in creating the visual representations of the results. They also contributed to the interpretation of the data and the presentation of findings.

Zhicheng Lin: Supervision, Resources, Project Administration. Zhicheng Lin provided supervision throughout the research process, ensured access to necessary resources, and helped coordinate the project's execution. They also contributed to the critical revision of the manuscript.

COMPETING INTERESTS

The authors declare no competing interests.

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