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From trajectory to behavior: Capturing individual travel details using an applet-based GPS tracking system

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ABSTRACT

Household travel survey data form the foundation of travel behavior modeling and transportation planning, yet traditional interview-based methods face significant challenges related to high labor costs and data quality limitations. Smartphone-based travel surveys have emerged as promising alternatives, but barriers to participation persist despite technological advances. This paper presents an innovative applet-based GPS tracking system designed to minimize participant burden through four integrated modules: (i) data collection via a freely-installed mini-program embedded within a widely-used social media platform, (ii) automated trip extraction using cloud-based algorithms, (iii) intuitive user interfaces for trip validation, and (iv) a comprehensive survey supervision platform. We evaluate this system through comparative analysis across three survey phases conducted in an urban district: an app-based pilot study, a traditional interview-based survey, and our applet-based field implementation. Results indicate that smartphone-based methods match interview-based methods in capturing trip chains, while significantly outperforming them in detecting multi-modal trip details. The applet-based survey approach also achieved notably lower recruitment rejection rates compared to the app-based method, demonstrating greater effectiveness in participant engagement. These findings underscore the feasibility and advantages of lightweight, participant-friendly smartphone-based travel survey methods, providing valuable insights for transportation research and planning practices.

1. Introduction

Household travel surveys represent the cornerstone of travel behavior analysis, providing critical data on individual travel patterns. These surveys capture essential information about trip characteristics—including timing, duration, transportation mode, and purpose—that fundamentally help understand mobility demands and inform land use planning and transportation infrastructure development (Ling et al., 2024; Yang & Zhang, 2025; Zhou et al., 2021).

The conventional interview-based approaches to travel survey encounter some persistent limitations. First, participants face substantial cognitive burdens when reporting detailed travel information, particularly for complex travel patterns involving multiple trips or multimodal segments (Yang et al., 2016; Zhou et al., 2022). This requires respondents to understand technical definitions of trips and transfers while accurately recalling specific details of their movements. Second, data quality issues arise from the reliance on human memory and estimation. While origin and destination locations might be accurately captured through address information, temporal data often suffers from over-reporting of trip durations (Houston et al., 2014). The total number of trips tends to be under-reported due to recall difficulties, especially for short-duration trips (Bricka et al., 2012; Wan et al., 2021). Third, the resource-intensive nature of traditional surveys typically results in infrequent data collection, limited sampling rates, and single-day observation periods. For example, the U.S. National Household Travel Survey was conducted in 2001, 2009, 2017, and 2022, with intervals of 5–8 years. Similarly, the 2019 Shanghai Household Travel Survey covered only 1 % of the population, limiting its ability to accurately capture rapidly evolving travel patterns and demographic shifts.

Smartphone-based GPS tracking technology has emerged as a

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promising alternative that potentially addresses these longstanding challenges. This approach offers several distinct advantages: it eliminates the need for manual trip reporting by passively collecting location data as users carry their phones (Houston et al., 2014; Vij & Shankari, 2015); it produces high-resolution spatiotemporal data that captures trip details with greater precision, including short trips frequently overlooked in self-reporting (Bricka et al., 2012; Hong et al., 2021); and it leverages widely adopted personal devices to enable continuous, large-scale data collection across diverse populations (Qu et al., 2024; Stanley et al., 2018).

Research over the past two decades has focused on addressing two fundamental challenges in smartphone-based travel surveys: converting raw GPS trajectories into meaningful travel diaries and improving survey participation and response rates. Substantial progress has been made in developing algorithms to extract travel information—from basic criteria-based approaches (Gong et al., 2012) and probabilistic models (Xiao et al., 2015; Yang, 2020) to more sophisticated machine leaning (Semanjski et al., 2017) and deep learning methods (Dabiri et al., 2020; Sadeghian et al., 2024). Concurrently, response methodologies have evolved from paper-based trip diaries (Bricka et al. 2012; Houston et al., 2014) to app-assisted manual annotation of transport modes (Nitsche et al., 2014; Assemi et al., 2016; Bjerre-Nielsen et al., 2020), and to apps with embedded trip inference algorithms (Fan et al., 2015; Zhao et al., 2015). Despite these technological advances, survey participation remains problematic due to practical concerns including installation burden and response requirements (Assemi et al., 2018).

To address these persistent barriers to implementation, we propose an applet-based GPS tracking system designed to minimize participant burden through three targeted solutions. First, by utilizing a lightweight mini-program that operates within a widely-used social media platform rather than requiring a standalone app installation, we significantly reduce technical barriers to participation. Second, by incorporating cloud-based algorithms for automated trip inference, we minimize manual reporting requirements. Third, by providing user-friendly validation interfaces, we simplify the response process, making it less time-consuming for participants to confirm their travel information. Based on our comprehensive study of the applet-based GPS tracking system and comparative analysis with other survey methods, the primary contributions of this research are threefold.

(i) We introduce a novel GPS tracking system that integrates four complementary modules: a freely-installed mini-program for frictionless data collection; cloud-based algorithms for automated trip inference; a simplified user interface for rapid data validation; and a supervision platform for monitoring survey progress. This integrated approach specifically addresses the key barriers to participation in smartphone-based travel surveys.

(ii) Our comparative analysis demonstrates that while smartphone-based and interview-based surveys perform similarly in capturing basic trip chains, smartphone methods significantly outperform traditional approaches in detecting complex multi-modal trips. This finding highlights the critical advantage of GPS-based methods for understanding increasingly complex urban mobility patterns.

(iii) The applet-based approach achieves substantially lower rejection rates compared to traditional app-based methods, while maintaining strong algorithmic performance in field conditions. These results demonstrate the practical feasibility of lightweight, burden-minimizing approaches for large-scale travel survey implementation.

The remainder is structured as follows. Section 2 displays a literature review on the existing GPS tracking devices and tests. Section 3 and Section 4 present our applet-based GPS tracking system and three-phase field surveys. Section 5 shows the results and discusses the findings. Section 6 presents the conclusion of the study, highlighting key findings, implications and limitations.

2. Literature review

2.1. GPS data collection and trip annotation

GPS devices have been employed for travel data collection since 1996, when the U.S. Federal Highway Administration (FHWA) organized a six-day field test involving 100 households in Lexington, Kentucky (Murakami & Wagner, 1999). The data collection equipment initially used was a GPS receiver installed in vehicles, with the battery powered by the vehicle's engine. Afterwards, handheld or wearable GPS loggers were employed to collect GPS data at the person level (Bohte & Maat, 2009; Chen et al., 2010; Bricka et al., 2012; Houston et al., 2014), requiring respondents to pre-charge and carry the devices throughout their travels, which however, imposed additional burdens (Ohnmacht & Kowald, 2014). To address these problems, GPS loggers were upgraded to be smaller, lighter, with longer battery life, and improved signal reception (Gong et al., 2014). But the size of participants was still constrained by the availability of GPS devices. From the early 2010 s, smartphones have gradually substituted for GPS devices due to their advantages: necessity in daily life, portability, and diverse sensors (e.g., accelerometer, barometer, and magnetic field) (Nitsche et al., 2014; Assemi et al., 2016; Seo et al., 2019; Bjerre-Nielsen et al., 2020). Additionally, the assisted-GPS (A-GPS) module and mobile network (GSM) also helped keep the device connected for tracking in areas where GPS signals are prone to being blocked or lost (Stanley et al., 2018).

Regarding GPS data annotation, respondents were required to report trips either during or after the data recording process. Annotation during travel was implemented by manually sending SMS messages or noting time and transport of mode in a smartphone app (Zhou et al., 2016), which was inefficient and inconvenient for participants. In contrast, prompted recall after travel was a more common way for trip reporting. Researchers asked respondents to complete a form detailing their trips with the assistance through web-based map services and track-maker software (Gong, 2012; Rasmussen et al., 2015). Moreover, some scholars developed toolkits to self-extract trips for data validation. Bohte and Maat (2009) designed a system composed of a GPS logger, a GIS-based inference module, and an interactive web-based validation application. Zhao et al. (2015) conducted a smartphone-based prompted-recall travel survey, using the Future Mobility Survey (FMS) app to handle data collection, processing, and validation. Fan et al. (2015) also developed a smartphone app called SmarTrAC that consisted of sensor data capturer, data processor, and user interface. Assemi et al. (2016) developed an app called ATLAS II that extracted trips with a prompted recall approach. Seo et al. (2019) employed online interactive estimation model and machine learning model to estimate trips, with these models capable of automatically updating with newly collected data. These designs significantly increased the efficiency and accuracy of reported data and also reduced the recall burden on respondents.

2.2. Travel mode and trip purpose inference

Deriving travel mode and trip purpose from GPS data was one of the most notable challenges in the application of GPS-based surveys. Researchers typically segmented GPS trajectories into trips and trip ends based on movement characteristics or stationary periods, using criteria or spatial clustering methods. Xiao et al. (2015) marked a trip end if the distance between any two points was less than 10 m and the duration was more than 90 s. While other studies, such as Gong et al. (2015), and Fu et al. (2016), proposed clustering algorithms based on cluster size and point density to extract trip ends.

For travel mode inference, the top-down strategy was widely applied by dividing a trajectory into trips, and each trip into single-mode segments; then identifying the transport mode for each segment (Mäenpää et al., 2017; Zeng et al., 2023). The key puzzle of this category of approaches was trip segmentation (Dalumpines & Scott, 2017). The existing work split a trip into single-mode segments based on mode transfer points, walking segments, or moving status change points. Assemi et al. (2016) matched the spatial proximity of stops to public transport stations for identifying bus/subway transfer nodes. Rasmussen et al. (2015) considered walking segments as the joints of motorized modes and used speed characteristics to identify them. Another category of approaches was based on the bottom-up strategy, which extracted features from a series of trajectory points for detecting segments involving one mode of transport; then converting the modes of segments into a complete travel mode (Yazdizadeh et al., 2019). Nitsche et al. (2014) grouped consecutive points within a time window as a unit and utilized a hidden Markov model to classify the travel mode for each unit. Su et al. (2016) found that increasing the window size introduced more noise compared to increasing the sampling frequency with feature vector. To detect transport mode of single-mode segments or time window points, a variety of machine learning models were applied, including support vector machine (Semanjski et al, 2017), convolutional neural network (Dabiri et al., 2020), long short-term memory (Xu et al., 2019), light gradient boosting machine (Liu et al, 2022), and sequence-to-sequence model (Zeng et al., 2023).

For trip purpose inference, geographic information system (GIS) was generally used to extract critical features. Xiao et al. (2016) matched each type of land-use by selecting features at both the polygon level and the point-of-interest (POI) level, and proposed an artificial neural network combined with particle swarm optimization to predict six categories of purposes. Ermagun et al. (2017) applied online location-based search and discovery services (Google Places API) to produce non-home/non-work trip purposes in real time upon the completion of the activity episode for the trip. Some scholars also identified home and work purposes based on visit frequency within a specific period when tracking individual mobility data over the long term (Calabrese et al., 2013).

2.3. Existing GPS-based field surveys

Field tests are important for verifying the feasibility and performance of emerging technologies. Table 1 lists some existing representative GPS-based field travel surveys. Bricka et al. (2009) conducted a GPS logger-based experiment in Portland, Oregon, by randomly assigning households into three survey groups (i.e., traditional survey approach, traditional approach with GPS, and GPS only), and revealed the non-response bias of each survey group across different socio-economics. Zheng et al. (2010) led the GeoLife project in which approximately 180 participants used GPS loggers and smartphones record their outdoor movement trajectories over five years. Cottrill et al. (2013) and Zhao et al. (2015) showed a smartphone-based prompted-recall travel survey in Singapore using a future mobility sensing (FMS) system, which involved about 800 recruited users for 14 days. Zhao et al. (2021) presented a pilot project called SBB Green Class in Switzerland, where about 140 participants were required to install a smartphone app for tracking their daily movements from 2016 to 2018. Sadeghian et al. (2024) conducted a three-week survey in Borlänge, Sweden, involving 91 volunteers who used GPS loggers for data collection.

Survey rejection is a critical challenge in the real-world implementation of smartphone-based surveys. Previous studies have examined rejection levels or response rates and their influencing factors (Zegras et al., 2018; Qudratullah & Maruyama, 2019a; Lugtig et al., 2022). For instance, Keusch et al. (2022) found that among 4,293 invited phone owners, only 14.5 % (623 individuals) installed the app, and of whose, 74.6 % (465 participants) completed full participation. In a study by Qudratullah and Maruyama (2019b) in Afghanistan, the results for Kabul city showed that out of 137 individuals recruited, 62.8 % participated in the survey, 81.4 % of participants submitted data, and 51.5 % of respondents completed the survey; in Khost city, 218 individuals were recruited, with 39.9 % participating, 75.9 % of participants submitting data, and 51.5 % of respondents completing the survey. Rieser-Schüssler and Axhausen (2014) found that response rates

Table 1
Some representative GPS-based field travel surveys.

Authors (year)	Survey area	GPS-based devices	Travel diary report	Survey size
Murakami & Wagner (1999)	Lexington, US	Hand-held computer (personal digital assistant, PDA) and GPS receiver	Telephone-based report for one-day travel	100 households for 6 days, vehicle-based trips
Asakura & Hato (2004)	Osaka, Japan	Personal handy-phone systems (PHS)	Activity diary report	i. 10 persons for 2 weeks at test phase; ii. 100 spectators in a sport event for 1 day
Bohte & Maat (2009)	Netherlands	GPS-based system (handheld GPS logger, rule-based algorithm, web application)	Web-based user interface to check travel behavior data	1,200 respondents for a week, 33,686 trips
Zheng et al. (2010)	Beijing and Shanghai, China	GPS receivers and GPS phones	Map-assisted trip labeling	65 users for over 10 months (Geolife project)
Chen et al. (2010)	New York, US	GPS logger with GIS-based algorithms	Paper travel diary for one designated travel survey day	i. 25 employees at transportation council for 1 week; ii. 24 students/staff for 5 weeks
Bricka et al. (2012)	Indianapolis, US	Wearable GeoStats GlobalSat device	Trip diary report	136 households (272 persons) for 24 h, 1,555 trips.
Houston et al. (2014)	Los Angeles, US	Portable QSTAR GPS logger device (model QT-1000x)	Valid travel log	279 households for 7 days
Nitsche et al. (2014)	Vienna, Austria	Android-based smartphone devices	Annotating transport mode during travel	15 volunteers for 2 months
Zhao et al. (2015)	Singapore	Future mobility sensing (FMS) system: smartphone app, server, and web interface	Web interface to validate the processed data	793 recruited users for 14 days
Assemi et al. (2016)	New Zealand; Australia	iOS-based smartphone app (ATLAS II)	labeling the extracted trips on the app	76 participants for an average of 4.9 days
Sila-Nowicka et al. (2016)	Scotland	GPS logger (i-Blue 747 ProS)	Not available	205 participants for 7 consecutive days
Zhou et al. (2016)	Shanghai, China	Android and iOS smartphone app	Telephone-based survey report	459 individuals for an average of 8 days
Seo et al. (2019)	Matsuyama, Japan	GPS mobile phones	Web-based diary	92 respondents for 14 days (4,120 trips)
Bjerre-Nielsen	Zealand, Denmark	Smartphone app	Manually recording daily	4 participants for 119 h (527 trips)

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Table 1 (*continued*)

Authors (year)	Survey area	GPS-based devices	Travel diary report	Survey size
et al. (2020)			transport modes on app	
Zhao et al. (2021)	Switzerland	Smartphone app	Not available	139 participants from 2016 to 2018 (242,012 trips)
Gillis et al. (2023)	Belgium	Smartphone app	Paper-based diary	237 individuals from 2016 to 2017 (10,395 trips)
Tabasi et al. (2024)	Sydney & Chicago	Android and iOS smartphone app	Manually recording trips on app	131 participants for 3 months in 2023 (3,672 trips)
Sadeghian et al. (2024)	Borlänge, Sweden	Renkforce GPS logger	Manually recording mode of transportation for each segment	91 participants for 3 weeks from 2019 to 2020 (11,539 trips)

tended to decline as survey burden increased, such as with long survey duration, complex instruments, and the requirement to report at the trip or stage level. Assemi et al. (2018) highlighted that the ease of app usage was significant to participants' intention to engage in the survey. To improve participation, Bürbaumer et al. (2022) pointed out that recruitment methods affected both registration and participation. Zegras et al. (2018) suggested enhancing interview verification procedures as a potential solution.

2.4. Motivation and goals

Although numerous studies have developed various smartphone apps for data collection and algorithms for trip extraction, improving participation and response rates in field implementation remains challenging. We propose an applet-based GPS tracking system to reduce installation barriers and response burden by using a freely-installed applet to replace general apps, an algorithm-embedded server to replace manual trip labeling or annotation, and a supervision platform for monitoring survey completion. Meanwhile, we examine the performance of the applet-based survey by comparing with traditional interview-based and app-based surveys conducted in Jiading Town, Shanghai, China, addressing their advantages and limitations, and providing insights into improving participation and response rates in large-scale household travel surveys.

3. Applet-Based GPS tracking system

3.1. Framework

The GPS tracking system we propose integrates an applet, a cloud server, and a web-based platform to efficiently capture residents' mobility trajectories and automatically extract trip information. The system consists of four key modules: data collection, data processing, data validation, and data supervision, as shown in Fig. 1. The collection and validation modules are implemented on smartphone through a freely installed mini-program developed based on the WeChat API (https://developers.weixin.qq.com/miniprogram/en/dev/framework/). WeChat is the most widely used social media platform in China, seamlessly integrating communication, social networking, payments, and lifestyle services into a single app. As of September 2021, WeChat had an impressive 1.26 billion monthly active users. The mini-program functions as a lightweight sub-application that operates entirely within the WeChat ecosystem, allowing participants to engage with the survey without installing separate applications—a critical advantage for reducing participation barriers. The data processing module is executed on a cloud server embedded with a series of pre-trained algorithms for inferring trip details from the uploaded trajectories, including departure and arrival time, origin and destination locations, mode of transport, and travel purpose. The data supervision module is a web-based platform designed to assist survey project coordinators in monitoring participation status and sending reminders to participants to complete their validation responses.

3.2. Module 1: Applet-based GPS data collection

For the survey implementation, individuals access the applet by

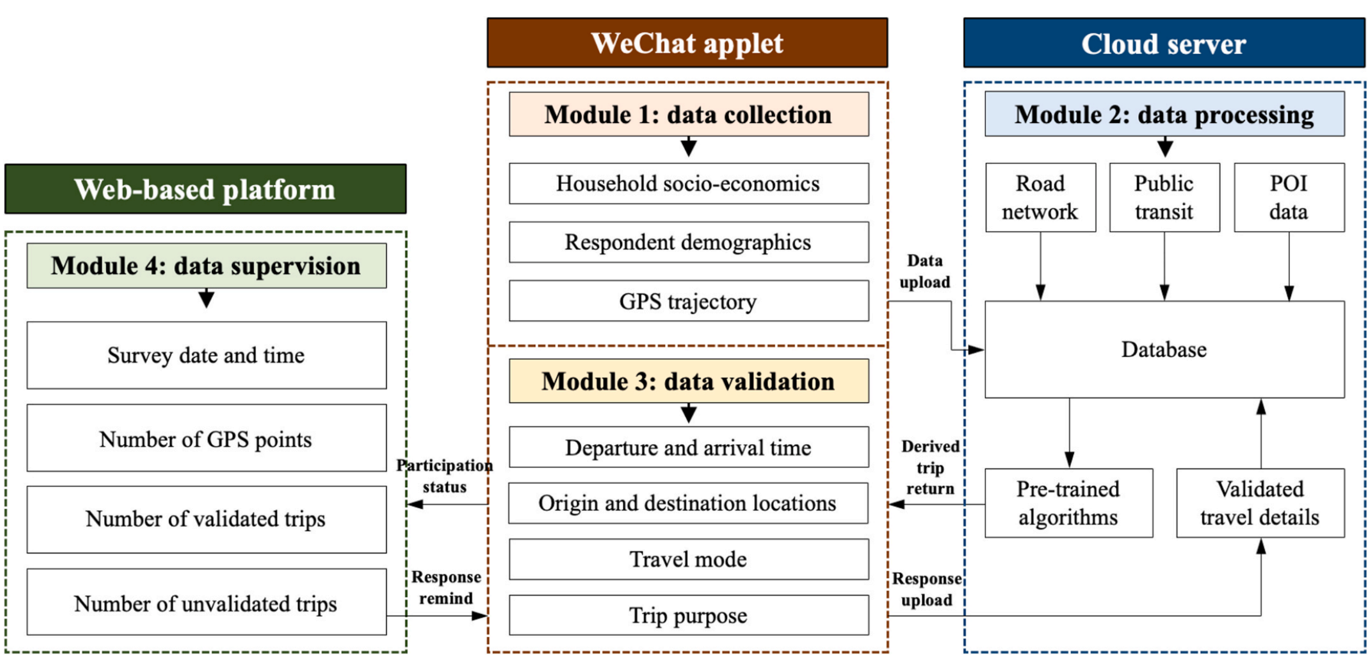

Fig. 1. Framework of the applet-based GPS tracking system.

scanning a QR code through their existing WeChat application and granting location permissions—eliminating the friction of downloading and installing a dedicated app. Upon registration, each participant is assigned a unique anonymous individual ID, while family members share a common household ID. When filling in socio-economic and demographic characteristics, participants provide their home and workplace locations via map positioning, which will serve as critical input for determining the activity type as either home or work in the process of trip purpose imputation. Once prepared, participants are instructed to maintain the operation of the mini-program and GPS continuously throughout the survey period. The collected trajectory data are automatically uploaded to the cloud server, where pre-trained models promptly partition the GPS trajectory into activity-trip episodes and derive trip information. These trips are subsequently returned to the respondents' smartphones and trigger validation reminder messages to their mini-programs. Meanwhile, the project coordinators are able to view these trips on the supervision webpage and provide respondents with data quality information and details on unvalidated trips if necessary. After participants complete the validation, travel diaries are formally submitted and stored in the database of the cloud server.

3.3. Module 2: Trip details inference from GPS data

The algorithms preset consist of trip end identification, travel mode detection, and trip purpose imputation. Here, we define some important terms. *Trajectory* is a sequence of GPS points that record one person's spatio-temporal movement. A *trip* is a process of movement in which a person travels from one physical place to another with a certain purpose. A *trip end* (a.k.a. *activity node*) is the connection node of a trip, generally characterized by clusters of GPS points. A *trip leg* is a single-mode segment within a trip during which a person travels using one mode of transport. *Mode transfer point* is the joint node between trip legs, referring to multi-modal trips.

For trip end identification, we propose a spatio-temporal density-based clustering approach. Assuming the one-day trajectory is symbolized as $Traj = \{P_i\}$, where $P_i = (t_i, x_i, y_i)$ represents the i-th point described by timestamp, longitude, and latitude. The point sampling rate is 1 s. First, we define the *k-nearest sequence* of P_i as consecutive points centered around P_i with a length of k, denoted as $Seq(P_i) = \{P_{i-\lfloor k/2 \rfloor}, \cdots, P_i \cdots, P_{i+\lfloor k/2 \rfloor}\}$. The *epsilon neighborhood* of P_i is defined as the set of adjacent points in $Seq(P_i)$ that fall within a circle centered at P_i with a radius of *eps*, i.e., $N_{eps}(P_i) = \{P_q \in Seq(P_i) | dist(P_i, P_q) \leq eps\}$, where *eps* represents the radius of the epsilon neighborhood. Then, P_i is labeled as a core point when the number of points in its epsilon neighborhood exceeds *minpts*, i.e., $|N_{Eps}(P_i)| \geq minpts$, where *minpts* is the minimum number required to meet the core point condition. As an extension of DBSCAN (Ester et al., 1996), the proposed clustering algorithm searches for core points within a k-nearest sequence to delineate temporal distances. Trajectory segment of consecutive core points are grouped into an initial cluster. We define a *cluster density* as a measurement of concentration degree, determined by the ratio of the number of core points to the maximum distance of any two points within the cluster. Since potentially mislabeled non-core points may split integrated clusters into multiple ones, we merge initial clusters that satisfy the spatio-temporal closeness criterion: an interval shorter than τ (180 s) and a distance less than δ (20 m). The merging process proceeds in descending order of cluster density until no further clusters qualify. Finally, clusters with a duration exceeding 300 s are extracted, and a classification model is employed to distinguish trip ends from mode transfer points.

For travel mode detection, we establish a bottom-up approach that combines random forest model with a merging algorithm. For trip trajectory $Trip = \{P_i\}$ ($i = 1, \cdots, m$), we partition it into trip slices using a sliding time window with a size of s ($s < m$) and an overlap rate of r ($0 \leq r < 1$). Note that overlapping the sliding window is beneficial for preserving information from the preceding slice to the succeeding one, which helps avoid abrupt changes in features when detecting trip legs. The trip trajectory is transformed into a sequence of trip slices $\{U_j\}$, where $U_j = \{P_i\}, i = (j-1)n + 1, \cdots, jn$, and n is the number of trip slices. First, a random forest model is employed to predict the travel mode for each trip slice. The categories of travel mode include walking, bicycle, car, bus, and subway. Second, a consecutive homogenous merging algorithm is used to detect trip legs and their travel modes. The sequence of predicted travel modes $\{Y_j\}$ is encoded into tuples $\{(Y_j, w_j)\}$ by assigning a weight w_j to measure the frequency of labels. Meanwhile, we define a core label as a travel mode whose associated weight is higher than *MinNum*, i.e., $Y^{(C)} = \{Y'_{jj} | w'_{jj} \geq MinNum\}$, where *MinNum* represents the minimum required number of slices to form a trip leg. Consecutive homogeneous labels are merged, and their weight is updated to the sum of the weights of the merged trip slices. In each iteration, we search for and modify the non-core labels to their nearest core label, and merge the new consecutive homogeneous labels until all non-core labels are transformed into core labels. The final travel mode tuple is decoded into a sequence of travel mode labels, and the segment in one mode is detected as a trip leg.

For trip purpose imputation, it is relatively complex due to challenges such as the diversity of activity categories and the dense distribution of points of interest (POIs) in center areas. We group activities from the household travel survey into nine main categories (i.e., home, work/education, shopping, catering, medical service, recreation, pickup/drop-off, and business) and use a two-stage method to infer the activity types of the extracted trip ends. First, home and work are identified using a random forest, supplemented with household socio-economics and spatiotemporal features. Second, for the remaining non-home-non-work activities, we employ an XGBoost model (Chen & Guestrin, 2016). We select features including household socio-economics, personal demographics, spatio-temporal characteristics, and activity motif characteristics.

3.4. Module 3: Derived trip data validation

Data validation is a crucial process to obtain ground-truth trip information from respondents for evaluating the performance of travel detail inference algorithms. To minimize participant burden while ensuring data quality, we design an intuitive interface that visually prioritizes validation tasks and simplifies the review process (Fig. 2). Once the algorithms complete processing a new trajectory, a red "new" label appears on the validation menu, and a red number appears on the survey date icon, indicating the number of unvalidated trips. Considering scenarios involving multimodal trips, we split trips into trip legs and validate them leg by leg. For intermediate legs within a trip, they share the trip purpose. Users can slide the screen to view these trips and easily revise potential mistakes through the operations of insertion, deletion, and modification. After revision is confirmed, the trip's status changes from yellow "unvalidated" to green "validated". The red labels disappear when all trips are validated.

3.5. Module 4: Survey data supervision

Data supervision is necessary for project coordinators to be capable of promptly checking participation status, especially when involving a large number of participants in the survey. We developed a comprehensive web-based platform that provides real-time monitoring capabilities, allowing coordinators to identify data quality issues and participation barriers before they significantly impact survey outcomes. This platform can track trajectory quality and validation progress while helping diagnose unexpected issues that may severely impact data collection. The issues we encountered in practice include the failure to record GPS data continuously for device incompatibility, respondents' reluctance to complete the validation process, and the tendency to

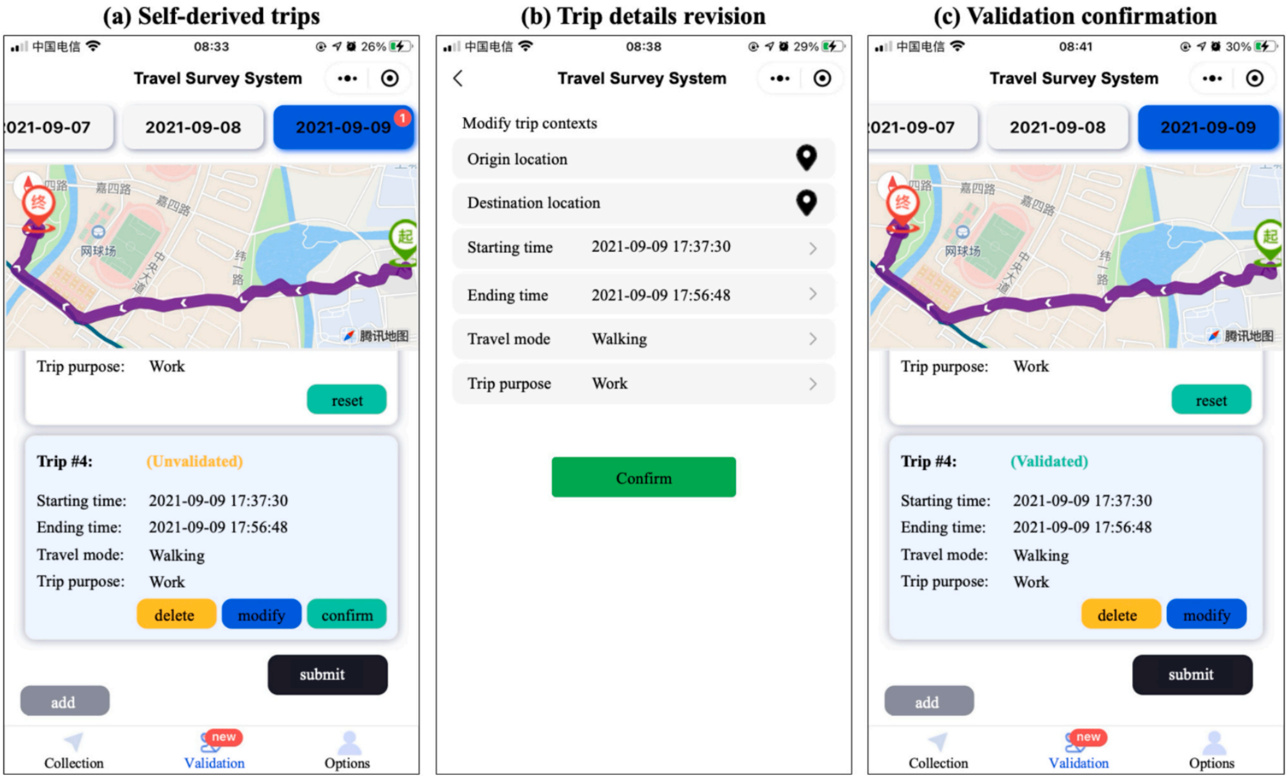

Fig. 2. Applet interface for trip validation.

confirm algorithm-generated trips without proper review. Coordinators checked travel information on the map to identify obvious errors, and respondents were required to revise and resubmit their validation records as needed. The developed web-based platform, as shown in Fig. 3, summarizes the data information, including the number of GPS points, the number of trips and their validation status, on the left and visualizes the trajectory of the selected trip on the right. The supervision platform provides efficient management services for project coordinators to promote the GPS-based survey conduction and obtain reliable travel details.

4. Multi-Phase travel surveys

We conducted travel surveys in Jiading Town, Shanghai across three distinct phases to develop and validate our methodology: an app-based voluntary test in 2014, an interview-based survey in 2021, and an

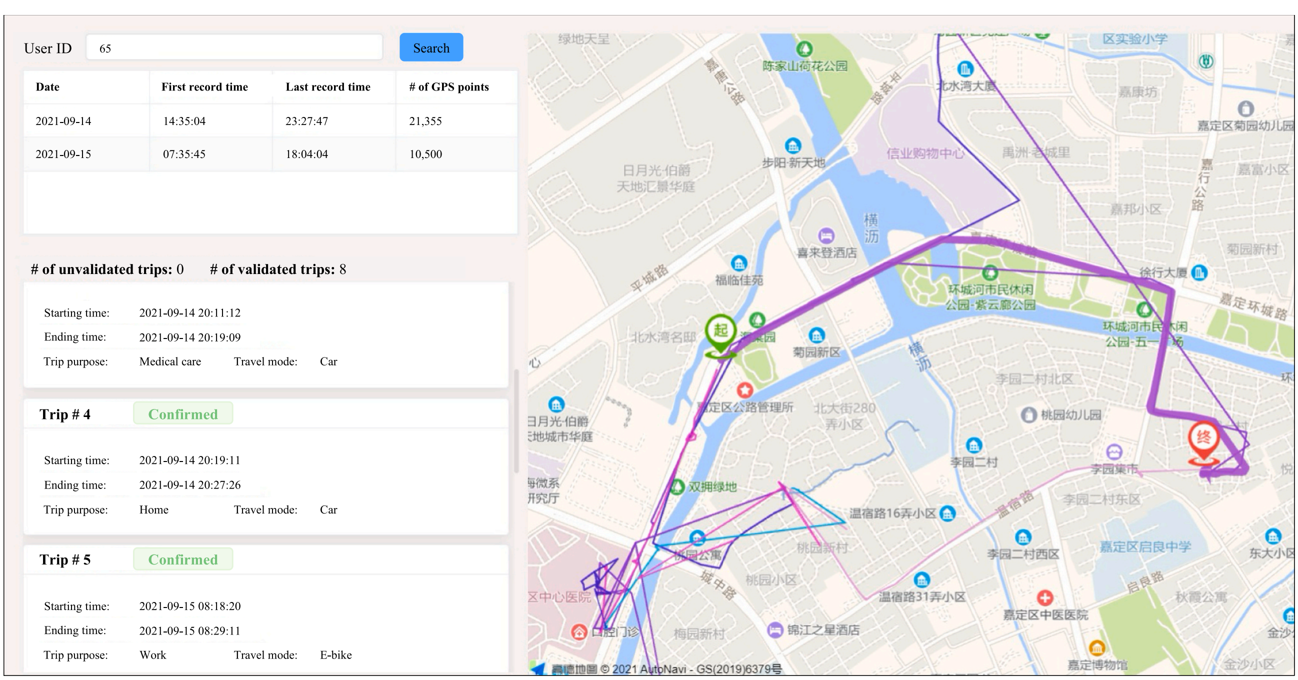

Fig. 3. Web-based platform for response supervision.

applet-based field survey in 2021. This sequential approach allowed us to compare different survey methods while addressing limitations identified in earlier phases.

Jiading Town is an administrative sub-division at the center of Jiading District (Fig. 4) with a high population density exceeding 18,000 residents per square kilometer. Jiading Town comprised 17 communities, each managed by an organizing committee responsible for daily affairs and service provision. These committees played a critical role in facilitating communication and building trust between researchers and residents.

4.1. Phase I: App-based voluntary test in 2014

We developed a smartphone app-based travel survey system (Zhou et al., 2022) in 2014 which is composed of a smartphone app for GPS trajectory collection, a cloud server with rule-based algorithms for trip detail inference, and a validation webpage. University students and staff were recruited to participate in a week-long test. Participants were required to install the dedicated app on their phones, maintain app and GPS functionality throughout the survey period, and validate their trips via the webpage at day's end.

To address rejection concerns related to privacy, installation burden, and validation requirements, we provided detailed usage instructions and offered a daily incentive of 50 CNY (about 7 USD). The survey was conducted in April 2014, with 22 participants generating 109 valid trajectories (averaging five days per participant). This initial phase provided valuable insights into participation barriers while establishing baseline performance metrics for our algorithmic approach.

4.2. Phase II: Interview-based household travel survey in 2021

As part of the 2021 Jiading District Transportation Planning Project, we conducted an interview-based household travel survey to understand residents' intra-city travel to central Shanghai and inter-city travel to neighboring cities. Following the methodology of Shanghai's quinquennial Household Travel Survey, the local government mobilized community officers to administer the survey using iPad-based e-questionnaires.

The officers scheduled appointments with respondents and conducted face-to-face interviews. The established trust between community officers and residents facilitated smooth survey implementation, resulting in 1,642 Jiading Town residents (approximately 2 % of the population) reporting their one-day trips. This traditional approach provided a methodological benchmark against which to evaluate our technology-enabled alternatives.

4.3. Phase III: Applet-based field survey in 2021

Building on insights from the previous phases, we conducted a field survey in 2021 using our freely-installable WeChat applet. By operating within the WeChat ecosystem, the applet eliminated the standalone app installation requirement—a significant barrier identified in our 2014 surveys. We also enhanced the system by updating the algorithmic components based on app-based data and integrating both collection and validation modules within the applet interface.

Our survey implementation followed a structured three-step process: recruitment, participation, and response. First, we contacted community officers by telephone to assess their willingness to engage with sampled residents for a 3-day survey period. Residents were offered a daily reward of 30 CNY (about 4 USD) for providing qualifying survey data. Second, our research team, accompanied by community officers, visited consenting residents to provide guidance on using the applet-based survey system, ensuring proper setup and addressing initial questions. Third, survey project coordinators collaborated with community officers to supervise data validation completion, ensuring timely and accurate trip verification by participants.

5. Results and Discussion

5.1. Survey participation and data collection overview

Table 2 summarizes statistics from the three travel surveys, including GPS trajectories, reported travel diaries, and demographic characteristics of trip-reporting participants. In the app-based test survey, 35 volunteers were recruited, 22 participated, contributing 109 person-days and 5,713,105 GPS points. In the applet-based field survey, 15 out of 17 communities accepted the invitation, with 263 residents recruited, 202 completing registration, and 179 contributing 526 valid person-days and 22,937,859 GPS points. On average, each app-based participant contributed 5 days of data, with approximately 52,400 GPS points, 2.79 trips, and 4.36 trip legs per day; each applet-based participant contributed 3 days of data, with about 43,600 GPS points, 2.76 trips, and 3.33 trip legs per day. For the interview-based household travel survey, 1,651 residents were recruited, and 1,642 reported at least one trip, resulting in 4,487 trips in total, with an average of 2.73 trips and 2.81 trip legs per person per day. Note that the number of non-trip respondents excluded

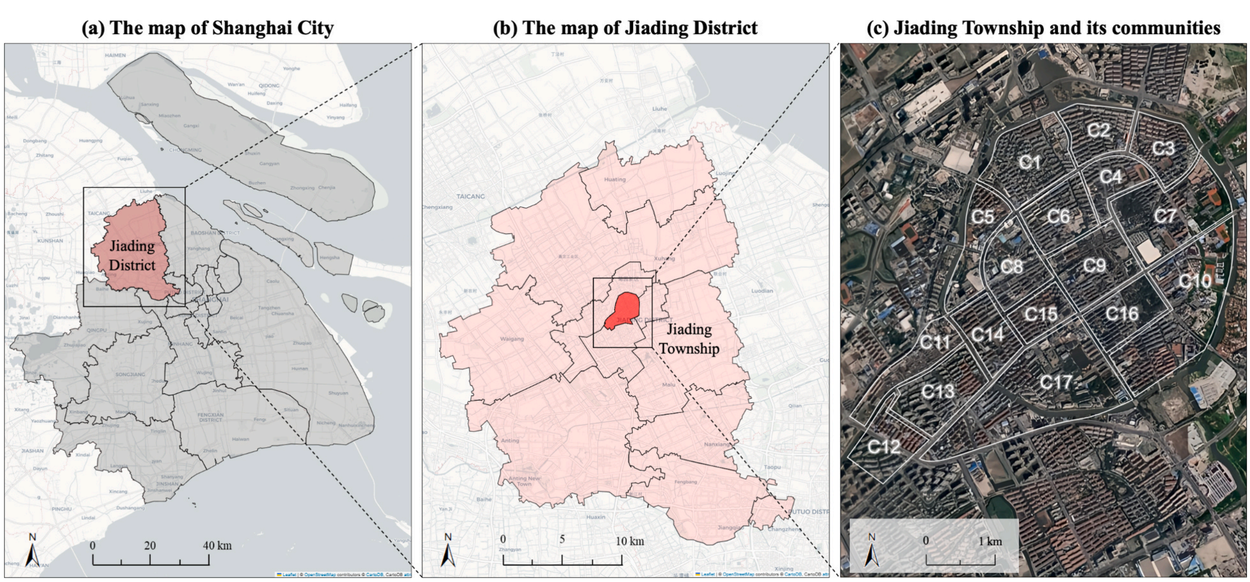

Fig. 4. The survey area of applet-based field survey.

Table 2
Summary of data from three travel surveys.

Categories	Characteristics	Travel surveys App-based (2014)	Applet-based (2021)	Interview-based (2021)
GPS trajectories	No. of valid participants	22	179	N/A
	No. of trajectories	109	526	N/A
	No. of GPS points	5,713,105	22,937,859	N/A
	Ave. trajectories per participant	5.0	3.0	N/A
	Ave. points per trajectory	52,413	43,608	N/A
Travel diaries	No. of individuals	22	179	1,642
	No. of trips	304	1,450	4,487
	Ave. trips per person-day	2.79	2.76	2.73
	No. of trips legs	475	1,753	4612
	Ave. trip legs per person-day	4.36	3.33	2.81
Demographic characteristics	Gender (female)	56.5 %	57.6 %	52.3 %
	Age (18–45 years old)	90.9 %	49.8 %	47.3 %
	Age (45–60 years old)	9.1 %	21.8 %	22.9 %
	Age (over 60 years old)	0 %	28.4 %	29.8 %
	Edu. (high school diploma)	21.7 %	32.8 %	23.1 %
	Edu. (college degree or higher)	78.3 %	44.9 %	42.6 %
	Occ. (students)	60.8 %	4.8 %	11.7 %
	Occ. (professionals)	21.7 %	25.3 %	22.5 %
	Occ. (entrepreneurs)	0 %	5.1 %	20.1 %
	Occ. (government)	0 %	16.7 %	7.4 %
	Occ. (retired)	0 %	35.3 %	31.8 %

Notes: Edu. = education, Occ. = occupation, N/A = not applicable.

from the trip analysis was 13 for the app-based, 23 for the applet-based, and 9 for the interview-based survey, respectively. Regarding demographic characteristics, the applet-based survey exhibited a notably different distribution of age, education, and occupation compared to the app-based survey, as the latter primarily involved college staff and students; whereas the interview-based survey, which targeted the same community residents, showed similar distributions.

5.2. Performance of trip detail inference

The performance of trip end identification was evaluated using precision and recall. Precision refers to the proportion of correctly identified trip ends among all identified, while recall is the proportion of correctly identified trip ends out of the total actual number. For the app-based data, with 584 trip ends, precision was 96.7 % and recall was 96.4 %. For the applet-based data, there were 1,931 trip ends in total, with a precision of 92.4 % and a recall of 89.2 %. Fig. 5 shows representative results of trip end identification across different number of dwell locations. Upon closer examination of the under-identified trip ends, we found that about half were short-duration stops of less than 300 s (the minimum stop duration for trip end identification), mainly for grocery shopping and pickup/drop-off.

For travel mode inference, the performance was evaluated with accuracy, which is defined as the ratio of the number of trips with correctly predicted travel modes to the total number of trips. the overall accuracy was 90.5 % during offline testing and 77.2 % during the online field survey. The precision for each sub-mode is presented in Fig. 6**(A)**. Non-motorized modes like “walking” and “cycling” obtained satisfactory accuracy, while motorized modes, especially “bus”, showed relatively poor performance in the field survey. This decline was partially attributed to missing points and the absence of integrated transit line information.

For trip purpose inference, the classification of “home” achieved a precision of 99.9 % and a recall of 100 % during offline testing, and a precision of 100 % and a recall of 91.4 % during online survey. The “work” classification attained a precision of 99.4 % and a recall of 99.1 % during offline testing but dropped to a precision of 71.8 % and a recall of 77.8 % in the field survey. The significant performance gap between “home” and “work” was closely related to the accuracy of reported locations. Residence locations were precisely positioned to participants’ homes, whereas work locations were self-reported. This discrepancy suggests that some participants did not provide accurate work locations in the field survey. For non-home non-work activities, the accuracy was 75.1 % for offline testing and 48.9 % for the online survey. The precision for each sub-purpose is shown in Fig. 6**(B)**. The “medical” got relatively good results, while the “business”, “shopping”, and “recreation” were performed poorly.

Despite the misidentification of trip ends negatively impacting travel mode inference, the overidentification of trip ends within multi-modal trips had only a minor effect. In the survey, some mode transfer points were mis-identified as trip ends. These over-identified trip ends were easy to merge during manual validations, and even helped promote the performance of travel mode detection. It also can be seen that the poorer performance of trip purpose inference. Typically, the identification of work resulted in a low accuracy. It reflected some unexpected issues that some of participants were unwilling to report or mis-report their working locations. Therefore, self-enhanced algorithms are necessary to adapt the masked information provided by participants and to learn from the true trajectories generated by their travel behavior.

5.3. Trip capture comparison between smartphone-based and interview-based surveys

To compare the performance of data collection across different survey methods, we examined the distribution of trips and trip legs between smartphone-based and traditional interview-based data. Notes that the demographic distribution in Table 2 indicates the similarity in travel behavior between the applet-based and interview-based surveys. The distribution of trip and trip leg frequency differed significantly between smartphone-based and interview-based data (see Fig. 7(a-b)). The distribution of trip frequency across the three datasets was similar, while the distribution of trip legs of interview-based data showed a higher proportion at larger frequencies: about 68 % of daily records contained two trip legs, and approximately 90 % of trip leg frequency was less than

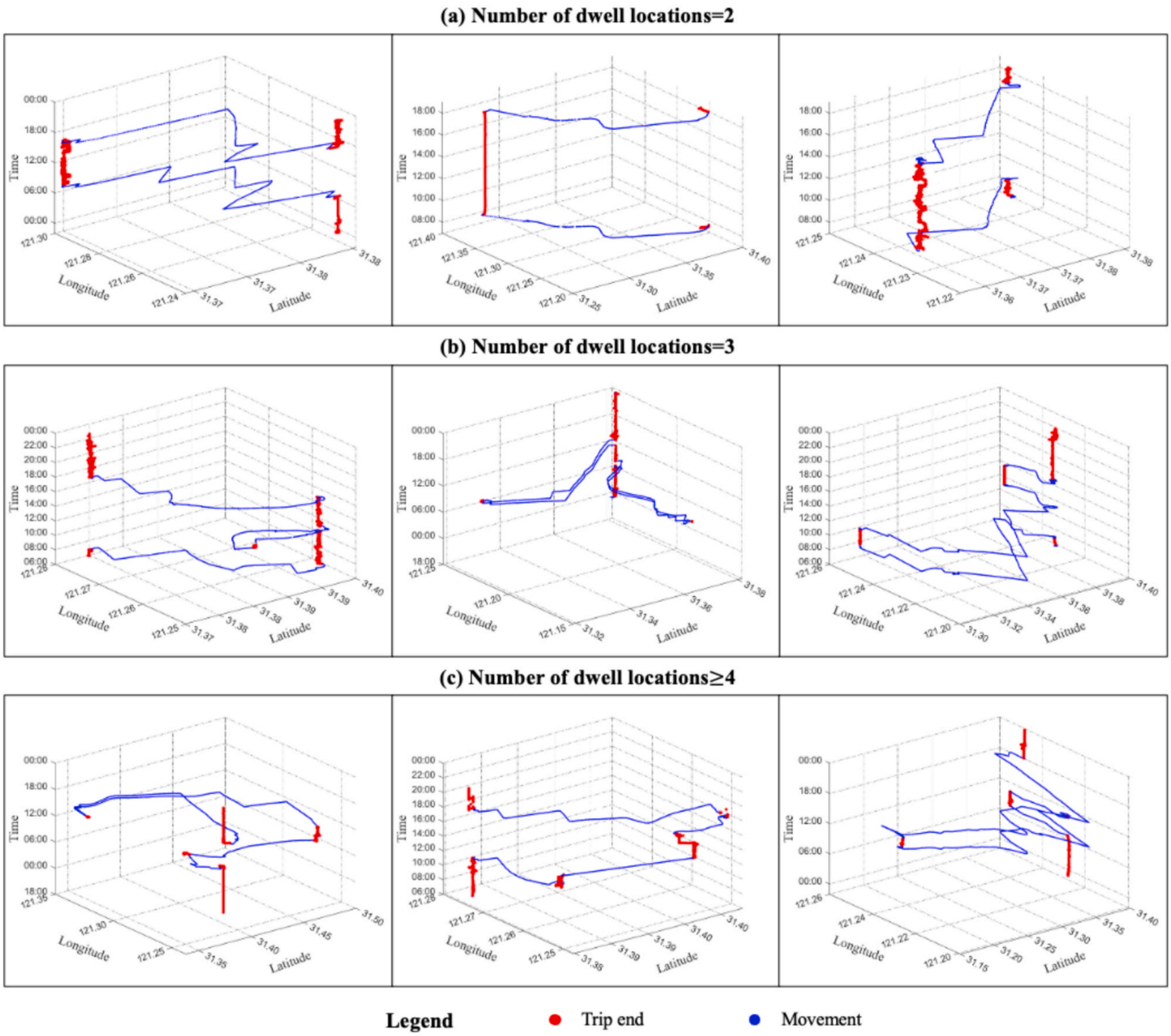

Fig. 5. Results of trip end identification.

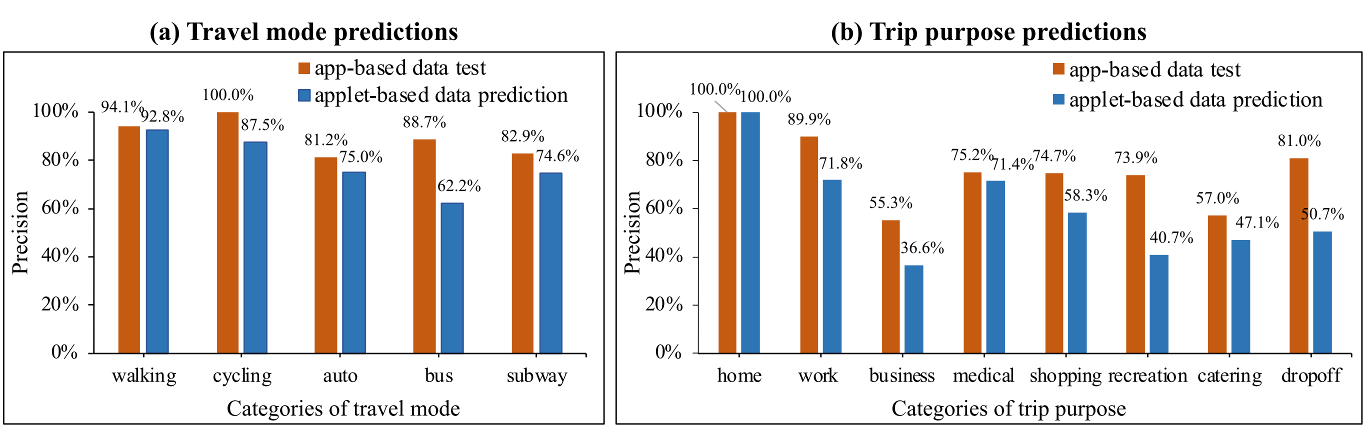

Fig. 6. Results of trip mode and purpose inferences.

four. In contrast, only 41 % and 47 % of records from the 2014 and 2021 interview-based data, respectively, had two trip legs, while trip leg frequencies exceeding four accounted for about 56 % and 40 %. This suggests that interview-based surveys may capture trips as effectively as smartphone-based surveys but are less capable of capturing trip legs.

To further investigate the differences in trips and trip legs, we examined the distribution of trip chains (i.e., activity node sequence) in a trajectory and travel mode sequence in a trip. First, the regular trip

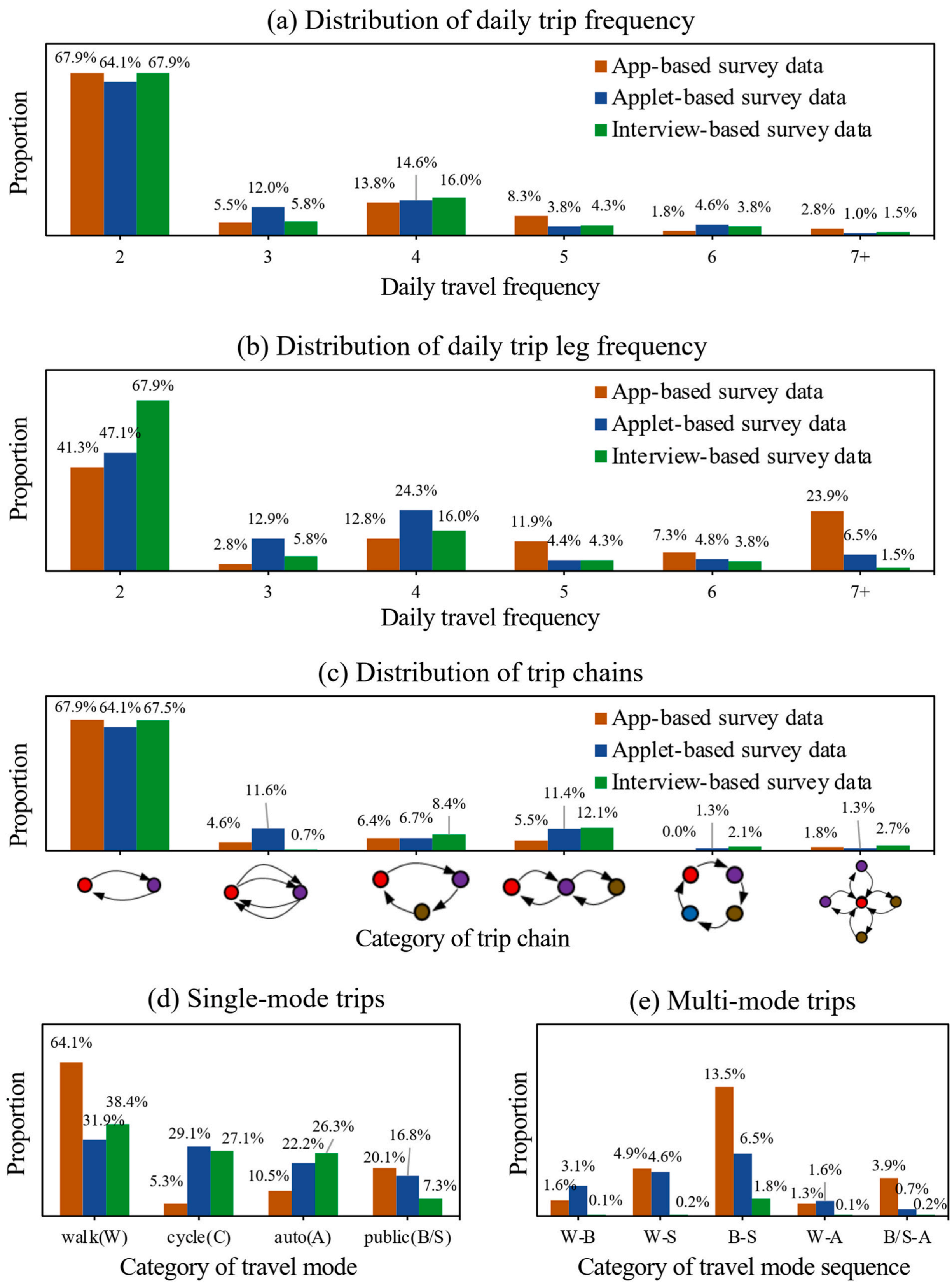

Fig. 7. Comparison of trips and trip legs between smartphone-based and interview-based data. Notes: symbols for travel modes: W-walking, C-cycling, B-bus, S-subway, A-auto. The category of travel mode sequences (e.g., "W-B") in multi-modal trips represents the transition between walking and bus, with similar meaning for other combinations of symbols.

chains were found to be as consistent as the distribution of trip frequence across the three datasets (see Fig. 7(c)). Second, regarding travel modes, the proportion of single-mode trips was comparable between the 2021 smartphone-based and 2021 interview-based data (see Fig. 7(d)). However, for complex multi-modal trips, the proportions were 25.3 % for the 2014 smartphone-based data, 16.6 % for the 2021 smartphone-based data, and only 2.3 % for the 2021 interview-based data, with 1.8 % of transfers between bus and subway reported (see Fig. 7(e)). This indicates that complex trips often involve transitions between motorized transport modes or between motorized and non-motorized modes, which causes the performance difference between smartphone-based and interview-based surveys.

5.4. Data quality assessment for applet-based and app-based surveys

To assess the quality for applet-based and app-based survey data, we established two indices: time coverage rate and point missing rate. The time coverage rate is defined as the ratio of the GPS recording time to the active hours during which a person is likely to generate trips. The active hours were set from 6 a.m. to 10p.m. based on the hourly distribution of activity-travel from the Shanghai household travel survey data (Zhou et al., 2024). The point missing rate is defined as the number of missing points divided by the trajectory duration, as both app-based and applet-based surveys collected GPS points at a constant frequency of 1 s. The time coverage rate measures the reliability of GPS data collection, with a higher coverage rate indicating a greater likelihood of recording the complete daily trip chains. While the point missing rate measures the effectiveness of data, with a lower missing rate indicating that more detailed travel information was captured.

The assessment results are presented in Fig. 8**.** Based on the time coverage, both the app-based and applet-based data exhibited high rates, meaning that the majority of participants with valid trajectories completed full-day data collection as required. However, in terms of the point missing rate, the applet-based data showed a significantly higher rate compared to the app-based data. According to survey feedback, the relatively high missing rate in the applet-based survey was primarily due to two factors. First, compatibility issues with smartphone brands, operation systems, and even WeChat versions were significant. We noticed that some sampled participants, particularly older adults, used outdated smartphones and older versions of WeChat. Second, interruptions of the WeChat app played a major role. The applet was easily interrupted by the heavy usage of WeChat, such as video and voice calls, which have increasingly replaced traditional phone calls as the most popular communication way among Chinese phone users.

5.5. Participation barrier analysis and rejection rate measurement

Survey participation barriers represent a critical challenge in smartphone-based travel surveys. Our comparative analysis revealed several key insights about the effectiveness of our applet-based approach in reducing these barriers. We systematically measured rejection rates across three distinct phases of the survey process: recruitment, participation, and response (Zegras et al, 2018). The recruitment rejection rate r_c is calculated as the combined effect of community officers rejecting phone call invitations and residents declining participation, expressed as $r_c = p_o + (1 - p_o) \bullet p_c$, where p_o represents the rejection proportion of community officers, and p_c denotes the rejection proportion of residents invited. The participation rejection rate r_p is defined as the ratio of individuals who did not engage in data collection among those who registered. The response rejection rate r_s is defined as the ratio of individuals who did not complete the validation response among those who participated in data collection.

The applet-based survey demonstrated significantly improved participation metrics compared to our earlier app-based approach, despite offering lower incentives. In the applet-based survey, 15 of 17 communities accepted phone invitations, with 263 residents recruited, 202 registered, 179 generating valid trajectories, and 156 completing trip validation. This resulted in a recruitment rejection rate of 32.2 %, a participation rejection rate of 11.4 %, and a response rejection rate of 12.8 %. The recruitment rejection rate, in fact, lies between p_c and r_c, i.e., 23.2 %~32.2 %, because rejection by community officers does not strictly mean we would be rejected by residents in the remaining two communities. By comparison, the app-based survey had a recruitment rejection rate of approximately 37.1 %, with only 22 of 35 recruited individuals completing participation and validation.

These results are particularly noteworthy considering the greater challenges faced in the applet-based implementation: recruiting general community residents rather than colleagues, and offering a substantially lower daily incentive (30 CNY vs. 50 CNY). The improved participation metrics strongly suggest that eliminating app installation barriers through the WeChat mini-program approach significantly enhanced participant willingness to engage with the survey.

Our findings align with previous research indicating that ease of use is a critical factor in survey participation (Assemi et al., 2018). The applet-based approach effectively addressed this by leveraging an existing platform with widespread adoption, thereby eliminating a major participation barrier. These results provide compelling evidence that technological approaches reducing participant burden—particularly by eliminating installation requirements—can significantly improve survey participation rates, even when facing other constraints such as reduced incentives.

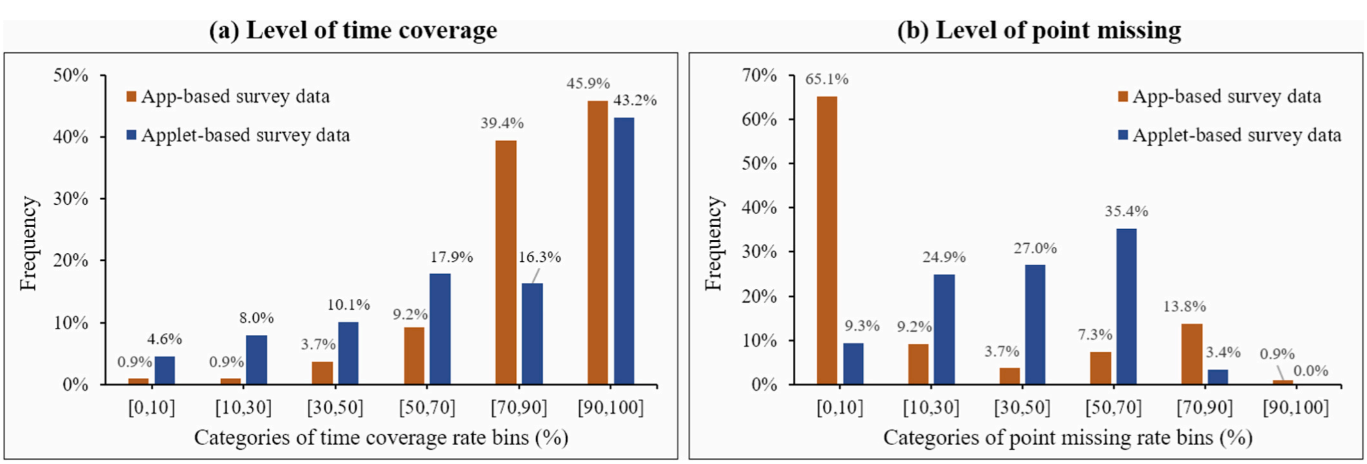

Fig. 8. Results of smartphone-based GPS data assessment.

6. Conclusions

This study introduced an applet-based GPS tracking system designed to overcome persistent barriers in smartphone-based travel surveys through four integrated modules. By replacing traditional app installation with a lightweight social media-based mini-program, automating trip inference with cloud-based algorithms, simplifying validation via a user-friendly interface, and enabling comprehensive survey supervision, our approach directly addressed critical implementation challenges. The field evaluation conducted in Shanghai provided a robust comparative assessment of interview-based, app-based, and applet-based methodologies.

Our applet-based field survey demonstrated promising engagement metrics, with 179 valid participants (from 263 recruited residents) contributing nearly 23 million GPS points and 1,450 validated trips. Comparative analysis yielded two significant findings regarding data quality: first, smartphone-based and interview-based methods captured comparable trip chains (average 2.76 vs. 2.73 trips per person-day), establishing the validity of GPS approaches for basic travel documentation; second, smartphone-based methods dramatically outperformed traditional interviews in detecting multi-modal trips (16.6 % vs. 2.3 %), highlighting their particular value for understanding complex urban mobility patterns. Furthermore, the applet-based approach achieved substantially lower recruitment rejection rates (23.2–32.2 %) compared to conventional app-based methods (37.1 %), confirming that reducing installation barriers and simplifying user interactions enhances participation willingness.

The field implementation revealed important considerations for future large-scale deployments. Most notably, demographic variations in technology adaptation presented unexpected challenges, particularly among older participants who often used outdated smartphones with limited compatibility. Additionally, the integration with a popular social media platform created both advantages (widespread availability) and challenges (interruptions during resource-intensive activities like video calls). These findings suggest that next-generation survey tools should incorporate broader device compatibility, more resilient background operation capabilities, and algorithms specifically designed to handle incomplete or interrupted data streams. By addressing these practical implementation challenges while building on the demonstrated advantages in participation rates and multi-modal trip detection, applet-based GPS tracking systems offer a promising pathway toward more frequent, representative, and detailed household travel surveys for transportation planning and travel behavior research.

CRediT authorship contribution statement

Yang Zhou: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Chao Yang:** Resources, Funding acquisition, Data curation, Conceptualization. **Quan Yuan:** Writing – review & editing, Writing – original draft, Validation, Methodology, Data curation. **Xiaoyi Ma:** Writing – original draft, Visualization, Validation, Software. **Fangyi Ding:** Writing – original draft, Validation, Software, Methodology, Data curation. **Tianren Yang:** Writing – review & editing, Supervision, Project administration, Investigation, Funding acquisition.

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