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Final Project Report

A Pilot Study to Integrate Mobility Data Collection APPs with Personalized Recommendation Systems

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16. Abstract
This pilot study explores the integration of mobility data collection applications with personalized recommendation systems to enhance user-specific travel suggestions and promote sustainable transportation behavior. We leverage the open-source NREL OpenPATH platform to collect detailed mobility data including travel trajectories, inferred modes, and user annotations from a cohort of participants over a one-year period. Our analysis identifies several challenges in the sensed data, including misclassification of transportation modes and inaccurate trip segmentation, which highlight the need for improved sensing and user interface design. To establish a foundation for recommendation modeling, we evaluate the ItemKNN algorithm on a filtered subset of the Yelp dataset. Results indicate that user history richness improves performance across precision, recall, and nDCG metrics. Building on these insights, we develop a prototype personalized recommendation system that dynamically suggests Points-of-Interest (POIs) based on location, time, and user behavior. This system incorporates a reward mechanism that offers incentives to encourage the adoption of suggested alternatives and collects user feedback to iteratively refine future recommendations. The findings suggest that integrating personalized recommendations with mobility tracking can create a closed-loop system where improved data quality enhances recommendations, which in turn drives user engagement and behavior change. This pilot demonstrates the feasibility of such integration and offers a blueprint for future research. Applications of this framework include scalable interventions for promoting active travel, reducing carbon emissions, and supporting individualized transportation planning through intelligent, adaptive systems.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

EXECUTIVE SUMMARY

This pilot study explores the integration of mobility data collection applications with personalized recommendation systems to enhance user-specific travel suggestions and promote sustainable transportation behavior. We leverage the open-source NREL OpenPATH platform to collect detailed mobility data including travel trajectories, inferred modes, and user annotations from a cohort of participants over a one-year period. Our analysis identifies several challenges in the sensed data, including misclassification of transportation modes and inaccurate trip segmentation, which highlight the need for improved sensing and user interface design. To establish a foundation for recommendation modeling, we evaluate the ItemKNN algorithm on a filtered subset of the Yelp dataset. Results indicate that user history richness improves performance across precision, recall, and nDCG metrics. Building on these insights, we develop a prototype personalized recommendation system that dynamically suggests Points-of-Interest (POIs) based on location, time, and user behavior. This system incorporates a reward mechanism that offers incentives to encourage the adoption of suggested alternatives and collects user feedback to iteratively refine future recommendations. The findings suggest that integrating personalized recommendations with mobility tracking can create a closed-loop system where improved data quality enhances recommendations, which in turn drives user engagement and behavior change. This pilot demonstrates the feasibility of such integration and offers a blueprint for future research. Applications of this framework include scalable interventions for promoting active travel, reducing carbon emissions, and supporting individualized transportation planning through intelligent, adaptive systems.

INTRODUCTION

The rapid evolution of smartphone technology has revolutionized the way transportation researchers collect mobility data and understand travel behavior (Berger & Platzer, 2015; Lopes et al., 2010; You et al., 2018). Smartphones are increasingly leveraged to passively and actively gather user movement patterns, leveraging GPS, accelerometers, and other sensors to capture granular travel trajectories (Korpilo et al., 2017; Lynch et al., 2019; Molloy et al., 2023). In parallel, personalized recommendation systems enabled by advances in machine learning and behavioral modeling have emerged as promising tools for influencing sustainable transportation choices by tailoring suggestions based on individual preferences and behaviors (Liu et al., 2021; Meena et al., 2024; Yuan & Zheng, 2024). However, these two research streams, mobility data collection and personalized travel recommendation, have largely evolved in isolation. We hypothesize that enhancing personalized recommendations also requires improvements in the quality of collected mobility data. By leveraging recent advances in adaptive sensing (You et al., 2020), uncertainty quantification (Wang et al., 2024; Zhou et al., 2021), and predictive modeling (Steentoft et al., 2024), the application can more effectively capture accurate, high-resolution data that faithfully represent users' travel trajectories and behaviors. Conversely, delivering high-quality, personalized recommendations is likely to boost user engagement, which in turn supports sustained, long-term use of the app across a diverse user base.

This study aims to bridge the gap between mobility data collection and personalized recommendations by investigating the integration of open-source mobility data collection platforms with recommendation systems to enable adaptive, user-specific travel suggestions. We begin with a comprehensive literature review focusing on three major components: (1) open-source platforms for mobility data collection, (2) recommendation systems used in travel domain, and (3) sources of public location-based recommendation datasets. By synthesizing insights from these domains, we identify existing technical capacities and highlight integration opportunities to enable a data-driven feedback loop between user behavior and system recommendation. As a preliminary investigation, we apply a baseline recommendation model to the Yelp dataset to explore how location-based recommendation data can inform travel activity suggestions. These early experiments demonstrate the potential for using points-of-interest (POI) data to generate personalized recommendations and serve as a foundation for incorporating richer mobility patterns. Building on these findings, we introduce our collected dataset using NREL's OpenPATH platform. This dataset contains detailed travel trajectories and user-reported annotations from a pilot cohort. We conduct exploratory data analysis to characterize typical travel behaviors. Based on these insights, we present preliminary results of travel behavior patterns derived from our collected data, followed by a discussion of data quality issues and the factors contributing to its limitations. Then we design a prototype personalized POI recommendation system with rewards to encourage users to accept the travel alternatives. We conclude by outlining the envisioned capabilities of the final application and its potential to inform long-term travel behavior change.

By closing the loop between mobility data collection and recommendation, this study offers a pilot framework to improve the relevance of travel suggestions tailored to users' individual travel behaviors. The proposed integration paves the way for more intelligent, sustainable, and user-centered transportation systems.

LITERATURE REVIEW

1. Open-Source Mobility Data Collection Platforms

The emphasis on open-source platforms in the context of mobility data collection stems from their inherent advantages of transparency (Bemmann et al., 2022), reusability (You et al., 2020), and the potential for customization (Al-Rahamneh et al., 2021). These platforms can play a crucial role in public access to mobility data collection tools, although they also present unique challenges.

NREL OpenPATH: It is an open-source, extensible smartphone platform for collecting travel diary data (Shankari et al., 2018). It consists of a mobile app for Android/iOS and cloud-based server components. The system continuously captures location traces (GPS coordinates), along with phone sensor data, e.g. accelerometer, to infer travel modes, and allows user input such as prompted annotations or survey responses. Data collection is largely automated - the app can detect trip start/end and record routes and modes (e.g. walk, bike, car, transit) without requiring manual input for each trip. The platform produces an output travel diary: a sequence of trips and segments with modes and purposes identified. The architecture follows an IoT-like sensor-server-client model: the phone acts as both sensor (collecting data) and client (displaying personalized information), while the server handles data upload, processing pipelines (often written in Python for extensibility), and provides a REST API for analysis and external integration. Crucially, NREL OpenPATH was built with extensibility in mind. It is fully open-source and modular, allowing researchers to customize surveys, add new sensors or analysis modules, and integrate with other tools with relatively little effort. In a pilot deployment (Shankari et al., 2018), over 150 users installed the app in one month, and the platform was found to be stable and usable, with over 85% of users retaining the app beyond 3 days. This demonstrates its viability for real-world studies. The platform also adds features like energy/emissions estimates for trips. NREL OpenPATH enables logging of multi-modal trips (e.g. segments by car, bus, bike, etc.) and automatically computes associated energy use and carbon footprint for each trip. It includes a dashboard interface for users and project administrators, supporting visualizations of individual travel patterns and program-wide monitoring. Because of its open design, OpenPATH is highly adaptable for integration (Greenlee et al., 2024). Developers can fork the code to build new functionality, or use its API to feed data into external applications. However, reported accuracies of automated mode detection typically range around 70-80% in the system, which limits the reliability of the data for downstream tasks such as learning users' travel behaviors.

OneBusAway: Initially developed as a real-time transit information provider, OneBusAway has been extended to include capabilities for passively collecting multimodal travel behavior data from users who opt-in to participate (Ferris et al., 2010b). This platform has been utilized in several U.S. cities, including New York City, Tampa, and Atlanta, for examining the impact of real-time transit information on ridership levels and overall travel behavior (Watkins, 2011). The data collected encompasses multimodal travel patterns and, with user consent, can potentially be linked to transit trip histories from smart card systems. The strength of OneBusAway lies in its ability to leverage an existing and often widely adopted transit information platform, thereby enabling large-scale data collection and facilitating natural experiments (Ferris et al., 2010a). When linked with other data sources, it can support disaggregate analysis of travel behavior. Nevertheless, data collection relies on user opt-in, and supplementary survey data collected alongside can be susceptible to recall bias and issues of sample representativeness. Furthermore, the availability and granularity of the data can be constrained by the policies of participating transit agencies and overarching privacy concerns.

Other Platforms and Standards: The landscape of open-source mobility tools and standards is continually evolving. The Open Mobility Foundation's Mobility Data Specification (MDS) is gaining traction as a standard for communication and data sharing, primarily between municipal authorities and private mobility service providers like e-scooter and bike-share companies. MDS is primarily aimed at regulatory and operational management and standardizes the data concerning vehicle status, location, and trips, explicitly excluding personally identifiable information of riders. General mobile sensing frameworks like AWARE (Ferreira et al., 2015; van Berkel et al., 2023) and the now-defunct Funf have also been used in research to log location and activity data on phones, but they require building custom analysis pipelines. There are also proprietary systems like Google's Location Timeline (Macarulla Rodriguez et al., 2018), Apple Health/Maps (Jung et al., 2019), or the former Moves app (Evenson & Furberg, 2017), which tracked users' movements and modes automatically. These commercial platforms demonstrate the feasibility and popularity of passive travel logging, but their data is not easily accessible for custom integration and raises privacy concerns. Thus, open platforms like NREL OpenPATH are favored in research since they allow full control over data and the ability to plug in new modules, e.g. a recommendation algorithm, directly.

In summary, the ecosystem of mobility data collection apps provides a strong foundation for integrated solutions. The platforms capture rich multimodal data (trips, modes, timestamps, sensors) in a structured way and often include features (APIs, modular code, dashboards) that make them adaptable.

2. Travel Recommendation Systems

Personalized recommendation systems for travel aim to tailor suggestions or advice to an individual's mobility needs and preferences. In the context of daily travel, e.g., commuting, errands, leisure trips, personalization can take many forms. We outline several key categories of travel-related recommendation systems: route planning and navigation, transport mode choice, departure time optimization, and energy efficient travel suggestions. These categories often overlap in practice. For instance, an APP might recommend a multi-modal route (combining mode choice and routing) that also happens to minimize energy use and is presented with a motivational message (nudging). Here we explore each category and give examples of how recommendations are formulated and what data they use.

2.1 Route Planning and Navigation

Route recommendation systems suggest optimal paths from A to B, typically aiming to minimize travel time or distance. Modern navigation apps (Google Maps, Waze, etc.) use real-time traffic data to recommend the fastest route (Santos et al., 2011). However, basic navigation is not strongly personalized - it generally assumes all users want the "fastest" or "shortest" route. Recent research highlights the need for more personalized route planning that accounts for individual preferences (e.g. avoiding tolls, favoring scenic routes, or preferring bike-friendly paths) (Funke & Storandt, 2015; Niaraki & Kim, 2009; R. Wang et al., 2022). Many current systems allow users to specify some static preferences (avoid highways, etc.), but do not truly learn or adapt to a user's behavior patterns in real time (Jayasuriya & Sumanathilaka, 2025). Another aspect is real-time adaptability: if an unexpected disruption occurs (accident, transit delay), a personalized system could account for the user's context (e.g. willingness to walk vs. wait) in rerouting (Mirchandani & Head, 2001; Szczerba et al., 2000). Some studies (Donoso et al., 2013; Lorenz et al., 2013; Ruiz et al., 2024; Zhang et al., 2022) are applying machine learning (e.g. reinforcement learning or collaborative filtering) to predict not just travel time but user satisfaction with routes, adjusting recommendations accordingly. Safety and comfort can also guide route recommendations: e.g., routing cyclists along quieter streets or pedestrians through well-lit paths (Sohrabi et al., 2022; Zaoad et al., 2023). In sum, route planning is evolving from one-size-fits-all directions to context-aware, user-specific navigation. An integrated platform would exploit the continuous data it collects (routes taken, travel times, feedback) to refine future route suggestions for that user, creating a feedback loop of improvement.

2.2 Transport Mode Choice Recommendations

Another class of recommendation focuses on which mode of transport a person should take for a trip. A personalized system can recommend a mode (or combination of modes) based on criteria like travel time (Vautard et al., 2021), cost (McCarthy et al., 2017), and personal preferences (Lind et al., 2015). Lai et al. (2023) propose the Balance Multi Travel Mode Deep Learning Prediction (BMTM-DLP) model, which extracts user-specific travel preferences from historical trip data, enabling a more personalized prediction of mode choice rather than relies solely on aggregate traveler characteristics. Mode choice recommender systems often tie into policy goals like reducing single-occupancy vehicle trips or increasing active travel. Xu et al. (2021) demonstrates how a personalized trip planning system can influence sustainable travel behavior by recommending eco-friendly modes such as walking, cycling, and public transit based on individual preferences and contextual data. There have been field experiments where commuters receive recommendations to switch modes along with incentives (W. Wang et al., 2022). Castellanos (2016) conducts a field study in Bogota, Colombia. It explores the effectiveness of both monetary and non-monetary incentives delivered via a gamified smartphone app to encourage modal shifts toward sustainable transport modes. Personalized mode recommendations can also factor in user constraints, e.g., knowing that the user has a bike available (Campigotto et al., 2017), or is physically capable of walking a certain distance (Arnaoutaki et al., 2021). Modern APPs like Citymapper (Tavmen, 2020) or Transit (Bian et al., 2022) compare modes, but a deeper personalization might integrate the user's own history from collected data to anticipate which mode they are likely to be comfortable with. Ultimately, mode-choice recommendation systems strive to present travelers with better alternatives to their default choice, in a user-friendly way.

2.3 Departure Time and Scheduling Optimization

Departure time recommendation systems aim to help users choose the optimal time for a trip, often to avoid congestion or crowds. Real-time navigation apps already incorporate some of this (e.g. "leave by 7:45 to arrive by 8:30") (Jeske, 2013; Mehta et al., 2019), but a personalized system could go further by learning a user's schedule constraints and typical flexibility. The incenTrip app (Xiong et al., 2020) targets departure time (as well as mode and route) optimization. IncenTrip provides real-time multimodal traveler information and uses large-scale models to predict congestion; it then personalizes incentives for each trip, encouraging users to travel at off-peak times if possible. In practical terms, incenTrip might tell a commuter: "If you leave 15 minutes later than usual today, traffic will be lighter and you'll earn reward points for helping reduce peak congestion." By aligning individual benefit (less delay, plus points or monetary rewards) with system benefit (smoother demand), such systems achieve a win-win. Khademi (2024) proposes a modeling framework that generates optimal departure time recommendations by extending existing departure time choice models to account for unreliable travel times. The study distinguishes between scenarios with constant versus time-varying travel time variances and demonstrates that system-generated recommendations can significantly outperform individual judgment, particularly during peak periods when travel time uncertainty is higher. This highlights the value of integrating data-driven departure time advice into personalized travel recommendation systems to minimize user travel costs and enhance overall efficiency.

2.4 Energy-Efficient and Eco-Friendly Recommendations

With growing emphasis on sustainability, recommendation systems have emerged that focus on energy efficiency and reducing emissions. These systems might recommend routes or modes that save fuel or electricity, even if they are not the fastest. For instance, an eco-routing engine can suggest a path that avoids steep hills and stop-and-go traffic to reduce fuel consumption (Fahmin et al., 2025; Woo et al., 2024). Google Maps introduced an "eco-friendly routing" option that by default shows the most fuel-efficient route when its ETA is comparable to the fastest route (Jovanovic et al., 2024). This feature uses AI to identify routes with fewer hills or less idling, and it displays the potential fuel savings to the user. Beyond routing, an integrated system can also recommend mode shifts for energy reasons, e.g. suggesting public transit or carpool to reduce carbon footprint (Shah et al., 2020). Some research prototypes, such as the Persuasive Coach for CO2 Reduction (PEACOX) (Schrammel et al., 2013), explicitly combined route planning with eco-feedback. The PEACOX provided a smartphone navigation app that offered eco-friendly travel suggestions and then gave users feedback on the environmental impact of their choices. By making users aware of their travel carbon footprint and showing improvements when they choose greener options, the system aimed to encourage sustained behavior change. A challenge here is balancing competing objectives: a route that is energy-efficient might be slower; a mode that is eco-friendly might be less convenient for the user. A personalized system can attempt to find the sweet spot, identifying opportunities when a user can reduce impact with minimal sacrifice (or even gain benefits like exercise). In summary, energy-focused recommendation systems extend the traditional notion of "optimal" travel to include environmental criteria.

3. Public Location-Based Social Network Data

Location-Based Social Network (LBSN) data is a valuable resource for understanding human mobility, user preferences, and social influence in spatial contexts (Bao et al., 2015; Kim et al., 2020). These datasets are typically collected from platforms where users voluntarily check in at various venues, generating rich spatiotemporal records. Public LBSN datasets have been widely used in research areas such as POI recommendation (Ye et al., 2010), mobility modeling (Cho et al., 2011), urban computing (Silva et al., 2020), and location prediction (Comito, 2020).

Table 1 presents a summary of several widely used public LBSN datasets, each with unique characteristics in terms of user scale, check-in density, and geographic coverage.

The Foursquare dataset (Bao et al., 2012) is collected at the city level, specifically targeting locations such as Tokyo (Deeva et al., 2020), New York (Sun, 2016) and London (Quercia & Saez, 2014). Beyond check-in and social relationship data, this dataset also provides enriched contextual information, including user profiles, and venue categories. However, it lacks temporal continuity, as the check-ins are not recorded with timestamps and cannot be used for sequence modeling. In contrast, the Brightkite and Gowalla datasets (Cho et al., 2011) include both user friendship networks and temporally ordered check-in sequences. Each check-in record contains geographic coordinates and timestamps, making these datasets suitable for modeling user mobility over time. The Gowalla dataset also offers user comments. The Yelp dataset (https://business.yelp.com/data/resources/open-dataset/) includes detailed information about local businesses, user reviews, and ratings. Each business entry contains metadata such as location, category, and star rating. The dataset also provides user profiles, which include check-in records, review text, and social connections through user friendship links. While the dataset spans multiple cities and contains a large number of users, it is characterized by a high degree of sparsity - many users have only a few check-ins or reviews. This makes the Yelp dataset a challenging but valuable resource for studying location-based recommendation systems, review modeling, and user behavior analysis in real-world settings.

Table 1 The characteristics of public LBSN datasets.

Dataset	Number of Users	Number of Check-ins	Check-ins per User
Foursquare	114,508	1,434,668	13
Foursquare (Tokyo)	10,057	921,874	92
Foursquare (New York)	7,832	315,472	40
Foursquare (London)	4,443	141,402	32
Birghtkite	58,228	4,491,143	77
Gowalla 1	196,591	6,442,890	33
Gowalla 2	53,944	4,128,714	77
Yelp	1,326,101	5,261,669	4

PRELIMINARY INVESTIGATION

To evaluate the performance of recommendation algorithms for POI recommendation, we assess ItemKNN (Deshpande & Karypis, 2004) on the widely used public LBSN dataset, Yelp (https://business.yelp.com/data/resources/open-dataset/). ItemKNN is a K-nearest-neighborhood-based method recommending items based on item cosine similarity. The characteristics of Yelp dataset are summarized in Table 2. To ensure the model has sufficient data to effectively learn user preferences and recommend subsequent locations, we apply two filtering strategies: a 5-filter and a 10-filter, which remove users and items with fewer than 5 and 10 check-ins, respectively.

Table 2 The characteristics of Yelp dataset.

Dataset	Number of Users	Number of Check-ins	Check-ins per User
Yelp (5-filter)	227109	3419587	15
Yelp (10-filter)	96168	2458153	26

We consider 70 nearest neighbors in the ItemKNN algorithm to provide recommendations for users. The dataset is split into training and test sets with a 4:1 ratio. Each user is presented with a candidate set of 1000 items, which includes items from the test set as well as randomly sampled items from the entire item pool excluding those the user has interacted with in the training set. To evaluate the recommendation performance, we adopt three widely used metrics in recommender systems:

- **Precision:** It represents the probability that a recommended POI is relevant. *P@n* is defined as the ratio of the recommended and relevant POIs over the number of recommended POIs. *Rel@n* denotes the number of relevant POIs recommended at top n.

$$P@n = \frac{Rel@n}{n}$$

- **Recall:** It is the probability that a relevant POI is recommended. *R@n* is defined as the ratio of the recommended and relevant POIs over the number of relevant POIs. Rel_{tot} is the total number of the relevant POIs.

$$R@n = \frac{Rel@n}{Rel_{tot}}$$

- **nDCG:** Discounted Cumulative Gain (DCG) is based on ranking position, and it measures the relevance of a recommendation list considering the relevance of the rank position. Ideal DCG (IDCG) represents the maximum achievable DCG with the same set of relevance scores but in the perfect ranking order. nDCG is the DCG divided by an ideal DCG that gives a normalized DCG. rel_k denotes the real relevance of POI k in the test set. In a rating-based dataset, this real relevance would be the rating that the user gave to that POI in the test set. In our case, as we only know whether (and when) a user has performed a check-in, we fix this ideal relevance to 1 as long as the POI appears in the test set of the user (every POI visited by the user in the test set is equally relevant). IDCG is computed in the same way as DCG but using the ground truth as the ranking.

$$DCG@n = \sum_{k=1}^{n} \frac{2^{rel_k} - 1}{log_2(k+1)}$$

$$nDCG@n = \frac{DCG@n}{IDCG@n}$$

Table 3 and Table 4 present the results of performances on 5-filter and 10-filter Yelp dataset respectively when recommending top n POIs to users where n = 1, 5, 10. When n increases, precision decreases. This indicates that the top-1 POI recommendation is more likely to be relevant. The chance of retrieving irrelevant POIs increases when expanding the recommendation list size. Recall increases with n for both datasets since more items are retrieved, increasing the chance of including relevant ones. nDCG increases with n, indicating that as the recommendation list expands, relevant POIs are still ranked relatively high, especially with richer user history in the 10-filter dataset. The 10-filter dataset, which retains users with more check-in history, consistently outperforms the 5-filter dataset across all metrics. This confirms that better user history improves the ability of ItemKNN to capture preference signals.

Table 3 Recommendation performance on Yelp (5-filter).

Metrics@n	n=1	n=5	n=10
Precision	0.212	0.133	0.095
Recall	0.060	0.153	0.194
nDCG	0.212	0.285	0.294

Table 4 Recommendation performance on Yelp (10-filter).

Metrics@n	n=1	n=5	n=10
Precision	0.289	0.205	0.158
Recall	0.058	0.176	0.247
nDCG	0.289	0.396	0.411

DATA COLLECTION

NREL OpenPATH (Shankari et al., 2018) is an open-source, extensible smartphone platform designed for collecting users' mobility data. It includes a mobile application available for both Android and iOS, along with supporting cloud-based server infrastructure. In our study, we leverage NREL OpenPATH to collect mobility data from participants, who are recruited through a dedicated website (https://uw-prs-openpath.nrel.gov/join/?sub_group=default) that outlines the study's purpose. The website interface is provided in Figure 1.

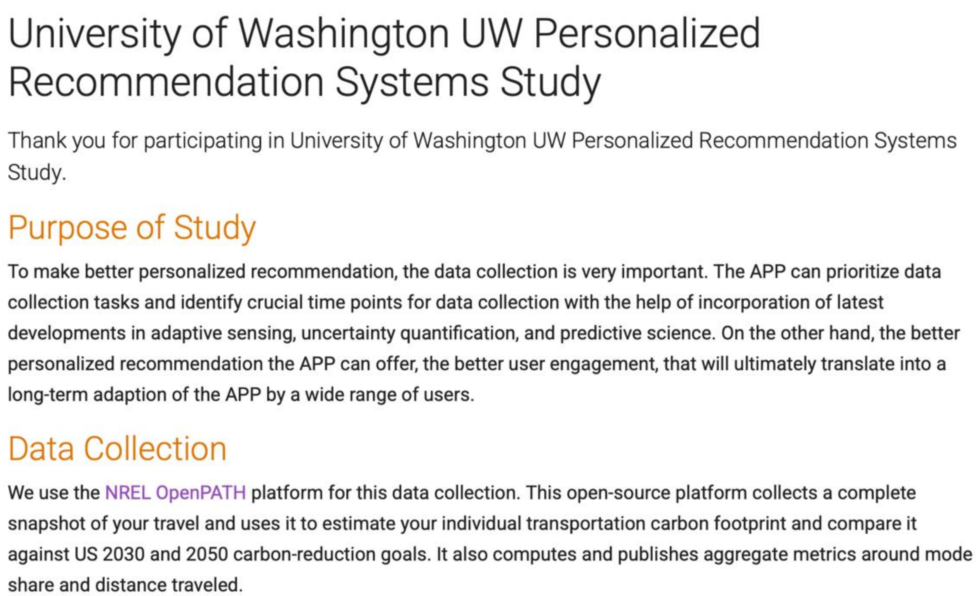

Figure 1 Website to recruit the participants to join our mobility data collection study using NREL OpenPATH.

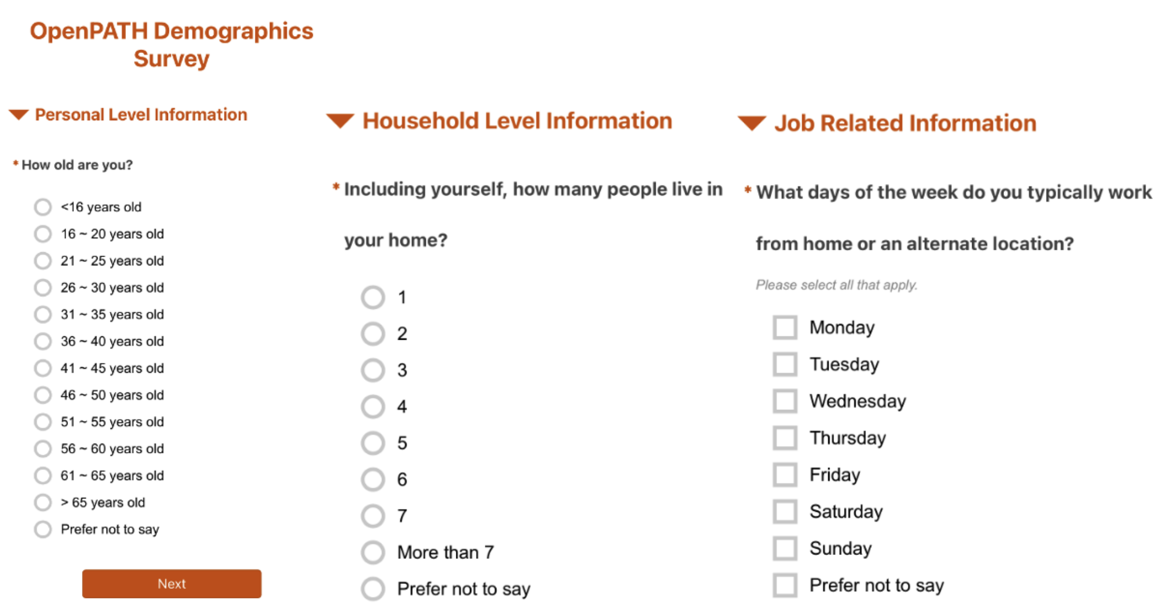

Figure 2 Some question examples in the survey, including personal level, household level and job related information, in NREL OpenPATH.

We customize the OpenPATH app interface (https://github.com/e-mission/nrel-openpath-deploy-configs/blob/main/configs/uw-prs.nrel-op.json) to support both the collection and visualization of the data relevant to our study. Upon account creation, participants are prompted to complete a demographic survey, which gathers personal, household, and job-related information. Example survey questions are shown in Figure 2.

Once the survey is completed, the mobile app begins collecting mobility data. The system continuously tracks GPS coordinates and uses smartphone sensor data (e.g., accelerometer) to automatically detect trips. It infers the trip's start and end times, locations, routes, travel modes, and distances. Participants can manually correct any misclassified transportation modes and specify the trip purpose. The app interface for trip tracking and editing is shown in Figure 3. The platform ultimately generates a travel diary, consisting of a sequence of trips and segments, each labeled with inferred modes and user-confirmed purposes.

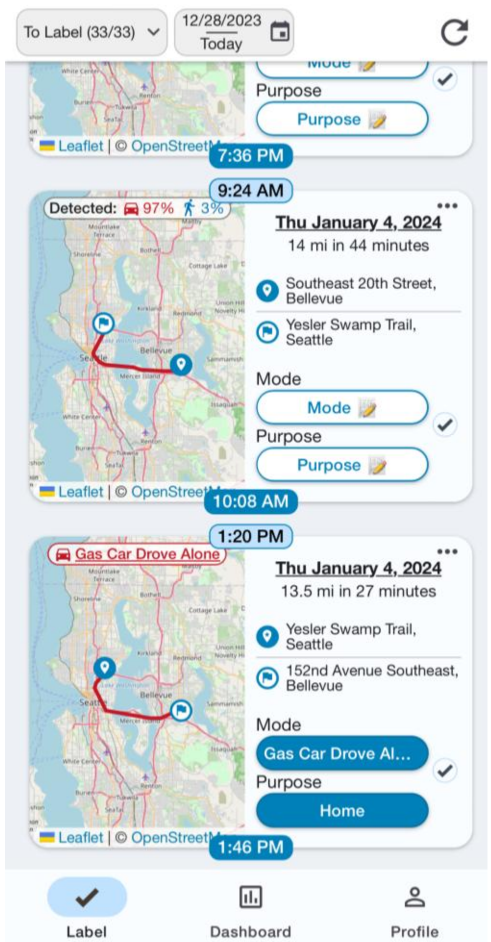

Figure 3 NREL OpenPATH APP interface.

We collected data from 10 participants, resulting in a total of 3,376 trips recorded between March 2024 and May 2025. Figure 4 illustrates the participant sign-up trend over the course of the study. Figure 5 displays a bubble map of all trips with starting and ending points located within the United States, with Washington State having the highest concentration of trips. Figure 6 shows a portion of the trip density heatmap for Washington State in May 2025, highlighting areas of frequent mobility activity.

Figure 4 Sigh-up trend of participants for our data collection study.

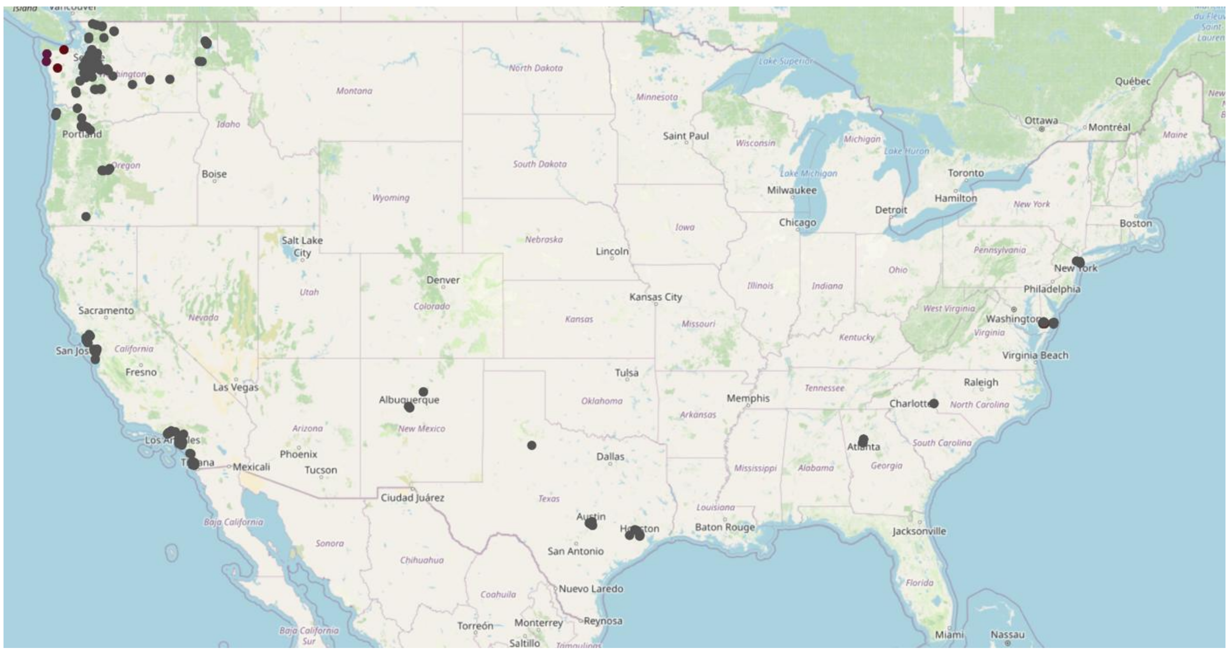

Figure 5 Bubble map for all the trips in the U.S. from March 2024 to May 2025.

The platform also includes features for estimating energy consumption and carbon emissions associated with each trip. NREL OpenPATH automatically calculates the energy usage and carbon footprint for individual trip segments based on the detected travel modes. Figure 7 presents an example visualization from the user interface, showing daily energy usage and emissions by week.

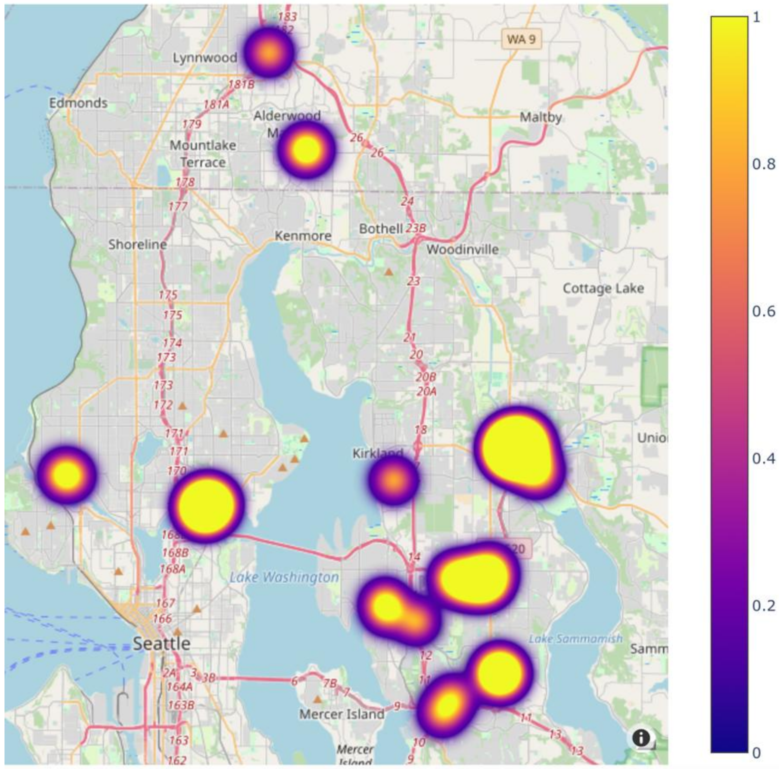

Figure 6 Density heatmap for some trips in the Washington state in May 2025.

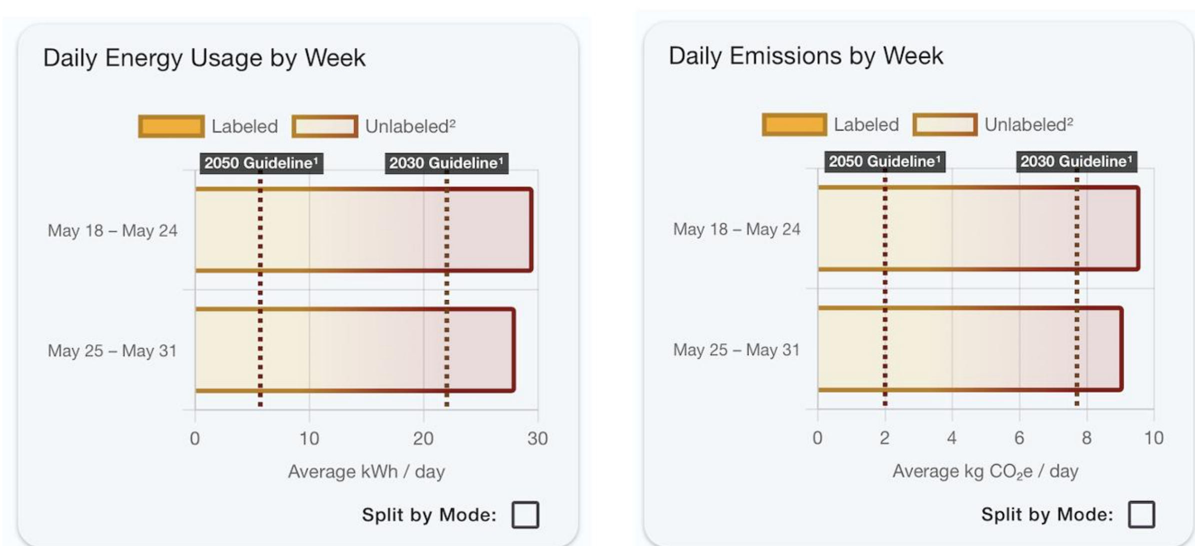

Figure 7 Daily energy and emissions by week in the user interface from NREL OpenPATH.

RESULTS AND ANALYSIS

The summary statistics of our collected mobility data are available on the website (https://uw-prs-openpath.nrel.gov/public/), where users can interactively adjust the metrics and time range to explore different subsets of the data.

Figure 8 shows the distribution of trips by transportation mode. Out of 10 participants, 3 did not contribute usable mobility data, resulting in a total of 3,376 sensed trips from the remaining 7 participants. Among these trips, the majority (50.8%) were classified as "IN_VEHICLE" (e.g., private car, taxi), followed by 26.8% marked as "UNKNOWN", and 18.5% as "WALKING". A smaller proportion was detected as "BICYCLING" and "OTHER". Of the 7 participants, 6 provided manual labels for their trips. For trips manually labeled by users (107 trips), "Walk" accounted for 31.8%, followed by "Gas Car Shared Ride" (29.0%) and "E-Car Shared Ride" (10.3%). Similar trends were observed in the 158 inferred trips, where "Walk" remained dominant at 32.3%, and "Gas Car Shared Ride" at 28.5%. When the APP's automatically detected labels are incorrect, users may voluntarily correct them, though this correction is not required. The results highlight a significant discrepancy between sensed and manually labeled data, suggesting that the app has limitations in accurately distinguishing between different transportation modes, e.g., walking and vehicular modes of travel.

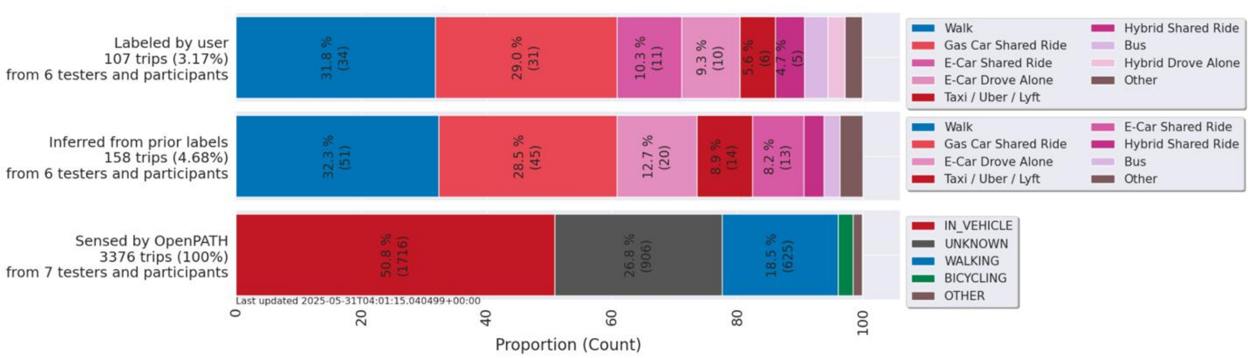

Figure 8 The number of trips for different transportation modes.

Figure 9 presents the total mileage distribution by transportation mode. In the sensed data, the largest share of distance was covered by "AIR_OR_HSR" (72.8%), indicating that long-distance travel modes contributed significantly to overall travel miles, despite being low in trip count. This is followed by "IN_VEHICLE" (22.1%), while "UNKNOWN" and "OTHER" made up 4.1%. In contrast, for user-labeled trips, most miles were associated with "Gas Car Shared Ride" (55.7%) and "E-Car Shared Ride" (16.3%). Inferred labels produced a similar pattern. These results suggest that while walking and short-range travel modes dominate in frequency, shared car rides (particularly gas-powered) dominate in terms of mileage.

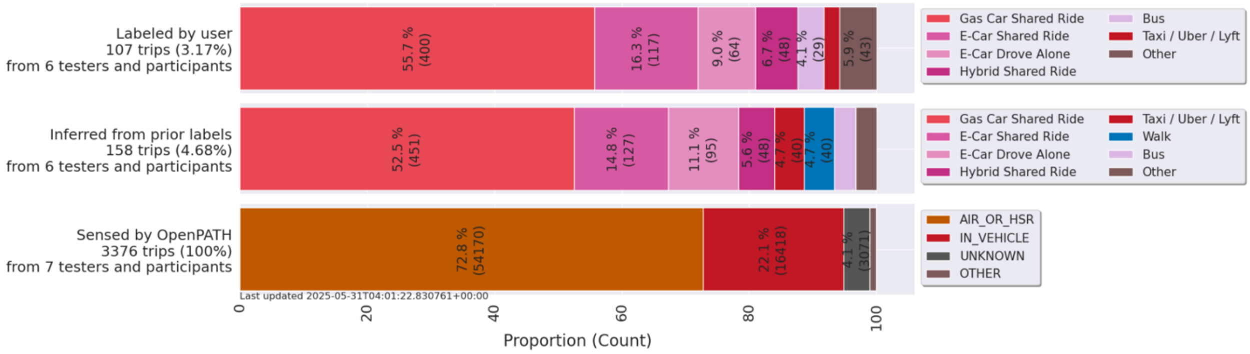

Figure 9 Total trip length (miles) covered by mode.

As shown in Figure 10, trip purpose data was provided for 107 user-labeled and 158 inferred trips. A substantial majority of trips fell under the "Other" category (60.9% user-labeled, 67.9% inferred), suggesting either a lack of predefined purpose options or unclear intent from participants. Among the clearly labeled purposes, "Home" trips were the next most common (11.2% user-labeled), followed by "Meal", "Recreation/Exercise", and "Shopping" trips. The diversity of trip purposes reflects the general, everyday travel behaviors of participants.

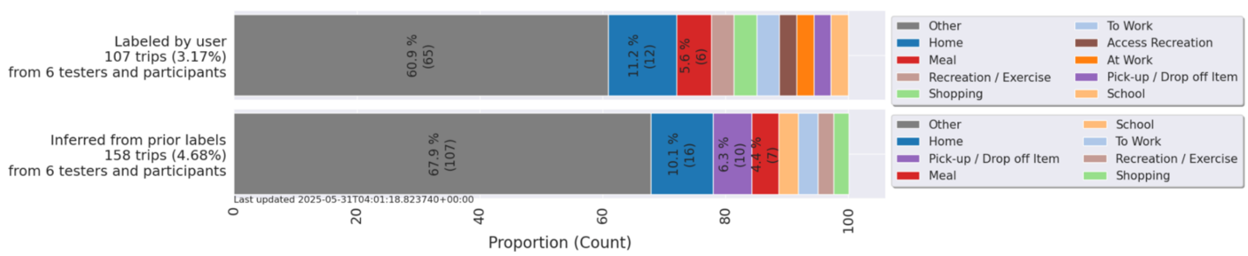

Figure 10 The number of trips by travel purpose.

Figure 11 shows the distribution of trips by weekday. The number of sensed trips peaked on Saturday (over 600 trips) and Friday, with the fewest occurring on Monday. This pattern reflects higher mobility during weekends, potentially due to non-work-related activities, while weekdays, especially Mondays, saw fewer trips, likely due to work-from-home schedules or reduced mobility at the start of the week.

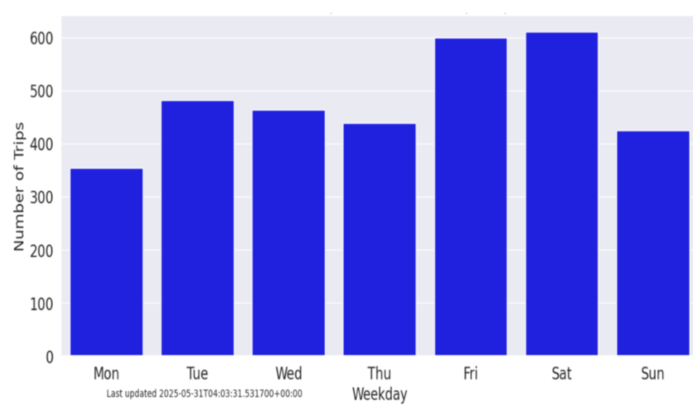

Figure 11 The number of trips by weekday based on 3,367 trips from 7 participants.

Despite the utility of the OpenPATH platform for mobility data collection, our analysis identified several recurring quality issues when comparing recorded trips to ground truth annotations from partcipants. These discrepancies affect the accuracy of the trip segmentation, mode detection, and location estimation. Below are the primary categories of data quality problems:

(1) Inaccurate Trip Segmentation

Several errors stem from the app's inability to properly segment trips:

- **Failure to detect trip end:** In some cases, the app continued recording even after the user had completed their trip, leading to overestimated durations and distances.
- **Splitting one trip into two:** Temporary stops due to traffic or user inactivity (e.g., stopping for a minute) were incorrectly interpreted as separate trips.
- **Combining two distinct trips into one:** When there was a significant pause (e.g., one hour) between trips, the app failed to segment them properly, merging them into a single continuous trip.

(2) Location Detection Errors

The app occasionally misidentified the start and end locations. For example, the user traveled by boat on Lake Washington, but the app inaccurately registered the start and end locations on land due to limitations in GPS signal interpretation over water.

(3) Incorrect Mode Detection

Errors in transportation mode classification were frequently observed. For example, when the user was walking, the app incorrectly detected the activity as biking. Such misclassifications suggest that OpenPATH's current sensing and classification algorithms may lack sensitivity to nuanced movement patterns, particularly for distinguishing between walking, biking, and short car trips.

(4) Route Mapping and Distance Misestimation

Trip paths recorded by OpenPATH occasionally deviated significantly from actual routes. For example, the app rendered the user's path as a straight line rather than following the road network, resulting in an underestimation of the trip distance and unrealistic trajectories.

PERSONALIZED RECOMMENDATION SYSTEM WITH REWARDS

To enhance user engagement and support sustainable travel behavior, we designed a personalized recommendation system that integrates reward-based incentives into mobility suggestions using the NREL OpenPATH platform. This system offers users customized POI recommendations, such as nearby parks, restaurants, gyms, or museums, paired with dynamic reward points to motivate behavioral adoption.

Figure 12 illustrates the overall system flow. When a user opens the OpenPATH app at a specific time and location, the backend recommendation engine suggests a personalized POI, denoted as p, accompanied by a reward point offer r. The user u can either accept or reject this recommendation, generating a decision c. Each interaction is recorded as a tuple (u,t,l,p,r,c), where t is the time and l is the location of the interaction.

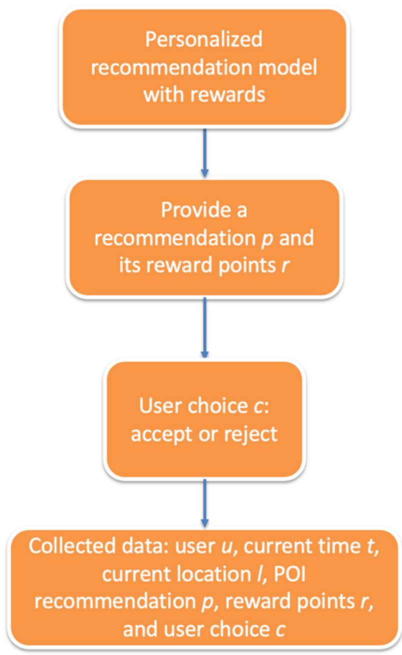

Figure 12 The overview of the proposed personalized recommendation system for travel location.

This process is designed to be iterative and adaptive. As the system collects more interaction data, it updates its recommendation and reward prediction models to better reflect individual user preferences. For example, if a user frequently accepts POI recommendations offering moderate rewards for walking to nearby parks, the system will prioritize similar suggestions in future interactions. Over time, the algorithm becomes increasingly personalized in both the types of POIs it suggests and the magnitude of rewards offered.

Figure 13 showcases a sample question presented to users. The interface dynamically highlights the recommended POI and the associated reward, prompting the user to make a decision. This interaction is lightweight and embedded in the natural app usage flow, ensuring minimal friction while collecting valuable feedback data. The integration of rewards serves dual purposes: incentivizing exploration of recommended alternatives and enabling more accurate learning of user travel preferences. Importantly, reward levels can be adjusted based on the likelihood of user acceptance, offering higher incentives for unfamiliar or less convenient alternatives, and reducing points for well-matched suggestions that users are likely to accept without additional motivation. By tuning both the content (POI type) and framing (reward magnitude) of recommendations, the system aligns individual incentives with broader transportation objectives, such as reducing car usage or promoting visits to underutilized locations.

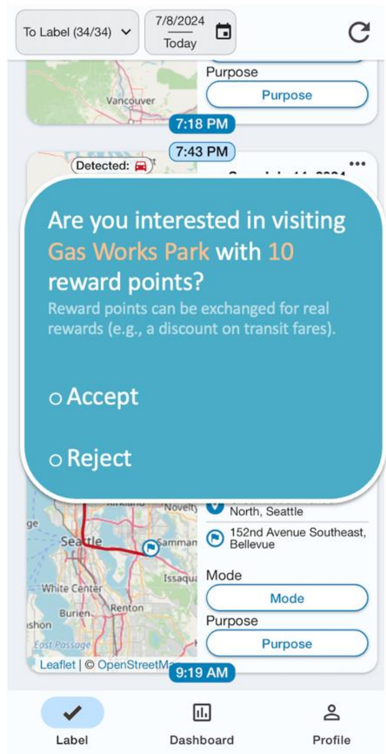

Figure 13 An example recommendation with rewards for users to answer.

Ultimately, the goal of this recommendation system is to build a data-driven feedback loop: better user data enables better recommendations, and better recommendations encourage more app engagement and behavior change. This pilot implementation provides a foundation for scalable, personalized interventions that can nudge individuals toward healthier, more sustainable travel behaviors while respecting user autonomy and preferences.

CONCLUSIONS

This pilot study demonstrates the feasibility and potential benefits of integrating mobility data collection platforms with personalized recommendation systems to influence individual travel behaviors. By leveraging the NREL OpenPATH platform, we collected detailed mobility traces and self-reported annotations from a small cohort of users over an extended period. Despite several data quality challenges including inaccurate trip segmentation, mode misclassification, and route estimation errors, the platform proved capable of capturing rich spatiotemporal mobility data essential for understanding user behavior. Our analysis of the collected data highlights diverse travel modes and purposes, revealing key discrepancies between sensed and labeled trips that must be addressed to improve system reliability. These findings underscore the importance of enhancing sensing accuracy and user interface design to support more consistent and interpretable data annotation.

On the recommendation front, we demonstrated that publicly available POI datasets like Yelp can effectively serve as training grounds for baseline recommender models. Our experiments with ItemKNN confirmed that users with richer mobility histories yield better recommendation performance across precision, recall, and nDCG metrics.

Building on these insights, we proposed and prototyped a reward-based, personalized recommendation system that dynamically adapts suggestions and incentives based on user preferences and behavioral responses. This system lays the groundwork for a feedback loop in which better data enables better recommendations, which in turn foster sustained user engagement and more sustainable travel choices.

Future work will expand the user base, refine the sensing and labeling accuracy of the data collection platform, and explore more sophisticated recommendation models, including reinforcement learning and causal inference frameworks. Ultimately, this integration offers a promising direction for developing user-centered, intelligent transportation systems that align individual incentives with collective mobility goals.

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