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Data fusion for travel analysis: linking travel survey and mobile device location data

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Abstract
Travel surveys typically collect detailed information about demographics and travel behavior of households and persons; but their sample sizes are often limited, and trip information is usually limited to a single day. In contrast, Mobile Device Location Data (MDLD) provides extensive and accurate trip records spanning multiple days for each person from a much larger sample, while demographic information for the individuals are always lacking due to anonymization. This study constructs data panels combining high-precision, long-term trip records from MDLD with detailed demographic information from a regional travel survey (RTS). Two probabilistic record linkage algorithms are employed to identify individuals with similar travel behaviors between RTS and MDLD datasets. The data panels constructed by the linkage algorithm captured not only peak-hour commutes but also off-peak travel and non-home-related trips, shedding light on previously underreported travel behaviors and offering a more holistic view of individuals' travel patterns. This comprehensive dataset also exhibits comparable demographic characteristics to the original RTS, showing that such data panel is a reasonable representation of the entire population. The integration of diverse datasets holds promise for revolutionizing travel behavior analysis and shaping the future of transportation planning in the era of mobile technology and big data.

Keywords Travel behavior · Mobile device location data · Travel survey · Probabilistic record linkage · Data panel

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Introduction

Urban transportation systems play a critical role in shaping the quality of life in cities, and understanding travel behaviors is essential for effective transportation planning and policy development. Traditionally, travel surveys have served as the primary data source for studying travel behaviors, providing valuable insights into commuting patterns and travel preferences (Nakamya et al. 2007). Typically, travel surveys gather data regarding individuals' socio-economic and demographic information, as well as a journey diary for a specific day, which includes information about the starting and ending locations, times, mode of travel, companions, and purpose of each trip (Hong et al. 2021). However, these surveys have several limitations that can impact the accuracy and comprehensiveness of the data collected, such as reporting bias, where people may inaccurately recall or report all of their travel activities, leading to underreporting or misrepresentation of certain trips (Clarke et al. 1981). Non-response bias is another concern, as certain groups of people may be less likely to participate in the survey, potentially skewing the representation of travel behaviors (Richardson et al. 1996). Moreover, travel surveys often have a limited timeframe, capturing data for only a specific day or short period (Stopher et al. 2008), and they may rely on relatively small sample sizes of participants (Stopher et al. 2011), limiting the representation of travel behaviors. Therefore, to overcome these limitations and obtain a more comprehensive and precise understanding of travel behaviors, there is a growing need to explore alternative data sources that can complement and enhance the insights derived from travel surveys.

In recent years, the landscape of travel data collection and analysis has been dramatically transformed by the rise of mobile devices and cutting-edge data collection technologies. With the widespread adoption of GPS-enabled smartphones and other mobile gadgets, an invaluable resource known as Mobile Device Location Data (MDLD) has become available (Yang et al. 2023). In contrast to conventional travel surveys, which rely on sporadic and self-reported data, MDLD distinguishes itself by accurately documenting the precise locations and movement trajectories of individuals throughout their daily routines (Hu et al. 2023; Ratti et al. 2006; Zhao et al. 2025). This continuous influx of high-resolution location data provides an intricate portrayal of travel behaviors, showcasing origin and destination points, travel routes, and durations spent at specific sites (Schüssler and Axhausen 2008). Through extended data collection periods, MDLD unveils the temporal dynamics of travel patterns, revealing differences between weekdays and weekends, peak and off-peak hours, and even seasonal variations in travel habits (Bachir et al. 2019). Additionally, MDLD illuminates recurring travel behaviors, exposing habitual routes and preferred modes of transportation among individuals, along with their frequently visited destinations (Ashbrook and Starner 2003).

Despite its promise, MDLD also has its own set of limitations. One of the main challenges lies in the lack of explicit demographic information, which limits its standalone applicability for conducting comprehensive travel behavior analysis (Rojas et al. 2016). Demographic factors play a crucial role in shaping travel patterns and preferences. For instance, age and employment status may influence the frequency and purpose of trips, with younger individuals and workers likely having different travel behaviors compared to retirees or students (Su et al. 2020). Similarly, household size and income level can impact choices of transportation modes and travel distances (Amoh-Gyimah and Aidoo 2013). By combining MDLD with traditional travel survey datasets like the Regional Travel Survey (RTS), researchers can

bridge the gap and create a more robust and comprehensive dataset (Rieser-Schüssler and Axhausen 2014; Wolf et al. 2001). At present, the research and application of the integration of survey data and location data mainly focus on two directions. One is GPS-based travel survey, where participants are asked to use hand-held GPS receiver (Murakami and Wagner 1999), wearable GPS devices (Hawkins and Stopher 2004), or smartphone Apps (Safi et al. 2015) to record their travel activities. A significant advantage of GPS-based travel survey is that the demographic information of participants are still self-reported, which makes it more reliable and detailed. However, a limitation of GPS-based surveys is the potential for sampling biases, as they depend on participants willing to respond to the GPS survey, similar to biases in traditional travel surveys (Stopher and Greaves 2007). In addition, both types of surveys share challenges related to representativeness, such as underrepresentation of certain demographics or travel behaviors. For example, GPS-based surveys often require participants to have access to GPS-enabled devices and the willingness to share location data, potentially excluding older adults, individuals with lower educational attainment, and less tech-savvy participants (Lugtig et al. 2022; Miyasaka et al. 2018; Oliveira et al. 2011). Conversely, traditional travel surveys face difficulties in achieving good response rates from younger individuals and heavy travelers (Bricka et al. 2012). To address these sampling bias issues in GPS-based surveys, studies have proposed methodologies such as hybrid data fusion (Wang et al. 2022), random spatial sampling (Maduekwe and de Vries 2019), and sample weighting (Frair et al. 2004). Incorporating these approaches can enhance the representativeness and overall value of GPS-based surveys. The other direction is applying population synthesis to location data, wherein socio-demographics in the location data are matched to the marginal control totals in aggregated census data (Janzen 2017) or household travel survey (Vo et al. 2024). However, this also requires a sub-sample of location data with known demographics, which is often scarce and challenging to obtain (Bwambale et al. 2021). There is a limited body of research focused on collecting long-term GPS trajectory data from travelers with known socio-demographic characteristics (Molloy et al. 2023). However, due to the high costs and challenges in maintaining participant engagement, the scale of such datasets remains relatively small compared to the large-scale MDLD.

This study proposes to enhance travel behavior analysis through the integration of MDLD and RTS datasets based on record linkage algorithms. Two data linkage approaches are utilized to connect individuals with similar travel behavior across datasets. The resulting data panels offer a more comprehensive representations of travel behaviors over multiple days, capturing not only peak-hour commutes but also off-peak travel and non-home-related trips. Additionally, they include representative population demographics, which contribute to the overall richness and reliability of the dataset.

The primary objectives of this study are as follows:

1. To explore the integration of MDLD and RTS datasets using two data linkage approaches: one based on a probabilistic method and the other on similarity-score method.
2. To construct data panels that offer a longitudinal perspective on individuals' travel behaviors, addressing some of the limitations of traditional survey methods.
3. To evaluate the effectiveness of each data linkage approach in capturing travel patterns and compare the characteristics of the integrated data panels with the original RTS and MDLD datasets.

4. To examine the representativeness of the data panels and discuss their potential implications for transportation planning and policy development.

In the following sections, we present the data used for data linkage, the methodology employed for panel construction, the results of the linking process, and a comprehensive analysis of the data panels, discussing the implications and potential applications of our findings for transportation planning and policy development.

Data

In this study, two primary datasets, whose data structure is elaborated in Table 1, are utilized to identify individuals with similar travel behaviors, and construct the data panel: trips collected in the Regional Travel Survey (RTS), and trips imputed from MDLD.

Regional travel survey (RTS)

The Regional Travel Survey (RTS), conducted by the Metropolitan Washington Council of Government (MWCOG) from October 2017 through December 2018, collected demographic and travel information from a randomly selected sample of 18,015 households with 39,325 individuals included in the metropolitan Washington region. Key components in the RTS Dataset include household, person, trip, and vehicle files. Trip details, including origin/destination, start/end times, mode of travel, and trip purpose are recorded. Demographic information of individuals, such as age, gender, household size, income level, and employment status are also included. While the RTS dataset provides valuable insights into the travel behavior and demographics of the surveyed individuals, it also has some limitations, for example, the RTS relies on a relatively small sample of participants, and is limited to information gathered on a single day, which may not fully capture the variations in travel behavior that can occur throughout different days of the week or across different seasons. Moreover, participants in the RTS might not recall or report all their trips, leading to incomplete trip records. Despite these limitations, the RTS remains a valuable source of information for understanding travel behavior in the region.

Table 1 Data structure of the two datasets

Dataset	Structure	Information Included
Regional travel survey (RTS)	Household file	Size, income, number of workers, drivers, and vehicles
	Person file	Age, gender, race, employment status
	Trip file	Origin/destination (census tract-level), start/end times (in minute), mode of travel, trip purpose
	Vehicle file	Make and model, year, fuel type
Mobile device location data (MDLD)	Raw location sightings	Anonymized device identifiers (ID), Latitude and longitude coordinates, Time stamps, Positioning accuracies
	With imputation	Home location of the traveler, Start and end time of the trip, Coordinates of the origin and destination of the trip, Imputed travel mode, Imputed trip purpose

Mobile device location data (MDLD)

The Mobile Device Location Data utilized in this study comes from a consistent national mobility data panel produced by the University of Maryland (UMD) team from multiple data vendors (Zhang et al. 2021). Generated from various positioning technologies such as cell phones, Global Positioning System (GPS), and location-based services (LBS), the MDLD comprises anonymous and accurate trip records from a much larger sample of individuals. The total sample includes over 68 million devices nationwide, each observed for at least 7 days in a given month with a minimum of 10 location pings per day. On average, devices were recorded for 24.2 days per month, with 234.4 sightings per day (Zhang et al. 2021). Like RTS Dataset, MDLD captures trip information including start and end time, coordinates of the origin and destination, the imputed travel mode, and the imputed trip purpose. Unlike the RTS, MDLD provides trip information for multiple days, offering a longitudinal perspective on individuals' travel behaviors. Also, MDLD collects information from a much larger sample of individuals due to the widespread use of mobile devices. By harnessing MDLD, researchers can gain a broader understanding of travel patterns over time for a broader sample of the population. However, the dataset lacks detailed demographic information due to anonymization processes that ensure privacy and data protection. While the MDLD provides valuable insights into travel patterns, the absence of demographic data limits the ability to analyze the relationship between travel behavior and specific demographic factors.

By combining the RTS's detailed demographic information with MDLD's high-precision, long-term trip records, the research aims to create a unique dataset that can provide insights into travel behavior trends and their connection to demographics at a broader scale. For the MDLD, we used the 2019 dataset, as it aligns closely with the 2018 RTS data. Anna Arundel County in the State of Maryland is chosen as the case study in this paper. To ensure data accuracy and relevance, both datasets were filtered to include only individuals and devices residing within Anna Arundel County. Additionally, the analysis was limited to trips occurring solely within the county, excluding any trips departing from or entering the county from different regions, to define a consistent case study area and to streamline the computational process. This filter was consistently applied to both datasets, ensuring it does not impact the accuracy or fairness of the analysis. Even with this exclusion, our method effectively identifies travelers with similar travel behaviors using their intra-county trips. It should be noted that the methodology is scalable to regional, state or national level.

Methodology

Figure 1 presents the methodological framework of this study. There are three major components: Data Preprocessing of RTS and MDLD, Identification of individuals with similar travel behaviors by two distinct approaches, and Construction of the data panel.

Data preprocessing

The data record linkage requires that both datasets have the same structure and comparable attributes. In the case of this study, the RTS already includes person information such as the

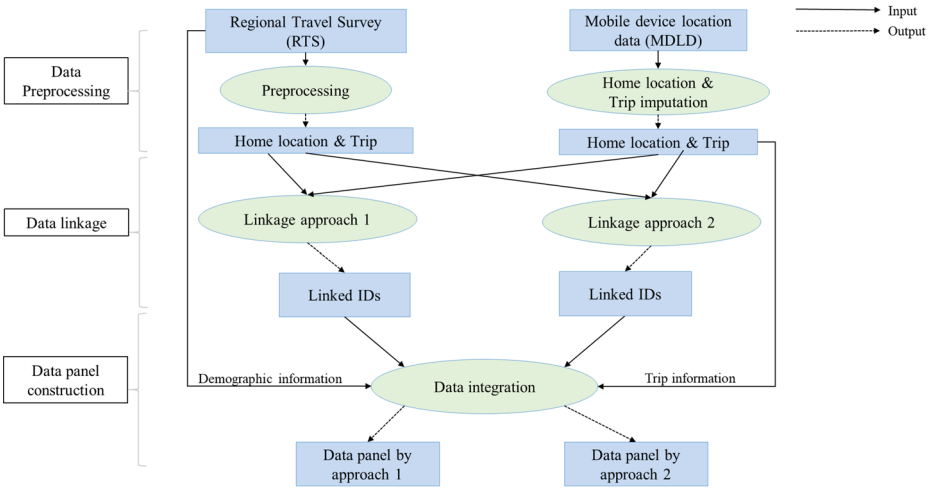


Fig. 1 Methodological framework

census tract of the home location, as well as trip details like census tract of origin/destination, start/end times, and more. However, the raw MDLD only contains location sightings with anonymized device identifiers (ID), latitude and longitude coordinates, time stamps, and positioning accuracies. To bridge this gap, a series of imputation algorithms are applied to derive the home location and trip information for each individual in the MDLD dataset (Zhang et al. 2021). A behavior-driven approach is utilized to identify devices' home locations, which are imputed as the census tract where the device is observed with the highest count of nights, hours, and sightings during nighttime. The workplaces are defined as the places with most observed hours and sightings during workdays. The work locations are distinct from the imputed home locations. (Pan et al. 2023).

For extracting trip information from the sightings, a tour-based method is employed. The algorithm recognizes essential tours based on the daily life centers—such as a typical home-destination-home tour composed of multiple trips between the daily life centers and other stops—and further examines location observations within each tour to construct the complete chain of trips. Between the major activity locations, the point-to-point travel time, distance, and speed from the current location observation to the previous sighting and the next sighting are examined through a recursive algorithm to identify the stops and trips.

The mode imputation process begins by separating air trips based on their distinct characteristics, such as being originated and destined at airports, having relatively longer distances, and exhibiting significantly higher speeds compared to ground transportation. A random forest model is then trained using various features, including the recording interval of sightings, distance, time, speed-related factors, and multimodal transportation network characteristics. This model classifies ground trips into Active Transportation (walking and biking), Motor Vehicle (automobiles and motorcycles), and Public Transit (buses and rail). The model achieves a cross-validation accuracy of 97.1% (Yang et al. 2022).

In addition, considering the imputed workplace, the purpose of each trip is determined with two steps. First, each trip end is assigned one of three labels: If the trip end matches the imputed home location of the traveler, it is labeled as "home". If the trip end matches

Table 2 Correspondence between categories of trip ends and trip purposes

Category of trip start - Category of trip end	Trip purpose
Home-Work/ Work-Home	HBW (Home-based work)
Home-Other/ Other-Home	HBO (Home-based other)
Work-Other / Other-Work	WBO (Work-based other)
Other-Other	OBO (Other-based other)

Table 3 Correspondence between travel mode in RTS and MDLD

Travel mode in RTS	Travel mode in MDLD
Auto (driver), Auto (passenger), Motorcycle, Taxi / Private Car, Uber/Lyft/Rideshare	Motor Vehicle
Bus, School Bus, Private Bus, Paratransit	Bus
Rail	Rail
Walk	Walk
Bike	Bike
Air	Air

the imputed work location of the traveler, it is labeled as "work", and all other trip ends are labeled as "other". Then, the correspondence between trip end categories and trip purposes is outlined in Table 2. Ultimately, each trip is labeled as either a HBW (Home-based-work), HBO (Home-based-other), WBO (Work-based-other), or OBO (Other-based-other) trip.

Finally, a daily trip roster is generated, where for each trip, a unique trip identifier, start and end time, coordinates of the origin and destination, trip purpose, and travel mode are included.

To conduct a comparison analysis between MDLD and RTS, several discrepancies need to be addressed. For instance, in RTS, trip purpose is divided into purpose for the trip origin and purpose for the trip destination. To align with MDLD, the trip purpose in RTS is converted using the correspondence outlined in Table 2. Similarly, for travel mode comparison, since modes in RTS are self-reported with more detailed categories, Table 3 is used to establish correspondences between RTS and MDLD modes, ensuring comparability. Additionally, the MDLD dataset may contain data from one or multiple recorded days for each device, while the RTS dataset records only one day for each person. To account for this difference, one day with the highest number of recorded trips is selected for each device in the MDLD data. This day is deemed to best represent the person and allows for meaningful comparisons between the datasets.

Data linkage

The record linkage techniques applied in this study rely on the methodology developed and extensively tested in Al-Khasawneh et al. (2025). Below, we provide a descriptive summary of this methodological work, and we refer interested readers to Al-Khasawneh et al. for further details. Figure 2 visually represents the data record linkage framework:

The framework presented above encompasses the fundamental steps involved in any data record linkage model, whether it is exact matching or supervised/unsupervised probabilistic matching. These steps include indexing/blocking, similarity measurement, and linking decision. However, each step may vary in its implementation across different record linkage

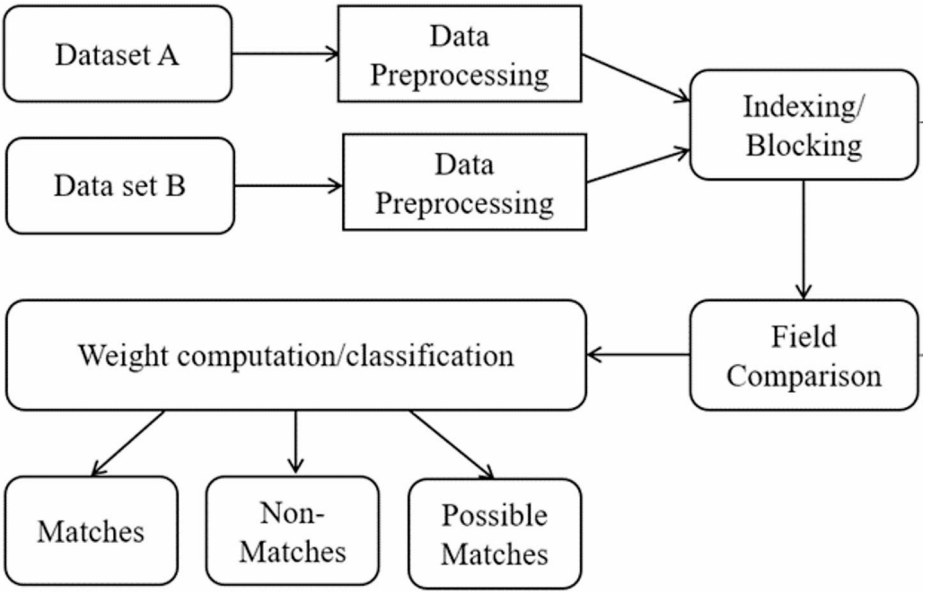


Fig. 2 Data record linkage framework

models. The selection of a specific model depends on various factors, such as the specific needs of the research, the characteristics of the data, the availability of previous knowledge, and whether partially true data is accessible for model training or not (Zhu 2017).

After data processing step described in the previous section, these datasets are structured at the trip-unit level, where each device/person may have one or more records representing the total number of recorded trips. However, this data structure presents a unique challenge for the matching process, given our aim to link persons/devices. Most matching techniques are commonly applied to datasets involving entities with single records, such as health data records and other administrative data sources (Enamorado et al. 2019; Fleming et al. 2012; Sayers et al. 2016). To address the challenges posed by the trip-unit level data structure in the matching process, we have developed two distinct approaches, both based on probabilistic record linkage principles. In the following sections, before presenting the two approaches, we provide a more detailed explanation of each of the record linkage steps that were incorporated into both approaches.

Indexing/blocking

The first step of data linkage is called indexing or blocking. This involves creating a list of potential candidate pairs between the two datasets for the comparison in the subsequent step. Initially, all possible pairs are formed into a matrix including all possible cases by exhaustively trying every entity from dataset A with every entity from dataset B. However, this exhaustive approach can result in significantly high computational time and reduce the algorithm's efficiency in finding matches. To address this issue, a more efficient approach is employed by eliminating many pairs through a process known as "blocking." Blocking involves grouping entities based on certain criteria, such as shared attributes or properties

(Jaro 1989). For example, candidate pairs may only be considered if they share the same zip code area. This way, the algorithm can reduce unnecessary comparisons and focus only on potentially relevant matches, thereby improving its efficiency. Blocking techniques are diverse and not constrained to merely grouping entities with identical attributes (Standard Blocking). In our study, we used Standard Blocking and we restricted our comparisons to individuals/devices residing in the same home tract area.

Field comparison

Following the indexing/blocking process, potential candidate pairs are compared for similarity using selected attributes called "matching variables". These variables are common to both datasets, and the comparison is done individually for each one. The results range from 0 to 1, with 0 indicating no match, 1 indicating a perfect match, and any value in between representing the degree of similarity. The similarity depends on the type of variables compared, such as string values, numeric, date, time, or location. This study focuses on time and geographic variables. Distances between departure and arrival times are computed in minutes, while distances between departure and arrival locations are computed in kilometers for each candidate pair. These values represent distances and are not similarity scores yet. To convert distances into similarity scores ranging from 0 to 1, a linear decay function is used (de Bruin 2022). The process involves two tuning parameters: "offset" and "scale". If a distance falls within the specified range, it gets a similarity score of 1. However, if the distance value exceeds the offset, the score starts to linearly decay from 1 to 0 at a rate of 1/scale (Fig. 3).

The selection of tuning parameters in this study is driven by the desired accuracy level and the allowable error defined for the analysis. For this investigation, the tuning parameters "offset" and "scale" were set to 15 min and 25 min, respectively, for departure and arrival times. Additionally, for departure and arrival locations, the tuning parameters "offset" and "scale" were configured to 1 km and 3 km, respectively. These values were determined as

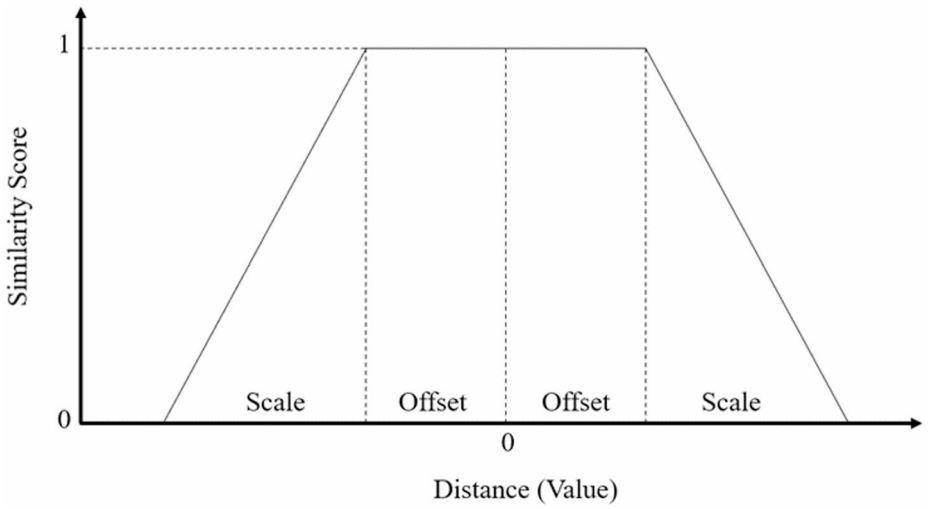


Fig. 3 Conversion of distances to similarity scores using linear decay function

maximum acceptable error thresholds, informed by the authors' expertise, to ensure the results align with the study's accuracy requirements and tolerable error margins.

Approach 1

The first approach uses a probabilistic method based on the Fellegi and Sunter theorem (Fellegi and Sunter 1969) for record linkage. We adapt this method to the trip-unit level, which helps identify matching trips among the datasets. All the previous steps were applied at the trip-unit level to compute similarity scores across potential candidates. However, it is essential to note that these are similarity scores, not probabilities. This is why we have chosen to use the Fellegi and Sunter method to convert these similarity scores into probabilities of matching. To convert the similarity score into a match probability, Bayes' Theorem is applied. To do this, we require the following information:

- *P*-Probability (Overall): This is the prior probability, which represents the expected proportion of duplicates in a dataset before any comparisons are made between records.
- M-Probability (for each variable): P(Variable Matches | Record is a Match) is the probability that two records with the same entity agree on the linkage variable.
- U-Probability (for each variable): P(Variable does not match | Record is not a match) is the probability that two records with different entities agree on the linkage variable.

Unfortunately, none of this information is available in our case, as we lack ground truth data or training data. Therefore, in approach 1, we estimated these parameters for each matching variable using an unsupervised algorithm facilitated by the Expectation-Maximization (EM) algorithm (Bauman 2006; Winkler 2000). Specifically, the EM algorithm iteratively performs two steps given the initial guesses of m, u, and p:

1. Expectation Step (E-step): Estimates the probabilities of a pair being a match or non-match based on their agreement patterns and current parameter values.
2. Maximization Step (M-step): Updates the parameters (M, U, and P) to maximize the likelihood of the observed data.

This process repeats until the parameters (M, U, and P) converge. The final matching probabilities are used to classify pairs of candidate trips into matches and non-matches based on a probability threshold of 0.5.

To find matches/links between devices and persons, we developed an algorithm that leverages unique matches to establish connections between individuals or devices. Since the matching at the trip level can result in multiple possible matches for each device/person, the algorithm searches for the most unique connections, assuming that the most unique links are the more reasonable matches.

Approach 2

The second approach is based on a similarity-based method. In this approach, we restructured the dataset, transforming it from the trip-level (where each row represents a single trip) to the person/device-level (where each row represents an individual or device). This

involved aggregating all trip information pertaining to each individual or device into a trip chain. Each trip chain is represented as a vector of one or more trips, with each trip including selected matching variables as departure and arrival times, as well as departure and arrival locations in longitudinal and latitudinal format. By restructuring the data in this way, we create a more manageable dataset that facilitates the application of similarity measures.

To measure the similarity between any candidate pairs, we have chosen to use the dynamic time warping algorithm (Muller 2007). This algorithm calculates the distance between the two candidate pairs, taking into account variations in the time and location axes. The resulting distance is then converted into a similarity score using a linear decay function, similar to the tuning parameter used in approach 1. The dynamic time warping technique is particularly effective in capturing patterns and similarities in time-series data, making it well-suited for our trip-based datasets. This method has been widely used in various data trajectory similarity studies (Gong et al. 2020; Hung et al. 2015; Sun et al. 2017). In the decision step, we determine the acceptance of matched devices based on a similarity score. Devices are linked if their similarity score is equal to the maximum value and greater than or equal to a specified threshold value. For this study, the threshold value was set to 0.5, meaning that candidate pairs with a similarity score of 0.5 or higher are accepted as matches. By leveraging trip itineraries, we achieved direct linking of devices to individuals without the need for the uniqueness algorithm utilized in approach 1.

For estimating probabilities (P, M, and U) in approach 1 and for indexing/blocking steps used in both approaches, we utilized the 'recordlinkage' package in Python (de Bruin 2022).

Data panel construction

Data panels are constructed for travelers linked by approach 1 and approach 2, respectively. The trip records in the data panel are sourced from MDLD, which captures trip information over multiple days with reduced reporting bias compared to traditional surveys, providing a longitudinal perspective on individuals' travel behaviors. The demographic information, including age, gender, household size, income level, and employment status, is obtained from RTS, where detailed and reliable demographic data is reported. By integrating these two data sources, we combine geospatial accuracy with detailed demographic information, addressing the limitations of both datasets and enabling a more nuanced analysis.

In the next section, we will present and compare the different characteristics of the four datasets: the original RTS, MDLD, and the panel data constructed with travelers linked by approach 1 and approach 2. We will also discuss and analyze the effectiveness of the two linking algorithms and the representativeness of the panel data.

Results

Comparison analysis of key characteristics across the four datasets

Sample size, timespan, and trip rate of the data panel

Table 4 presents a summary of key statistics, including sample size, timespan, and trip rate, for different datasets: RTS, MDLD, travelers linked by approach 1, and travelers linked by

Table 4 Sample size, timespan, and trip rate comparison

	RTS	MDLD	Linked_approach1	Linked_approach2
Number of travelers	1,383	23,224	617	977
Median number of days in a month	1	10	10	13
Mean number of days in a month	1	11.4	10.89	13.14
Median number of longest consecutive days in a month	1	4	3	5
Mean number of longest consecutive days in a month	1	5.413	4.843	6.273
Median trips per day	2	2	2	2.5
Mean trips per day	2.837	2.772	2.215	3.140

approach 2. Note that the linkage process involved utilizing RTS and a representative day of MDLD to identify linked travelers. Subsequently, the travel patterns of these linked travelers were analyzed for the entire month to which the observed week belonged. This approach simulates the construction of such data panel, allowing for longer-term tracking of travel behaviors using MDLD data.

As shown in Table 4, MDLD originally covers a significantly larger sample size compared to RTS, with 23,224 travelers observed within just one week. This number is over 16 times greater than the total number of travelers in RTS, which includes 1,383 individuals. The substantial sample size in MDLD enhances the likelihood of finding travelers with similar travel behaviors in both datasets. Consequently, approach 1 successfully matched 617 travelers from MDLD with RTS, while approach 2 achieved 977 matches. These numbers represent approximately 44.6% and 70.6% of the travelers in RTS, respectively. It is important to note that these percentages do not reflect the performance of the linking algorithms in terms of accuracy. Instead, they indicate the proportion of travelers from RTS whose travel behaviors can be found to overlap with those in MDLD. Given that RTS and MDLD are two distinct datasets, this overlap percentage is influenced by the actual degree of overlap between the populations represented in these datasets. This suggests that incorporating trip records from more days in MDLD could further increase the number of travelers matched with RTS.

One notable distinction is that RTS collects trip records for each responder on a single travel day, while MDLD provides trip records for an average of 11.4 days per traveler in a month. On average, the longest consecutive travel days observed for each MDLD traveler is 5.413 days. This highlights one of the advantages of MDLD, as it captures daily, weekly, and seasonal variations in travel behaviors due to its multiple-day coverage. For travelers linked by approach 1, the average number of days is 10.89, and the average longest consecutive days is 4.843, both of which are less than those in the entire MDLD dataset. Conversely, travelers linked by approach 2 show averages of 13.14 days and 6.273 longest consecutive days, both exceeding the entire MDLD dataset. This indicates that approach 1 tends to link travelers with shorter timespans in MDLD to RTS, while approach 2 is more capable of identifying travelers appearing over more days.

Regarding the trip rate, travelers in RTS are recorded to have an average of 2.837 trips per day, which closely aligns with the average of 2.772 trips per day made by travelers in MDLD. It should be noted that these numbers are slightly lower than the typical trip rate found in other datasets. This discrepancy can be attributed to our exclusion, as mentioned in Sect. 2, of any trips departing from or entering the county from different regions. This filter-

ing step was applied to ensure the accuracy and relevance of the data. Upon examining the travelers linked by approach 1, an average of 2.215 trips per day was observed. Conversely, travelers linked by approach 2 demonstrated an average of 3.140 trips per day. This suggests that approach 1 is more inclined to identify individuals who undertake fewer trips, whereas approach 2 is better suited for detecting more active travelers. Considering that approach 2 can also identify travelers appearing in more days, it is reasonable to assume that the data panel constructed based on the linking results from approach 2 will include a higher proportion of active travelers.

Socio-demographics

Table 5 presents the results of socio-demographics for the individuals residing within Anna Arundel County in RTS, individuals linked by approach 1, and individuals by approach 2. The results are calculated with person weights from RTS.

The average age in RTS is 38.4 years old, which is almost the same as the average age of individuals linked by approach 2. Individuals linked by approach 1 exhibit a slightly younger average age of 37.7 years old. While there are some slight differences in age distribution among the three datasets, such as more individuals between 45 and 60 years old and fewer individuals between 25 and 45 years old in individuals linked by approach 1, the Kolmogorov-Smirnov Test reveals that the p-values for comparing the entire RTS with individuals linked by approach 1 and approach 2 are 0.7851 and 0.9155, respectively. Both p-values are significantly greater than 0.05, indicating insufficient evidence to reject the null hypothesis that these datasets do not come from the same age distribution. The median age is 39 in all three datasets, which closely aligns with the median age of 38.4 reported in the 2018 American Community Survey from the United States Census Bureau (Bureau 2018). The gender distributions across the three datasets show similar proportions with approximately 54% of individuals being female and 46% being male in all datasets. The share of the female population in ACS is 50.5%, indicating a slight difference in sampling methodology or demographic composition between the two datasets. The race distributions are also consistent, with the highest percentage of individuals being white, accounting for nearly 80% across all datasets, similar to the 76.37% reported in ACS. The distributions of employment status demonstrate comparable patterns among the three datasets. More than 50% of indi-

Table 5 Socio-demographics comparison

Demographics	RTS	Linked by Approach 1	Linked by Approach 2
Age: Average	38.4	37.7	38.5
Age: Median	39	39	39
Gender: Female	54.0%	53.9%	53.0%
Gender: Male	46.0%	46.1%	47.0%
Race: White	79.7%	76.9%	79.5%
Race: African American	5.9%	6.1%	6.2%
Race: Asian	2.1%	1.7%	2.2%
Race: Hispanic	1.1%	1.4%	1.3%
Employment status: Worker	50.1%	51.5%	52.2%
Employment status: Retired	15.2%	13.2%	14.9%
Employment status: Unemployed	2.2%	2.7%	2.3%
Employment status: Student	2.7%	3.3%	2.6%

viduals in all datasets are workers, aligning with the 51.4% reported in ACS. It is notable that the percentage of workers among individuals linked by approach 1 and approach 2 is higher than in the overall RTS. This finding may be attributed to the fact that workers generally make more trips than non-workers, increasing their likelihood of being linked with MDLD, given that the linkage algorithms are based on trip characteristics.

In conclusion, the distribution of various socio-demographic attributes across the three datasets is generally similar, suggesting that the data panel constructed by the linkage algorithm exhibits comparable demographic characteristics to the original RTS. Thus, it can be considered as representative of the population, similar to the RTS dataset itself. The consistency in socio-demographic profiles enhances the validity and applicability of the data panel for studying travel behavior and making informed decisions in transportation research and planning.

New insights on travel behaviors from the linked datasets

Trip duration

Figure 4 illustrates the distribution of trip durations across the four datasets, with dashed lines representing the respective means. The average trip duration in RTS is 14.8 min, closely followed by MDLD with an average of 14.9 min, making the red and green dashed lines nearly indistinguishable. However, variations are observed among linked travelers. Those linked by approach 1 display an average trip duration of 17.56 min, indicating that although they make fewer trips per day, their individual travel times are longer. Conversely, travelers linked by approach 2 exhibit an average trip duration of 13.00 min, indicating a tendency for more frequent short trips per day. This pattern is consistent with the density curves, where the share of short-duration trips (less than 15 min) for travelers linked by approach 1 (represented by the blue curve) is significantly lower than that for travelers linked by approach 2 (represented by the purple curve).

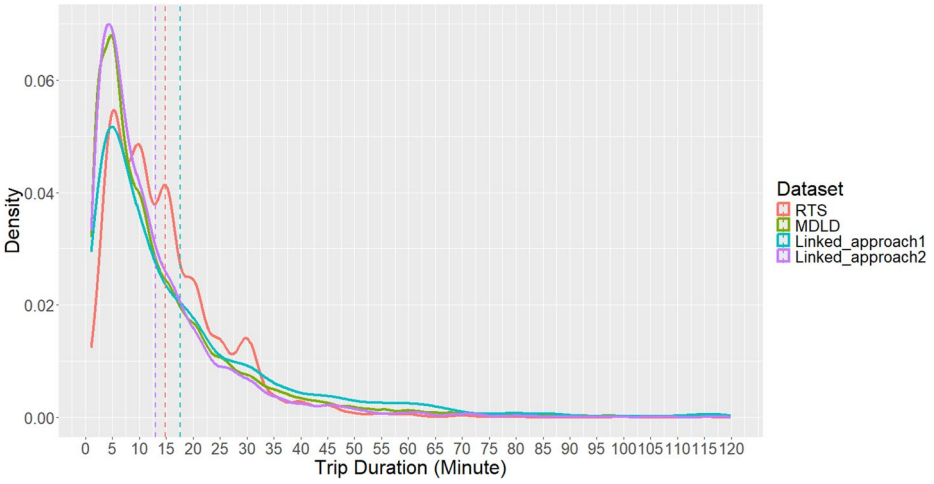


Fig. 4 Density of trip duration in minute

Furthermore, Fig. 4 reveals that trip durations in RTS cluster around multiples of five minutes (e.g., 5, 10, 15…), indicative of "reporting bias" or "rounding bias" commonly encountered in surveys (Rietveld 2002). When respondents are asked to report specific trip details, such as start and end times, they tend to round or approximate their responses to convenient intervals, like 5-minute increments. In contrast, the density curves of trip duration in the other three MDLD-based datasets appear smoother. This is due to the passive collection of travel information in MDLD, which does not rely on self-reported data from survey respondents. Consequently, reporting bias is significantly reduced or eliminated in MDLD, making it a valuable and reliable resource for studying and understanding travel patterns and behaviors.

Time of day and day of week

The departure hour and arrival hour distributions of recorded trips are presented in Fig. 5(a) and (b), respectively. Across all four datasets, a consistent trend is observed in the temporal distribution, with significantly higher traffic volume during peak periods (7:00–9:00 and 15:00–18:00) compared to other times of the day. However, a noticeable discrepancy exists between RTS and the other three MDLD-based datasets, with RTS reporting fewer trips during off-peak hours, particularly during the night (21:00–5:00). This reveals the presence of off-peak travel underreporting in travel surveys, wherein individuals tend to report fewer off-peak trips compared to what is actually revealed in MDLD. This phenomenon has also been reported in other studies (Chapleau et al. 2018).

The reasons for off-peak travel underreporting in RTS may be twofold: Firstly, respondents may have difficulty accurately recalling and reporting off-peak trips, especially if they occur infrequently and are not as memorable as peak-hour travel. Secondly, compared to peak-hour trips, respondents might perceive off-peak trips as less relevant or important, especially if they are part of continuous activities or involve short distances, leading to their omission from the reported trips.

This underreporting of off-peak travel in RTS can lead to an imbalanced representation of travel behavior, resulting in an underestimation of off-peak travel patterns. Consequently, RTS may not fully capture the true extent and nature of off-peak travel activities. The higher proportion of trips during midday and late night in MDLD-based datasets indicates that MDLD can be advantageous in addressing this bias. By providing continuous tracking of travel behavior, MDLD offers a more comprehensive and accurate representation of all travel activities, regardless of the time of day.

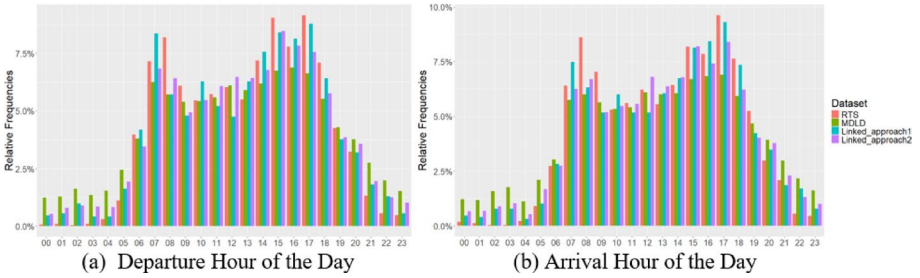


Fig. 5 Distribution of trips by the hour of day

Regarding the comparison between travelers linked by the two approaches, it is evident that travelers linked by approach 2 exhibit a relatively higher share of off-peak trips and a lower share of peak trips compared to travelers linked by approach 1. This suggests that approach 1 tends to identify individuals following a more regular timetable throughout the day, while approach 2 captures a broader range of travel patterns, including more off-peak travel activities.

Figure 6 presents the distribution of trips by day of the week. As RTS only includes weekdays as travel days, Fig. 6(a) displays the relative frequencies of trips during weekdays for the MDLD-based datasets to facilitate a meaningful comparison. Meanwhile, Fig. 6(b) illustrates the distribution of trips for all seven days of the week in the three MDLD-based datasets. This distinction highlights one of the major contributions of MDLD, as it overcomes the limitations of self-reported surveys by providing continuous tracking of travel activities.

From Fig. 6(a), it is evident that RTS records a higher proportion of trips on Monday and Wednesday compared to MDLD, whereas MDLD records a higher proportion of trips on Thursday and Friday compared to RTS. Figure 6(b) reveals that travelers linked by approach 1 make slightly more trips during weekdays and fewer trips during weekends compared to travelers linked by approach 2. This finding suggests that approach 1 may tend to link more regular commuters, who primarily travel on weekdays, while approach 2 captures a broader range of travel patterns, including individuals who travel on both weekdays and weekends.

4.2.3 Trip purpose and mode

The analysis highlights the variation in the distribution of trip purposes, especially the proportion of home-based trips, as depicted in Fig. 7, which underscores the disparities in travel patterns captured by the RTS and MDLD datasets. In RTS, the proportion of home-based trips (home-based-work and home-based-other) is recorded at 77.29% in total, significantly higher than the three MDLD-based datasets, where home-based trips constitute 61%-62% of the total. This pattern corroborates the discussion in Sect. 4.2.2, indicating that the design and limitations of the RTS data lead to a primary emphasis on trips originating from home and then returning home, which are common and essential travel patterns. As a result, other types of trips, especially those made during off-peak hours for non-home-related purposes, are not adequately represented in the RTS dataset. This omission leads to an incomplete picture of overall traffic pattern and may result in an underestimation of traffic volume during off-peak periods. Therefore, by integrating MDLD into the analysis, researchers can gain valuable insights into the full spectrum of travel patterns, enabling more accurate and

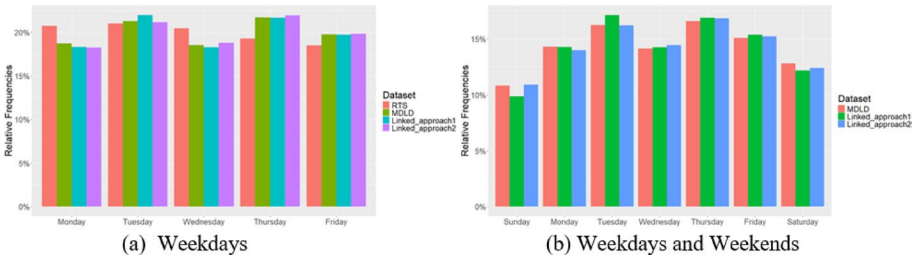


Fig. 6 Distribution of trips by **a** weekdays, and **b** weekdays and weekends

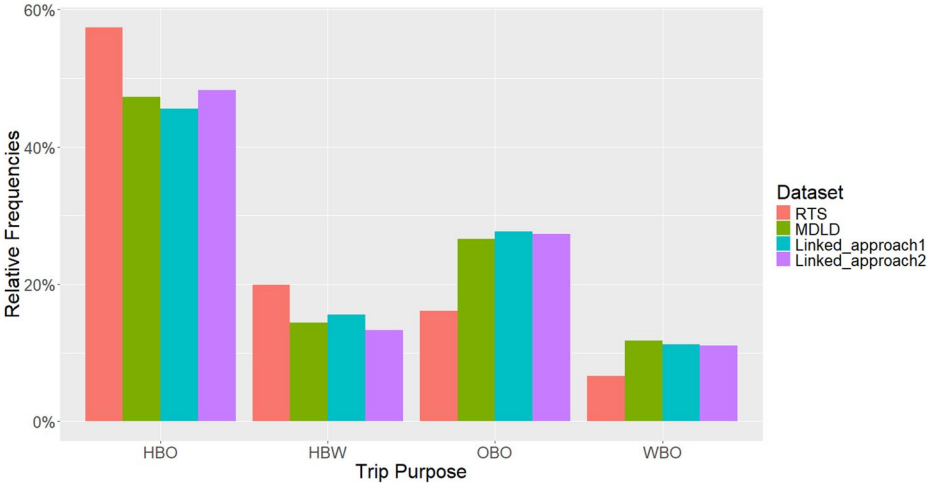


Fig. 7 Distribution of trip purposes

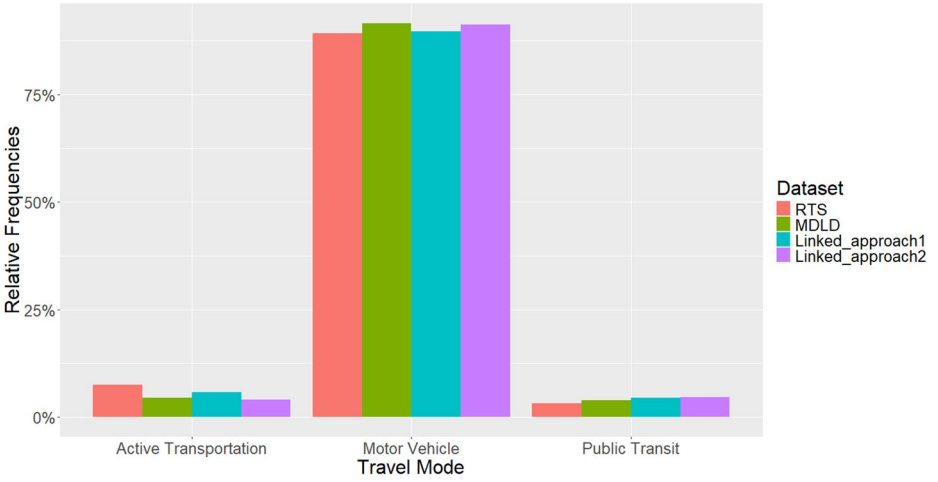


Fig. 8 Distribution of travel modes

inclusive assessments of traffic volume during both peak and off-peak hours. The distribution of trip purposes for travelers linked by approach 1 and approach 2 are both similar to the distribution observed in the entire MDLD dataset. This indicates that the linkage algorithm employed in the study does not introduce bias in terms of trip purposes.

Figure 8 presents the relative frequencies of travel modes—Active Transportation (including walking and biking), Motor Vehicle (automobiles and motorcycles), and Public Transit (buses and rail)—across four datasets. Motor Vehicles dominate across all datasets, comprising approximately 90% of the relative frequencies. In contrast, Active Transportation and Public Transit account for much smaller shares. This consistent dominance of motorized personal vehicles highlights typical travel behaviors in the study area, likely

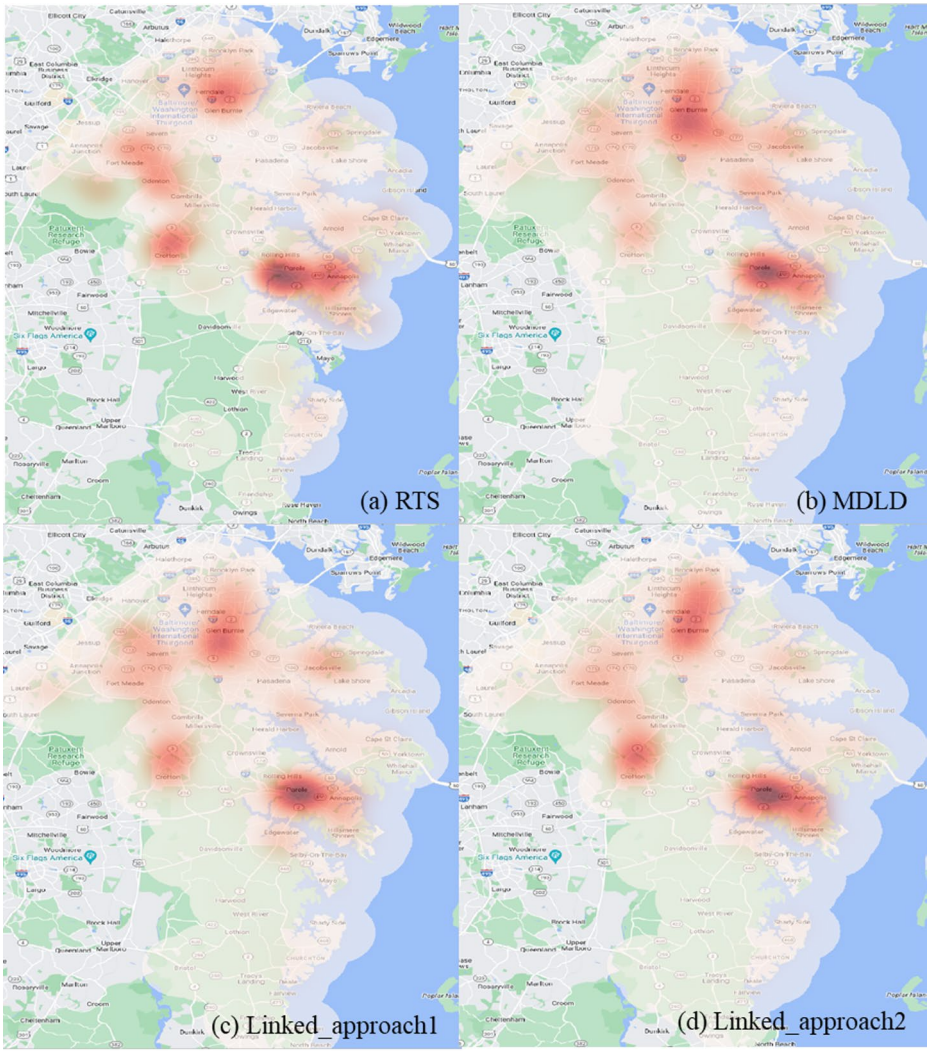


Fig. 9 Heat maps of destinations of trips

reflecting a reliance on private vehicles due to limited public transit or active transportation infrastructure. Despite slight variations between datasets, the travel mode distributions remain highly consistent overall.

Heat map of trip destinations

Figure 9 presents heat maps of trip destinations from the four datasets, with a focus on trips within Anna Arundel County as mentioned previously. The spatial distribution of trip destinations is found to be generally consistent across all four datasets. Annapolis, the county's largest city, emerges as a prominent hotspot, along with other densely populated towns like Glen Burnie and Crofton. This observation reinforces the reliability and validity of

the MDLD data and the linkage approaches employed in the study, as the trip destinations exhibit a reasonable and coherent spatial pattern.

However, there is still a noticeable discrepancy between the heat maps of RTS and MDLD. In RTS, trip destinations appear to be more discrete, with certain rural areas showing no trip records (evident in the bottom left area of the map). Conversely, the MDLD-based datasets exhibit a more widely distributed pattern, covering nearly all areas within Anna Arundel County. This difference may be attributed to the fact that RTS has a smaller sample size compared to MDLD, with trip records collected for a single day for each participant. Consequently, trips made in some rural areas are likely underreported in RTS. MDLD, on the other hand, emerges as a promising data source to address this limitation. By providing continuous movement records over multiple days and encompassing a larger sample size, MDLD offers a more comprehensive representation of travel behavior. This comprehensive coverage ensures that trips made in various areas, including rural regions, are adequately captured, leading to a more accurate depiction of spatial travel patterns within the county.

Conclusion and discussion

In this study, we propose to enhance travel behavior analysis by integrating Mobile Device Location Data (MDLD) with the Regional Travel Survey (RTS) datasets. Our goal was to address some of the limitations of traditional travel surveys and leverage the advantages of MDLD to create more comprehensive representations of individuals' travel behaviors. Two distinct data linkage approaches were utilized to connect individuals across datasets with similar travel characteristics, resulting in the construction of data panels that provide valuable insights into travel patterns.

MDLD offered continuous and high-resolution information on individuals' movements over multiple days, providing a detailed picture of daily, weekly, and even seasonal travel activities. By combining this geospatially accurate data with the rich demographic information from RTS, the data panels provided a more complete representation of travel behaviors. Our approach captured not only peak-hour commutes but also off-peak travel and non-home-related trips, shedding light on a broader range of travel behaviors and offering a more holistic view of individuals' travel patterns. This dataset also allowed us to analyze travel behaviors over extended periods, providing a longitudinal perspective on travel habits that was often challenging to achieve with traditional survey data.

While our approach showed significant promise, it is essential to acknowledge some limitations. While MDLD provides continuous location data, there may still be gaps in the dataset due to factors such as poor network coverage, battery depletion, or device malfunctions. The effectiveness and accuracy of the home location identification and trip imputation algorithm also needs further validation. The data linkage process also presents challenges, particularly in dealing with multiple possible matches at the trip level. Our algorithm addressed this by leveraging unique matches to establish connections between individuals or devices. While this approach was effective, it is crucial to further explore and refine data linkage methods to ensure accuracy and reliability in large-scale applications. In addition, we acknowledge that focusing on the day with the highest number of recorded trips may not account for day-to-day variations. To address this, future studies could incorporate multiple days of data or apply weights across a broader time period to better capture the full range of

travel behaviors. While census tracts balance data resolution and feasibility, smaller units could improve matching precision if available, while larger units may reduce spatial detail. Future studies could assess the impact of spatial unit choice to guide researchers in selecting the most appropriate unit based on data availability and study goals.

Despite these challenges encountered, the findings of our study offer valuable insights for transportation planning and policy-making. By analyzing travel behaviors across various time periods and demographic groups, policymakers can better understand the specific needs of individuals and communities, enabling more targeted transportation services. For example, transportation planners can use these results to design services that better match actual usage patterns, such as adjusting transit schedules based on observed off-peak demand or targeting areas for improved first/last-mile connectivity. Policy analysts can evaluate the impact of teleworking or seasonal travel trends on congestion and emissions, helping to shape strategies such as flexible work policies or congestion pricing. Metropolitan planning organizations (MPOs) can also leverage the longitudinal perspective to validate and refine travel demand models, ensuring they reflect evolving behaviors more accurately over time. As data collection technologies continue to advance, the integration of diverse datasets presents an opportunity to enhance travel behavior analysis and inform the future of transportation planning in the era of mobile technology and big data.

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Data availability No datasets were generated or analysed during the current study.

Declarations

Conflict of interest The authors declare no competing interests.

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