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Assessing Travel Data Accuracy Across Data Platforms: Evidence from Smartphone-based Travel Diaries of University Students in Sydney

Xianliang Liu

School of Civil and Environmental Engineering, University of New South Wales, Sydney, NSW 2033, Australia

ABSTRACT

Smartphones have been used to collect data on people's travel behaviour, but the quality of this data varies in accuracy and completeness. Using Google Maps Timeline and Fourstep, three study days in October-November 2025 were analysed for travel logs of 20 university students in Sydney. Collect records from both platforms and organise and align them by participant and day. Python was used to convert Google Maps Timeline JSON files into a structured dataset and obtain anonymised Fourstep records from the platform backend. The accuracy of trip completion, temporal-spatial consistency, segmentation accuracy, mode recognition accuracy and participant-level error rate were also recorded. FourStep had a finer division of trips and fewer missing or misclassified segments; Google Maps Timeline was better at locating major activity spots and some types of motorised travel. The mean error rate was 1.3% for Fourstep and 18.9% for Google Maps Timeline, with a significant within-participant difference, $F(1,19)=10.67$, $p=0.004$. The findings indicate that platform choice should depend on the intended modelling task rather than on a single notion of accuracy.

KEYWORDS

Data Platform; Travel Data; Accuracy.

1. PROBLEM STATEMENT

Mobile-focused travel diaries can collect rich mobility information with less participant effort than traditional paper-based questionnaires. Google Maps Timeline and Fourstep differ in how they detect locations, segment trips and infer travel modes, so the resulting diary can vary even for the same participant and day. The analytical value of these data therefore depends on whether the recorded trips accurately represent daily mobility.

Based on the aforementioned research, although technically feasible to apply mobile devices and GPS-related data, platform-specific problems remain. The above measures distinguish between travel and residence, classify mobile operations, authenticate users, and spread information in various ways. Therefore, the same person on the same day may have different travel records and route logs, and some factors may be missing or incorrectly labelled. These changes will affect the next travel-demand forecasts and policy responses.

As a result, this study uses smartphone-based travel diaries from 20 university students in Sydney to compare Google Maps Timeline and Fourstep. The analysis focuses on trip accuracy and coverage, segmentation, mode recognition, error rates, data usability and practical applicability. Records from

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the same participant and study day are aligned to identify platform-specific strengths and limitations rather than to assume that one platform is universally superior.

2. LITERATURE REVIEW

2.1. Data Platform

A data platform can serve as a repository for multidimensional travel information, allowing relevant records to be organised for subsequent research.

With the development of the framework for travel behaviour, many scholars have been studying it to some extent. Google Maps Timeline provides a good mobility journal function that several research projects have used to collect data. Fisu et al. (2024) developed a way to evaluate mobility based on Google Maps Timeline and used various analysis methods for over 400 Gen Z learners in Indonesia. Li and his colleagues (2024) have developed a way to add Google History Location data to the current travel survey system to solve this problem. Google Maps Timeline is a special data asset. Shankari and others (2018) built an e-mission platform to automatically acquire GPS data and monitor sensors for changes in behaviour. Manual collection of behavioural perception data and system-generated supplementary questionnaires were used. Various results are organised travel diaries, route simulations, carbon footprint evaluation competitions and assessments, etc. Tabasi et al. (2024) introduced the Fourstep software, based on the open-source project OpenPath and improved from e-mission. The tool can be used to collect travel-route data passively via GPS and sensors, but users must still manually provide information on how they travelled. It is a multi-functional meeting record recording instrument. Patterson et al. (2019) constructed a survey system for the Itinerum open-source platform based on the above attributes to motivate users to organise their trips and express their travel wishes. The Study Administrator can generate assessments and surveys at any time during the research period to monitor the students' study progress and collect or process data. Each of these models needs people to voluntarily provide some information.

Some high-end structures have been released recently. Piras and his colleagues (2018) have built a mobile infrastructure for autonomous behaviour monitoring. Tailored Data Transfer Using the IPET Framework. Therefore, it will automatically record all the user's activities and behaviours to offer customised entertainment recommendations. Operating Adjustments are made for the internal audit.

Unified Surveillance. Use positive and negative "incentive signals" to increase the participation of people in behavioural change initiatives. Berger and Platzer (2015) have developed the SmartMo architecture based on privacy; subjects need to provide a registration token before submitting any additional information, and this identification code is securely protected and stored.

2.2. Difficulty

Provide strong support for the information-gathering stage and ensure the longevity of the study results. Some deficiencies of the current methods exist.

A specific method for determining the research object is not provided. Cash et al. (2022) believe that the reliability and credibility of this research can be guaranteed by meeting the criteria of academic rigour and integrity in the methodological design of the foundational framework; Tyrer and Heyman (2016) pointed out that such a deficiency is due to a violation of ethical survey regulations and has ultimately damaged both the accuracy and scholarly prestige of the study. Martinez-Mesa et al. (2016) believe that statistical sampling is a moral problem, so they have ignored it in the early stages of research planning. The above problems are serious; therefore, the foundational ethical principle of traditional public health research has been the collection of data through manipulation of large-scale datasets.

The first set of travel data has some deficiencies and will lead to certain problems.

Transformation Obstacles. Shankari and his colleagues (2018) have found that platform-specific mechanical integration is still a problem, and there is no standardised JSON structure for mobile journey information on iOS and Android. Tabasi et al. (2024) indicated that the travel-oriented components in the main JSON file were various and had many structural problems and deficiencies in data organisation. In addition, mismatches may occur between timestamps recorded by different data sources.

2.3. Methodology

First, some observations and other means will be employed.

Frameworks. Amrutha Lekshmi et al. (2016) collected data by means of local inquiries and government databases, but the quantity of such data was small. As the traditional way has not met people's actual needs for displacement, Chang and his team (2019) have developed a machine learning structure based on data fusion and synthesis.

First, a framework is established to collect data on human behaviour; therefore, the method and scope of this collection will affect the quality of the following dataset. Cools et al. (2021) have employed many ways to collect data; at the same time, the scope of observation has expanded, several intelligent sensors are used to record comprehensive logs, and a verification process for assessment has been introduced.

Assessment of GLH Information Resilience Based on Holistic Data Fusion and Comparative Analysis.

Analyze the data and extract results from GLH records for five different brand/system smartphone models over a 12-day period. Molloy and his colleagues (2022) have built strong travel-assistance architectures based on cellular hardware and GPS technology.

About 3,700 people are using mobile phones for GPS collection.

To obtain the necessary data and improve the speed and efficiency of data collection, extraction and analysis for this study, data cleaning and organisation were carried out. Many previous studies have been conducted to develop an independent data-processing platform or enhance the existing system to meet the demands of this particular investigation. Xia and his colleagues (2021) extended the original Kepler.gl system to add tools for acquiring, filtering and evaluating data, which increased the scope and value of Google Maps Timeline datasets considerably; Jiang et al. (2023) have also developed an excellent neural network model called STAWnet that combines a Gated Temporal Convolutional Network with a Dynamic Attention Network to tackle the problem of data depletion in traffic sensor networks. In addition to data from intelligent sensors, this paper will also handle data obtained through conventional means; Xue et al. (2022) have pointed out a research gap in combining the two types of data for traditional travel forecasting techniques and subsequently put forward a new approach for forecasting human mobility as a language translation problem.

2.4. Ethical Issues

The first concern is data privacy and security. Van Hulst et al. (2020) pointed out shortcomings in the current logistics supervision system, such as poor data security; further, in terms of how data is used, they employed a cognitive lens and thus addressed privacy-preserving logistics information screening problems effectively through federated machine learning. At any time during the transmission and storage of data, there is a risk of disclosure. Jack and Marset (2014) have shown that the behaviour of individuals in large-scale cooperation and personal involvement increases the risk of task data leakage and moral deviation. All sensitive and personal data in the collected datasets need to be protected during the sampling period.

2.5. Practical Applications

GPS data are now frequently used in evaluating the performance of practical transportation demand models. Ribeiro and others (2014) in Brazil are representative cases; they used GPS-generated data along with self-reported statistics in multivariate logistic regression modelling and found that the analytical accuracy was significantly improved by adding GPS-derived variables in this study. Sivalingam et al. (2024) have carried out many studies on GPS acquisition techniques and data sources, and built a quality assessment model. Scully and his colleagues (2017) used GPS-generated data and self-reported travel history to study food-environment exposure.

Governments around the world will add GPS telematics to their daily life. Harrison et al. (2020) have compiled numerous studies and methods in various countries to this point. Baum and Howe (2016) provided two empirical cases in marginalised areas to show that GPS-derived data can promote urban development and streamline traffic management. The International Transport Forum (2016) reported that the transportation facilities and regulations are outdated and lack automated monitoring. They have built a "data-driven transport policy" system based on real-time GPS data and transit design simulations. Nahmias-Biran et al. (2023) indicated that both the volume of data and the impact of traditional travel surveys have been declining. Therefore, they collected data on more than half of the cellular phone users in a certain country using GPS records for a data analysis. They have used this data to study the structure of domestic travel demand and proposed a technique for authorities at both the technical and administrative levels. Haamer et al. (2025) proposed a way to determine travel paths based solely on GPS data and put forward some recommendations for the reform of public transportation.

3. RESEARCH PLAN AND FLOWCHART

3.1. Research Plan

This study evaluates Google Maps Timeline and Fourstep using matched travel records from 20 university students in Sydney. The evaluation focuses on data accuracy, trip coverage, sampling burden, data availability, segmentation, mode recognition and participant-level error rates.

The sample is limited to 20 university students and therefore does not represent the wider Sydney population or other age groups.

Travel records from both platforms are aligned by participant and study day. Google Maps Timeline data require JSON conversion before analysis, whereas anonymised Fourstep records are obtained from the platform backend. The analysis compares the two outputs and reports their respective strengths and limitations.

3.2. Research Flowchart

Based on the preliminary research framework, the research flow is shown in Figure 1.

4. METHODOLOGY

4.1. Data Collection and Processing

4.1.1. Data Collection

Twenty university students in Sydney provided paired data from Google Maps Timeline and Fourstep for the selected study days in the course of this research. Only the same group of people can be used for comparison; it is not representative of all Sydney residents.

4.1.2. Data Processing

Exported nested JSON files of Google Maps Timeline data were converted into structured trip-level tables using Python, and these tables contained attributes such as timestamp, origin and destination coordinates, distance, duration, and platform-assigned travel mode. Four-step records were obtained from the platform backend as anonymised structured data and filtered to the same participants and observation days.

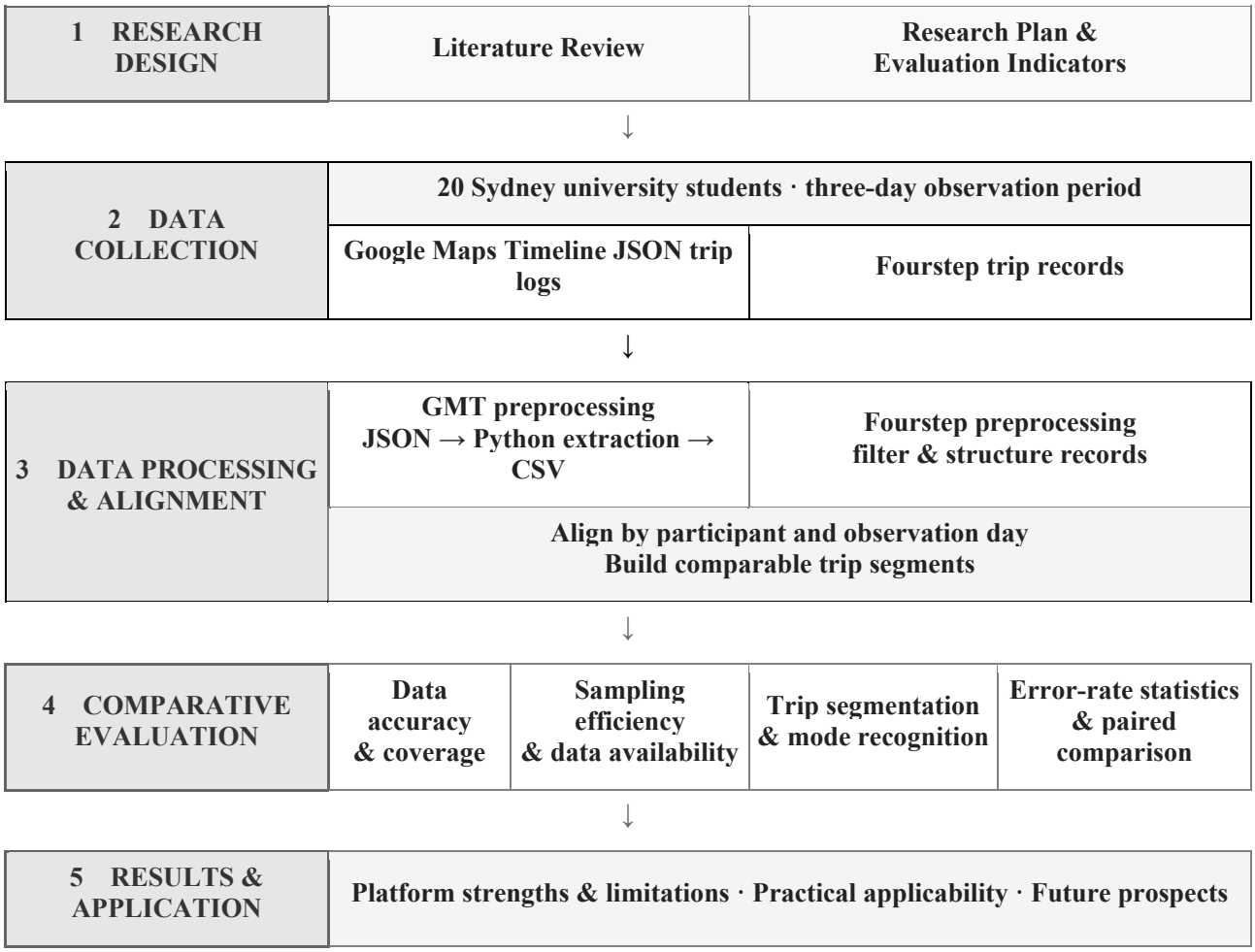


Figure 1. Research Flowchart

4.2. Dimensions of Comparative Analysis

Compare the accuracy and coverage of trip data, sampling efficiency, data availability, segmentation, mode recognition and participant-level error rates.

4.2.1. Data Accuracy and Trip Coverage

Verified that the accuracy of the data by cross-referencing with the platform's data and checking whether the departure/arrival places, times, routes and modes of transport were reasonable and consistent. Coverage of trips refers to whether short trips, stays and multimodal trips are included in or excluded from the count.

Because participants in Sydney commonly combined walking with public transport and other modes, the analysis also considered whether each platform retained the connecting segments needed to reconstruct a complete trip chain.

Evaluation Indicators are:

(1) The deviation between the actual travel route of the participants and the recorded route of the two platforms. For example, one platform records a complete trip, while the other platform splits the trip into two or more parts for its own reasons, that is, multiple trips are recorded. For two platforms, data will be obtained directly from participants or from the platform backend.

(2)The deviation between the actual departure time, arrival time and the recorded time of the two platforms. Data will also be taken directly from participants or from the platform backend.

4.2.2. Sampling Efficiency

Sampling efficiency was considered descriptively through the level of user interaction, dependence on manual confirmation, device compatibility and the extent to which missing data could arise from non-response or technical problems. Differences between Android and iOS operation were treated as a practical platform consideration rather than as a separate outcome measure.

4.2.3. Data Availability

Data availability refers to exportability, structural consistency and the amount of preprocessing required before analysis. Google Maps Timeline required JSON parsing and restructuring with Python, whereas Fourstep records were obtained in a structured backend export. The comparison therefore considered both data quality and the processing burden associated with each source.

4.3. Analytical Methods

4.3.1. Statistical Analysis

For each platform, descriptive analysis summarised the number of recorded segments, missing or problematic records, segmentation behaviour and mode-classification patterns. Participant-level error rates were calculated as coded errors divided by the total number of platform records for that participant.

4.3.2. Comparative Analysis

Records from the two platforms were matched by participant and study day using time, origin/destination coordinates, duration and travel context. Because the same participants contributed data to both platforms, the error-rate comparison was treated as a within-participant analysis.

5. DATA PROCESSING, COLLECTION AND STATISTICS

5.1. Cleaning and Structuring of Timeline Data

The Google Maps Timeline data used a nested JSON structure. To create comparable trip records, the study extracted departure and arrival times, the longitude and latitude of the starting and finishing points, distance and duration from each trip. A new 'Source' column was used to distinguish the participant/data source, and all data were then exported in CSV format for subsequent analysis.

5.2. Data Collection and Statistics

5.2.1. Sample Data of Fourstep

Fourstep records were collected for the same 20 participants over three selected days in October and November 2025. The backend export contained time-stamped trip segments with origin and destination coordinates, platform-assigned travel mode, distance and duration. Records were filtered to the observation days and participant identifiers used in the matched comparison. Table 1 summarises the Fourstep sample.

Table 1. Summary of Fourstep Sample Data

Participant	Data Period	Day 1	Day 2	Day 3	Total
1	11.4 - 11.6	6	8	2	16
2	10.28 - 10.30	4	10	8	22
3	10.28 - 10.30	10	4	10	24
4	10.28 10.30 10.31	6	14	20	40
5	10.31 - 11.2	8	4	6	18
6	10.30 - 11.1	4	4	4	12
7	10.28-10.30	11	16	10	37
8	10.30 10.31 11.2	10	4	3	17
9	11.6 11.8 11.10	6	8	4	18
10	10.29 - 10.31	28	4	11	43
11	10.28 - 10.30	4	8	10	22
12	10.28 - 10.30	6	10	8	24
13	10.28 - 10.30	14	7	10	31
14	11.1 - 11.3	4	16	8	28
15	11.7 - 11.9	4	6	10	20
16	10.29 -10.31	12	10	0	22
17	11.1 - 11.3	11	15	8	34
18	10.31 11.1 11.3	18	9	6	33
19	10.28 - 10.30	16	4	24	44
20	11.9 - 11.11	33	9	26	68

5.2.2. Sample Data Collection of Google Maps Timeline

Each of the 20 participants also exported three days of Google Maps Timeline data in JSON format. The files were parsed into structured CSV records using Python and filtered to the same observation days as the Fourstep data. The resulting records contained time-stamped trip segments, origin and destination coordinates, platform-assigned travel mode, distance and duration. Table 2 summarises the Google Maps Timeline sample.

5.2.3. Error Rate Statistics

An error was coded when a travel segment was missing, when clearly separate movements were incorrectly merged, when a short trip was represented as a long stay, or when another record-level inconsistency could be confirmed against the matched travel information. Table 3 reports the coded error counts for the two platforms.

6. DATA ANALYSIS

6.1. Self-Data Accuracy Analysis

The first stage evaluates the internal consistency of each platform's records before comparing them directly.

6.1.1. Data Accuracy of Google Maps Timeline Platform

Google Maps Timeline generally captured major activity locations and motorised travel episodes, but several records showed extended walking segments, missing short trips or long stationary periods classified as movement. These issues reduced completeness for some participant-days.

6.1.2. Data Accuracy of Fourstep Platform

Fourstep produced more detailed segmentation and fewer missing records. Origins, destinations and trip times were generally consistent with the matched participant records, and pauses between trips were retained more systematically. Its main trade-off was a greater need for user confirmation and interpretation.

Table 2. Summary of Google Maps Timeline Sample Data

Participant	Data Period	Day1	Day2	Day3	Total
1	11.4 - 11.6	4	4	2	10
2	10.28 - 10.30	1	4	2	7
3	10.28 - 10.30	3	1.5	1.5	6
4	10.28 10.30 10.31	6	8	10	24
5	10.31 - 11.2	3	0.5	0.5	4
6	10.30 - 11.1	1	4.5	0.5	6
7	10.28 - 10.30	5	9	7	21
8	10.30 10.31 11.2	5	2	2	9
9	11.6 11.8 11.10	4	5	2	11
10	10.29 - 10.31	8	4	1	13
11	10.28 - 10.30	1	5	8	14
12	10.28 - 10.30	3	4	4	11
13	10.28 - 10.30	10	4	7	21
14	11.1 - 11.3	3	14	2	19
15	11.7 - 11.9	0	9	4	13
16	10.29 - 10.31	0	2	0	2
17	11.1 - 11.3	4	8	3	15
18	10.31 11.1 11.3	10	6	7	23
19	10.28 - 10.30	0	0	0	0
20	11.9 - 11.11	13	4	6	23

Table 3. Summary of Error Conditions

Participant	FSP-Total	FSP-Error	GMT-Total	GMT-Error
1	16	0	10	4
2	22	0	7	1
3	24	0	6	2
4	40	0	24	3
5	18	0	4	1
6	12	0	6	1
7	37	0	21	1
8	17	1	9	1
9	18	1	11	0
10	43	0	13	0
11	22	0	14	1
12	24	0	11	0
13	31	0	21	1
14	28	1	19	1
15	20	1	13	3
16	22	0	2	1
17	34	0	15	0
18	33	2	23	4
19	44	0	1	1
20	68	0	23	3

6.2. Comparative Analysis of Data Accuracy for the Two Platforms

6.2.1. Alignment of Travel Records on the Same Day

For privacy reasons, the four-step records were anonymised and linked to Google Maps Timeline only by study ID and travel data. Synchronize the same-day records based on time, origin/destination coordinates, duration and travel context, then determine which ones are accurate.

6.2.2. Difference Analysis

Over the same period, Fourstep recorded more travel segments than Google Maps Timeline for most users. This mainly occurred because Fourstep retained more short connecting movements, while Google Maps Timeline more often grouped them into larger activity episodes. The segment counts for the three observation days are shown in Figures 2(a)-2(c).

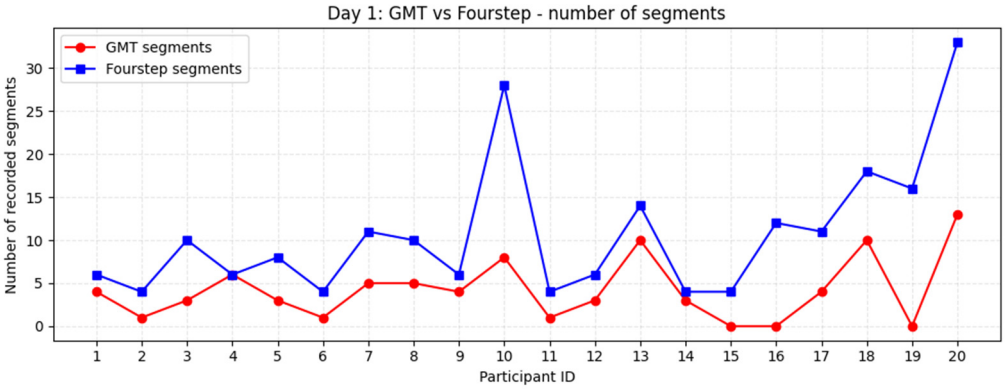


Figure 2(a): Recorded segments on Day 1

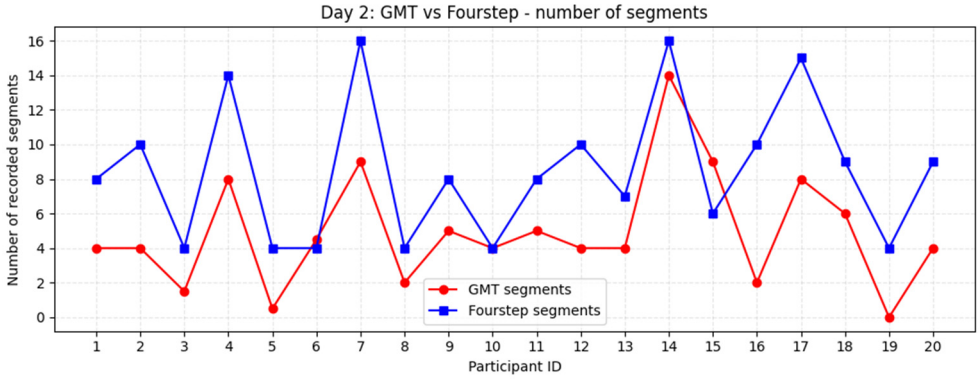


Figure 2(b): Recorded segments on Day 2

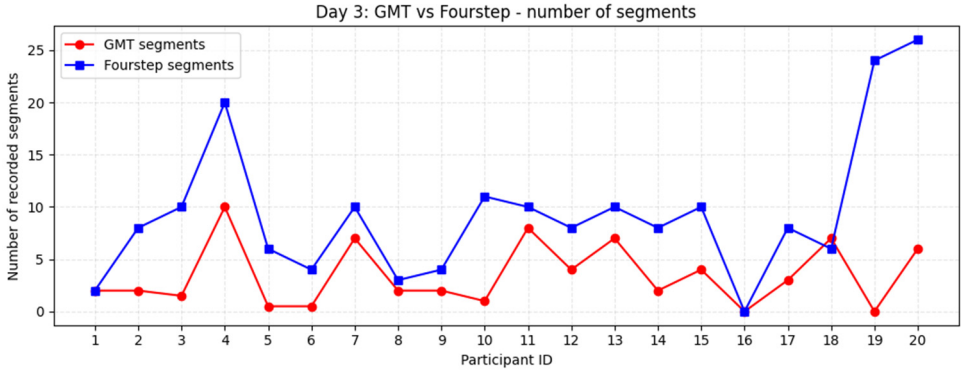


Figure 2(c): Recorded segments on Day 3

Google Maps Timeline still had some advantages in identifying the main nodes of activity and classifying some motorised modes, such as train and bus travel. FourStep has increased the number of short connection moves, but the two platforms are thus not the same and do not have the same degree of accuracy.

6.3. Comparative Analysis of Platform Data Division

6.3.1. Segmented Comparison of Platform Time and Space

Google Maps Timeline organised mobility around the detected activities and places. In a weak-signal area, a short connection move can be added to the previous episode or skipped.

Four-step treatment of continuous movement and intervening rest can be used to generate a denser sequence of trip records. It has added more details to the trip chain, but now also needs to be explained.

6.3.2. Comparison of the Processing of Stay and Fuzzy State

Google Maps Timeline only records explicit place information for relatively long-term and stable stays; otherwise, a period of little movement is often mistaken for walking or short-distance displacement.

Fourstep represented stays primarily through the intervals between trips. This reduced omission of pauses but required additional user or analyst interpretation to identify the purpose of a stay.

6.3.3. Comparison of Travel Mode Division

Google Maps Timeline provided more differentiated mode labels for motorised travel and performed comparatively well for train and bus recognition. Its main weakness was the tendency to merge short walking connections into a larger trip.

Fourstep clearly separated walking and cycling but was less specific for some medium- and long-distance motorised trips. In this sample, its segmentation was stronger than its detailed mode classification. These differences are summarised in Table 4.

Table 4. Analysis of Passenger Mode Splits for the Two Platforms

Comparing dimensions	Fourstep	Google Maps Timeline
Overall partitioning strategy	Biased segmentation	Bias to merge
Walking treatment	The walking segment was heavily subdivided	Walking is often integrated into an entire trip
Public transport/motor vehicle segment	Clear transfer nodes	Transfers or short stops may not be listed
Stay / Place	Needing to be inferred through time intervals	Clear record

6.4. Error Rate Analysis

6.4.1. Chart Analysis

An error was coded when a segment was missing, when clearly separate movements were merged, when a short trip was represented as a long stay, or when another record-level inconsistency was confirmed against the matched travel information. Participant-level error rate was calculated as coded errors divided by total platform records. The participant-level error rates for the two platforms are shown in Figure 3.

Fourstep error rates were low across most participants: 16 of 20 participants had no coded errors, and the sample mean error rate was approximately 1.3%.

Google Maps Timeline showed greater variability. Several participants had error rates above 30%, and one participant had a 100% rate because only one record was captured and that record was coded as erroneous.

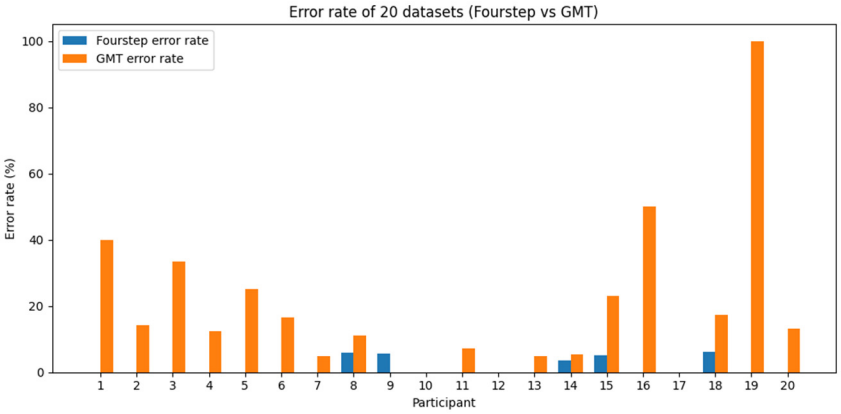


Figure 3. Error Rates for Both Platforms of Twenty Participants

These results indicate a clear difference in record-level reliability within this sample, while the single-record 100% case also shows why percentages should be interpreted together with record counts.

6.4.2. ANOVA Analysis

Because the same 20 participants contributed data to both platforms, the error-rate comparison was treated as a within-participant test. The repeated-measures one-factor analysis yielded $F(1,19)=10.67$, $p=0.004$.

This result rejects the null hypothesis of equal mean error rates at the 5% significance level and is consistent with the descriptive pattern shown in Figure 3.

The mean error rate was 1.3% for Fourstep (SD=0.024) and 18.9% for Google Maps Timeline (SD=0.236). The corresponding partial effect size was $\eta^2p\approx0.36$, indicating a substantial platform effect within this matched sample.

Based on the statistics from a sample of 20 people, it cannot be assumed that others will have the same results.

6.5. Analysis of Practical Application Capability

6.5.1. Analysis of Model Applicability

Platforms are not suitable for all purposes; they vary by use. FourStep has good division and a low rate of missing or invalid data; therefore, it is suitable for travel-chain reconstruction, and Google Maps Timeline passively collects and recognises major activity locations and some motorised modes and is favourable for wide-ranging activity-pattern analysis.

6.5.2. Analysis of Applicability of Policy Formulation

The Two Platforms also have different deployment costs. Google Maps Timeline is highly automated and integrated with a popular consumer ecosystem, so it requires less effort from the participants. FourStep needs to be activated more frequently but offers richer trip-level data. The platform for policy-oriented applications needs to be accurate, low-burden for users, simple to operate, and ensure good privacy protection.

Do not assume that the results will be the same in other countries, on different devices or for other groups of users. Re-validate after any modification to the study population or technical environment.

6.6. Comparative Analysis Results and Future Prospects

The difference between the two platforms can be viewed as a design feature of the platform rather than an absolute difference in accuracy of the two systems. FourStep supports more precise trip divisions and user confirmations; Google Maps Timeline is built on passive detection of extensive activities.

The two platforms have different distributions of these indicators; one has recorded more segments but failed to specify some modes, and the other has identified the main activities correctly but omitted short connecting movements. In the future, a large number of various samples will be collected independently for high-resolution tests of both platforms.

7. RESULTS AND PROSPECTS

7.1. Results

This study compared smartphone-based travel diaries of 20 university students in Sydney using Google Maps Timeline and Fourstep. Completeness of trips, trip segmentation, mode recognition, participant-level error rates and practical data utility have also been investigated.

Fourstep provided more granular trip segmentation and had fewer missing or invalid records; Google Maps Timeline was better at displaying the locations of significant activities and some motorised travel modes. The mean error rates of Fourstep and Google Maps Timeline were 1.3% and 18.9%, respectively.

Therefore, based on the purpose of research, a platform selection can be made rather than using a single, universally excellent platform.

7.2. Prospects

The sample for this study is limited to 20 university students, the observation period is only three days, and some user-provided data in FourSteps are not available in Google Maps Timeline.

Next, a considerable number of samples will be tested in the other operating systems and compared with an independent high-resolution reference in these environments.

Extensions will help to determine whether the observed differences among the platforms can be generalised to other samples of Sydney students.

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