Detecting Travel Nature of Individuals during Movements Using Cluster-Based Model

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ABSTRACT: *While travelling from place to places movement data is recorded that gives insights and the long-term change of individual travel behaviour. In this work we advocate a clustering-based framework to identify travel behaviour patterns and detect potential change periods on the individual level. Initially we draw the significant visits that outline individual characteristic movement. Next after using the trip data, and trip duration as travel behaviour dimensions, we compute the similarities of trips and group them into clusters using hierarchical clustering. The trip clusters represent dimensions of travel behaviours, and the change of their relative proportions over time reflect the development of travel preferences. Then we employed two models to find changes in travel behaviour patterns namely the Herfindahl-Hirschman index-based method and the sliding window-based method. We have experimented the design with the data from a large-scale longitudinal GPS tracking data study in which users had access to a Mobility-as-a-Service (MaaS) offer. The methods successfully identify significant travel behaviour changes for users. We found that the proposed design for behaviour change detection provides valuable insights for travel demand management and evaluating people's reactions to sustainable mobility options.*

1. Introduction

Individual mobility is currently primarily based on the private car. Owning a car is associated with a high level of comfort and flexibility [39], as it is always available and can reach most places while offering a safe and personal space. However, conventional car dependence is inherently unsustainable as internal combustion engine cars are a major emitter of greenhouse gases [34]. Therefore, a successful transition towards a sustainable transportation system must find ways to reduce individual car ownership and support individuals in engaging in a more sustainable mobility lifestyle [42]. One of the main strategies to reduce private car ownership is Mobility-as-a-Service (MaaS), a concept where multiple shared modes are integrated with public transport to facilitate intermodal travel [31]. Despite the popularity of MaaS as a concept, there is currently only limited empirical evidence on how exactly MaaS will influence travel behaviour [16]. To evaluate the impact of MaaS, it will be necessary to collect substantial behavioural data and detect whether and to what extent individuals change their behaviour

when exposed to a MaaS.

Travel behaviour refers to the decision-making process of individuals moving across space and making use of the transport facilities [12, 23]. Each individual has a set of preferred travel behaviours, collectively forming a travel pattern that is stable over the short term and evolves over the long term [9]. To correctly evaluate MaaS as an instrument for behaviour change, it is necessary to detect the long-term evolution of individuals' travel behaviour patterns. Apart from the evaluation of MaaS, detecting behaviour change on an aggregated level helps transportation planners to manage travel demand, understand the impact of transportation policies (e.g., congestion pricing, road space rationing), and evaluate people's reactions to new transportation infrastructures [27]. At the individual service level, detecting changes in travel patterns allows personalized location based services to adapt to individual travel behaviour change [17], monitor mobile phone intrusions [36], and detect hidden drivers for usage-based insurance pricing [8].

Motivated by the broad applications, many researchers have focused on travel behaviour change over the recent years [15, 20]. Studies on individual travel behaviour change mainly employed travel panel data and analysed the causes and directions of the behaviour change. For example, Lin *et al.* [24] investigated the role of social network and social environment in the relationship between residential relocation and travel behaviour change. In their study, travel behaviours are represented by trip frequency, travel time, and modal split. A study by Jain *et al.* [18] analysed the process of travel behaviour change associated with the adoption of a car-sharing service, in which the travel behaviours are represented by the amount of travel and mode choices. Overall, limited studies have focused on the detection and changing speed of the new behaviours using panel data, partially since those discrete-time panel data were not suitable for observing a dynamic process [22]. In the era of ubiquitous computing, billions of personal devices connect us to the web and enable the generation of data sets that reflect large-scale human digital traces. Compared to actively obtained travel survey data, these data sets passively and continuously record the whereabouts of individuals over time, offering new opportunities for data-driven approaches to study individual travel behaviour change.

Analysing travel behaviour and detecting its change is challenging because continuous individual movement traces are noisy, and travel patterns are latent in the movement data. To partially mitigate this issue, previous studies most often use aggregated indexes (e.g., total travel time per day) for describing travel behaviours [20]. Although this processing method can extract the essential travel behaviour, an aggregation level needs to be predefined, and some fine-grained details might be omitted during the aggregation process. Therefore, this study uses the amount of travel (trip duration and distance) and mode of transport as features to describe travel behaviours and employ clustering methods to identify travel behaviours directly at the trip level.

We develop a clustering-based framework that utilises passively tracked data to detect changes in individual travel behaviour patterns. Two change detection methods are proposed and analysed using a real-world, large-scale GPS tracking data set that evaluates the effect of introducing a MaaS offer to the study participants. The remainder of the paper is organised as follows. Section 2 reviews related work on individual travel behaviour change detection. Section 3 presents the clustering-based change detection framework developed in our study. Section 4 describes our case study data and pre-processing steps. Section 5 explains the case study results. Section 6 summarises the main contributions of our study and highlights future research directions.

2. Related work

Research on individual travel behaviour change has primarily focused on short-term changes, often called anomalies, outliers, or intrapersonal variability. A generic technique used to detect this type of change when the change is not known a priori is to model the dominant pattern from the data as a standard pattern and identify observations that deviate from this pattern as potential anomalies [7]. Many methods have been developed to model the dominant pattern and detect short-term travel behaviour changes, such as clustering-based methods, frequency pattern mining methods, and generative models. An example of using a cluster-based method is given in [41]. The authors used a hierarchical clustering method to identify normal clusters of trajectories and detect anomalous taxi routing patterns that lie outside these clusters for inferring taxi fraud or traffic incidents. As a complementary example, a study by Sun *et al.* [36] utilized a frequent pattern mining technique and modelled the mobility sequence of an individual as a mobility trie. The frequent transition pattern between places is generated based on this mobility trie, and a less frequent travel sequence is considered abnormal. An example of using generative

models is shown in [37], where a generative two-dimensional Latent Dirichlet Allocation model was developed to capture routine patterns of individuals and predict future movements. Trajectories with low predictability are considered abnormal and are used to indicate potential changes in travel behaviour patterns.

In contrast to a large number of studies in short-term pattern change detection, less attention has been given to detecting long-term, persistent pattern changes of individual travel behaviours. This long-term pattern change is also called structural pattern change, change point detection, or concept drift in time series analysis and has been studied in fields such as statistics [25, 35], econometrics [4], and sequential pattern mining [40]. However, those methods have not been well utilized in analysing the evolution of individual travel patterns.

Recently, a few studies explored the long-term travel pattern change of individuals. Zhao *et al.* [44, p. 74] defined this type of change as "abrupt, substantial, and persistent changes in the underlying patterns of travel behavior". To detect this pattern change, they used a Bayesian approach to model the probability of a pattern change at any given time. The study examined the changes in three dimensions of travel behaviour: travel frequency, spatial dimension, and temporal dimension. Although the method is shown to be robust to noisy observations of travel behaviours, it assumes that travel incidences are independently generated from an underlying distribution in each dimension, thus missing the temporal dependency among one dimension and the correlation between different dimensions. To account for the pattern change reflected in other dimensions of travel behaviours, Jonietz and Bucher [20] considered multiple daily and weekly aggregated mobility features, including travel duration, distance, speed, CO_2 emission, and frequently visited places. The detection of pattern change is based on whether each feature value deviates from the historical average value by a certain threshold. The framework could signal anomalies in each feature dimension but failed to consider travel behaviour as a whole. By contrast, the clustering method used in our study considers the correlations between different dimensions of travel behaviours (i.e., transport mode, distance, and duration) and separates them into clusters that represent different latent travel behaviour patterns.

3. Method

We aim to identify personal mobility preferences and detect possible travel behaviour changes over a long time scale [33]. This proposed framework consists of three main steps: (1) Using the individual conducted trips and visited locations, we define the activity set containing preferred locations and extract important trips that depict individual characteristic movement. (2) These trips are analysed to infer personal travel behaviours based on similarity measures and a clustering algorithm. (3) We then detect changes in the travel behaviours using the Herfindahl-Hirschman Index (HHI) and sliding window-based change detection methods. The flowchart of this framework is shown in Figure 1.
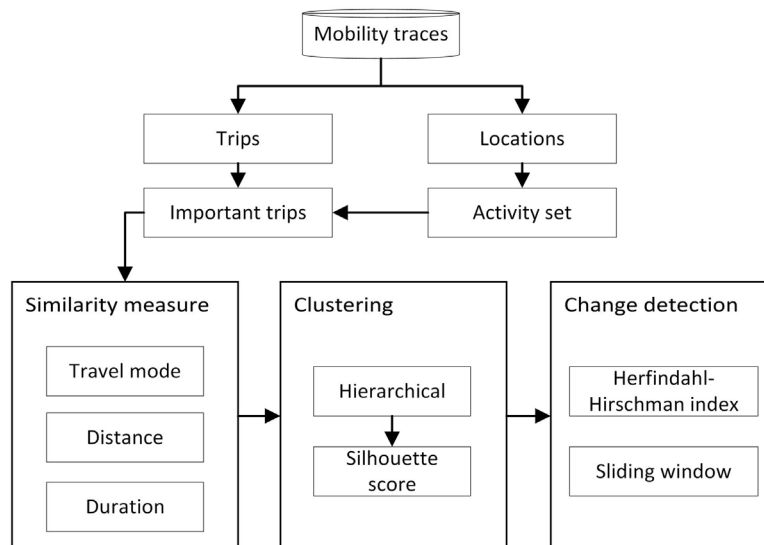

Figure 1. The flowchart of the framework. We extract important trips based on the activity set, identify individual travel behaviours and detect changes over time via a clustering framework

3.1. Important Trip Extraction

Individual travel sequences are dynamic and complex [19] and often exhibit substantial variability regardless of changes in the travel pattern [44]. Therefore, the extraction of characteristic movements could benefit the travel pattern identification. From an activity- based analysis point-of-view, trips are seen as an induced demand for out-of-home activities, and trip and activity should be combined during analysis [33]. A recent study measured the location importance by its activity duration and proposed a concept of activity set, containing the most important locations in one's daily life [2]. Following up on this idea, we identify trips that arrive at one of the locations in the activity set, noted as important trips that reflect individuals' major travel patterns.

The activity set $AS_i(t) = \{l_1, l_2, ...l_k, ..., l_C\}$ is defined as the set of all locations l_k that the individual i visited at least twice and spent on average more than 10 minutes/week during a given time window Δt preceding time t [2]. $C \in N$ is the cardinality of the activity set and called capacity. The activity time criterion ensures that only long-stayed locations are included in the activity set, and the time window Δt controls the strength of this criterion.

We further define the important trip set $IT_i(t)$ of the individual i in week t as all trips that arrive at any location within the activity set. We set the time window $\Delta t = 5$ weeks in this study, following an empirical study that reported that the destination-choice preferences of an individual stabilizes after five to ten weeks [33].

3.2. Trip Similarity Measurement and Clustering Algorithm

The trips included in any important trip set $IT_i(t)$ are considered to contain information regarding the individuals' main travel behaviours. They are then fed into a clustering-based framework for identifying groups of trips with similar travel choices. We focus on high-level semantic information attached to each trip and consider trip mode, trip distance and trip duration as features. These are essential dimensions reflecting individual travel behaviour and have been employed in various travel behaviour change studies [24, 30].

The travel mode information of trips is represented as a sequence since each trip is a combination of triplegs with a single travel mode. This property makes the travel mode comparison a sequence similarity measurement problem. Nevertheless, we are more interested in what mode exists in a trip than the order of modes for analysing travel behaviour. Therefore, we regard travel mode sequences as sets and measure their Jaccard distance. For example, given two mode sequences, we reconstruct them into set $A = \{mode_{A1}, mode_{A2}, ..., mode_{Ai}\}$ and set $B = \{mode_{B1}, mode_{B2}, ..., mode_{Bj}\}$, respectively. The Jaccard distance $d_J(A, B)$ is then represented as:

$$d_J(A,B) = 1 - J(A,B) = 1 - \frac{|A \cap B|}{|A \cup B|}$$

where $J(A, B)$ is the Jaccard similarity coefficient, defined as taking the ratio of the intersection over the union of the sets A and B. Thus, the pairwise distance matrix of trip modes D_{mode} is constructed by calculating the Jaccard distance between each pair of trips.

Trip distance and trip duration are two features characterising the amount of travel. We measure the distance and duration similarity of trips with the Euclidean distance and obtain two pairwise similarity measurement matrices D_{dist} and D_{dur}.

The selected semantic features are combined into the final similarity matrix D_{all}:

$$D_{all} = \omega_1 D_{mode} + \omega_2 D_{dist} + \omega_3 D_{dur}$$

where ω_1, ω_2, and ω_3 are the corresponding weights that control the importance of D_{mode}, D_{dist} and D_{dur}, respectively. The weight values can be defined equally for each of the dimensions (i.e., $\omega_1 = \omega_2 = \omega_3 = 1/3$), but they can also be set differently when certain dimensions need to be strengthened. To ensure consistent distance scales, each distance matrix is *min-max* normalized to be in the range from 0 to 1.

We perform clustering on the similarity matrix to identify the group of trips with similar travel behaviour. This is achieved using hierarchical clustering that produces a hierarchy of clusters using agglomerative (bottom-up) or divisive (top-down) algorithms [21]. The linkage standard that defines how the distance is measured between two clusters is the key design choice for hierarchical clustering. Previous work reported that complete linkage is suitable for determining a relatively compact cluster [41, 1]. For complete linkage, the distance $D(X, Y)$ between clusters X and Y is defined as:

$$D(X,Y) = \max_{x \in X, y \in Y} d(x,y)$$

where $d(x, y)$ is the distance between element $x \in X$ and $y \in Y$. To quantitatively evaluate the clustering label assignments and select the optimum cluster number, we adopt the silhouette coefficient as an internal measure of validation, which measures both the degree of cohesion within a class and the degree of dispersion between classes [32].

In this study, we adopt the complete linkage method and choose the cluster number with the highest average silhouette coefficient [43]. The outcome of this section is a class label assignment for each trip that groups similar trips to identify individuals' typical travel behaviour.

3.3. Travel Behaviour Change Detection

The travel share of trip classes can show mobility choices and imply travel behaviour changes when compared across time. We denote the time series as $X_i = [x_i(1), x_i(2), ..., x_i(t)]$ where $x_i(t)$ represents the trip class shares for important trips $IT_i(t)$ at time step t. Our aim is, therefore, to detect possible changes of $x_i(t)$ over the whole study period. We propose two such change detection methods: the HHI-based method and the sliding window-based method.

The HHI was first proposed in economics as a measure for market concentration and is currently widely used for measuring individuals' mode or activity choice variability [38, 14]. In the context of this study, HHI is adopted as a measure for the choice variability of trip classes. The HHI of trip class variability $h_i(t)$ for individual i at time t is given as:

$$h_i(t) = \sum_{n=1}^{N} s_n(t)^2$$

where N is the number of different trip classes, and $s_n(t)$ represents the trip shares of the nth class conducted at time t. A higher $h_i(t)$ value indicates that travel is concentrated on a few dominant trip classes, and a lower value suggests the different travel behaviours are more evenly selected by the individual i. We obtain $h_i(t)$ for each time step t and the original time series X_i is represented as a time series of HHI $H_i = [h_i(1), h_i(2), ..., h_i(t)]$. As a change in H_i indicates a change in the preferences towards each trip class, we regard it as a change in individuals' travel behaviour.

To detect changes in H_i, we adopted a robust peak detection algorithm developed for time series data [5, 20]. The algorithm detects peaks in a time series when the values lie beyond a number of standard deviations from a moving average. It takes three input parameters: *lag* that controls the size of the moving window; *threshold*, denoted by λ, that determines the number of standard deviations (i.e., z-score); and *influence* that controls how much influence new data points will have on the moving average and standard deviation. At each time step t, a moving average μ_t and standard deviation σ_t are calculated using data within the moving window. A data point is considered a peak if its value $u > \mu_t + \lambda * \sigma_t$ or a valley if its value $v < \mu_t - \lambda * \sigma_t$.

The sliding window-based method processes data in a sequential fashion. Considering the time series X_i, to determine whether a change occurs from time step t_{start} to t_{end}, we measure the travel share difference of trip classes between these two time steps and compare it against a predefined threshold τ. Operationally, we consider any trip class proportion change larger than 30% (i.e., $\tau = 0.3$) as a change in travel behaviour, in order to set a restrictive definition of change [15]. For a given time step t_i, the algorithm measures the class share difference between t_i and any time step t_n, $n \in [1, i]$ preceding it. $t_{start} = t_n$ is found if the difference is the largest of all possible n's and also larger than τ. We then find $t_{end} = t_m$ by maximizing the difference

between t_{start} and any time step t_m, $m \in (i, t]$ succeeding t_i. To prevent the generated change window from being too large, we impose that the share difference between t_{start} and t_{end} should be monotonically decreasing or increasing. Moreover, the algorithm ensures that no overlapping change periods for each individual are detected.

The outcome of this section is the change detection result for each individual. The HHI-based method outputs the peak detection results where sudden changes in trip class variability are recorded, whereas the sliding window-based method detects the starting and ending time steps where changes have occurred.

4. Case Study

We adopt mobility data from a large-scale pilot study that evaluates the effect of a MaaS offer. The pilot study, conducted by the Swiss Federal Railways (SBB), is named SBB Green Class[1] [26, 6] (denoted as SBB GC in what follows) and involves 138 Switzerland-based participants. Although the participants were primarily selected based on their geographic location, the participation preconditions led to a bias towards the middle- and upper-class people with high mobility demand. The participants were mostly working full-time and aged 47.3 ± 7.6 according to the socio-demographic survey.

From November 2016 to January 2018, the participants were provided with a battery electric vehicle, a general public transport travel card for unlimited travel on public transport in Switzerland, as well as access to several car- and bike-sharing programs. As part of the pilot study, the participants were asked to install a GPS-tracking application on their smartphones that records their daily movement. The application uses a MOTIONTAG[2] back-end and segments the tracking data. It creates a *tripleg* when a person is moving continuously with the same mode of transport and a *staypoint* when a participant remains stationary. Study participants were required to annotate their tracking data in the application. Staypoints were annotated with a high-level purpose (home, work, errand, leisure, wait, and unknown) and triplegs with the used mode of transport (car, e-car, train, bus, tram, bicycle, e-bike, walk, airplane, boat, and coach). Figure 2 maps the recorded triplegs with user-labeled transport mode. Although we only plot the triplegs within Switzerland, SBB GC contains user movements all across the world - the occasionally conducted cross-border and inter-continental trips are also recorded.

The triplegs and staypoints provided by the GPS-tracking application are further aggregated into *trips* and *locations* according to the movement data model [3, 13]. We regard a staypoint as an *activity* if it has an important purpose (everything except for wait and unknown) or if its duration is longer than 25 minutes [26]. Trips are then constructed as the sequence of all triplegs between two consecutive activities. Moreover, locations are defined as important places visited more than once. Due to GPS recording error, multiple visits to the same location might create staypoints with different coordinate referencing. To tackle this problem, we use the DBSCAN method to create locations as spatially aggregated staypoints for each user. DBSCAN uses a set of neighborhood characterization parameters ϵ and *min_samples* to depict the tightness of the sample distribution [20]. $\epsilon = 50$ (m) [2] and *min_samples* = 1 is selected in this study, meaning that staypoints in the proximity of 50m of each other will be merged into a single location, and no staypoints will be discarded in this process.

We calculate the temporal tracking coverage of each user, defined as the proportion of time the user's whereabouts are recorded in the data. To ensure high temporal tracking coverage, we only include users who are tracked for more than 300 days and whose tracking coverage is consistently higher than 60% during their tracking period. After user filtering, 193,637 staypoints and 344,740 triplegs from 93 individuals remained, aggregated into 46,489 ocations and 181,479 trips. These pre-processing steps are implemented using the *trackintel*[3] library.

We analyse the user's moving behaviour at the trip level. Each trip's distance and duration is measured as an aggregation of its containing triplegs. Also, multiple travel modes could exist within one trip, referred to as intermodal trips [28, 29]. In fact, in the SBB GC study, 29.4% of all trips contain more than one travel mode. Walk is commonly considered a transition between other travel modes and we do not consider these trips as intermodal. As a direct result of the provided MaaS offer, mode combinations of train with car and e-car are most frequently found.

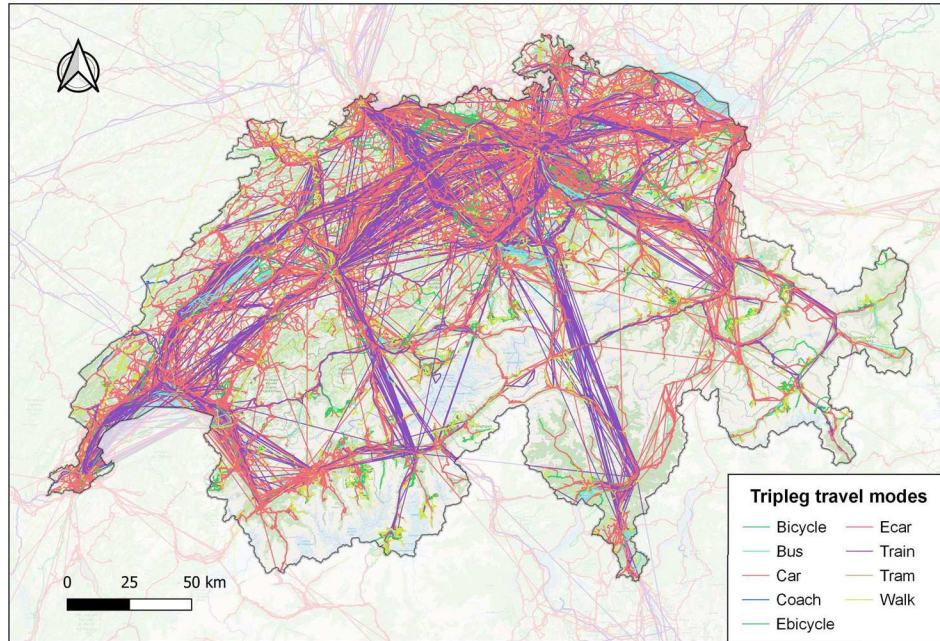[1] https://bit.ly/3d0k2qD

[2] https://motion-tag.com/

[3] https://github.com/mie-lab/trackintel

Figure 2. The recorded triplegs with different travel modes within Switzerland in the SBB GC data set.

5. Results

5.1 Delineating Travel Behaviours

Important trips that contain an individual's travel behaviour information are first obtained. We find that the number of important trips for each individual is stable across time; that is, individuals conduct the same number of trips to their preferred locations, despite the time of observation (detailed empirical evidence shown in Appendix A). This property makes the important trip set ideal in the study of individual travel behaviour.
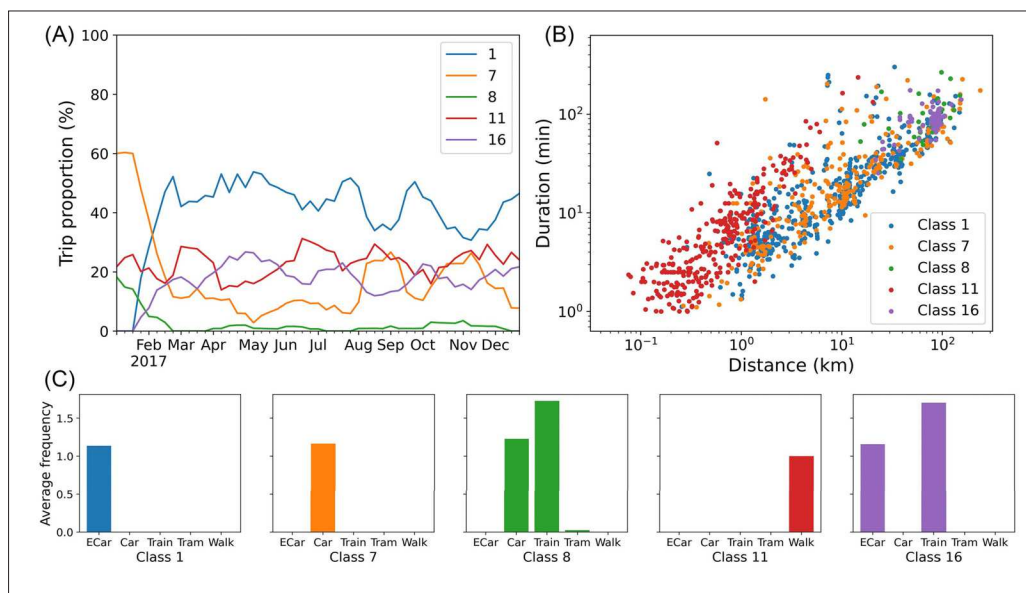

Figure 3. Travel preference identification result for a sample user. (A) The trip proportion evolution for different trip clusters. The x-axis is the ending time of a 5-week sliding window. (B) The distance and duration scatter plot showing each cluster's distribution on a log-log scale. (C) The average frequency of travel mode within each trip cluster

The similarity measure and clustering pipeline accepts trips that belong to any important trip set, measures their semantic similarities and outputs class labels for these trips. Since we are interested in analysing travel mode change after introducing the MaaS offer and hope to interpret the change, we set the weight parameter $\omega_1 = 0.50$ and $\omega_2 = \omega_3 = 0.25$ in the similarity measurement. Figure 3 shows the results of the clustering label assignment of a sample user. As each trip class represents a typical travel behaviour, the proportion of travel in each trip class delineates the user travel preferences across time (Figure 3(A)). The details and separations of the travel behaviours can be visualized in each of their dimensions using distance-duration scatters (Figure 3(B)) and travel mode frequency (Figure 3(C)).

For this particular user, we observe a preference in using train and car (Class 8) and train and e-car (Class 16) mode combinations for long-distance and -duration trips. Moreover, car (Class 7) and e-car (Class 1) modes are mainly used for shorter trips, with indistinguishable duration and distance distributions. Considering the temporal dimension, we report a sharp increase in the trip proportion travelled in Class 1 and 16 at the beginning of the study period (Figure 3(A)), which is most probably due to the introduction of the MaaS offer leading the user to switch from car to e-car. Compared to frequency-based statistics, our clustering-based framework groups trips according to the similarity definition, which considers mul tiple trip semantic dimensions simultaneously. In short, with the information provided in Figure 3, we can delineate the individual's mobility preferences and their evolution over time.

5.2. Travel behaviour Change Detection

With the proposed HHI-based and sliding window-based method, we detect change points or regions where the user has changed the travel behaviour. Figure 4 shows the change detection result for the same user as Figure 3. The sliding window-based method detects regions where a trip proportion change larger than the threshold $\ddot{A}$ occurs (Figure 4A). The algorithm successfully detects the travel behaviour change at the beginning of the study period. The length of the change window represents the speed of a certain change; here, the change took seven weeks. By comparing the lengths of the change windows, we can quantitatively evaluate the speed of travel behaviour change.

The HHI index of the trip class shares and the moving average and upper/lower bound obtained from the peak detection algorithm are shown in Figure 4B. We set the input parameter *lag* = 5 to detect sudden changes, *threshold* = 3 to only include extreme changing points, and *influence* = 1 considering a change is usually substantial and persistent. The corresponding signal detection result is shown in Figure 4C. These signals capture changes in the HHI index that correspond to sudden changes in the trip class shares and individual travel behaviour. The detected signals mostly correspond to the peaks and valleys from the most dominant trip class, which also has the most considerable influence on the HHI index. However, the algorithm cannot detect signals at the beginning of the time series since the initialization of the moving time window is needed.
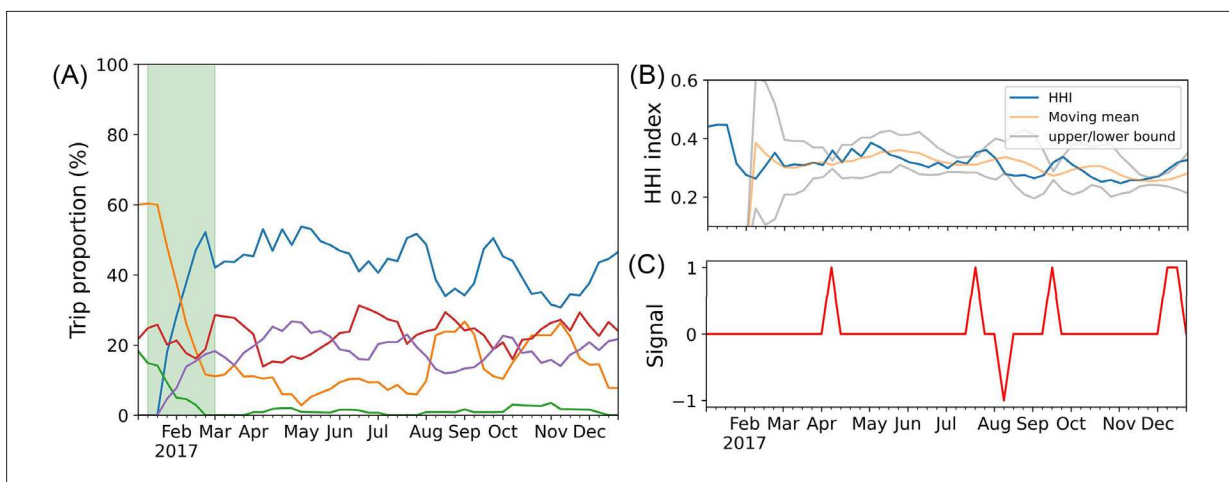

Figure 4. The change detection results for a sample user. (A) Sliding window-based change detection. Change periods are shown in light green areas. (B) The HHI index evolution and corresponding moving mean and upper/lower bound of thresholds. (C) The peak signal detection result with peak (1) and valley (-1) signals reflect sudden changes in the HHI time series

To validate our change detection result, we report user groups with different behaviour changes when applying the methods to individuals in the SBB GC data set. This is shown by the sliding window-based change detection result for selected users in Figure 5. In total, 92.5% of the users (86 out of 93 individuals) are observed to have started to change their travel behaviour within the first five weeks, most likely due to the MaaS offer introduction that promotes users to switch from regular cars to e-cars. However, the speed of this change varies for users, ranging from 4 to 13 weeks. With a median changing speed of 7 weeks and a standard deviation of 2.3 weeks, substantial user heterogeneity is observed in response to the same triggering event (compare Figure 5A and B as an example). This result shows that the speed of adapting to a new travel behaviour triggered by introducing new mobility options is relatively slow and heavily influenced by personal factors. As a comparison, home location change usually causes a more rapid shift in travel behaviour; an example of this is shown in Figure 5C. The individual switched back and forth between two home locations, leading to abrupt and periodic changes in the two most dominant trip classes. Also, a small number of users have no change periods detected (Figure 5D) because the trip class shares are relatively stable over the study period. From another perspective, the magnitude of the travel behaviour change is not large enough to be detected by the proposed algorithm. This suggests that the extent of the travel behaviour change triggered by MaaS introduction also varies across individuals.
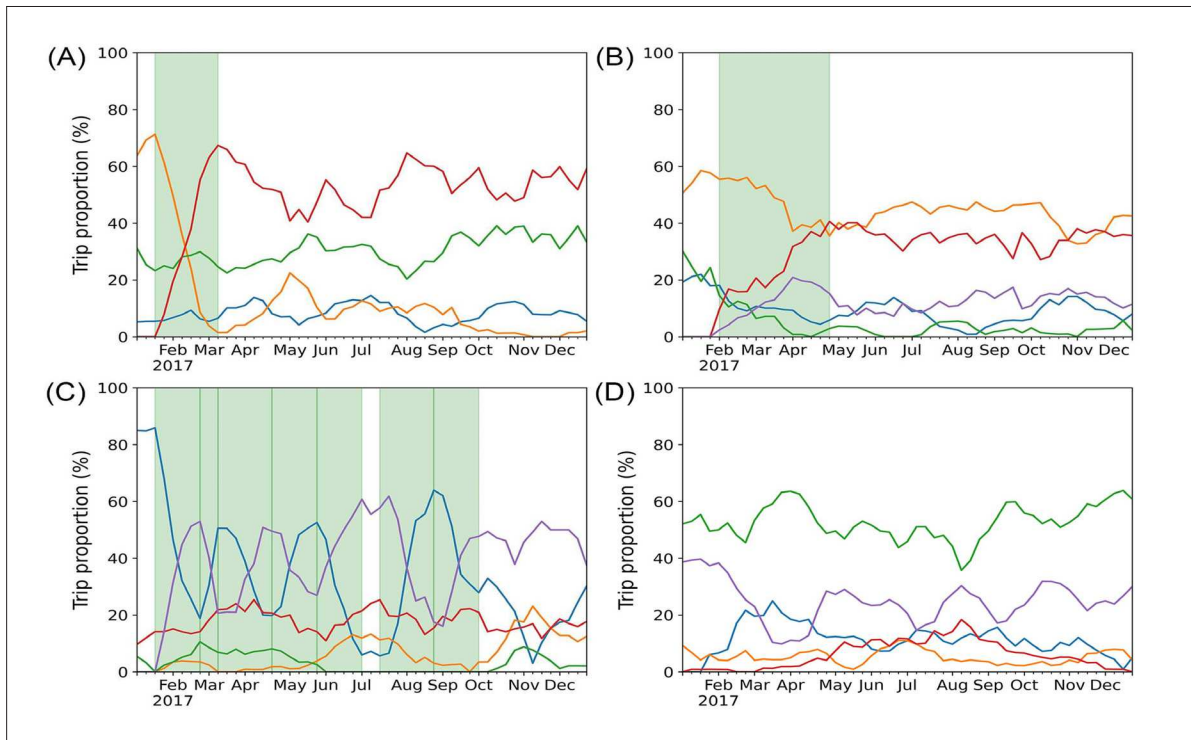

Figure 5. Sliding window-based change detection result for different user types. Change periods are shown in the light green area. (A) A user who changed the travel behaviour relatively fast; (B) a user who took more time to adjust to the new travel behaviour; (C) a user who has periodic travel behaviour; and (D) a user whose travel behaviour change is not large enough to be detected by the algorithm

6. Discussion and Conclusion

This study presents a clustering-based framework to detect travel behaviour changes from individual mobility traces. Specifically, we extract trips that arrive at important locations in individuals' daily mobility and consider trip mode, distance, and duration as features describing travel behaviour. These features are then fed into a trip similarity measure and clustering pipeline that generalizes individual movements into travel behaviours. Furthermore, we propose methods to detect possible changes in the travel behaviour time series. The proposed pipeline is successfully applied to a real-world GPS tracking data set collected through a pilot study in which a MaaS offer is introduced at the beginning of the tracking period.

In particular, we propose the HHI-based method and the sliding window-based method for detecting travel behaviour changes

over long time series. The HHI based method analyses the variability of travel behaviour choices and detects a change if the variability significantly deviates from its previous trend. The sliding window-based method monitors the preference towards each travel behaviour and signals a change if any behaviour shows a large change in its travel share. Combined with a labelled data set, we can also attribute potential causes and analyse the detected changes. With the change duration information obtained from the sliding window-based method, we analyse the effect of the MaaS offer on the travel behaviours in our case study. We find that these induced behaviour changes are heavily user-dependent. Moreover, compared to changes triggered by relocation, changes caused by additional mobility options usually occur slower in time.

The proposed change detection method is data-driven and identifies change periods from the statistical distribution of travel behaviour. We believe that this framework is generalisable to tracking datasets within other contexts, with flexibility given from the design choice parameters (e.g., the weights in the similarity measurement). We see several future directions based on the results of this study. First, the proposed change detection pipeline can be applied online to streaming data; however, we lack the information of whether the clustering algorithm is sensitive enough to detect newly occurred travel behaviours. This needs to be tested in an online setup. Second, a sensitivity analysis on the choice of the weight parameter for each semantic feature is beneficial if the proposed pipeline is to be employed in other applications. Third, previous research has reported that residential neighbourhood has an important impact on people's travel behaviour [10, 11]. Combining the mobility traces of SBB GC participants with land-use information could help validate the behaviour change detection results with other studies. Last, the user-dependent influence of MaaS suggests that an analysis on the relationship between individual actors and travel behaviour change is needed to understand the effect of MaaS offers on personal travel behaviour.

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Appendix A

A Stability of Important Trips

For each individual, we form the activity set at different time steps t and extract the important trip set $IT_i(t)$ containing trips that arrive at any location included in the activity set. The size of the important trip set represents the number of trips to familiar locations, which we denote as trip capacity T_i. We are interested in the relation between T_i and t: if T_i does not depend on the time of observation (i.e., irrespective of t), T_i is a conserved quantity over time; otherwise, T_i is not stable and might be influenced by individual factors and seasonality effects [19].

We first report that on a collective level, the average trip capacity T does not depend on time t. This is shown using a linear fit of the form $T = a + b \cdot t$, and through testing the hypothesis H_0: $b = 0$ under independent 2-samples t-tests. Using a time window size of 5 weeks, the angular coefficient $b = -0.001 \pm 0.007$ is not significantly different from 0, and the hypothesis H_0: $b = 0$ cannot be rejected (p-value: $0.86 > 0.05$). This stability is tested using the different choices of time window size t, as reported in Table 1. For each choice of t, we find no evidence for rejecting the hypothesis that the average trip capacity does not change in time.

At the individual level, we look at the net gain $G_i(t)$ of the important trip set $IT_i(t)$. The net gain $G_i(t) = A_i(t) - R_i(t)$ is defined as the difference between the number of trips that are respectively added $A_i(t)$ and removed $R_i(t)$ at time t. We find that for each individual, the average net gain across time $<G_i>$ is closer as its standard deviation $<G_i>$ to 0, i.e., $|<G_i>| / \sigma_{Gi} < 1$, indicating that $<G_i>$ is not significantly different than 0. Therefore, for the SBB GC population, the trip capacity is stable at the individual level. This result suggests that individuals always conduct the same amount of travel to their important activity locations. Moreover, this stability is measured as roughly 23 important trips per week for a typical user in the SBB GC data set, despite the choice of the window size t (Table 1).

Table 1 Hypotheses testing for trip capacity with different window sizes. For every window size t, the null hypothesis H_0: $b = 0$ cannot be rejected (p-value > 0.05).

Window size Δt	Intercept a	Slope b	Standard error	p-value	p-value>0.05
4	23.14	-0.002	0.007	0.78	True
5	23.13	-0.001	0.007	0.86	True
6	23.16	-0.002	0.007	0.81	True
8	23.24	-0.007	0.007	0.33	True
10	23.17	-0.009	0.007	0.23	True
15	22.92	-0.011	0.008	0.16	True
20	22.62	-0.012	0.009	0.20	True
30	22.09	-0.006	0.014	0.66	True
40	21.58	0.015	0.025	0.56	True

Table 1. Hypotheses testing for trip capacity with different window sizes. For every window size t, the null hypothesis H_0: $b = 0$ cannot be rejected (p-value > 0.05)