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RESEARCH ARTICLE

Detecting Pattern Changes in Individual Travel Behavior Based on a Bayesian Method

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ABSTRACT This paper focuses on the long-overlooked phenomenon that individual travel patterns are not always stable over the long term and may change due to seasonal changes, moving, and work schedule changes. Unlike previous studies that identified sudden peak points, this paper treats travel pattern change as a change point detection problem in a time series and defines change as ''sudden, substantial, and continuous''. Considering the complexity of travel behavior, this paper measures changes in travel patterns in three dimensions: time, space, and frequency, and establishes a Bayesian change point detection model. A nine-month period of private car GPS data from Aichi, Japan, is used for an example analysis. The results show that the Bayesian approach can effectively identify travel pattern changes. Compared with the traditional GLR, the proposed method in this paper has higher recognition accuracy with lower model complexity. Meanwhile, the experimental results show that individual travel patterns may change in only one dimension or in multiple dimensions at the same time. Based on this, the correlation analysis of travel patterns in the temporal and spatial dimensions is carried out, and it is verified that there is a certain positive correlation between the two. The Bayesian change-point detection model proposed is robust and generally applicable to other fields besides travel patterns.

INDEX TERMS Travel pattern, change point detection, Bayesian method, travel behavior analysis.

I. INTRODUCTION

The research of individual travel behavior is essential to uncovering travel rules and guiding scientific decision-making. Travel behavior refers to the incidence of individuals who adopt a certain mode to travel from an origin to a destination at a certain time, which can be directly observed. There is a certain regularity of individual travel behavior that can be characterized as a ''pattern''. The travel pattern is a higher-level generalization of an individual's travel behavior, where each pattern refers to a collection of limitations and preferences that specify a particular choice [1]. Travel patterns are not directly available but can be expressed in terms of the distribution of observed travel behavior.

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Most of the previous studies assumed that individual travel patterns were stable and did not change [2], [3]. This is indeed true for short periods of time, but individual travel patterns are likely to change in the long term. Since activity is endogenous to travel, when an individual's activity schedule changes for a variety of reasons, his or her travel pattern will change accordingly. For example, as work schedules change with the seasons, their travel patterns for commuting will also change. When people relocate their houses from the suburbs to a downtown area closer to the office, they may reduce car use, shorten travel distances, and adjust commute times. These events in life have been called ''windows of opportunity,'' which can change a person's daily routine [4]. Less research has been done on when and how these changes occur.

Ignoring the instability of travel patterns over time can lead to difficulties in adapting to changes in travel demand.

Some scholars have also raised a similar question, namely that the estimation of travel time may be impacted by daily changes [5], [6]. These changes include some random daily changes and some long-term, systematic changes in individual travel patterns. Detecting long-term individual travel pattern changes is the basis for modeling time-varying behavior. It is necessary to distinguish frequent travel patterns from occasional travel behaviors.

Survey data were frequently utilized in the literature to estimate how people's travel behaviors changed over time [7]. Whereas, Kitamura et al. [8] demonstrated that discretization time data was an unreliable instrument for describing the dynamic of travel behavior accurately, and continuous data was required. With the rapid rise of information and communication technology (ICT) in recent decades, travel behaviors can be continually recorded by massive data sources (cell phone data, GPS data, smart card data, etc.) on a vast scale and for a long time [9].

Change Point Detection (CPD) is the problem of identifying the time point in a time series when a sudden change in behavior patterns occurs. This study uses nine months of continuous GPS data from private cars from Aichi, Japan, to study how long human regular travel will last at the individual level and when people's regular travel will change systematically. In this study, it is described as a CPD in time series analysis. Since travel patterns are difficult to observe directly, they need to be portrayed in multiple dimensions. This study measures patterns in three dimensions: time, space, and frequency. At the same time, in order to distinguish from previous studies that only identified unexpected peaks, the changes in pattern need to satisfy the three properties of being sudden, substantial, and continuous.

The contributions of this study are threefold: (1) An online Bayesian change-point detection model is proposed that enables the estimation of the probability of a change in an individual's travel pattern at any given moment with lower complexity and higher robustness. (2) Three dimensions of time, space, and frequency are established to completely characterize travel patterns, and the correlation of travel pattern changes in the time and space dimensions is analyzed. (3) It can contribute to the advancement of models of adaptive travel behavior that are able to recognize changes in travel patterns automatically and adjust model parameters accordingly.

The remaining part of this paper is structured as follows: Section II reviews earlier relevant literature; Section III proposes a Bayesian change point detection model; Section IV presents the data used in this paper and part of the parameter settings for the experiments; and Section V provides visualization of the experimental results and analysis of the model accuracy. Finally, the study concludes with conclusions and future work.

II. LITERATURE REVIEW

Previous studies on the changes of travel patterns mainly focused on the influence of social, policy, cultural, and psychological factors [10], [11], [12], [13] and how to use these factors to infer the changes in travel patterns [14], [15], [16]. Haasa et al. adopted the mobility biographies framework with the relatively recent latent class transition analysis to detect various travel patterns and determine how life events affect changes in travel behavior [17]. Goulias used mixed Markov latent class (MMLC) models to analyze the dynamic characteristics of daily changes in individual activity participation and travel [7]. Zhao et al. built a probability distribution function (PDF) of the feature sequences to further fit the priori probability model and analyze the distribution of these changes over time [18].

A larger portion of recent studies have focused on changes in travel patterns in cities during the COVID-19 [19], [20], [21]. Based on the population movement data of Chinese cities at the beginning of the epidemic outbreak, the changes in travel patterns are analyzed at the aggregate level [19]. Wang et al. measured the changes in travel patterns in terms of total trips, trip recovery, and trip distance [20]. Using a statistical change-point approach to analyze the collected mobility time series, the model is able to estimate if and when a local mobility pattern changes significantly [21]. However, the above studies mainly focus on the state of inter-city mobility and do not examine the changes in urban travel patterns.

There were many studies that used deep learning methods for vehicle target detection. Ahmed [22]proposed an algorithm based on the combination of Convolutional Neural Networks (CNN) and optical flow feature tracking for vehicle detection and counting in complex traffic scenarios. SHAKHBOZ [23] proposed a joint method for multi-class target detection and semantic segmentation for the two fundamental problems of target detection and semantic segmentation in autonomous driving systems. An effective real-time method [24] was adopted to combine the vehicle detection and tracking process with periodic updating of the feature points at regular intervals of a certain number of frames, resulting in robust feature points. Ahmed [25] proposed a real-time algorithm for detecting and counting moving vehicles based on YOLOv2 and feature point motion analysis. The application scenario of such studies is the traffic characteristics of set counts for a specific roadway cross-section at a given time period. This paper is based on the individual level and uses the pattern change point identification of private car travel in frequency, time, and spatial dimensions over a long period of time.

As for the detection of changes in long-term travel patterns, the existing literature is quite limited. McInerney et al. proposed an information theory measure, namely ''instantaneous entropy'', to detect occasional abnormal travel activities [26]. This method did not clearly identify the pattern changes; however, it focused on finding the unexpected peaks of individual travel activities. The purpose of his research was to identify events or observations in the data that do not cohere with the expected pattern, but he did not suppose that the travel patterns would change over time. Zhao et al. proposed a method to detect whether a pattern has changed [27].

TABLE 1. Comparison of methods with related studies.

Reference	Method	Travel pattern			Long time period	Disadvantages
		Tme	Space	Frequence		
Kamruzzaman et al. [10], Yang et al. [21]	Statistical methods			√		Only for quantifiable indicators
Zhou et al. [11]	Information Entropy Weighting		√		√	No individual level analysis
De Haas et al. [17]	Latent transition analysis				√	Reflects changes in travel vehicles only
Goulias et al. [7]	mixed Markov latent class			√		Limited by the detrimental effects of sparse tables.
Zhao et al. [18]	Probability distribution functions	√	√	√	√	Only monthly distributional changes are identified, not the moment of change
Ahmed et al. [25]	YOLOv2					Higher demand for data, hard to meet with travel data
McInerney et al. [26]	Instantaneous entropy	√		√	√	Finding the unexpected peaks of individual travel activities, not stable change points
Kengne et al. [30]	Likelihood method				√	Only for data that conforms to the Poisson distribution

Unlike previous studies, this paper treats this problem as a CPD in long time series, and the subject of the study is travel patterns. The "change point" in this study refers to the moment when the structure of the time series changes from one state distribution to another, which is different from the abrupt change of data caused by sudden noise or disturbance.

Depending on the detection delay, there are two types of detection methods: methods based on real-time analysis and methods based on retrospective analysis [28]. The detection methods based on real-time analysis are mostly derived from the autoregressive model and its deformation. Gombay analyzed the CPD mechanism when any parameter in the autoregressive model changes [29]. According to Kengne, the great likelihood technique can be used to estimate the parameters before and after a change in a time series that follows the Poisson distribution [30]. Lund modeling for periodic time series [31]. However, owing to the unpredictability of some time series, the autoregressive model may have difficulty obtaining good prediction results.

The CPD method based on retrospective analysis requires not only the observation data before the moment to be measured but also the subsequent data of the moment. The detection mechanism is generally based on the probability distribution test of the time series, and the more typical methods are: Bayesian test [32], [33], [34], likelihood ratio test [35], [36], [37] and cumulative sum test [38], [39]. The original Bayesian method was offline [33], [34]. Adams et al. first proposed an online Bayesian approach under the hypothesis that the time series data are independently and identically distributed and gave a calculation method to predict the probability distribution of the data at the next moment based on the data value at the current moment [32]. Koyama et al., for time series with a Poisson distribution, give a new strategy for calculating the likelihood ratio of the series, and a change point decision is achieved by hypothesis testing [35]. Compared with the CPD method based on real-time analysis, the method based on retrospective analysis has better robustness and more accurate detection results.

In this paper, the Bayesian CPD method proposed by Adam [32] is used. The main reasons are as follows: first, Bayesian method is based on retrospective analysis, using all the data seen so far, and the estimation results from a semi-global perspective are robust and have higher accuracy. Second, Bayesian methods can define the change framework more accurately. It reflects pattern changes through probabilities and can adjust change points by controlling the probability threshold, which is more flexible.

III. METHDOLOGY

Travel behavior includes information about when, where, in what way, the frequency of travel, etc. In order to portray travel patterns more completely and accurately, this paper describes travel in three dimensions: time, space, and frequency. These three dimensions are correlated but to some extent independent, and an individual's travel pattern may change in one dimension while remaining unchanged in the other dimensions. For example, when a student's school schedule changes, the travel pattern changes in the temporal dimension while remaining unchanged in the spatial and frequency dimensions. It may also change in multiple dimensions in the meantime. For instance, when moving to a place closer to work, travel patterns change in both temporal and spatial dimensions.

A. PROBLEM DESCRIPTION

Travel behavior can be represented by a series of chronologically ordered observation sequences $X = \{x_1, x_2, \cdots\}$, where x_t denotes travel behavior at time t. t is the time step, usually expressed as 1 day or 1 week, both of which are natural cycles of human activity [40]. When the data period is long, a week is chosen to be more representative, because travel patterns on weekdays and weekends tend to have greater variability. As the time period Q increases, more travel information is covered and the model is more robust, but it may result in delayed detection or poor granularity of detection. In order to balance robustness and accuracy, this paper chooses a multiple of one week as the time period, i.e., $Q = 7, 14, 21, \ldots.$

The model assumptions are as follows: (1) The correlation of the three dimensions of time, space, and frequency and the order dependence of travel sequences within each dimension are not considered. (2) It is assumed that x_t independently obeys some potential distribution $P(x_t|\theta)$, θ is the distribution parameter. The definition of $P(x_t|\theta)$ is given based on the x_t sample space. (3) Only discrete measures of x_t are considered, which is consistent with the traditional behavior hypothesis in travel behavior modeling and is more general.

When the travel pattern changes over time, it is hypothesized that the form of the distribution $P(x_t|\theta)$ remains unchanged while the parameter θ changes. According to the pattern change properties we defined in Section I, this study only focuses on "sudden, substantial, and continuous" changes in θ.

Being sudden indicates that the change of time unit relative to t is instantaneous; if the previous pattern stops at moment t, then the following pattern begins at moment $t+1$. Suppose x could be split up into some separated parts, and each part corresponds to a certain pattern. The boundary dividing two adjacent parts is the change point, that is, the start time of the new pattern. In the period from i to $j-1$, the measured values $x_i, \ldots, x_{j-1}$ appear in some form of probability distribution $P(x_t|\theta_{i:j-1})(i \le t \le j-1)$ and $P(x_t|\theta_{i:j-1})(i \le t \le j-1)$ are independent identically distributed. In time step j, $\theta_{i:j-1}$ becomes $\theta_{j:k-1}(j < k-1)$, where $\theta_{j:k-1}$ basically differs from $\theta_{i:j-1}$ and lasts for a long period.

Actually, the real change points i, j and k are not known. A model is needed to detect when substantial, continuous changes in θ occur. We need to set thresholds to identify substantial, continuous changes. In the subsequent model, the interaction of the two is considered, i.e., the product of the two attributes is used to identify the change point. Smaller but long-term changes are likely to be assigned the same probability as larger but short-term changes. In addition, we adopt the binary variable y_u to indicate if u has changed, so that the probability distribution $P(y_u = 1|x_{1:t})(u \le t)$ of y_u can be calculated in the case of the data we have seen so far.

B. SPECIFICATION OF BEHAVIOR DISTRIBUTIONS

First, in the dimension of frequency, times of travel or total number of days traveled in a period of time can be used to denote x_t. Assuming that x_t indicates whether the private car is used on the day of time t, then it follows the Bernoulli distribution. The probability density function can be written as:

$$p(x = b|\theta^{(0)}, \theta^{(1)}) = \theta^{(b)} \tag{1}$$

where b is 0 or 1, which is used to indicate whether residents use private cars to travel on that day; $\theta^{(0)}$, $\theta^{(1)}$ is a parameter representing the probability distribution when b is 0 or 1, respectively, where $\theta^{(0)}$=1-$\theta^{(1)}$. They change if a pattern is changed in the frequency dimension. Identify whether the travel pattern has changed in the frequency dimension by detecting whether the parameter value has changed.

In terms of spatial dimension, the travel location choice is considered as a categorical variable due to the poorly defined location attribute. At each time step, each individual can visit a location 0, 1, or multiple times. x_t is the set of samples taken from the categorical distribution, reflecting individuals preferences for all feasible locations, and follows a polynomial distribution for the case of multiple sampling from multiple classifications. Assuming that there are M locations to consider, $x_t^{(M)}$ is an M-length vector representing the number of visits to the Mth location during time step t. $\theta^{(\mathrm{m})}$ represents the probability of occurrence of the Mth location. For non-negative integer $b^{(1)}, b^{(2)}, \ldots, b^{(M)}$, its probability density function is characterized by:

$$\begin{aligned} &p(x_t^{(1)} \\ &= b^{(1)}, \quad x_t^{(2)} = b^{(2)}, \ldots, x_t^{(M)} \\ &= b^{(\mathrm{M})}|\theta^{(1)}, \theta^{(2)}, \ldots, \theta^{(M)}) = \frac{n!}{\prod_{m=1}^{M} b^{(m)}!} \prod_{m=1}^{M} (\theta^{(m)})^{b^{(m)}} \end{aligned} \tag{2}$$

$n = \sum_{m=1}^{M} b^{(m)}$ is the number of times a traveler visits all locations in a time step. The categorization probability distribution of all potential results is specified by the parameters $\theta^{(1)}, \theta^{(2)}, \ldots, \theta^{(M)}$. Whenever patterns change, they change.

In the temporal dimension, the definition similar to that in the spatial dimension, assuming that x_t obeys a polynomial distribution. The 24-hour day is discretized into 8 segments with 3-hour time intervals. Using the average of departure and arrival times as the midpoint, each trip is assigned a 3-hour time period. Similarly, the polynomial distribution in the temporal dimension is specified by Equation (2). The only difference from the application in the spatial dimension is that results for the temporal dimension correspond to time periods rather than areas, and the totality of results is M = 8.

The model sets the travel behavior in the frequency dimension as a Bernoulli distribution because using an alternative distribution with fewer parameters works better when the number of possible values of the data is sparse. The main reason for setting the travel behavior in the temporal dimension and spatial dimension as polynomial distributions is their flexibility to capture any data structure. However, these distribution forms are not limited and can be adjusted based on data characteristics or the way they are defined.

C. BAYESIAN CHANGE DETECTION

Based on the online Bayesian approach proposed by Adams [32], a slightly improved Bayesian CPD method is proposed. The majority of the formulation is also applicable to other issues.

Every time point t corresponds to a segment of a travel pattern. For the current segment, the end point is not known. c_t denotes the segment line length at t, i.e., the time from the last change point to t, which may be any integer between 0 and t. When t is a change point, $c_t = 0$; if not a change point, $c_t = t$. The posterior distribution of c_t is computed based on considering the results $p(c_t|x_{1:t})$ observed so far, which corresponds to inferring the last change point.

In this problem, we assume that $p(x_t|\theta_{t-c_t:t})$ obeys Bernoulli distribution in frequency dimension, and obeys polynomial distribution in temporal and spatial dimension. Here we set a priori $\theta_{(0)}$ for $\theta_{t-c_t:t}$. Note: $\theta_{t-c_t:t}$ determine the probability distribution $x_{t-c_t:t}$, but only from $x_{t-c_t:t-1}$ estimation. When $c_t = 0$, there is no data available to estimate the probability distribution, then $\theta_{t-c_t:t} = \theta_{(0)}$. They both belong to the exponential family. When there is a super parameter $\beta^{(0)}, \beta^{(1)}, \ldots, \beta^{(Q)}$, the posterior distribution also has an updated super parameter. Therefore, $p(x_t|c_t, x_{1:t-1})$ is transformed into:

$$\begin{aligned} p(x_t^{(0)} = b^{(0)},\quad x_t^{(1)} = b^{(1)}|\beta'^{(0)}, \beta'^{(1)}) \\ = \frac{\Gamma(n+1)\Gamma(\beta'^{(0)} + \beta'^{(1)})}{\Gamma(n + \beta'^{(0)} + \beta'^{(1)})} \prod_{m=0}^{1} \frac{\Gamma(b^{(m)} + \beta'^{(m)})}{\Gamma(b^{(m)} + 1)\Gamma(\beta'^{(m)})} \end{aligned} \tag{3}$$

where $\Gamma(\cdot)$ is the gamma function. $b^{(0)} = 0, b^{(1)} = 1$, which is used to indicate whether the residents use private cars to travel on that day. $m = 0$ or 1 and the parameter m is updated using the following formula, where $\beta'^{(m)} = \beta^{(m)}$ for the $\forall m$, $c_t = 0$.

$$\beta'^{(m)} = \beta^{(m)} + \sum_{i=t-c_t}^{t-1} x_i^{(m)} \tag{4}$$

The polynomial distribution's conjugate prior is Dirichlet distribution $\beta^{(1)}, \beta^{(2)}, \ldots, \beta^{(M)}$, and the posterior prediction obeys a Dirichlet polynomial distribution with updated super parameters $\beta'^{(1)}, \beta'^{(2)}, \ldots, \beta'^{(M)}$. Therefore, $p(x_t|c_t, x_{1:t-1})$ can be rewritten as:

$$\begin{aligned} p(x_t^{(1)} = b^{(1)},\quad x_t^{(2)} = b^{(2)}, \ldots, x_t^{(\mathrm{M})} \\ = b^{(\mathrm{M})}|\beta'^{(1)}, \beta'^{(2)}, \ldots, \beta'^{(M)}) \\ = \frac{\Gamma(n+1)\Gamma(\sum_{m=1}^{M} \beta'^{(m)})}{\Gamma(n + \sum_{m=1}^{M} \beta'^{(m)})} \prod_{m=1}^{M} \frac{\Gamma(b^{(m)} + \beta'^{(m)})}{\Gamma(b^{(m)} + 1)\Gamma(\beta'^{(m)})} \end{aligned} \tag{5}$$

where $\Gamma(\cdot)$ is a gamma function, $n = \sum_{m=1}^{\mathrm{M}} b^{(m)}$ and the updating of the parameter $\beta'^{(m)}(m = 1,2,3,\ldots,\mathrm{M})$ is similar to Equation (4), the only difference is that the value range of $x_i^{(m)}$ is wider. When $\beta'^{(m)} = \beta^{(m)}$, for $\forall m$, $c_t = 0$:

$$\beta'^{(m)} = \beta^{(m)} + \sum_{i=t-c_t}^{t-1} x_i^{(m)} \tag{6}$$

The Bayesian CPD method proposed here is able to estimate the probability distribution of the latest change point, which is necessary in time-varying models. But for other applications, in order to better understand the dynamics of behavior in time series, we need to infer the whole process of change or pattern before the last change point.

D. CHANGE POINT INFERENCE

Assume that a total of K changes occur before time step t and $y_{u,-k}$ is used to represent whether the kth latest change point ($k = 1, 2, \ldots, K$) that occurs at time step u. For instance, the 2nd most recent change point is the previous change of the 1st most recent change. Based on the Bayesian method, it can be deduced that:

$$P(y_{u,-1} = 1|x_{1:t}) = p(c_t = t - u|x_{1:t}) \tag{7}$$

$P(y_{u,-1} = 1|x_{1:t})$ indicates the probability of the most recent change at u based on the data up to t. It is further extended and used to determine the probability of changes at u or $P(y_u = 1|x_{1:t})$. To accomplish this, one can estimate $P(y_u = 1|x_{1:t})$ for any given k and marginalize across the kth order as shown in the following example:

$$P(y_u = 1|x_{1:t}) = \sum_k P(y_{u,t} = 1|x_{1:t}) \tag{8}$$

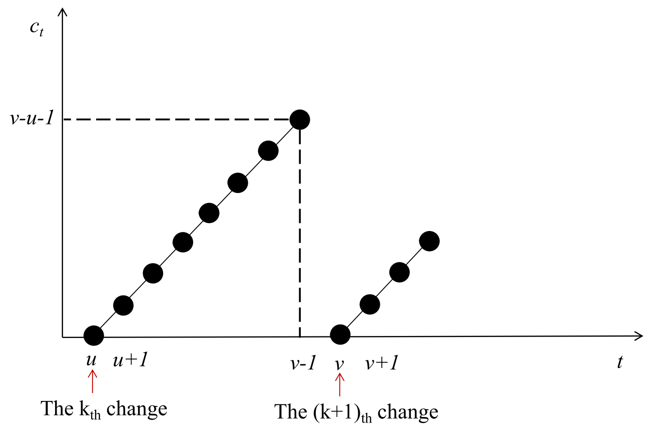


FIGURE 1. Schematic diagram of successive changes in patterns.

Assuming that the last change point (that is, the latest change point k = 1) can be calculated by Equation (7). By providing an order dependency between $y_{u,-k}$ and $y_{v,-k+1}(k > 1, u < v)$, this problem can be solved. As shown in Fig.1, if a pattern changes at v, the probability of the last change at u is the same as $c_{v-1} = v-u-1$ that of the previous change. Therefore:

$$\begin{aligned} &P(y_{u,-k} = 1|x_{1:t}) \\ &= \sum_{v=u+1}^{t-k+1} P(y_{v,-(k-1)} = 1|x_{1:t}) P(y_{u,-k} = 1|y_{v,-(k-1)} = 1, x_{1:t}) \end{aligned} \tag{9}$$

Now the probability of pattern change at any particular time can be estimated based on Equations (7), (8), and (9).

IV. DATA AND MODELING

A. DESCRIPTIVE ANALYSIS OF DATA

As a result of the growing use of in-car navigation systems, GPS data has recently grown in importance and been incorporated into numerous studies on travel behavior. But owing to privacy concerns, many researchers had to use probe data that came from commercial cars instead of private cars. Therefore, many attributes of travelers could not be considered in their research. This research makes use of GPS private car data to study the travel behavior of individuals.

This study is based on GPS data from private cars in Aichi, Japan, in 2017. More than 200 residents took part in the survey. The private cars were equipped with vehicle-mounted devices that captured their driving behavior (such as acceleration) and GPS trajectory data. Participants uploaded data to the internet every week. These data were collected over approximately nine months (2017/3 to 2017/12). The data also had some missing values because not all participants participated in the whole period.

TABLE 2. Traveler characteristics.

Characteristic	Number	Characteristic	Number
Drivers		Cars	
Genders(number)		Type(number)	
Male	104	Normal	50
Female	5	Hybrid	59
Age (years)a		Capacity(kg)b	
≤35 years	19	≤1000	39
35-50 years	43	1000-1500	24
>50 years	47	>1500	46
Occupation (number)		Displacement (L)c	
Company employee	27	≤1.6	22
Organization employee	62	1.6–2	55
Unknown	20	>2	32

a Mean age = 46.64 years; standard deviation = 10.78.
b Mean capacity = 1,378.52 kg; standard deviation = 590.30.
c Mean displacement = 1.92 L; standard deviation = 0.40.

After data processing, we obtain the 109 individuals that can be used in this study. Table 1 shows the detailed information of drivers. Based on preliminary statistical analysis, the properties of these residents are summarized as follows.

B. PROCESS OF MODELING

In order to test the pattern change detection method proposed in this study, we used a data set of 109 private car trip records of Aichi in the past year provided by Toyota. Aichi is a ‘‘city on wheels’’, and its transportation system is mainly private cars. Therefore, it is valid and reasonable to use private car travel data for validation. In order to convert GPS records into time-series data, the value of Q needs to be explored, where Q is used to represent how many days are in each time step.

In the frequency dimension, we set $Q = 1$ day because the data of usage frequency is relatively intensive, and the frequency dimension of this study is to investigate whether the residents use the car every day. Almost all residents in this data set use it every week. Setting Q to a week will result in covering up the original data, which is supposed to show the change of individual travel patterns. However, in the spatial and temporal dimension model, we set $Q = 7$ days, and the travel records of each resident are summarized once a week. On the one hand, in the temporal dimension, the parameters updated in the later stage of our model are too large to be calculated by some computer languages such as Python. On the other hand, it is found that most of the residents' spatial position observations are relatively sparse and discontinuous.

In order to prevent inconsecutive observations, we extract the longest period of continuous activity from each resident and summarize the time in weeks. The aggregation of time in the unit of a week will not cover up the changes in individual travel patterns in the spatial and temporal dimensions shown by the data.

For each resident, weekly observations from the three dimensions of frequency, time, and space can be derived. In terms of frequency, the measure is whether to travel each day. If the respondent travels, it is indicated by 1, and if they don't travel, it is indicated by 0. Note that the trip can only be observed when residents travel with onboard GPS. Therefore, the travel frequency captured by GPS long-term trajectory data is likely to underestimate the real frequency. However, in the spatial dimension, we can observe the real travel location from the GPS long-term trajectory data, and we use the map grid data in the original data to divide Aichi County into 73 blocks. In this work, we regard the area where people travel as the approximate location where people visit.

In the temporal dimension, however, the cardinality of travel behaviors is fixed as $\mathrm{M} = 8$ (the number of time periods), while in the spatial dimension, M varies from individual to individual. For a particular resident, only areas visited throughout the observation period are taken into account in the study. The average number of areas visited by residents was 17.88, and the standard deviation was 6.02. As shown in Fig.2, the distribution of the number of access locations per resident varies significantly, which means different patterns in the spatial dimension.

GPS long-term trajectory data records a consistent subset of individual travel behaviors, that is, all the behaviors related to the use of private cars. Any change in private car travel may correspond to a change in a person's overall travel pattern. Although this paper only uses private car travel data for empirical study, the change detection model is universal and can be applied to various data sources for human mobility.

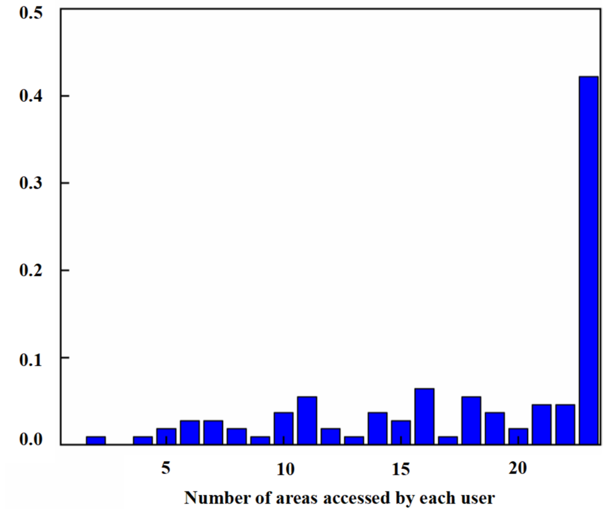


FIGURE 2. Distribution of the number of visited areas per resident.

V. RESULTS

A. VISUALIZING INDIVIDUAL-LEVEL RESULTS

Due to the lack of a priori information on changes in private car travel patterns, the model prior is set non-preferential for all possible outcomes. Based on the experience of previous scholars [27], $\lambda = 30$ weeks in the hazard function is set to indicate the existence of a constant prior probability of a change every 30 weeks. The model sensitivity is subsequently adjusted by adjusting this parameter. Similarly, the Dirichlet prior parameter is set to $\beta^{(m)} = 0.1, \forall m = 1, 2, \ldots$.

It is important to emphasize that this paper aims to detect changes in travel patterns at the individual level, so targeting a few individuals for validation is valid. There are significant differences in the personal attributes of individuals in the dataset, and random selection of some individuals can be done without loss of generality.

Fig.3, 4, and 5 display the detection results of three innominate residents. In order to show the results of each dimension, we present 9 subgraphs for each resident, and all 3 subgraphs represent a dimension. All subgraphs share a common x-axis, which represents the activity week sequence of residents. Suppose there are t days in the sequence. The first row shows the input data. The travel pattern in the frequency dimension is a one-dimensional array of length T, represented by bars. The travel patterns in the temporal and spatial dimensions are an M^*T sparse matrix, where row m and column t indicate the frequency of the mth result in week t. The matrix is presented in the form of a heat map, with the color shades of the cells in proportion to the frequency values.

As shown in Fig.3, the travel pattern of resident 1 is similar to a typical commuter, who makes most of her or his travels in the morning and evening rush hours and frequently from two locations.

The grid plot's second row represents the individual dimensions of $p(c_{t-1}|x_{1:t-1})$ estimated over time and is a $T * T$ matrix visualized with a heat map. It can be seen that just half of the grids have actually meaningful probability values, due to the fact that c_t cannot be greater than t. In most cases the probability values tend to be small, so this paper uses the logarithm of the probabilities to describe them. Thus, the color depth of the grid in the figure is proportional to the logarithm of $p(c_t|x_{1:t})$. It's worth mentioning here that the order depends on $p(c_t|x_{1:t})$. As the pattern continues to expand, t and c_t both increase (as shown in Fig.3). In order to detect a pattern intuitively in the thermal graph, we can find a black line parallel to the diagonal connecting left-bottom corner and the upper right corner. This example can be found in the temporal dimension of resident 1 in Fig.3 and the spatial dimension of resident 3 in Fig.5.

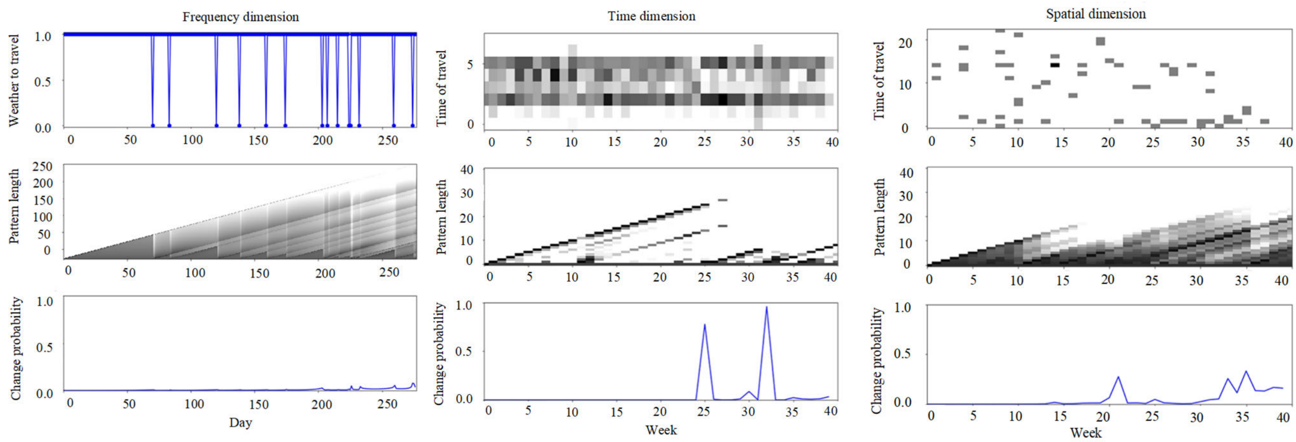
Detecting a change point from the heat maps is not an easy task. To facilitate identification, the third line of the graph shows the estimated probability of behavior occurrence, i.e., $P(y_u = 1|x_{1:t})$, where $u \leq T$. When $P(y_u = 1|x_{1:t})$ is updated with the arrival of new observations, only the estimated result of the last time step is shown, that is, the result when $t = T$. From these curves, we can accurately point out the exact time when the private car travel pattern changes. From Fig.3(a) and Fig.3(c), we find that for resident 1, the frequency and spatial dimensions of travel patterns have not changed during the 40 week observation period. On the contrary, resident 3 in Fig.5 seems to change her or his private car travel pattern in all dimensions.

The changes in temporal and spatial dimensions do not always occur at the same time. As shown in Fig.5(b), the pattern changes of resident 3 occur in the temporal dimension at 11, 21, and 33 weeks whereas they occur in the spatial dimension at 30 weeks (Fig.5(c)). We also find that residents 1 in Fig.3 and residents 2 in Fig.4 change their private car travel patterns in only one dimension. In the spatial dimension, the probability of all change points is less than 0.5, and there is no obvious change. These examples demonstrate the diversity of ways that individual travel patterns change and highlight a phenomenon found by previous scholars in public transport travel behavior: pattern changes may occur in just one dimension.

B. MODEL PERFORMANCE EVALUATION

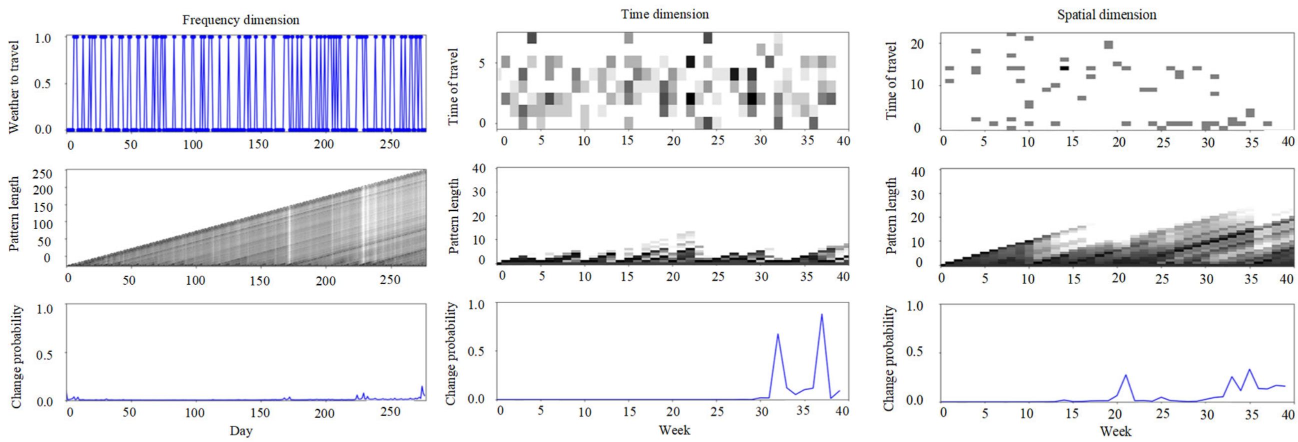
It is not enough to just use the model to do some empirical research. Although the visualization results show that the method has a good effect to some extent, we need a more systematic model evaluation method to appraise it.

As before, the Bernoulli distribution is used in modeling the travel patterns in the frequency dimension, and the polynomial distribution is used in the temporal and spatial dimensions. Model evaluation requires setting a null model as a control baseline, and the null model assumes travel patterns have not changed. Since changes in travel patterns are not directly observable, the model needs to be evaluated by weighing its goodness-of-fit and complexity. In this paper, the detection of more change points is used as a criterion for a more complex model.



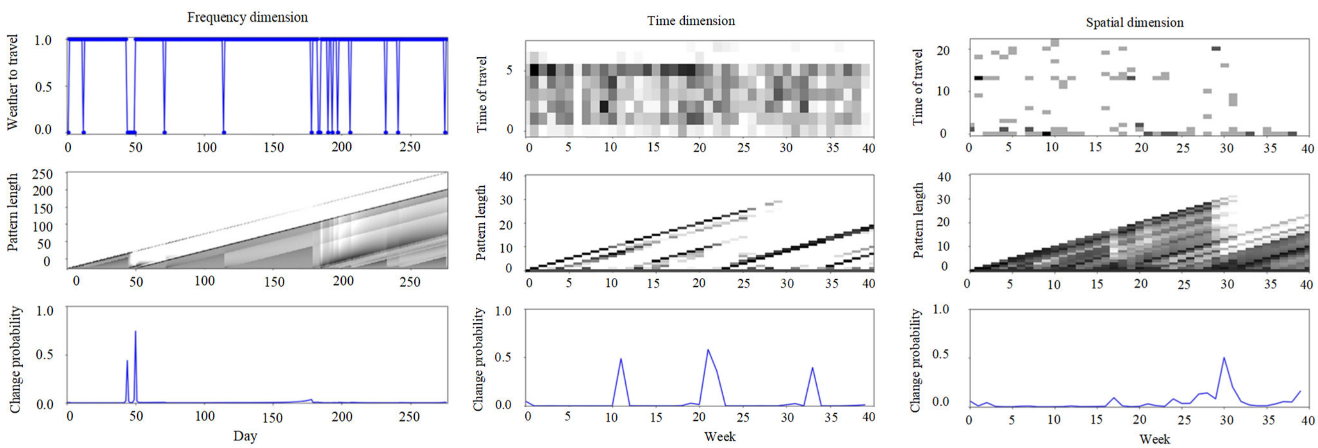
a. Detected results in frequency dimension b. Detected results in time dimension c. Detected results in spatial dimension

FIGURE 3. Detected results of travel pattern change of resident 1.



a. Detected results in frequency dimension b. Detected results in time dimension c. Detected results in spatial dimension

FIGURE 4. Detected results of travel pattern change of resident 2.



a. Detected results in frequency dimension b. Detected results in time dimension c. Detected results in spatial dimension

FIGURE 5. Detected results of travel pattern change of resident 3.

Assuming that K change points are detected at the time step $u_1, u_2, \ldots, u_k$, the observed individual travel pattern $x_{1:T}$ is divided into $k + 1$ parts. When the model parameters are permitted to change at different parts, an improved goodness of fit is guaranteed, but at the same time, it leads to an increase in model complexity. This relationship between the null and

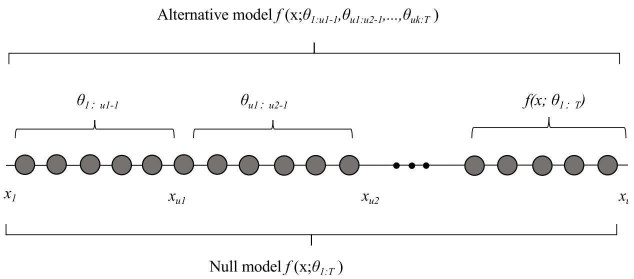


FIGURE 6. Model complexity of change detection methods.

alternative models is similar to that between the null and alternative hypotheses in statistics, and a comparison of these two models is shown in Fig.6.

Based on the Akaike information criterion (AIC) and the Bayesian information criterion (BIC), the overall performance of the model can be evaluated. Both are evaluations of the effect of statistical models for a certain dataset. The lower the AIC or BIC, the better the model. The two indexes both contain the penalty term of the number of parameters in the model. The penalty in BIC is greater than that in AIC. AIC and BIC are calculated as follows:

$$\begin{aligned} AIC &= 2H - 2\ln(L) \\ &= 2J(K+1) - 2\ln(L) \end{aligned} \tag{10}$$

$$BIC = \ln(T)H - 2\ln(L) \tag{11}$$

Here $H = J \times (K+1)$, where J is the number of parameters of each divided part.

$$\begin{aligned} L &= L(\psi, \beta|X)P(X|\psi, \beta) \\ &= \prod_{k=0}^{K} P(X_k|\theta_k)P(\theta_k|\beta)d\theta_k \\ &= \prod_{k=0}^{K} \prod_{t=u_k}^{u_{k+1}-1} \int P(x_t|\theta_k)P(\theta_k|\beta)d\theta_k \end{aligned} \tag{12}$$

In order to better evaluate the Bayesian approach, we contrast it with the the traditional GLR model. The GLR model is based on the algorithm proposed by Appel and Brandt [31]. Likelihood ratio tests are performed on the two models at each time step u. The data of length r before time step u is used as the reference window, and the data of length s after u is used as the test window to infer whether there are significant differences between the data in the two windows. The results indicate that when the travel pattern changes, the GLR model identifies multiple consecutive change points with significant before-and-after differences. To handle this problem, we set an interval of at least 4 weeks between successive change points. The critical value p is set to 0.05, and $r = s = 8$ is set in the GLR test.

To demonstrate how the two approaches vary, we compare the GLR of a specific resident (i.e., resident 3 in the last section) in Fig.7 with the change points detected by the Bayesian method. The vertical red dotted line represents a definite change point.

Table 2 presents the results of CPD for all users in the two models. Among the 109 residents, 119 changes in the frequency dimension, 152 changes in the temporal dimension, and 60 changes in the spatial dimension were detected by the Bayesian method. Generally speaking, the change of travel pattern is a low-probability event. For each user, the probability that the weekly travel pattern changes in the dimensions of frequency, time and space are 2.73%, 3.49%, and 1.38%, respectively.

However, such results are influenced by the probability threshold selection. The default setting in this study is to adopt $P(y_u = 1|x_{1:t}) > 0.5$ to infer whether the time step u changes. By adjusting the threshold, we can detect more or fewer changes depending on the sensitivity required. As seen in Fig.7, there is more but smaller variation in the frequency dimension compared to the other dimensions, with only a small fraction of the variation being significant. This may be due to the fact that the observations in the frequency dimension are more unstable and susceptible to interference, making it difficult to infer patterns.

As shown in Table 2, in the frequency dimension and spatial dimension, the GLR model detected more pattern change points, almost five to seven times more than the Bayesian model. In the temporal dimension, change points from fewer residents but more were identified. The GLR model's great sensitivity could cause it to overreact to data noise. In the quantitative assessment of AIC and BIC, the Bayesian model is about as effective as the GLR model in the temporal dimension, but significantly better than the GLR model in the frequency and spatial dimensions. In addition, the differences between AIC and BIC in the temporal dimension are relatively small, probably because they are the average of all residents in the dataset and most residents do not have pattern change. In conclusion, the results show that the Bayesian method can effectively detect the change points of travel patterns with robustness.

C. SPATIAL AND TEMPORAL CORRELATION ANALYSIS OF TRAVEL BEHAVIOR

Through the visualization of individual travel patterns, we confirm a phenomenon found by previous scholars in public transport travel behavior, namely, that is possible for individuals to change their travel patterns in only one dimension. Based on the experimental results, it can be intuitively guessed that there is some correlation between pattern changes in the time-space dimension, while there is no obvious correlation in the time-frequency and space-frequency dimensions. Additionally, in the field of public transportation, predecessors have also found that people's travel behavior has a strong correlation in the spatial and temporal dimensions. That is, if people's travel pattern changes in one dimension, it may also change in another dimension. In this section, we formally analyze the correlation between the spatial and temporal dimensions of individual travel behavior to make up for the blank of previous studies.

We summarize the change probabilities of all private car travelers each time step in temporal and spatial dimensions for all private car users. These two probabilities, namely

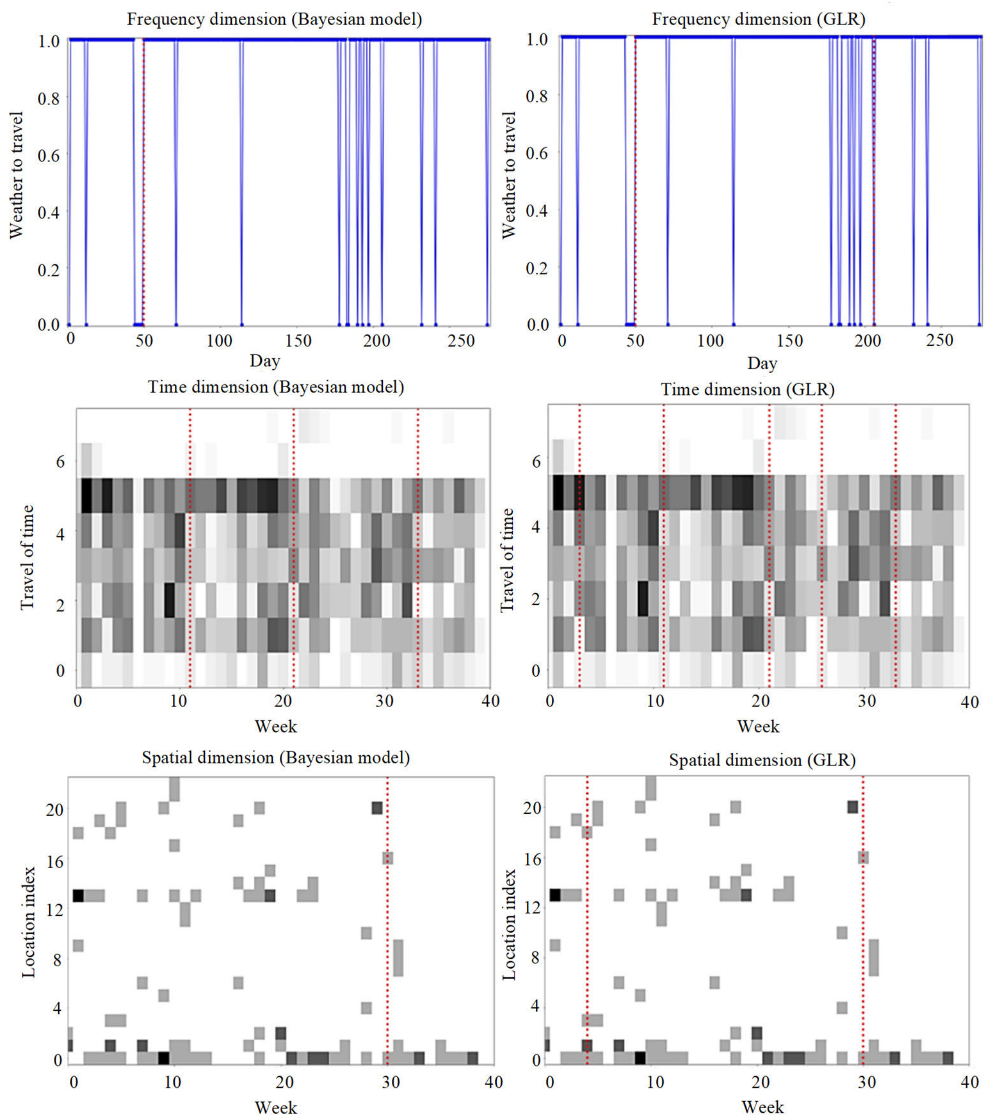


FIGURE 7. Comparison of change point detection results between Bayesian method and GLR method.

TABLE 3. Model evaluation results between Bayesian method and GLR method.

	GLR model			Bayesian model		
	frequency	time	space	frequency	time	space
Number of change points	750	247	293	119	152	60
Change point per user	6.89	2.30	2.74	1.09	1.39	0.55
AIC per user	207.33	1044.56	244.35	57.52	955.76	182.20
BIC per user	222.50	1076.92	291.92	114.63	911.50	293.22

$p_{(time)}$ and $p_{(space)}$, correspond to each other. Pearson correlation coefficient is calculated for the temporal and spatial dimensions to measure the correlation between the two dimensions:

The Pearson correlation coefficient between $p_{(time)}$ and $p_{(space)}$ is $R = 0.259$.

The Pearson coefficient needs to satisfy the condition that two continuous variables are linearly correlated. Considering the generalizability of the data, this paper further explores the correlation of the temporal and spatial dimensions using conditional expectation to calculate the expectation of the probability of change in the other dimension under the

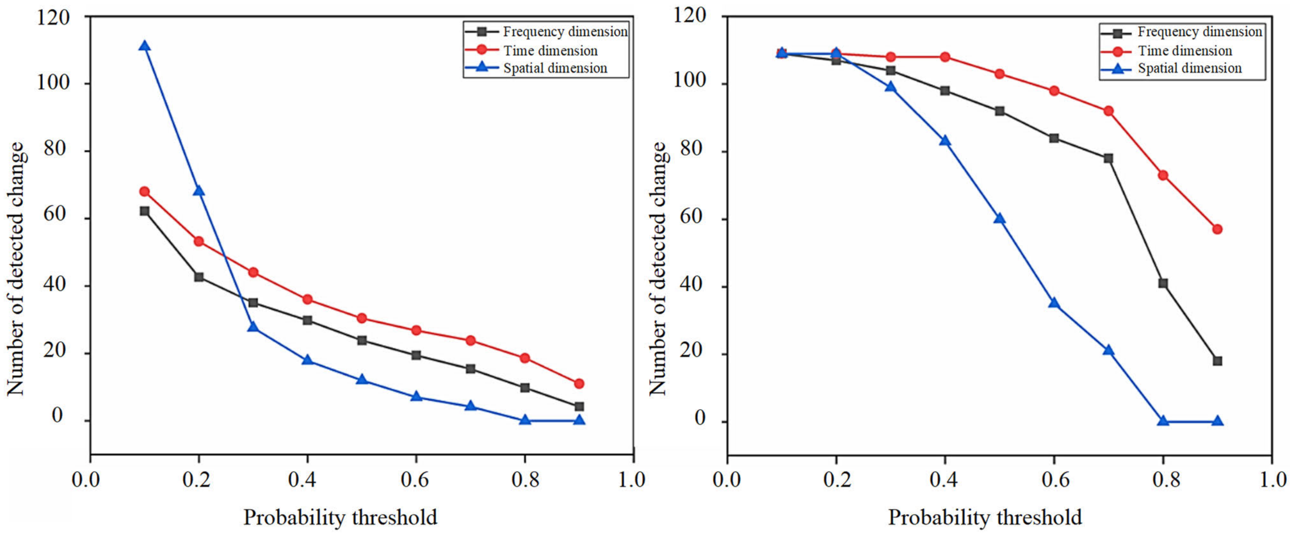


FIGURE 8. Variation of the number of detected change points with probability thresholds.

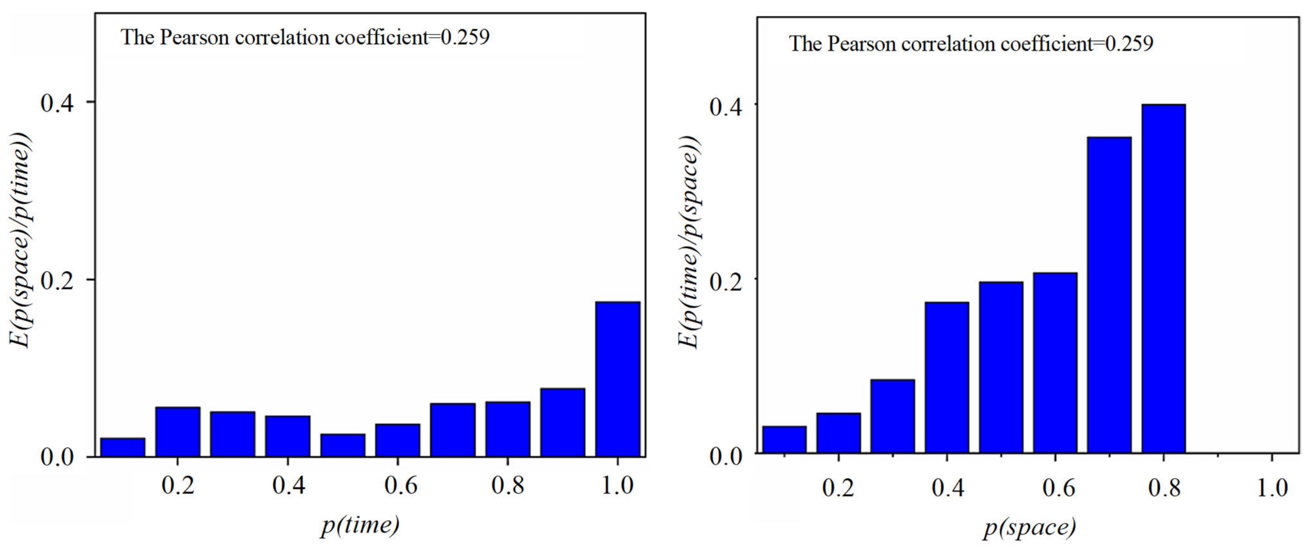


FIGURE 9. Conditional expectation of spatial-temporal change probability.

condition of change in one dimension. First, the probabilities of the temporal dimension $p_{(time)}$ are divided into 10 groups between 0 and 1 that are distributed equally apart. Then, the expectation of the probability of the spatial dimension $p_{(space)}$ is calculated conditional on the probability of the temporal dimension $p_{(time)}$ being in 10 groups. Every conditional expectation is therefore a vector made up of ten group averages. Here some groups have null values because there is no probability of a change in individual travel pattern in just that probability range. The results are shown in Fig.9.

If there is a significant positive correlation between two dimensions, the conditional probability expectation of both dimensions will increase with the increase of coordinates, and the change direction should be the same. Through Fig.9, it can be seen that there is a weak positive correlation between $p_{(time)}$ and $p_{(space)}$. We can intuitively see that the conditional expectations of the two dimensions increase with the increase of x coordinate, and the change direction is consistent. Moreover, when $p_{(space)}$ is between 0.6 and 0.8, the expectation $p_{(time)}$ is greater than 0.2; When $p_{(time)}$ is greater than 0.9, $p_{(space)}$ is expected to be greater than 0.1. In general, there is a positive correlation in the temporal-spatial dimension. However, it might not be as significant as expected.

VI. CONCLUSION AND FUTURE WORK

This paper focuses on the long-neglected problem that individual travel patterns change with job scheduling, seasonal changes, and moving and establishes a travel pattern change detection model using a Bayesian method. The model can effectively estimate the probability of individual travel patterns changing at any point in time, providing a basis for accurately grasping the travel patterns and demand changes of urban residents.

Since travel patterns are long-term, regular generalization of travel behavior that is not directly observable. This paper portrays travel patterns in three dimensions: frequency, time, and space, and detects change points in each dimension, respectively. Unlike other studies that detect outliers, the change points in this study need to meet the ''sudden, substantial, and continuous'' character, which is considered as a CPD problem in time series.

The robustness and accuracy of the model in identifying change points were verified by analyzing long-term GPS data of private cars in Aichi, Japan, for a period of nine months. Meanwhile, the results are compared with the traditional GLR method and show that the Bayesian method can ensure high accuracy and better noise immunity with lower model complexity. The Bayesian change point detection model proposed in this paper can optimize the problem that the traditional GLR model is weak against interference and will identify outliers as change points. Moreover, the model can detect more or less significant changes by adjusting the probability threshold to adapt to the requirements of different sensitivities in complex application scenarios.

According to the experimental results, individual travel patterns may change in only one dimension or in several dimensions simultaneously. This proves that it is more accurate and reasonable to recognize pattern changes in three dimensions, and can adequately account for the possibility of changes occurring in only a single dimension. The paper also reveals that changes that occur simultaneously in both time and space are more likely. Based on this, this paper further analyzes the correlation of travel patterns in the temporal and spatial dimensions and uses conditional expectation to verify that there is a certain positive correlation between the two. This can play an important role in revealing individual travel mechanisms and exploring the reasons for changes in travel patterns.

According to our limited knowledge, this study may be the first one to use this approach to detect travel pattern changes from private car GPS long-term trajectory data. This method is universal and can be used to infer other fields of individual travel behavior and the change of general human mobility.

It provides a new possibility for targeted travel demand management. In addition, it will also provide some help for customized travel under the Maas platform. If we use this model for those residents who have recently changed their family location or moved, it may be more efficient when we formulate travel demand management strategies. This methodology can be applied to track public opinion in response to the adoption of particular urban development projects as a tool for policy evaluation, like commercial development squares or congestion pricing strategies.

This study provides a data-driven method to detect changes in private car travel patterns. However, due to a lack of ground-truth information, this change is not attributed to specific reasons. The future research will focus on finding out the reasons for the change in private car travel patterns. GPS-assistance surveys can be used to collect information about changes in travel patterns and their causes.

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