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Estimation of Route-Choice Behavior Along LRT Lines Using Inverse Reinforcement Learning

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Abstract: As the decline of public transportation in rural areas becomes a growing concern, initiatives to introduce attractive next-generation transportation systems to promote public transportation usage are being considered across various regions. In Toyama City, Toyama Prefecture, where the next-generation light rail transit (LRT) system has been introduced, the number of users has significantly increased compared to before its introduction, with some users riding the LRT for the sake of the experience itself. On the other hand, there is a demand for a more micro-level and quantitative evaluation of the impact that the LRT has on the liveliness of areas along its route. Therefore, this study uses inverse reinforcement learning (IRL), a type of machine learning, to build a model that estimates route-choice behavior along the LRT lines based on behavioral trajectories generated from smartphone location data. The model is capable of evaluating the characteristics of location data with high accuracy. The findings indicate that routes along the LRT lines tend to be selected, suggesting that both the appeal of the LRT itself and the attractiveness of the spaces along its route contribute to this tendency.

Keywords: LRT; big data; machine learning; inverse reinforcement learning

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1. Introduction

1.1. Background and Objectives

In recent years, various next-generation transportation systems have garnered attention, with many attractive transportation modes being developed and introduced across different regions. One notable example is light rail transit (LRT), a next-generation tram system, introduced in Toyama City, Toyama Prefecture, and Utsunomiya City, Tochigi Prefecture, Japan. LRT is expected to improve not only transportation convenience but also the overall appeal of public transport systems. Both cases have seen significant utilization, and LRT is anticipated to serve as a potential solution to the ongoing challenges of declining regional public transportation and the shrinking of local cities in Japan.

Focusing on LRT in Toyama (Toyama LRT), which replaced an existing railway line, there has been a significant increase in the number of passengers compared to the period before its introduction. Additionally, effects such as the emergence of trips made specifically to ride the LRT and an increase in the outing rates of residents along the line have been observed [1]. Various surveys and studies suggest that the introduction of LRT contributes to the revitalization of the areas it serves.

On the other hand, challenges exist regarding the methods for evaluating the effects of LRT. In traditional survey methods, respondents may overestimate the appeal of LRT, which can lead to a discrepancy between their responses and actual behavior. Moreover, simply counting the number of LRT users may not fully capture the effects that LRT brings to the areas along the route.

This study therefore aims to achieve the following two objectives.

1. To generate accurate behavioral trajectories based on personal mobility data.
2. To analyze route-choice behavior along LRT lines and to evaluate the factors that lead to route choice.

For the first point, detailed and continuous behavioral trajectories along the LRT route are estimated from actual movement data by utilizing smartphone location data, which enables the acquisition of individual movements. It is hypothesized that behavioral trajectories can be accurately generated by using inverse reinforcement learning (IRL), one of the methods using artificial intelligence, and that when behavioral trajectories can be generated with high accuracy, the micro-level behavior of each individual can be captured continuously.

The second point is to estimate route-choice behavior along LRT/non-LRT routes based on the behavioral trajectories generated by IRL: the hypothesis is that the choice rate of LRT routes will be high because LRT itself is assumed to be attractive; it can be said that LRT lines have the potential to attract people and that spatial development and the implementation of events along LRT lines will be effective from the perspective of improving the liveliness of the area.

1.2. Review of Existing Research

The existing studies can be broadly categorized into three main areas: research on the evaluation of LRT characteristics, research on estimating travel behavior using smartphone location data, and research on the modeling of travel behavior using IRL.

1.2.1. Research on Evaluation of Light Rail Transit (LRT) Characteristics

Various studies and reports have been conducted on the characteristics of LRT from different perspectives. According to previous research [1], it has been shown that in the case of Toyama LRT, there are trips where riding the LRT itself is the purpose of the journey, a factor not typically considered in traditional transportation-mode choice studies. Additionally, a review of existing research that compiles LRT characteristics from cases introduced around the world reveals that LRT has contributed to commercial revitalization [2], reduction in urban environmental impact [3], and improvement in landscape quality [4]. It has also been pointed out that demonstrating the effects LRT brings to the areas along its route is essential for gaining public consensus on its introduction [5]. Furthermore, a report by the Ministry of Land, Infrastructure, Transport, and Tourism [6] highlights the need for new approaches and methods that integrate city planning with LRT. The report also summarizes that designing vehicles and stations as city symbols can contribute to creating a lively urban environment [6]. From a practical policy perspective, it can be said that LRT has a more significant impact on cities compared to other transportation modes.

These points suggest that the unique characteristic of LRT lies in its ability to influence the landscape and vibrancy of the areas along its route. However, quantitative evaluations of the impact LRT has on these areas have not been sufficiently conducted in existing research, particularly from a micro-level perspective that focuses on individual behaviors generated along the route.

1.2.2. Research on Estimating Travel Behavior Using Smartphone Location Data

In recent years, the widespread use of ICT devices such as smartphones has made it possible to obtain detailed, real-time movement data on an individual basis as big data. This section reviews studies that estimate travel behavior using smartphone location data. Ishii et al. [7] compared smartphone location data with traditional survey results and examined their reliability. The location data showed a high correlation with traditional survey results, demonstrating the usefulness of smartphone location data in urban transportation surveys. Furthermore, Yoshiba et al. [8] constructed a model to identify bus usage using location data and conducted demand forecasts.

Similar to the present study, there are many studies estimating behavioral trajectories from observed location data; Lima et al. [9] estimated the travel routes of each individual from the location data of private cars and clarified the characteristics of individual route choice based on the frequency of use. Similarly, Xu et al. [10] estimated the travel routes of private cars from personal application data and combined them with data from other surveys to understand their characteristics.

Although various estimation methods have been used to estimate travel behavior utilizing smartphone location data, each method and dataset has its strengths and weaknesses, and research is still in progress. Moreover, most studies have focused on accuracy verification, with few studies accumulating results that connect to actual transportation policy proposals.

1.2.3. Research on Modeling Travel Behavior Using Inverse Reinforcement Learning (IRL)

This study aims to model route-choice behavior along LRT routes using an IRL model and quantitatively evaluate it. This section reviews studies that have modeled travel behavior using IRL. Hirakawa et al. [11] quantitatively evaluated the behavioral characteristics of seabirds using an IRL model, while Alsaleh and Sayed [12] did the same for cyclists' behavioral characteristics. Both studies demonstrated that IRL models offer higher accuracy compared to traditional methods. Additionally, the authors [13] proposed a travel behavior estimation model using IRL and showed that IRL can evaluate human movement with high accuracy even with a low sampling rate. It was also shown that the model has a certain degree of applicability to different times and spaces.

Some studies have also used IRL to construct route-choice models; Zhao and Liang [14] constructed a route-choice model with IRL incorporating deep learning and were able to estimate route choice with higher accuracy than conventional methods under certain conditions. Oßwald et al. [15] similarly constructed a route-choice model using IRL and showed that it was able to estimate routes in line with the subject's personal and cultural preferences.

Although IRL can evaluate behavioral characteristics with high accuracy across various subjects, the majority of studies are limited to verifying the accuracy of the method, and few studies have examined the estimation and factors of route selection in urban areas as in this study.

1.3. Positioning of the Study

While various studies have examined the effects of LRT from different perspectives, there has been insufficient evaluation at the micro level, such as analyzing the behavior generated along the route. On the other hand, the use of big data, including smartphone location data, is expanding, and analyses using AI methods like IRL have provided valuable insights. Therefore, this study aims to model and quantify the effects of LRT on areas along its route by using IRL based on actual movement data from smartphone users. The novelty of this study lies in the fact that IRL was used to generate behavioral trajectories from smartphone location data, and in the fact that the effect of LRT introduction along LRT lines was quantitatively evaluated in the form of route-choice rates from actual movement data.

1.4. Overview of the Study

In this study, the impact of LRT on route-choice behavior is quantitatively evaluated using smartphone location data and IRL by following the steps below:

1. Organize the characteristics of Toyama City, Toyama Prefecture, and the Toyama LRT, which are the target of this study, and the details of the smartphone location data used in the analysis.
2. Construct an IRL model to quantitatively evaluate behavioral trajectories from a vast amount of smartphone location data.
3. Estimate route-choice behavior for trips between the central station and the city center, and calculate the selection rate of routes along the LRT vs. non-LRT routes.

4. Compare the service levels of the LRT and other transportation modes, as well as the environment along the routes, to examine the factors influencing the selection of LRT routes.

2. Target of the Study and Overview of the Data Used

2.1. Overview of the Toyama LRT

This study focuses on analyzing the Toyama LRT in Toyama City, Toyama Prefecture. Toyama Prefecture is located in the Chubu region of Japan, and its capital, Toyama City, is the largest city in the prefecture, with a population of approximately 400,000 and an area of about 1200 square kilometers. Toyama City has implemented various public transportation revitalization policies, including the introduction of the LRT. As part of these policies, the Toyama LRT was launched in 2006, following the renovation of existing rail lines and some route modifications, with services operating between Toyama Station and Iwasehama. After its opening, ridership increased, with a particularly notable rise in usage and outdoor activity rates among elderly residents. In 2009, the tram network was transformed into a loop line, improving circulation within the city center. Furthermore, on 21 March 2020, the northern line running towards Iwasehama was connected with the southern line, which runs through the city center, allowing for through services (referred to as the "North–South Connection"). The expansion of the above routes is organized in Figure 1. The color is changed for each year of opening. Through the expansion of the route network shown in the figure, the LRT's role as a mode of urban transportation within the city is expected to grow.

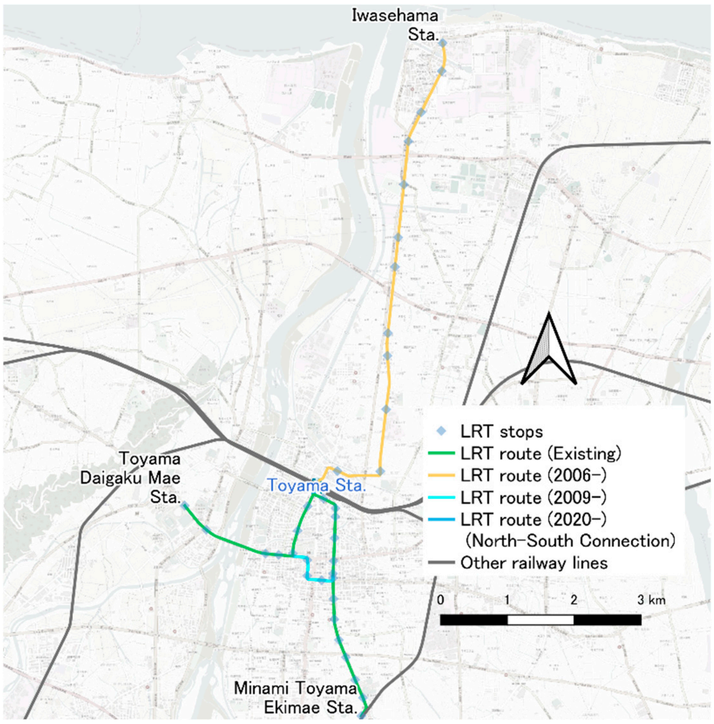

Figure 1. Toyama LRT route map and year of operation.

2.2. Overview of the Data Used

Table 1 provides an overview of the data used in this study. The smartphone location data utilized in this research were collected by KDDI Corporation with the consent of its customers. The location information was determined by smartphone devices based on GPS and other methods, and, similar to existing research [16], it was estimated through a four-step process: determining movement and stay locations, extracting trip data, estimating movement volume from all trip data, and performing expansion estimations.

The distribution of the aggregated trips was confirmed to align with trends observed in previous research [7].

Table 1. Overview of the data used.

Target	Toyama City, Toyama Prefecture
Data Acquisition Range	Within a 3 km radius from Toyama Station
Data of Acquisition	14 March 2020~26 April 2020
Spatial Resolution	100 m mesh

This study focuses on the period before and after the North–South connection project, which commenced on 21 March 2020. The analysis used data spanning 44 days, covering the period before and after the connection. In terms of spatial resolution, a 100 m mesh was set, considering the road widths in the target area and the errors in the location data obtained. It should be noted that the positioning intervals vary depending on the smartphone device, with differences ranging from several minutes to several tens of minutes.

As shown in Figure 2, the number of data samples, including the number of observers (i.e., the number of smartphones being tracked) and the average number of observations per person, remained relatively consistent throughout the target period, and there were limited changes in data characteristics due to the observation period. It should also be noted that the number of observations in March remained constant because some of the data were aggregated after a certain period, following privacy protection procedures.

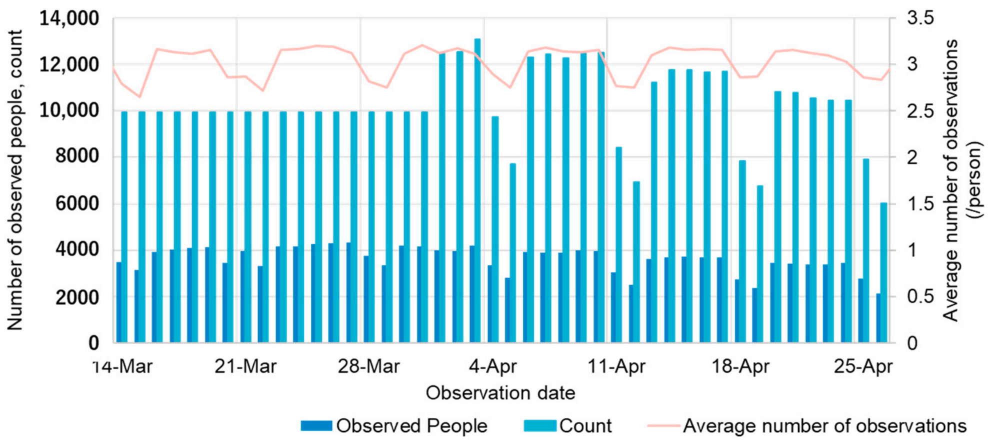

Figure 2. Transition of the number of observations in the used data.

For the analysis in this study, point cloud data, which are linked to trip units by ID (with each point holding latitude, longitude, and observation time), were used. However, due to the non-uniformity of the positioning intervals mentioned earlier, behavioral trajectories estimated through simple linear interpolation of the point cloud may differ from actual movements. Therefore, a method to complement the behavioral trajectories is necessary to accurately understand the movements.

3. Construction of a Transportation Behavior Estimation Model Using IRL

This chapter describes the construction of an IRL model focused on Toyama City in order to estimate behavioral trajectories more accurately from location data and conducts model accuracy verification.

3.1. Overview of IRL

In recent years, reinforcement learning (RL) has been widely used in AI research. However, for subjects where it is difficult to clearly define the optimal state, such as the route selection, the application of RL is challenging due to the difficulty in setting rewards. To address this, IRL was developed as a method to estimate unknown rewards through the iteration of RL. In IRL, it is assumed that the observed behavioral trajectory maximizes rewards, and the reward function (which calculates the optimal reward) is estimated.

In the model used in this study, a grid space is set up in which the virtual agent moves through a 100 m mesh of the target area, and continuous action trajectories are generated by IRL based on actual positional observations according to the steps mentioned below. The flow of IRL is shown in Figure 3. Each letter in the figure corresponds to the equations described later.

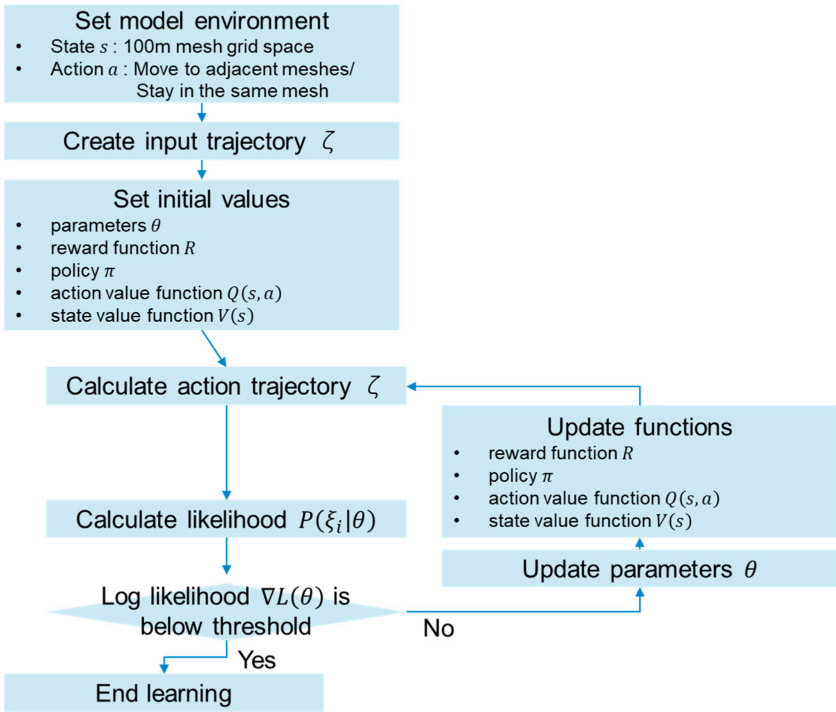

Figure 3. Flow of IRL.

After setting up the model environment, input trajectories are generated. This is a set of one-hot encodings, with observed meshes set to 1 and all other meshes set to 0, according to the observed data. Moreover, initial values are set for each function used for IRL. As shown in Equation (1), the reward function R is assumed based on the behavioral trajectory ζ, and θ is the parameter. The reward values for each state are estimated by the reward function R.

$$\mathrm{R}(\zeta|\theta) = \theta^T \boldsymbol{f}_\zeta \tag{1}$$

In addition, policy π is the behavior in each state and is a function of the action value function Q, as expressed in Equation (2), and the action value function Q and state value function V are expressed as Equations (3) and (4), respectively, where γ is a parameter and P' is the transition probability.

$$\pi(a|s) \propto exp(Q(s,\ a)) \tag{2}$$

$$Q(s,\ a) = \mathrm{R}(\zeta|\theta) + \gamma \sum_{s'} P'(s'|s,\ a) V(s') \tag{3}$$

$$V(s) = \log \sum_a exp(Q(s,\ a)) \tag{4}$$

Iterative calculations on these functions are used to generate continuous action trajectories that most accurately represent the characteristics of the input trajectories. This study adopts the maximum entropy (ME) method for the iterative calculation. The ME method can calculate the optimal reward function by inputting the behavioral trajectory even if the optimal behavior for each state is unknown. In the iterative calculation, the parameter θ is optimized through repeated calculations so that the likelihood $P(\zeta_i|\theta)$ satisfies the following Equation (5).

$$\sum_{i=1}^{M} P(\zeta_i|\theta)\boldsymbol{f}_{\zeta_i} = \frac{1}{M}\sum_{i=1}^{M}\boldsymbol{f}_{\zeta_i} \tag{5}$$

In the maximum entropy method, a uniform probability is assigned to unobserved behavioral trajectories, and θ is expressed by the following Equation (6). Here, M represents the number of observed behavioral trajectories.

$$\theta = arg\ max_{\theta}\left\{\frac{1}{M}\sum_{i=1}^{M}\theta^{T}\boldsymbol{f}_{\zeta_i} - \log\sum_{i=1}^{M} exp\left(\theta^{T}\boldsymbol{f}_{\zeta_i}\right)\right\} \tag{6}$$

Using the above equation, the gradient of the log-likelihood $L(\theta)$ is expressed as shown in Equation (7), and iterative calculations are performed until this gradient falls below a certain value.

$$\nabla \mathrm{L}(\theta) = \frac{1}{M}\sum_{i=1}^{M}\boldsymbol{f}_{s_i} - \sum_{i=1}^{M} P(s_i|\theta)\boldsymbol{f}_{s_i} \tag{7}$$

When the elements of the reward function are replaced with actual location data, the rewards can be represented by the number of observations in each mesh (state), and the behavioral trajectories can be represented as the movement paths of smartphone users.

3.2. Flow of the Transportation Behavior Estimation Model

In this study, a model combining IRL and RL is constructed to quantitatively evaluate behavioral characteristics. The flow of the model is as follows:

1. Split and obtain location data on a daily basis.
2. Use IRL to quantitatively evaluate behavioral trajectories and estimate the state values, which are the feature quantities for each state.
3. Perform RL using the obtained state values as rewards, and generate behavioral trajectories that satisfy specific conditions based on the behavior value function.
4. Use the generated behavioral trajectories to quantitatively evaluate route choices.

In this study, IRL is used to generate behavioral trajectories from smartphone location data. These location data are discrete point cloud data, which are a collection of points where smartphone location information is observed, and because these data do not discriminate between moving and staying, it is not possible to directly grasp the number of people staying or the duration of their stay. Therefore, it is necessary to determine whether a person moves or stays when generating a behavioral trajectory. In this case, movement/staying is determined based on the observed position and time, but in many existing studies (e.g., [9,10]), discrimination is based on detailed location data obtained from specific samples in which special applications have been installed. This provides location information with high accuracy and the positioning intervals are generally the same. However, unlike the above, the data used in this study are heterogeneous in terms of positioning interval and positioning error, which may lead to estimation errors due to missing values when existing methods are applied. Specifically, as shown in Figure 4, the presence of areas where data have not been obtained may cause a discrepancy between the actual trajectory and the interpolated trajectory. In this study, therefore, an IRL model that can interpolate the behavioral trajectories of each individual by learning the data of others as well is considered effective.

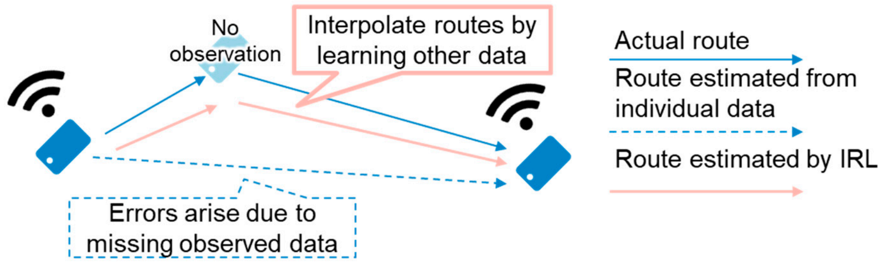

Figure 4. Comparison of route estimation based on individual data and IRL.

3.3. Model Accuracy Verification

An IRL model was constructed following the process outlined in the previous section. As examples of the aggregated observation counts per mesh and the distribution of state values estimated by the model, the estimates for March 14 are shown in Figures 5 and 6. It is evident that higher state values are estimated around Toyama Station, the city center, and along major arterial roads with high traffic, suggesting that the model can generally evaluate the characteristics of actual human flows.

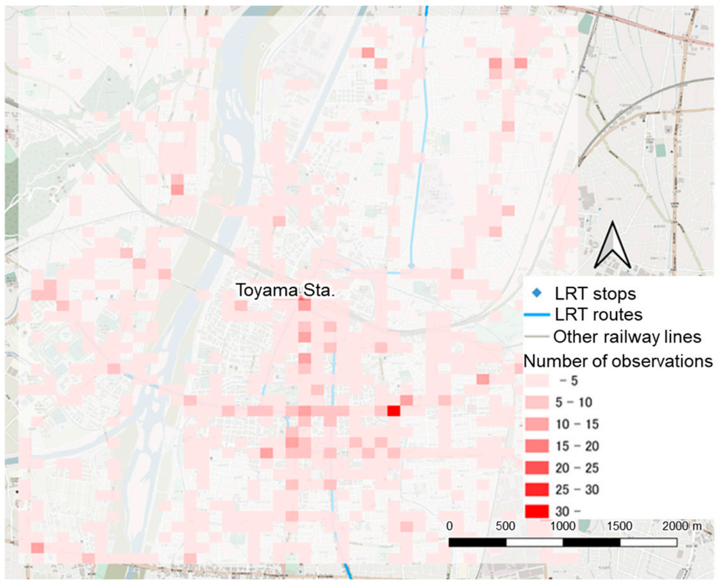

Figure 5. Distribution of observations per mesh (14 March).

IRL has the characteristic of outputting behavior as continuous trajectories from point clouds. As a result, higher state values are estimated around meshes with a higher number of observations. Considering the continuity of movement, it can be inferred that the model estimates trend closer to the actual movement.

Next, the accuracy of the estimates is quantitatively evaluated. If a high correlation is found between the magnitude of the observed values and the estimated state values, it can be said that the model has successfully estimated human flows. Therefore, the model's accuracy was verified by comparing the correlation between the estimated state values and the observed values. The coefficient of determination (R^2) for each day is shown in Figure 7. On all days, the coefficient of determination exceeded 0.9, suggesting that the characteristics of the location data were estimated with very high accuracy.

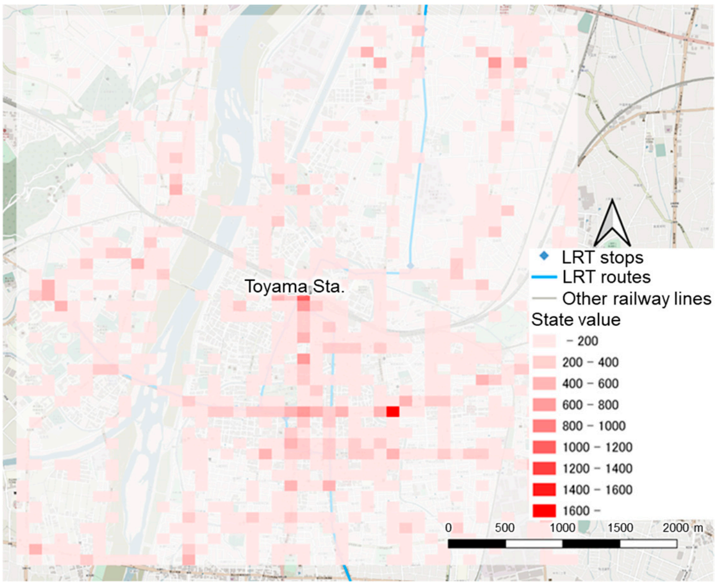

Figure 6. Distribution of estimated state values (14 March).

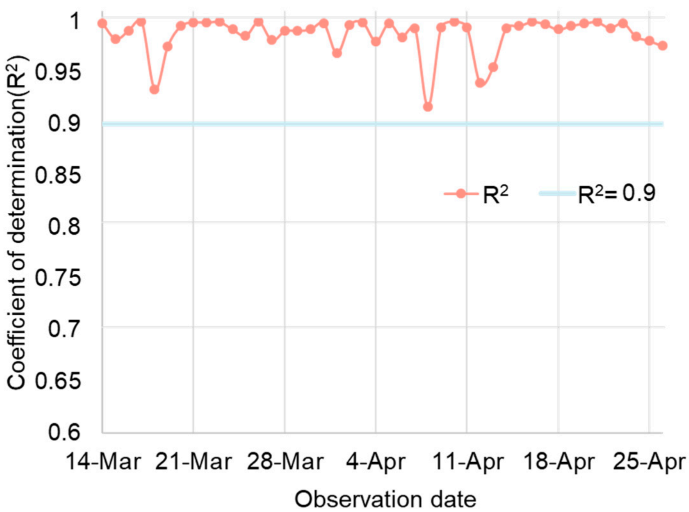

Figure 7. Coefficient of determination for each day's model.

4. Analysis of Route-Choice Behavior Along the LRT Line

4.1. Overview of the Route-Choice Model

The model constructed in the previous chapter can estimate and generate movement trajectories. Using these movement trajectories, route choices are estimated. This study aims to compare routes along the LRT line (LRT routes) with those not along the LRT line (non-LRT routes). Therefore, in the route-choice estimation, the selection rates of routes that pass through the LRT line and those that do not are calculated. To account for potential positioning errors, a route is considered to pass through the LRT line if 70% or more of the total meshes it passes through are determined to be on an LRT route.

In this context, "LRT route" refers to meshes within 100 m of the LRT lines, while "non-LRT route" refers to meshes beyond this 100 m range. According to the Ministry of Land, Infrastructure, Transport, and Tourism, public transportation corridor areas are defined as being within an 800 m walking distance of railway stations and within a 300 m walking distance of bus stops. Although the 100 m range set in this study is considerably shorter from that perspective, the aim of this study is to analyze behavior in areas in close physical proximity to the LRT, rather than simply considering access to the LRT stops. The LRT line meshes (292 in total) account for 12.8% of the entire target area (2288 meshes).

Non-LRT lines include areas such as arterial roads without the LRT and shopping streets that are narrow or do not face the LRT. This study examines the liveliness by comparing LRT lines and non-LRT lines. In the subsequent Figure 8, the LRT route refers to the red-colored area, while the non-LRT route refers to the remaining blue-colored area.

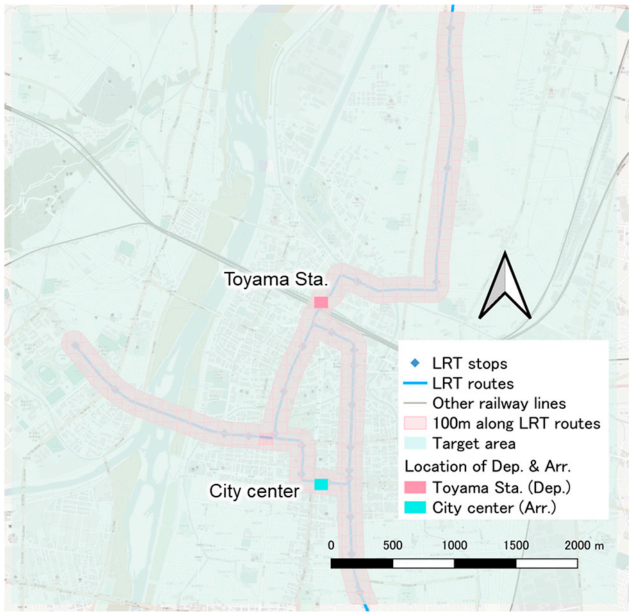

Figure 8. Positional relationship between the departure point and the destination.

4.2. Analysis of Route Choice from the Central Station to the City Center

This section evaluates the route-selection rate from a specific departure point to a specific destination. In this study, the analysis focuses on the movement from Toyama Station, the central station, to the city center, which is assumed to be a frequently traveled route. The model constructed in the previous chapter is used to estimate the route-selection rates for LRT routes and non-LRT routes.

The positions of the departure and arrival mesh areas, along with the mesh areas along the LRT line, are shown in Figure 8. The destination mesh is located in an area where large commercial facilities and other businesses are concentrated in the city center. From the map, it is evident that the shortest route is via the road heading south from Toyama Station. In this case, it is assumed that private cars or buses, rather than the LRT, would be used. Figure 9 shows the route-selection rates for LRT routes and non-LRT routes.

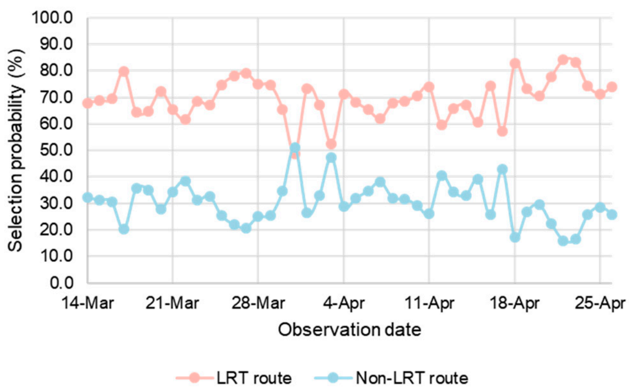

Figure 9. Transition of route-selection probabilities for LRT/non-LRT routes.

From Figure 9, it is shown that the route-selection probability for LRT routes is approximately 20–40% higher than for non-LRT routes, even though the LRT route is a detour.

This suggests that for trips from Toyama Station to the city center, the rate of selecting the LRT as a transportation mode is higher than that of private cars or buses.

To clarify the factors influencing route selection, comparisons are made between the LRT and other transportation modes, as well as an evaluation of the unique value that the LRT offers. To ensure the validity and comprehensiveness of the comparison criteria, the derived and primary elements shown in the hierarchical structure of Figure 10, proposed in previous research [17], are used to organize the analysis at each stage. The left axis represents the utility of movement, and for the fundamental elements, positive utility is obtained—meaning that the more relevant factors there are, the higher the probability of selecting that behavior.

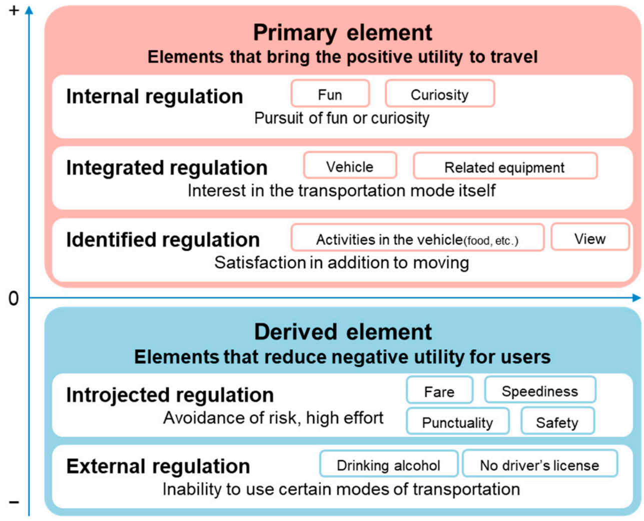

Figure 10. Hierarchical organization of factors in route selection.

4.3. Comparison of Selection Factors Between the LRT and Other Transportation Modes

In this section, the selection factors for LRT use, bus use, and private car use are compared, primarily from the perspective of the derived elements shown in Figure 10.

When comparing LRT and buses, the fares were the same. When making comparisons regarding journey times, the time-reliability perspective was also taken into account and the journey times were estimated including the time of delays. Therefore, with regard to the delay times of LRT and buses, the delay times for each transportation mode on a certain day were obtained from the published GTFS-R data for each public transport system in Toyama City [18], and the expected delay per use was calculated based on the number of observations. The distribution of the obtained delay times is shown in Figure 11.

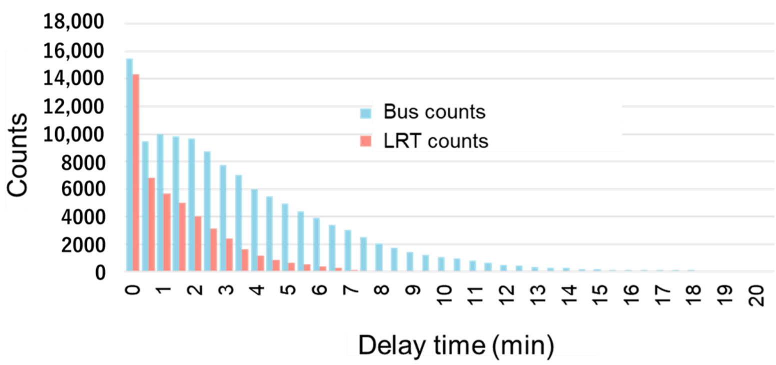

Figure 11. Distribution of delay counts for buses and LRT.

From the distribution of delay times, it can be seen that buses consistently have longer delay times compared to the LRT. To quantitatively evaluate the delay times, the expected delay time was calculated using Equation (8), shown below. Here, the expected delay time $D(m)$ for a transportation mode is represented as the sum of the products of the delay time $d(t)$ at class t and the observed proportion (relative frequency) $E(t)$ in that class.

$$D(m) = \sum_{t=T} d(t) \times E(t) \quad (8)$$

By organizing the travel times that take delays into account using the above process, the result still shows that buses have shorter travel times, even considering the delay time. Focusing solely on travel time, buses are more likely to be chosen. However, since bus delay times vary depending on the time of day, it is possible that the choice of transportation mode is evaluated based on factors such as the maximum delay or the mode of delays at specific times, rather than the daily average as considered in this study. It should also be noted that the evaluation of travel time may differ depending on each user.

When comparing the LRT with private cars, especially in terms of speed, private cars can arrive in about one-third of the time it takes the LRT. The time required by private cars was estimated using Google Maps [19] between Toyama Station and the bus stop in the city center. No significant changes in estimated journey times were found between weekdays and holidays or at different times of day. From the result, even considering factors such as being unable to use a car when drinking alcohol or not possessing a driver's license, and slightly lower punctuality, private cars remain a strong alternative.

The comparison results based on the above analysis are summarized in Table 2. Categories where each transportation mode excels are marked with ○, while categories where it is inferior to other modes are marked with △ or ×.

Table 2. Comparison of derived elements for each transportation mode.

Introjected regulation	LRT	Bus	Private vehicle
Cost (fare)	○ (210 yen)	○ (210 yen)	-
Speed (Required time)	× (14 min)	△ (10 min)	○ (5 min)
Punctuality (Estimated average delay)	○ (Estimated delay: 1.4 min)	△ (Estimated delay: 3.6 min)	△
Required time considering delay	△ (15.4 min)	○ (13.6 min)	-
Safety	○	○	△
External regulation	**LRT**	**Bus**	**Private vehicle**
Drinking alcohol	○	○	× (Not allowed)
No driver's license	○	○	× (Not allowed)

Based on the estimates and considerations of the derived elements, it cannot be said that the LRT is necessarily superior when choosing a transportation mode from Toyama Station to the city center. In other words, it is unlikely that routes along the LRT are more likely to be chosen. Therefore, it is assumed that other factors may encourage route choices along the LRT. In the next section, the fundamental elements contributing to these factors will be examined.

4.4. Consideration of LRT Route Selection Factors

In this section, the factors that contribute to the selection of LRT routes are examined from the perspective of the fundamental elements presented earlier.

First, from the perspective of integrated regulation, it is assumed that people are attracted to the LRT vehicles themselves, leading to the use of the LRT. Specifically, at Toyama Station, the LRT platform is located right in front of the ticket gate, making it easily recognizable to visitors exiting the station, which likely leads to increased use. On the other hand, buses require movement to the bus stop in front of the station, and since there are no tracks like the LRT, it is unclear which bus to take, which is likely why the selection probability for buses is lower.

Additionally, from the perspective of identification regulation, the attractiveness of spaces along the LRT line is considered a contributing factor. Along the Toyama LRT line, attractive spaces have been developed, including the design of the LRT stops, the display of monuments along the route, and the installation of street furniture that allows for resting. It is assumed that people feel more comfortable moving through and lingering in the spaces along the LRT line compared to bus routes, which are congested with heavy traffic, leading to the selection of LRT routes. In this context, the desire to enjoy the journey itself, a factor of higher-level internal regulation, may also contribute to the route selection.

5. Conclusions

5.1. Key Findings

In this study, with the aim of quantifying the impact of the LRT on the railway lines, the analysis focused on route-choice behavior. Using IRL, behavioral trajectories could be generated with high accuracy from smartphone location data, and the estimated behavioral trajectories were used to tabulate route-choice behavior in two categories: LRT routes/non-LRT routes. The results show that the proportion of journeys from Toyama Station to the city center via the LRT line is high. Through comparison with other transportation modes, it was suggested that the unique value of the LRT led to the selection of routes along the LRT line.

Through the analysis in this study, it was shown that there are factors that appeal to the desire to use and visit the LRT and LRT lines. The results suggest that LRT lines have the potential to attract people and can contribute to regional revitalization through the utilization of the space along the lines. In Toyama City, which was the subject of this study, measures have been implemented to utilize the space along the line, such as the installation of benches where people can stay, the expansion of pedestrian space, the introduction of a transit mall, and the implementation of events along the line, creating a bustling atmosphere along the line. Through the total design of destinations and transportation modes, it will be effective to implement measures to revitalize the LRT line by making use of the synergy between the attractiveness of the destination facilities and the attractiveness of the LRT itself.

5.2. Future Challenges

In this study, route-choice behavior was analyzed using actual movement data from smartphone location data. To estimate more clearly the factors that contribute to route choice, it is necessary to analyze not only location information, but also information on personal attributes such as age and place of residence. Furthermore, in order to gain a more detailed understanding of the behavior along the route and the specific factors that lead to route choices, more detailed surveys, such as questionnaires for visitors and residents along the LRT line, are needed.

Further research on the effects of LRT will contribute to the realization of urban transportation policies that utilize LRT not merely as a transportation mode but as a tool for urban development.

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remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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