Future Urban Mobility with MaaS

Investigating Spatiotemporal Characteristics of Demand Responsive Transport (DRT) Service for the Disabled through Survival Analysis

Jong-Hun Son and Do-Gyeong Kim

Dept. of Transportation Engineering, University of Seoul, Seoul 02504, Korea
Graduate School, Dept. of Urban Big Data Convergence, University of Seoul, Seoul 02504, Korea

1. Introduction

In modern society, the right to travel is recognized as a fundamental right that must be guaranteed to all members of society, in order to have a normal life and to participate in a variety of social activities. However, special population groups such as elderly people and people with disabilities and residents of certain regions like urban suburbs developed with low density have relatively poor accessibility to various means of transportation, and as such still are faced with many restrictions on freedom of movement (Papanikolaou et al., 2017).

Recently, personal mobility services such as bike-sharing and scooter-sharing have been introduced as means of first and last mile transportation to guarantee the right to travel and improve mobility. Efforts to provide these are being implemented around the world (Fishman, 2016; Bielinski and Wanza, 2020). While these new services are expected to be effective in achieving mobility improvements in areas with few public transport services, it seems not an alternative to solve mobility restrictions for groups such as the elderly and disabled because it is not easy to ride for those people.

Instead, as an alternative first and last mile transport solution to connect those groups with the major transport network, Demand Responsive Transport (DRT) is being widely used all over the world (Papanikolaou et al., 2017). The global DRT market is expected to grow from $2.8 billion in 2017 to $551.61 billion in 2030, and the fleet size is predicted to grow from 24,100 units to 5.8 million units in the same period (Intelligent Transport, 2018).

With respect to the characteristics of DRT that it does not have a fixed route and schedule and operating routes are determined based on the user's request, Demand Responsive Transport (DRT) is being widely used all over the world (Papanikolaou et al., 2017). The global DRT market is expected to grow from $2.8 billion in 2017 to $551.61 billion in 2030, and the fleet size is predicted to grow from 24,100 units to 5.8 million units in the same period (Intelligent Transport, 2018).

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ABSTRACT

The importance of Demand Responsive Transport (DRT) has increased as it guarantees the right to travel and improves mobility for special population groups such as disabled people and low income households. In order for DRT to become a sustainable means of transportation, it is necessary to keep the quality of DRT service above a certain level that might be expected by users, and thus DRT service needs to be provided evenly over time and space. This study aims to investigate the spatiotemporal characteristics of DRT service based on waiting time in terms of service equity. For the analysis, operating data of DRT for people with disabilities provided from the Seoul Metropolitan Government were used and a survival analysis was employed to derive median waiting time. The results showed that there exists a difference in median waiting time over time and space, indicating that DRT service for disabled is not evenly provided over time and space. The results of using a heat map and Kernel density plot with median waiting time also confirmed that the spatiotemporal imbalances of DRT service exist throughout Seoul. One of the major reasons for this phenomenon might be the uneven spatiotemporal distribution of supply as expected.

1. Introduction

In modern society, the right to travel is recognized as a fundamental right that must be guaranteed to all members of society, in order to have a normal life and to participate in a variety of social activities. However, special population groups such as elderly people and people with disabilities and residents of certain regions like urban suburbs developed with low density have relatively poor accessibility to various means of transportation, and as such still are faced with many restrictions on freedom of movement (Papanikolaou et al., 2017).

Recently, personal mobility services such as bike-sharing and scooter-sharing have been introduced as means of first and last mile transportation to guarantee the right to travel and improve mobility. Efforts to provide these are being implemented around the world (Fishman, 2016; Bielinski and Wanza, 2020). While these new services are expected to be effective in achieving mobility improvements in areas with few public transport services, it seems not an alternative to solve mobility restrictions for groups such as the elderly and the disabled because it is not easy to ride for those people.

Instead, as an alternative first and last mile transport solution to connect those groups with the major transport network, Demand Responsive Transport (DRT) is being widely used all over the world (Papanikolaou et al., 2017). The global DRT market is expected to grow from $2.8 billion in 2017 to $551.61 billion in 2030, and the fleet size is predicted to grow from 24,100 units to 5.8 million units in the same period (Intelligent Transport, 2018).

With respect to the characteristics of DRT that it does not have a fixed route and schedule and operating routes are determined based on the user's request, its efficient operation can be an important factor in terms of making it a cost-effective system. As such, many earlier studies have focused on improving overall system efficiency, such as improving operational efficiency and reducing operational costs through the optimization of scheduling, routing, and vehicle location (Fu, 2002; Gupta et al., 2010; Torkjazi and Huynh, 2019).
A study by Gupta et al. (2010) proposed an optimal scheduling method of demand responsive paratransit and the operational benefits through linkage with taxis, while another research developed a simulation based approach for the arrangement of paratransit vehicles in a city to help the operators build a more developed and productive paratransit system (Fu, 2002). Another scheduling strategy for a DRT system can be found in Torkjazi and Huynh (2019). They focused on the development of an effective strategy that can accommodate non-reserved calling users during the reserved schedule movement of a paratransit vehicle to improve operational efficiency.

In addition, there have been studies to attempt to the development of operational strategies for DRT systems under the occurrence of specific events. Karlaftis et al. (2004) analyzed how to operate paratransit effectively when a large event such as the Olympics occurs and Perez et al. (2020) developed a methodology that predicts cancellation of reservations or no-shows of paratransit users through machine learning for the preparation of specific situations.

Prior literature review indicates that a number of studies mainly deal with optimization problems to improve the efficiency of the overall DRT system. Considering that DRT is operated in a “dial-a-ride” format, however, it is expected that the service quality of DRT will depend on how quickly the service could be provided after a request occurs. Despite the importance of service quality, research dealing with service improvement has been seldom conducted, except for a study that tried to identify factors affecting dwell time (Garnier et al., 2020).

This study aims to provide some insights for the service improvements of DRT system, particularly focusing on waiting time because it can be regarded as one of the primary measures for evaluating the service quality of DRT system as mentioned above. More specifically, this study attempt to investigate the service equity of Demand Responsive Transport for Disabilities (DRTD), being operated for the disabled in Seoul, based on median waiting time obtained from a survival analysis because it is not expected to be evenly provided across time and space.

### 2. Data Description

#### 2.1 Seoul DRTD Call Data

The data used in this study is Seoul DRTD call data provided from the Seoul Facilities Corporation, which was established by the Seoul Metropolitan Government for the purpose of contributing welfare promotion among the citizens through effective management and operation of facilities.

The DRT service for the disabled people in Seoul, which is also referred to as Call-taxi for the disabled, started with 100 vehicles in 2003 to promote the mobility of the disabled, and as of 2021, a total of 683 DRT vehicles are in service throughout Seoul. The DRT service is provided only to wheelchair users or persons with walking disabilities, and those who wish to use the service are required to register as a member. Although service coverage is limited to Seoul, a one-way service is sometimes provided for those who wish to travel outside of Seoul.

Since the Seoul DRTD is operated on a request call basis, the dataset includes the date and time when calls, vehicle assignment, boarding and alighting time, the coordinates of origin destination, and trip purpose (back to home, treatment, religious activities, rehabilitation, etc.). For the analysis, a total of 381,750 data collected for four months in 2019, i.e., February, May, August, and November, were used. The number of DRTD usage in 2020 was found to decrease compared to the previous years due to the impact of COVID-19. The final dataset for the analysis was constructed after the raw data went through a pre-processing step that excluded data where the origin of a call was not within Seoul or which had missing values.

The average and median waiting time for all the data were 65.3 minutes and 58.5 minutes, respectively, indicating that the data have a right-skewed distribution which has a larger average

![Average Waiting Time Distribution When an Event Occurs](Fig. 1)

### Table 1. Number of Calls and Waiting Time per Month

| Month     | Total number of calls | Avg. waiting time (min) | Ride call Number of calls | No-Ride call Number of calls | % | % |
|-----------|-----------------------|-------------------------|----------------------------|-------------------------------|---|---|
| Total     | 381,750               | 65.3                    | 302,032                    | 79.1                          | 79,718 | 20.9 |
| February  | 82,977                | 64.8                    | 64272                      | 77.5                          | 18,705 | 22.8 |
| May       | 97,258                | 66.4                    | 78447                      | 80.7                          | 18,811 | 19.3 |
| August    | 103,687               | 58.0                    | 82909                      | 80.0                          | 20,778 | 20.0 |
| November  | 97,828                | 72.3                    | 76404                      | 78.1                          | 21,424 | 21.9 |
than the median as shown in Fig. 1. Of the 381,750 requests, approximately 79.1% of calls led to a ride; for the remaining calls, the ride was not successful due to reasons such as cancellation by users or refusal by the drivers. Regarding the number of monthly calls, August had the highest and February had the lowest among the months studied as shown in Table 1. With respect to the average waiting time, August (58.0 minutes) had the shortest and November (72.3 minutes) had the longest. The percentage of ride calls by month was at its lowest in February (77.5%) and at its highest in May (80.7%), showing no significant difference.

To perform a survival analysis, it is essential to determine the time to event (duration) of each observation object, i.e. request in this study. The time to event is the time taken until an event occurs within a defined observation period; the same observation object may have a different time to event value depending on the length of observing time and whether the event occurs. The process of using the DRTD service consists of several steps, i.e., calling (requesting) → vehicle assigning → boarding → alighting. Since the objective of this study is to analyze the waiting time, which is the time taken for a user to board a vehicle after requesting, through a survival analysis, the event was defined as boarding and the time to event was defined as the time it took from requesting to a boarding.

The observation period for the analysis was set to be from 12 AM to 6 AM the next day (a total of 30 hours) to reflect a case where a call was made at a late time such as late at night and the vehicle assignment or boarding happened the next day. According to the success or failure of boarding, the type of DRTD call is classified into 3 cases, as shown in the Fig. 2; vehicle assignment or boarding took place successfully (Case 1), vehicle assignment was made but boarding did not occur (Case 2), and both vehicle assignment and boarding took place successfully (Case 3). In a survival analysis, Case 1 is referred to as complete data, whereas Case 2 and Case 3 are defined as censored data.

2.2 Variables

Three kinds of variables were employed for the analysis; time variable, event variable, and covariates. Time variable, which is also referred to as duration in a survival analysis, is the waiting time (minutes) it takes for a user to board a vehicle after requesting. Whether or not a boarding occurred is defined as an event variable. In this study, a total of three covariates were used to determine whether there is a spatiotemporal difference in the operating level of DRTD service. First of all, peak covariate was set to investigate time varying characteristics, the scale of medical personnel was set as a covariate to investigate spatial characteristics, and the availability of vehicles covariate was set to consider spatiotemporal characteristics simultaneously. The unit of time and space is 1 hour and administrative district (The Seoul city is divided into 25 autonomous districts, which is called “gu”, and 425 administrative “dong” sub-units. The reason for using district as the analysis unit is because many missing values occur in the median waiting time calculated in the survival analysis with the unit of administrative “dong”), respectively.

2.2.1 Peak

This variable is set to explain the variability of waiting time for DRTD service according to the changes in traffic volume by time zone. The characteristics of commuting hours in Seoul is that traffic increases and traffic congestion occurs on major roads and the use of public transportation is also high, making it difficult for the disabled to use public transportation comfortably and conveniently. For this reason, 7 AM – 9 AM and 6 PM – 8 PM were set as peak times and the remaining time period was set as non-peak time.

2.2.2 The Number of Medical Personnel

In general, it is reasonable to expect that the waiting time will be relatively long in regions with high demand for the DRT service. Therefore, as a spatial characteristic that can affect waiting time, it is necessary to set a variable that can represent the high or low demand in each region as an explanatory variable. Based on the data used in this study, when looking at the purpose of travel for the disabled, it is quite similar to the characteristics of usage in the cities adjacent to Seoul (Seok, 2012; Bin and Park, 2015). For example, excluding the purpose of returning home (32.3%) and other purposes (32.4%), 30.5% had the travel purpose of rehabilitation treatment. Since medical facilities for rehabilitation and treatment were likely to serve as a representative attraction, the number of medical personnel (doctors, dentists, nurses, etc.) working at medical facilities in each district can be used to indirectly reflect the size of the medical facilities, which are the spatial characteristic of each district. The reason for this is because it was difficult to obtain medical facilities related data for this study. All of the areas were divided into two categories based on the median value: the low group and the high group.

2.2.3 Availability

This variable is used to explain how quickly a user can use the DRT service in terms of time and space. This variable is calculated
by separating and summarizing the empty vehicles that users can utilize in time and space from the data on vehicle status (‘empty car’, ‘customer on board’, ‘waiting for ride’, etc.) based on vehicle operation information saved at approximately 1-minute intervals. For survival analysis, 45 – 55%, which is considered as the center of data distribution, was set as a medium level, with the values less than 45% set to low level and the values greater than 55% set to high level.

3. Methodology

Survival analysis is a statistical method that performs analysis based on the time to event (duration). It is possible to reflect censored data where no event has occurred or to intuitively observe the change of the observation group over time (Bewick et al., 2004). There are three major methods that can be used in a survival analysis.

The first is parametric methodology, which assumes the data distribution as a specific distribution such as Weibull distribution, Exponential distribution, etc. The second is non-parametric methodology, which can be used when the distribution of survival time is unknown by estimating the survival function without assuming a specific distribution of survival function. The Kaplan-Meier method and Life-table method are the most frequently used non-parametric methodologies. Finally, the third is semi-parametric methods such as Cox’s Proportional Hazard Model, which has both parametric and non-parametric characteristic (Cleves et al., 2008; Kleinbaum and Klein, 2012b).

In this study, the parametric methodology was not used because the distribution of survival time of the data was not known. Instead, the median waiting time for a single factor was derived and utilized through the non-parametric methodology, the Kaplan-Meier method.

3.1 Kaplan-Meier Method

The survival function \( S(t) \) means the probability of survival up to time \( t \) (no event occurs). If the cumulative probability distribution function representing the probability of an event occurring at time \( t \) is \( F(t) \), the survival function \( S(t) \) can be defined as follows:

\[
F(t) = Pr(T < t) = \int_0^t f(t)dt,
\]

(1)

\[
S(t) = Pr(T \geq t) = 1 - F(t).
\]

(2)

The methodology used to estimate the survival function in this study is the Kaplan-Meier method, which is used to analyze the survival rate of a single covariate. The single covariate must be a categorical variable, not a continuous variable. The formula to calculate the survival function is as follows (Bewick et al., 2004):

\[
S(t) = \prod_{i=1}^{r} \left(1 - \frac{d_i}{n_i} \right) = p_1 \times p_2 \times \ldots \times p_n \times p_i = S(t-1) \times p_i,
\]

(3)

where 
- \( d_i \) = The number of event occurrences at time \( i \)
- \( n_i \) = The number of events not occurring at time \( i \)
- \( p_i = 1 - \frac{d_i}{n_i} \) = Survival rate at time \( i \)
- \( S(t) \) = Survival probability at time \( t \)

After Kaplan-Meier analysis, there are various methods that can be used to test the difference in survival time (in this study, waiting time) according to the category of the covariate. In this study, the Wilcoxon test was used. In the Wilcoxon test, the null hypothesis is that the risk function has the same survival function between categories. In other words, the significance of median waiting time difference, which is set as the research index in this study, can be determined by testing that the distribution of survival periods is the same (Kleinbaum and Klein, 2012a).

4. Results and Discussions

Table 3 shows the median waiting time calculated from the Kaplan-Meier analysis and Wilcoxon analysis results for each variable. From the analysis, it was found that all variables had statistically significant differences between categories within

| Variables      | Description                    | N    | %     |
|----------------|--------------------------------|------|-------|
| **Time Variable** |                                |      |       |
| Duration       | The time takes until a boarding is completed | 381,750 | 100.0 |
| **Event Variable** |                                |      |       |
| Event: Ride   | 1 if a boarding is completed   | 302,032 | 79.1  |
| 0 otherwise   |                                | 78,718  | 20.9  |
| **Covariates** |                                |      |       |
| Peak           | 1 for peak period (7 – 9, 18 – 20) | 102,377 | 26.8  |
| 0 otherwise   |                                | 279,373 | 73.2  |
| Medical Personnel | 1 if the number of medical personnel is less than median | 153,734 | 40.3  |
| 0 if greater than median |                          | 226,016 | 59.7  |
| Availability   | 1 if availability is below 45% (Low level) | 157,247 | 41.2  |
| 2 if availability is between 45% and 55% (Medium level) |        | 57,516  | 15.1  |
| 3 if availability is greater than 55% (High level) |                           | 166,987 | 43.7  |
With the variable ‘peak’ to determine the variability by time, the median waiting time in the non-peak time was found to be shorter than that of the peak time. This seems to be the result of the disabled’s travel pattern. Since rehabilitation and treatment are the dominant portion of travel purpose and return commute after treatment and rehabilitation mostly occurs during peak hours, the demand for the service is concentrated during peak hours. In addition, the road traffic conditions during peak periods, which were inferior to those of non-peak hours, also caused the result.

With regard to the variable “Number of medical personnel”, the median waiting time was found to be shorter in the regions where the size of medical facilities was relatively large compared to those in the other regions, and this difference was also statistically significant. In terms of the size of medical facilities, it was expected that the median waiting time for larger areas would be longer because there are more demands in larger areas compared to small areas. However, the finding was contrary to general expectations. The reason for this is probably that DRT vehicles tend to be relatively concentrated in areas with large medical facilities, which have higher attraction power to collect the disabled, making it possible to respond to demands more smoothly.

With regard to the variable ‘availability,’ the median waiting time is expected to have an inverse right-down relationship with availability, because the level of vehicle supply is considered to be good when the availability is high. However, from the analysis, the relationship between availability and median waiting time was found to be a U-shape, with a longer median waiting time in high availability status than in medium status. This result might be because the variable of ‘demand,’ other than the relationships between the two variables, affected the result as an external factor.

As explained above in the size of medical facilities, the places with high availability of vehicles have the characteristics of high power to attract people, so there is more demand to use the service even when availability is high. This might lead to longer waiting time. For better understanding this issue, more in-depth research on the relationship between availability and average waiting time is required.

Next, a visual analysis was performed as shown in Fig. 3 to identify the spatiotemporal distribution characteristics of median waiting time. The y-axis represents 25 spheres, which are the spatial units defined in this study, and the x-axis represents the time period divided into 1 hour intervals from 12 AM to 11 PM. A darker color in each cell means a higher median waiting time. For the cells marked with diagonal pattern, the median waiting time was not able to be obtained from the survival analysis, indicating that the number of calls that completed vehicle assignment and ride did not exceed 50% of the total number of calls that occurred in the time and space of the cell. This is because of cases where a user cancels a request because the waiting time is too long, or the driver does not receive a call. The differences in colors on the horizontal and vertical axes indicate service variability over time and space, respectively.

With respect to time, two highest points, which indicate that median waiting time is the highest, were observed between 5 – 7 am and between 3 – 5 pm. This result is very closely associated with vehicle operation. At that time, all vehicles are finished driving and return to the garage, so the possibility of dispatching is very low. During the late night and early morning hours, the median waiting time is more likely to increase, showing a downwardly convex parabolic shape over time.

In the late-night and early-morning hours, there was a large
variation in the median waiting time by regions, unlike in the daytime (10 AM − 1 PM); this imbalance in service availability was found to become particularly severe during the late nighttime (9 PM − 12 AM).

Figure 4 shows the distribution of median waiting time (each cell) by space-time shown in Fig. 3 according to availability and number of calls. Availability implies the concept of supply, while call implies the concept of demand. This analysis was conducted to understand the characteristics of supply and demand when the aspect of spatiotemporal imbalance is similar.

For better understanding of temporal characteristics, Fig. 4 was redrawn through the Kernel density estimation as shown in Fig. 5, with availability (supply) and request (demand). The concept of Kernel density estimation is to smooth the histogram (discrete) and transfer it to a probability density function (continuous). This

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**Fig. 4.** Scatter Plot of Median Waiting Time with Availability and the Number of Calls

**Fig. 5.** Results of Kernel Density Analysis: (a) Area I, (b) Area II, (c) Area III, (d) Area IV
makes it possible to know how dense the waiting times are and in which area they are concentrated (Weglarczyk, 2018).

As shown in Fig. 5, four different kernel density plots were generated based on the availability and the number of requests for a specific time period and space. The detailed meanings of each area are as follows:

During the late night and early morning hours (12 AM – 6 AM, 9 PM – 11 PM), it was found that availability was generally low and the number of calls was mostly distributed low in Area I (Fig. 5(a)). At this time, users are more likely to experience long waiting times, and not even half of the demand could be met. This seems to be because the demand is at the lowest level at that time, but the supply cannot even cover it.

For requests occurred in the morning (7 AM – 9 AM), the supply usually occurred at a higher level than the early morning (Area II, Fig. 5(b)), while the demand was also high. It seems that a spatiotemporal service imbalance still exists, but it was somewhat resolved compared to in the early morning hours. This seems to be because there is sufficient supply of vehicles to cover demand, as the majority of DRT drivers go to work (start business) at 7 AM – 8 AM (Seoul Facilities Corporation, 2019).

With regard to the waiting time during the daytime (10 AM – 3 PM), the availability and number of calls are the highest, but the time zone is where the service is provided relatively uniformly in terms of time and space throughout Seoul. In Seoul, a relatively uniform service supply is provided because additional DRTD drivers are provided during the daytime. There also were several outliers, which shows that in some regions and time periods more demand occurred, even though the vehicles were available at a high level. While the availability is high, it is likely that the waiting time was slightly higher than medium because of this.

For the evening time (4 PM – 8 PM), it was observed that the spatiotemporal service imbalance became severe despite the decrease in demand compared to the daytime. When comparing Area III (Fig. 5(c)) and Area IV (Fig. 5(d)), it was found that the distribution of available vehicles is widespread in Area IV. This suggests that the consistency of available vehicles in terms of time and space, rather than an increase or decrease in demand, has more influence on the provision of balanced services for DRTD. In this time period, drivers who went to work in the morning (7 AM – 8 AM) close their business for the day, and this may cause their vehicles to be concentrated in specific areas where the parking lots are located. This seems to cause a big difference in the distribution of availability.

Based on the analytical results explained above, several implications can be suggested as follows: The waiting time during peak time period was found to be longer compared to the non-peak time, indicating that the number of vehicles operated for peak time periods needs to increase to accommodate the excessive demand.

Regions with a high concentration of medical facilities were found to have relatively longer waiting time. This result might be due to the fact that the majority of trips of the disabled people are associated with treatment and rehabilitation, that is, regions with higher number of medical related facilities could be regarded as traffic zones where trip production and attraction occur frequently. This indicates that the location of medical facilities might be one of the primary factors that should be considered when establishing the strategies of DRT vehicle dispatch.

The demand for the DRT service is not evenly distributed over space and time, and this leads to the unbalanced distribution of DRT vehicles. Since the imbalance of DRT vehicles exacerbates the level of service for DRT system, vehicle reallocation strategies through real-time monitoring need to be established to enhance the level of service for DRT system.

5. Conclusions

This study aims to verify the spatiotemporal imbalance and characteristics of waiting time, which users can intuitively feel and is expected to have a great influence in determining the service level, using the call data of DRTD operated by Seoul, and attempted to identify the causes of imbalances.

Spatiotemporal DRTD service was investigated through median waiting time which was obtained from a survival analysis. For better understanding of spatiotemporal characteristics, three covariates were employed: peak and non-peak time, the number of medical personnel, and the availability of vehicles at a specific time and space. Survival analysis results showed that there were statistically significant differences in median waiting time depending on the category of each covariate.

The spatiotemporal investigation of median waiting time provides some insights that there exists an imbalance of DRTD service, which indicates the availability of DRTD service is not equal over time and space. The main factor causing this imbalance seems to be the spatiotemporal variation of vehicle availability resulted from the imbalance of supply and demand of DRTD.

Uniform provision of a service has a major influence on determining user satisfaction in terms of punctuality. DRTD has a fixed demand group and users are likely to use it repeatedly. When using the DRTD, a user predicts the time it takes for his or her travel and moves accordingly. If there is an imbalance in service, this prediction will not be accurate, and this will be a factor deteriorating user satisfaction. Therefore, it is a critical strategy in terms of service quality improvement to allow users to consistently experience a reasonable level of waiting time, no matter when and where they use the service.

It was clearly found that the supply could not meet the demand during the late night and early morning hours. It is necessary to better understand the demand trend, which changes over time and space, and to arrange vehicles in a manner that is sufficiently balanced to resolve the demand. This is likely to suppress the occurrence of spatiotemporal imbalances for the service by consistently maintaining the availability level suitable for the service demand level through the improvement of driver's commuting schedule, control of vehicle location, and eradication of unauthorized refusals, etc. In addition, the average waiting
time when a ride was successfully obtained was 65.3 minutes and the median waiting time was also 60 minutes or more. This seems to be a rather long time for a user to wait. An effort should be made to increase the number of vehicles and drivers, and thus to shorten the waiting time.

In a future study, it is necessary to investigate the correlation between availability and waiting time because it was found in this study that availability has a major effect on waiting time. Availability seems to be determined by various temporal and spatial factors such as changes in traffic conditions over time, the presence of various demand generating facilities, and commute hours of DRTD drivers. Even factors such as a driver’s working attitude may affect availability. Therefore, further research on this seems to be necessary.

In this study, to minimize the effect of seasonal characteristics, one month of data is collected and analyzed for each quarter and 25 administrative districts were set as a spatial range that can be classified according to covariates containing spatial attributes such as the number of medical personnel and availability. It is expected that more reliable and practical problem-solving solutions can be derived if the temporal range of the study is expanded, the spatial range is subdivided, or the spatial unit is set in consideration of various spatial factors such as the characteristics of income level, worker level, housing type, traffic flows level, green spaces, and distribution of facilities that cause demand for DRTD, rather than being based on administrative districts. Furthermore, a further study needs to be conducted to investigate how the spatiotemporal characteristics of Seoul differ from that of other cities.

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Not Applicable

ORCID

Jong-Hun Son  https://orcid.org/0000-0002-5278-2054
Do-Gyeong Kim  https://orcid.org/0000-0002-3532-5564

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