Characterization of driving behavior in terms of distance with the promotion of electric vehicles

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ABSTRACT

The environmental issues have gained more and more attention from people. The rising demand of using vehicles made the emission from transportation has increasing effect on environmental problems. Electric vehicles (EV) as one of the solution to lower the Greenhouse Gas (GHG) emission, is widely discussed by many researchers. The benefit of utilization and the characteristics of promotion target of EV are discussed in this dissertation.

The first part of this dissertation discussed the substitution of EV for conventional vehicles in a university wide carsharing system. The daily travel distance (DTD) of shared vehicles is simulated by distribution functions. The normal, lognormal, gamma, exponential and Weibull distributions are applied to the DTD, and lognormal performed best among five alternatives. As an improvement of the distribution function, a mixture model consists with two lognormal components is also applied to the DTD, and found to be better fitted than single distribution functions for most of vehicles. The result of best fitted form is used to determine the list of replaceable vehicles. Taking two types of EV as references, the driving and purchase cost between EV and conventional vehicles are discussed in this part. The result shows the smaller driving cost of EV could make it even with the extra purchase cost of it. Moreover, the CO_2 emission is estimated before and after substitution, the carsharing system with EV can reduce the emission. The amount of available electricity from EV at the peak hour is determined in this part, and is

found out to be able to achieve peak-shaving for the electricity consumption.

Even though the benefit of using EV is determined in the first part of this dissertation, the limited driving range could still prevent individual buyers from vehicle electrification. The variables that affect people's driving distance should be determined, in order to understand people's driving habit.

Therefore, the second part of this study focuses on the characteristics of individual vehicle users. This part first examines the distribution of DTD data from private vehicles which mostly belong to Toyota citizens. The examination of mixture model from 2 components to 9 components shows the mixture model with 7 components could explain the driving pattern of the most vehicles. However, the effect of other explanatory variables on DTD requires further study by survival analysis. Both the pooled and panel survival models are tested for DTD and other explanatory variables with lognormal, log-logistic and Weibull durations. The significant scale parameter for constant in the panel model implies the existence of individual difference. The log-logistic duration is the best performed for both pooled and panel model. Overall, the log-logistic duration model with a normally distributed constant is the best fitted model here, but with less significant variables compared to the pooled model. The weather condition is proved to have significant effect on the driving distance. The better fuel efficiency vehicle owners are regarded as more adoptable for EV, so as for those who has a job with fixed commuting distance.

Even though the age is proved to have a significant positive effect on the driving distance, the small number of elderly drivers in the second data set made this result to be less convincible. The driving behavior of elderly drivers could be quite different since their driving abilities are always questioned.

Therefore, the last part of this dissertation examines the data collected from elderly drivers. In this part, we managed to focus on the psychological thinking for different age groups, and the effect caused by their driving attitude. As mentioned before, the driving ability would be questioned with the age grows. Thus, we also applied aptitude test to evaluate the drivers' driving ability. Both pooled and panel models are applied to this data set, and rather than simply tried with normally distributed constant in panel model, we tested six distribution form for the constant. The result shows the lognormal duration with normally distributed constant is the best fitted form among all the alternatives. The model result suggests even though both variables for weather information are significant, but they play quite small effect on the DTD. The variables for psychological thinking are showing different effect among different age groups. The young-old drivers (aged from 65 to 74) do have the tendency toward longer DTD, but not largely affected by their psychological status. On the other hand, the driving attitude variables are playing significant positive effect on the driving distance of old-old drivers (aged over 75). The old-old drivers are more adoptable for EV considering their DTD, but EV with autonomous functions could be a better choice for them since they have more tendency toward risky driving behavior.

The benefit of using EV identified in the first part can help vehicle manufacturers to more specifically understand the advantages of using EV, so that it could be easier to promote EV to the market. Drivers' attitude towards EV could be various, the limited driving range of EV could be one man's meat and another man's poison. The latter part of the dissertation focuses on determining the characteristics of EV adopters, especially considering the limited driving range of the existing EV. The case study of Toyota City points out age may have strong effect on the driving distance. However, the finite number of elderly drivers in the Toyota case leads the result to be clarified. Thus, the last part focuses on the driving behavior in terms of distance of elderly drivers. The result of this dissertation shows the driving range of existing EV could meet about 95% of the individual users' daily driving demand. However, since the old-old drivers (aged over 75) have tendency towards risky driving behavior, it is better to provide them the EV with autonomous functions.

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ABBREVIATIONS AND ACRONYMS

AFT	Accelerate Failure Time
AIC	Akaike Information Criterion
COI	Center Of Innovation
DTD	Daily Travel Distance
DR	Driving Recorder
EPA	Environmental Protection Agency
EV	Electric Vehicles
GHG	Greenhouse Gas
GPS	Global Positioning System
Imp	Impulsive group
ImpSS	Impulsive Sensation Seeking
JMA	Japan Meteorology Agency
JR	Japan Railway
JST	Japan Science and Technology Agency
K-S	Kolmogorov-Smirnov test
LL	Log-likelihood function
MEXT	the Ministry of Education, Culture, Sports, Science and Technology
MMSE	Mini-Mental State Examination
NU	Nagoya University
OLS	Ordinary Least Squares
PDF	Probability Density Function
PH	Proportional Hazard
PSPDS	Psychosocial Purpose of Driving Scale
SS	Sensation Seeking group

TMT	Trail Making Test
TMT-A	Trail Making Test part A
TMT-B	Trail Making Test part B
V2G	Vehicle-to-Grid
ZKPQ	Zuckerman-Kuhlman Personality Questionnaire

CHAPTER 1 Introduction

1.1 Background

The Global Energy Review 2020 reports that global electricity demand decreased by 2.5% in first season of 2020 compared to 2019, it was not only because of the Covid-19 but also because the weather in January and February was milder than in 2019. Electricity is used to support our daily life and is also a main resource of Greenhouse Gas (GHG) emission. The Overview of Greenhouse Gases and Sources of Emissions by Environmental Protection Agency (EPA) shows in 2018, 27% of GHG emission came from electricity generation, but it is still not the biggest source of GHG emission, 28% of GHG emission came from transportation. Transportation sector is not only the largest GHG producer, but also the largest consumer of total final commercial energy demand in the case of Malaysia in 2005 (Shekarchian et al., 2011). As mentioned in Joos et al. (2001), the carbon dioxide affects weather condition such as surface-air temperature, precipitation and cloud cover, this could lead to ocean thermal expansion. Thus, both electricity generation and transportation should be more focused out of the environmental and sustainable consideration.

In the case of Japan, according to Paris Agreement, Japan is committed to reducing GHG emission by 26% by 2030 for the goal of limiting global temperature rises. In order to reach this goal, Japanese government made a plan for energy mix, the renewable energy power source need to reach 22-24%, and the real energy efficiency need to be reduced by 35% based on Basic Energy Plan: Policy considerations to 2030. Nuclear power was another strong provider for electricity, but Japan has become more cautious about the use of nuclear energy in the mid- to long-term energy policy after the tragic loss of the Fukushima Daiichi nuclear plant accident in 2011, the direct economic cost estimated by Japan’s Cabinet Office is $210 billion. Japan is suffered with natural disasters, as mentioned in Kingston. (2012), some 20% of the world earthquakes occurred in Japan. The frequent disaster result in a considerable loss of the electricity dependency on nuclear power, and also brought more thoughts on other post-disaster safety issues such as evacuation behavior and emergency power resources.

One alternative to serve as emergency power resource is electric vehicles (EV) with the help of Vehicle-to-Grid (V2G) system. The battery of EV can serve as a temporary storage of electricity, and provide the energy back to grid when necessary through the V2G system (Mets et al., 2011; Zhou et al., 2011). Thus, it is possible to use EV as emergency power resource, and it can also be a solution to cut the peak load during daily life (Kempton and Tomić, 2005; Guille and Gross, 2009; Lee et al., 2017). Additionally, the reduction in the Global Warming Potential (GWP) is considered to be another benefit of using EV (Casals et al., 2016; Hawkins et al., 2012). Wu et al. (2018) estimated GHG emissions from battery EV and predicted the total life cycle GHG reduction would reach 13.4% in 2020.

However, the acceptance of EV needs to be considered for promoting it. Neumann et al. (2010) made a thorough study of the user acceptance of EV, the motivation of trying new technology as well as environmental protection consideration would drive them to EV, and a range of 140 to 160 km is sufficient for more than 94% users' daily needs. However, after considering the cost of electricity, Tamor et al. (2013) suggested the optimal EV range should be 240 to 320 km.

Therefore, the optimal EV range may differ among various groups of people, and people may hold different acceptance of EV. The study of daily driving distance could help us in understanding daily driving pattern in order to determine the optimum EV range, predict the financial and environmental benefit of utilizing EV, and people's acceptance towards EV.

1.2 Aim of the study

As discussed above, the promotion of EV requires various of studies, so that the limited battery range could fit the travel demand of consumers, especially the daily travel distance should be focused in order to determine the battery size. Moreover, from the perspective of EV producer, it is not enough to understand the customer's attitude towards purchasing EV by simply understanding their daily driving demand. The other characteristics should also be focused when considering the suitable EV driving range for a specific consumer groups.

Before the promotion of EV towards individual buyers, we first determine the benefit of using EV in a carsharing system. The quantified benefit of using EV could help us in the promotion by providing real numbers of environmental and financial benefit. The original equipped internal combustion engine vehicles in the carsharing system could be replace by EV with a suitable driving range, and the list of replaceable vehicles is determined by the best fitted form of each vehicle. After the substitution, EV in the carsharing system can not only fulfill the driving demand of original vehicle, but could also provide electricity back to grid when necessary under the help of V2G system. The amount of CO_2 reduction should be determined here to achieve the environmental benefit. Additionally, whether the available electricity in EV could achieve peak-shaving should be determined here as energy consumption benefit of substitution. The travel and purchase cost is also discussed here as financial benefit of using EV rather than conventional vehicles.

After determine the benefit of using EV based on the driving distance, we want to focus on not only the driving pattern of distance, but also the variables that affect driving distance. The study of the variables that effect on driving distance could help EV manufacturers to determine the characteristic of their target customer, in order to promote the suitable EV to adopters. The mixture distribution with more components is used here as the improvement of using distribution function to reveal the driving pattern in terms of distance. Additionally, the driving distance is examined with other explanatory variables by hazard duration model, which can reveal the drivers' preference on DTD. In this way, the target group for adopting EV could be more clarified by information such as their occupation type, personal situation or current vehicles.

The attitude towards purchasing EV differs among different groups of people. In the third part of this study, we would like to be more focused on the different age groups. The aptitude test result to evaluate their driving ability, and the questionnaire for their driving attitude among different age groups would be more focused in this part. The driving attitude itself could result in different attitude towards EV. In this part, whether the elderly drivers could be EV adopter would be determined especially on their driving attitude.

1.3 Research structure

The structure of this dissertation is shown in Figure 1.1. This dissertation has been divided into six chapters. The first chapter introduces the research background and the aim of this study. The second chapter gives a general review of previous studies involving electric vehicles, the distribution of driving distance, other explanatory variables that affect driving behavior, and the utilization of survival analysis in the field of transportation.

In Chapter 3, the distribution test is applied to university car fleet data in order to simulate the driving patterns of carsharing users. Five distribution function as well as mixture model are used to simulate the driving habit of carsharing system in terms of distance. This chapter mainly determines the benefit of utilizing EV in carsharing system. The purchase and driving cost between EV and conventional vehicles are compared in this chapter. The amount of available electricity from EV is also determined in order to reach the goal of peak-shaving. The CO_2 reduction after substitution is calculated as the environmental benefit of using EV in a carsharing system.

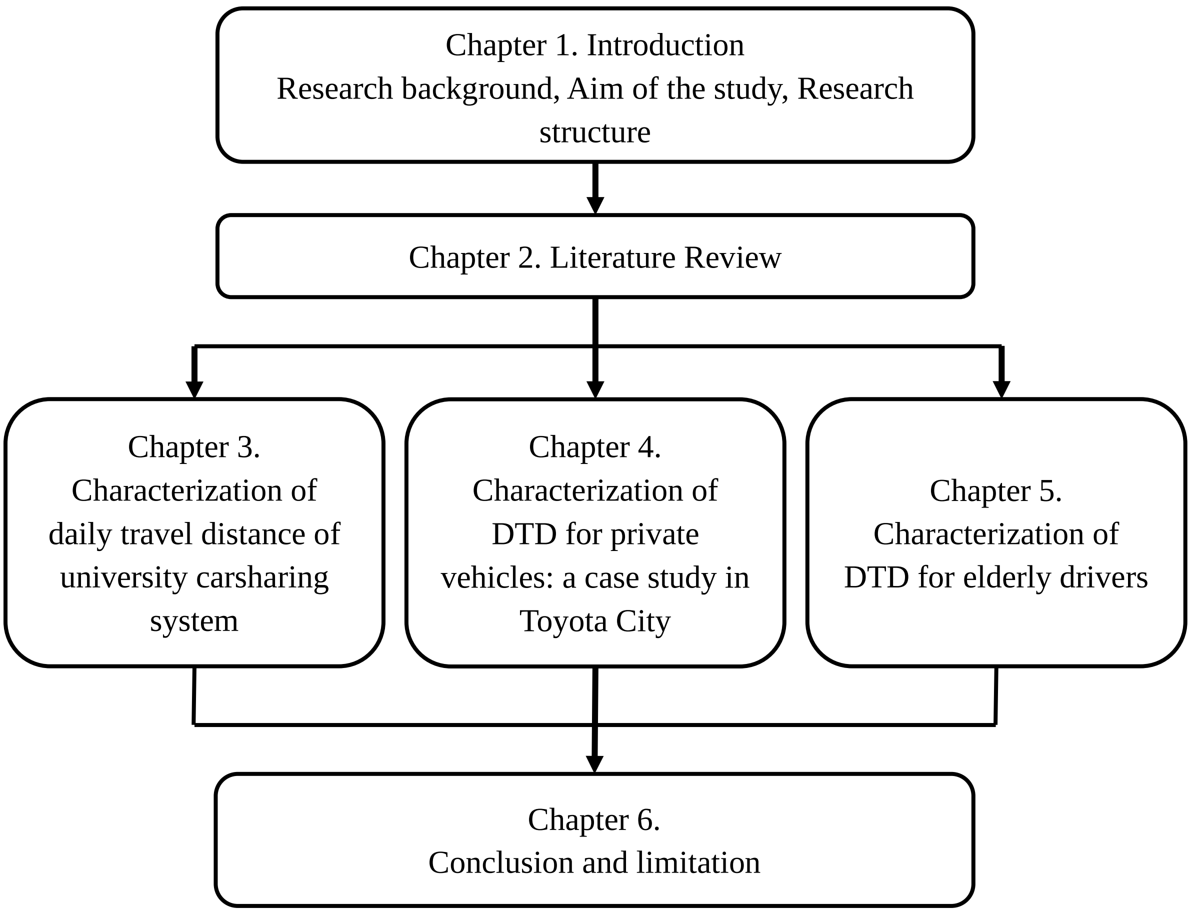


Figure 1.1 Structure of the dissertation

In Chapter 4, the distribution functions as well as survival model is applied to the data collected from private vehicles in Toyota City. The driving pattern in terms of distance could be better explained with other explanatory variables by survival analysis. Both pooled and panel survival model is applied to the data, the significant scale parameter for constant implies the existence of individual difference. The significant explanatory variables could be used to determine the characteristics of the drivers who have tendency for shorter daily distance as EV adopters, since their driving demand could be easier fit with the driving range of existing EV.

In Chapter 5, we applied a similar study as previous chapter. The hazard duration model is applied to the DTD data with other explanatory variables. As an improvement of previous chapter, six distributions are used as the assumption for constant in the panel duration model. This chapter applied models on the data of elderly driver, and the driving ability and psychological status are more focused in this chapter. The psychological status is interacted with 3 different age groups in order to examine the effect of driving attitude among different age groups. The result could be used to identify the people who are more adoptable for EV, and the suitable EV for them.

The conclusion of this dissertation and the limitation is discussed in the last chapter.

CHAPTER 2 Literature Review

2.1 Electric vehicles

The electric vehicle (EV) is claimed to have the potential to reduce GHG emission (Casals et al., 2016; Hawkins et al., 2012; Wu et al., 2018) and peak-shaving (Kempton and Tomić, 2005; Guille and Gross, 2009; Lee et al., 2017). As mentioned in Smith et al. (2011), EV is seen as having potential for reducing oil dependency and GHG emissions in transportation use, and in Martin and Shaheen (2011), car-sharing is reported to have the ability to reduce GHG emissions as a whole. The benefit of EV could be enlarged by the combination with carsharing system or Vehicle-to-Grid (V2G) system. Cocca et al. (2019) designed an electric free floating car sharing system, and the result shows few charging station are enough to make the system self-sustainable. Luè et al. (2012) describe the electric vehicle-sharing system as a green move. Lemme et al. (2019) also suggests the adoption of EV in car sharing system could play an important role in sustainability. Fleury et al. (2017) mentioned as carsharing allows individuals to benefit from a private car without all the usual constraints.

As mentioned in Bishop et al. (2016), V2G may be used to store electricity generated off-peak, and it could be a great solution to cut the peak load (Lee et al., 2017). This viewpoint if supported by many other researches, Mets et al. (2011) also mentioned the V2G system can provide the operating reserve

However, the benefit will not be clearly expressed until EV reached a reasonable market share. The limited battery size restricts the promotion of EV. Many approaches have been made from different aspects to solve this issue.

Hardman et al. (2018) summarized 5 key insights of consumer preference with EV, which includes infrastructure, the access to the charging infrastructure, the cost of charging and the impact of charging. Many studies focused on the influence of charging behavior and facility. Bailey et al. (2015) applied an analysis on Canadian new-vehicle buyers, and found out that public charger awareness is not a strong predictor for plug-in EV interest, other variables such as the availability of charging at home are more important. Franke and Krems. (2013) examined the charging behavior of EV users and found out they charged vehicle three times per week on average, drove about 38 km per day. Björnsson and Karlsson. (2015) suggests the availability of charging infrastructure at work places would encourage commuters to be early adopters for EV. Xi et al. (2013) developed a simulation-optimization model which can determine the location of EV chargers. Schücking et al. (2017) unlike the previous mentioned studies, focused on the different charging strategies for EV in Germany.

Other studies focused on the driving distance of EV. Niklas et al. (2020) examined the usage data in Germany and California, and found out EV is used similar as conventional vehicles for long-distance travel (>100 km). In the case of Beijing, Shi et al. (2019) suggested that with home charging and existing public charging infrastructure, the existing EV is feasible to replace a significant portion of gasoline vehicles. Similar result is also obtained in Pearre et al. (2011), the analysis shows even with limited range, electric vehicles could provide a large fraction of transportation needs. Melliger et al. (2018) conducted research to understand the impact of range limitations in Switzerland and Finland, the result shows the prevalent EVs in 2016 can already meet 85-90% of the national trips.

Considering the environmental benefits of using EV as well as the peak-shaving potential, it is possible to vigorously promote the use of it to replace the conventional vehicles. However, when it comes to a specific user, whether the current limited battery range is enough for daily travel demand still requires basic analysis on the distance.

2.2 Distribution of daily travel distance

As mentioned above, to popularize the EV against its limitation, more studies focused on driving pattern, especially in terms of daily travel distance for multiple purposes. Hao et al. (2016) studied the driving distance to optimize the charging pattern for location and type of charging infrastructure selection. Khan and Kockelman (2012) analyzed the Seattle household driving data, and compared the driving cost between conventional vehicles with plug-in EV.

The early study conducted by Greene (1985) estimated the daily travel distance and the implications for limited range vehicles, discussed thoroughly on gamma distribution. Normal distribution is used in Neubauer et al. (2012) and the result shows distance with a batter EV has a strong impact on the cost-optimal range, charge strategy and battery replacement schedule. Weibull distribution is applied in Traut et al. (2011) to driving distance, and confirmed by Plötz et al. (2017) as better performed than lognormal and gamma distribution, it yields reliable estimates for EV applications.

Other studies did not utilize conventional single distribution. Pearre et al. (2011) examined the distribution of maximum daily mileage to optimum the EV daily range needs, but didn't use any distribution function as previous studies. Tamor et al. (2013) characterized the individual trip chain length frequency can be represented by a mixture distribution combined by an exponential and Gaussian distribution. A more complex mixture model is applied in Li et al. (2016), the study divided drivers into 9 groups so that the diversity of travel demand of different drivers can be examined for the design of a proper EV battery size.

2.3 Explanatory variables

The study of distributions for driving distance reveals the pattern and regularity of driving, but does not explain the cause of the regularity. Holz-Rau et al. (2014) studied driving distance along with other explanatory variables such as population density and personal information by ordinary least squares (OLS) regression, the result shows the inhabitants of city with lower population and lower density would travel longer than the inhabitants of city with higher population density. In this way, the study of explanatory variables could help in understanding the reason of different driving distance patterns.

Many different factors are used as explanatory variables have been discussed for better understanding in driving behavior. As mentioned in Manaugh et al. (2010), the socioeconomic factors have a statistically significant correlation with commuter distance, it could underscore the importance of home-work location with respect to urban form and job accessibility. Additionally, other factors may also play important role in travel behavior. In the early study by Niemeier and Morita (1996), gender is focused to distinguish the different travel behavior, women tend to spend more time on shopping and family support activity duration than men.

A case study in Michigan conducted by Meinrenken et al. (2020) attempts to optimize the EV range by studying driving distance, the research considers the distribution of charge distance by different age of drivers, the result shows drivers aged over 55 have a higher peak in the distribution compare to other age group. Moreover, Onishi (2020) pointed out elderly drivers have unique driving characteristics such as physical condition and cognitive factors. Morgan and King (1995) pointed out that elderly are more likely to have cognitive, motor and sensory perceptual deficits affecting their driving performance. Thus, elements like physical condition, cognitive impairment and visual acuity are more focused when studying the behavior of elderly drivers.

The Trail Making Test (TMT) and Mini-Mental State Examination (MMSE) are widely used to assess the driving ability (Freund et al., 2008; Takahashi et al., 2017). TMT provides information on visual search, scanning, speed of processing, mental flexibility and executive functions, it is used to measure the cognitive processing speed and load (Arnett and Labovitz, 1995; Horikawa et al., 2009). TMT consists of part A (TMT-A) and part B (TMT-B), TMT-A requires individual to draw lines sequentially connecting 25 encircled numbers, TMT-B requires individual must alternate between numbers and letters (Tombaugh, 2004). Instead of directly using the score of TMT-A and TMT-B, many studies utilized the difference score between TMT-A and TMT-B (Reitan and Tarshes, 1959; Klesges, 1984), while Golden et al. (1981) utilized a ratio of TMT-B to TMT-A. Both difference score and ratio could be used to measure the cognitive status.

The Mini-Mental State Examination (MMSE; Folstein et al., 1975) is another popular clinical screening tool for cognitive impairment, it measures orientation to time and place, immediate recall, short-term memory, calculation, language, and constructive ability (Molloy et al., 1991). In the early study of prediction and assessment of driving performance for drivers diagnosed with probable Alzheimer’s Disease, MMSE was found to be a significant predictor of final on-road result (Fox et al., 1997). Freund et al. (2005) applied MMSE to elderly drivers and compared the score with a self-rated driving evaluation performance.

Visual acuity is another element to evaluate driving ability, it is required procedure to obtain a driver’s license (Keeffe et al., 2002). Wood et al. (2010) investigated the effects of simulated visual impairment on nighttime driving performance for young participants (aged from 18 to 36), while McGwin et al. (2000) evaluated associations between visual function and self-reported difficulty with relatively elder drivers (aged from 55 to 85).

The psychological thinking is gaining more attention as another aspect of influencing driving behavior. The Zuckerman's (1994) Impulsive Sensation Seeking (ImpSS) theory is a well-known extensive research on the relationship of personality traits. Jack and Ronan (1998) applied ImpSS in order to show the personality differentiated between high- and low-risk sport participants. It is used in studying the behavior of gambling activities (McDaniel and Zuckerman, 2003) and other risk behavior such as alcohol, cigarette and drug use (Robbins and Bryan, 2004). Evans et al. (2006) also applied ImpSS to study the smoking and caffeine intake behavior, and it is also associated with Parkinson's disease. In the field of transportation, the ImpSS, as a subscale of the Zuckerman-Kuhlman Personality Questionnaire (ZKPQ) is applied to study eco-driving tendency behavior in Zuraida and Widjaja (2017), it plays an important role in confirming risky behaviors such as risky driving (Zuckerman and Aluja, 2015). The 19 items in ImpSS can be divided into 2 subscales as "Impulsive" and "Sensation Seeking" (Fernández-Artamendi et al., 2016). The Psychosocial Purpose of Driving Scale (PSPDS) is another measurement of psychological thinking for drivers, it is measured to link the young drivers' psychosocial driving purpose with risky driving behavior (Scott-Parker et al., 2015). The purpose of driving has been studied by many researchers (Tseng, 2013; Scott-Parker et al., 2015), PSPDS is evaluated with 7 driving purpose items for young drivers in Scott-Parker et al. (2015).

The explanatory variables that has been studied for driving behavior could be concluded as socioeconomics, aptitude test result and psychological status.

2.4 Survival model

As mentioned above, the study of DTD could be conducted by utilizing distribution functions, therefore, it would lack the consideration of other explanatory variables. The regression model, on the other hand, could help in considering the effect on DTD by other variables, but it ignores the regularity of DTD itself. In this way, survival model could cover both considers.

The survival model is classified as nonparametric, semiparametric and fully parametric in Washington et al. (2011). The model is usually used to study the duration data, and hazard function could be represented as:

$$h(t) = f(t)/[1 - F(t)] \tag{2.1}$$

where, t is a random parameter as the duration, $f(t)$ is the probability density function for t, and $F(t)$ is the cumulative density function for t.

The nonparametric model is distribution-free, which means it doesn't have an assumption on the distribution function, and is not covariate with other explanatory variables. Therefore, the application of such model is very limited. The semiparametric assumes the dependent variable is covariate with other explanatory variables, but not limited to the distribution function. This approach was developed by Cox (1972). The fully parametric model assumes both a distribution function on the duration data, and a parametric assumption on the covariates.

Survival analysis has enjoyed widespread use in many fields, developing an understanding of the factors that determine the time that transpires until or between the occurrence of specific events is often an important analytic focus (Hensher and Mannering, 1994). In the field of transportation, both time and distance is used as study subject of survival analysis.

Guo et al. (2012) applied survival analysis to study the influence of on-street parking on travel time, the variables as effective lane width and parking maneuvers have significant impact on the travel time. In the field of transportation, the study of time is always safety problems. Haque and Washington (2014) studied the reaction times of young drivers distracted by mobile phone conversation. Speed reduction time of drivers at bicycle crossroads is studied by Bella and Silvestri (2018) to avoid the occurrence of accidents and improving the cyclist safety. In Ali et al. (2019), the gap time for lane-changing is modelled using a survival model to examine the effects of the connected vehicle environment on safety during lane-changing. The study of traffic incident duration could help in the implementation of strategies to reduce incident duration, leading to reduced congestion and secondary incidents (Hojati et al., 2013). In addition to the traffic research, Hasan et al. (2013) examines the hurricane evacuation time with a random-parameter hazard-based model.

Compared to the massive studies of time using survival model in the field of transportation, the research on distance is still very limited. Anastasopoulos et al. (2012) conducted a conventional study to identify important factors that determine activity-based travel distance, that can help to better understand travel behavior in terms of trip distance. Ding et al. (2017) focused on the commuting distance, investigated the influences of environment characteristics and individual factors. As mentioned above, the electric vehicle has a limitation of driving distance due to the battery size. Thus, the transport habits of new energy vehicle users may also change, and it has been studied by Anastasopoulos et al. (2017), the study found it to be affected by variables such as traveler socio-economic and demographic characteristics and trip purposes. The spatial hazard based model used the “distance to a vehicle” as the prospective decision on choice set formation behavior in selecting vehicles, and provided a starting point for carsharing organizations to optimize their pod locations (Jian et al., 2016).

CHAPTER 3 Characterization of daily travel distance of university carsharing system

The usage pattern differs from various type of users. The carsharing system hold quite unique pattern since the vehicle is used by more than one user. The driving habits of university members would be more related to the work-rest pattern, since the university usually close during weekend.

Therefore, this chapter explains the characteristic of DTD of university carsharing system. Due to the environmental consider, the quantitative driving pattern in in terms of distance could help in determining the Electric Vehicles (EV) to replace the original vehicles in the sharing system. Thus, with the help of Vehicle-to-Grid (V2G) system, the peak shaving potential is also discussed in this chapter. Addition to the benefit of electricity, the CO_2 emission reduction could also be achieved by EV, and the amount is also discussed in this chapter.

3.1 Data descriptive analysis

The data set is collected from Nagoya University carsharing system. The carsharing system is only available to university members. Nagoya University is a national university located in the capital of Aichi prefecture. The campus holds 3.2 km^2, located in the Nagoya City

(35°09′17″N 136°58′01″E). The university carsharing system records the usage data of the shared vehicles and is used in this study. The fleet of carsharing system hold 54 general purposed vehicles, and are used by employees including administrative workers and researchers. The fleet include two diesel vehicles, five hybrid vehicles, and the rest are gasoline vehicles, and is shown in Figure 3.1. The carsharing system would record the information of vehicles such as department, vehicle ID, vehicle type, and the basic usage information as the time of check-out and check-in, the odometer of check-out and check in. However, not all the vehicles have the information recorded. In this way, we can only analyze the data collect with 48 vehicles from October 2014 to September 2015.

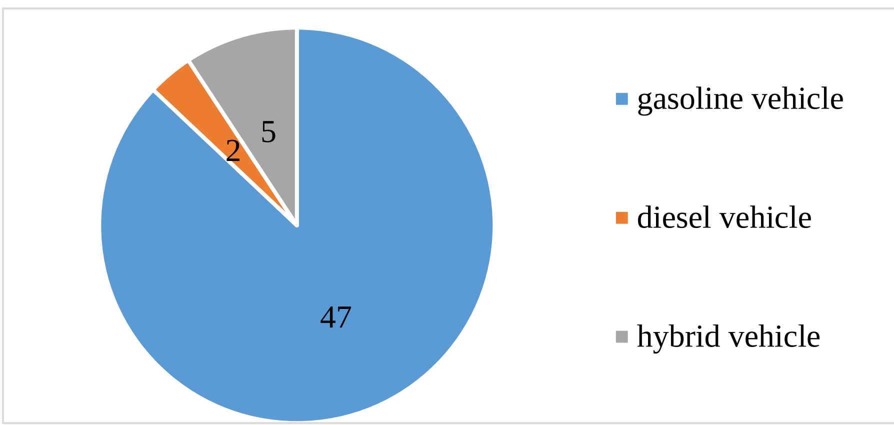


Figure 3.1 Number of vehicles for each type

These vehicles belong to different departments, and only department employees can use the vehicles in that department. Therefore, the vehicles are not completely shared by all university members despite their department. Table 3.1 illustrates the number of vehicles belong to each department. The number of vehicles is not allocated in proportion to the number of personnel in the department. Even though the school of engineering holds the most employee members, but it only holds two vehicles. This would lead to an unbalance of usage frequency in vehicles.

The driving distance for each data set could be very different, since the vehicle belonging and user are various. Figure 3.2 illustrates the average Daily Travel Distance (DTD) conducted on different weekdays for the first data set. The average DTD is quite similar among working days, but users tend to make long trips during weekends. Additionally, the difference in the use rate between weekdays and weekends is in line with the work-rest pattern of people.

Table 3.1 Number of vehicles belong to each department

Department	Number of vehicles
Secretariat	8
Museum	1
Faculty of Science	5
Graduate School of Environmental Studies	12
Research Institutes	10
Faculty on Liberal Arts	3
Physical Education Center	1
School of Informatics and Science	2
School of Agricultural Science	10
School of Engineering	2

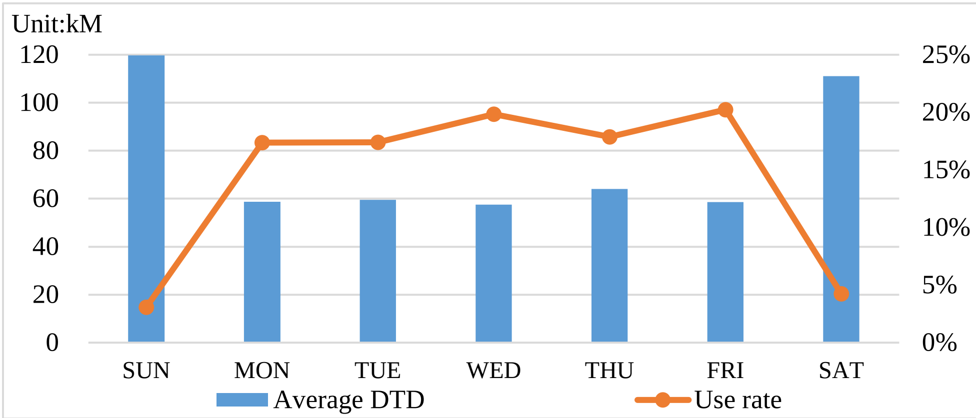


Figure 3.2 The average DTD and use rate for each vehicle by different days in a week

Figure 3.3 illustrates the average DTD and daily use rate of each vehicle in different month of a year, the use rate is calculated as the number of trips divided by the number of vehicles that is used during that day. The use rate in January is the lowest, which is understandable because of the new year break. The use rate in July is the highest, but the average DTD is relatively short, which implies university members tend to travel frequently but short distance in July. On the contrast, the use rate reaches a local valley in May, but the average DTD is relatively long.

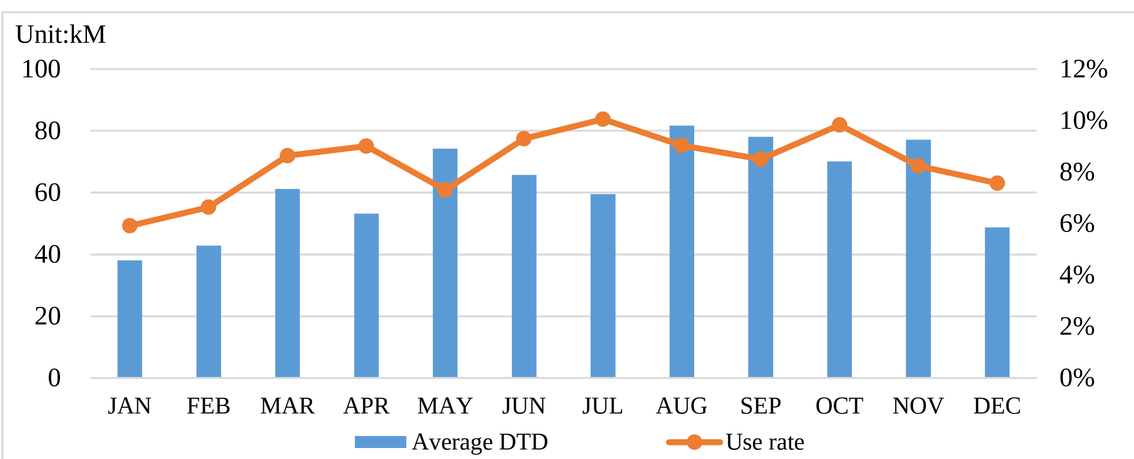
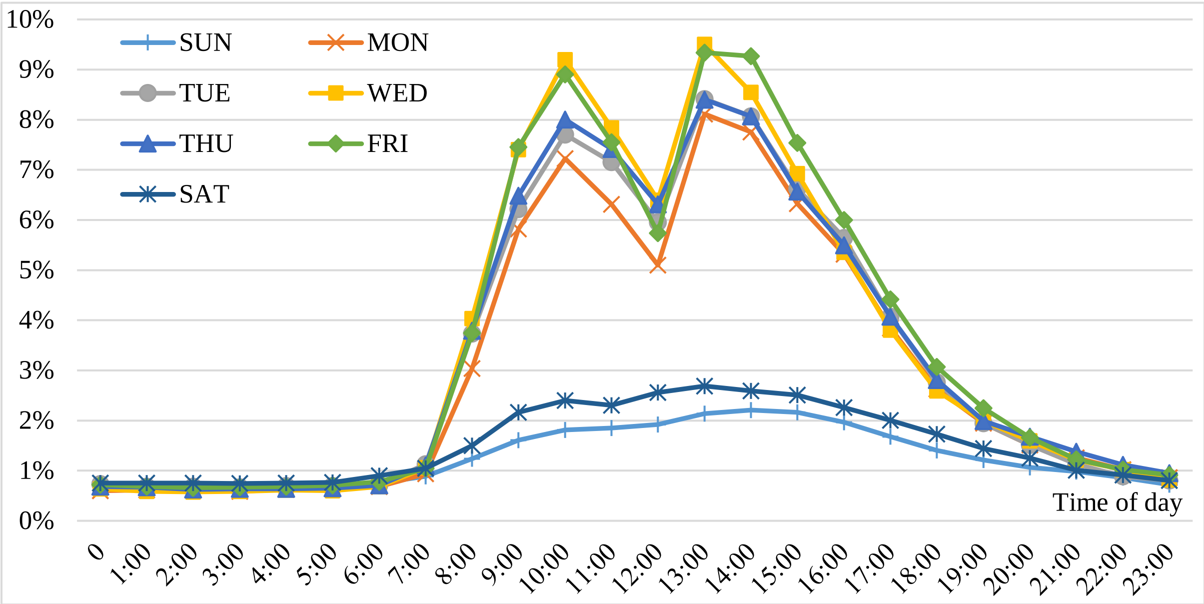
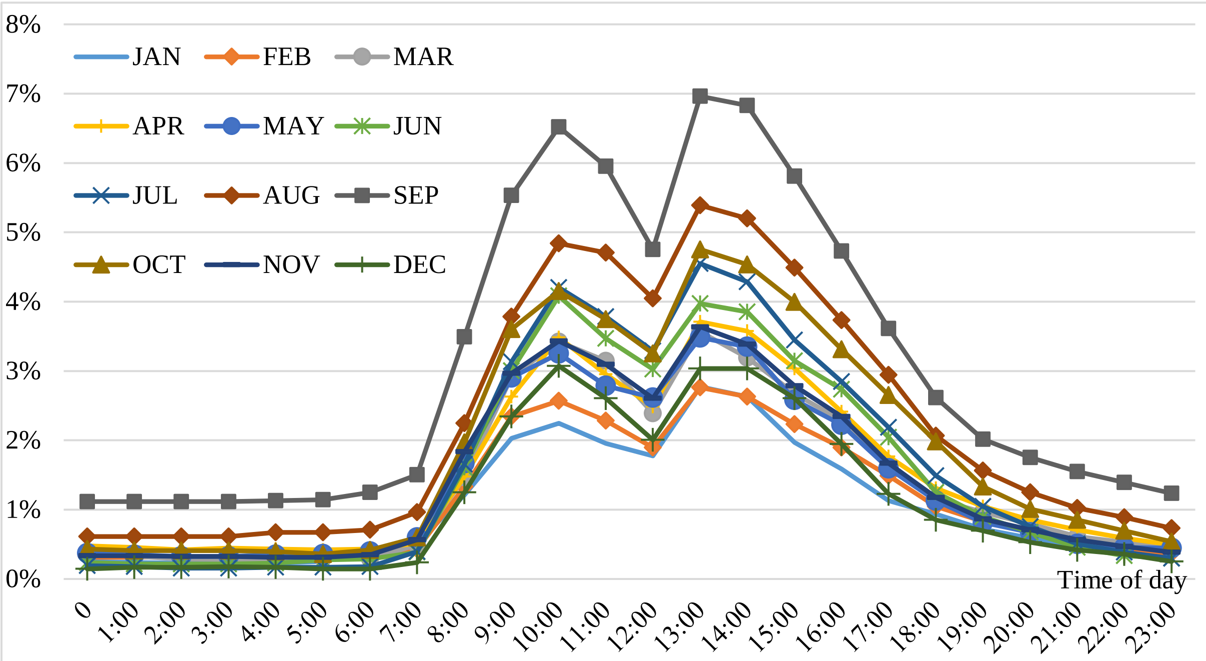


Figure 3.3 The average DTD and daily use rate of each vehicle in different month



(a) By day of week



(b) By month of year

Figure 3.4 The average use rate for all vehicles in different time of a day

Figure 3.4 illustrates the average use rate for all vehicles among different time of a day. It counts percentile of the vehicle in use during that hour of the day in a week or a month. The use rate in both Figure 3.4 (a) and Figure 3.4 (b) reaches a local minimum in 12:00, this is consistent with people's work-rest pattern, it is lunch time for most of people. Two peaks in the use rate are clear shown in both figures, 10:00 and 13:00 respectively.

Similar as mentioned above, the use rate during weekdays is higher than in weekend. In Figure 3.4 (b), about 7% of the trips in 13:00 are made during September, the number of vehicles in use is the highest for all the 24 hours.

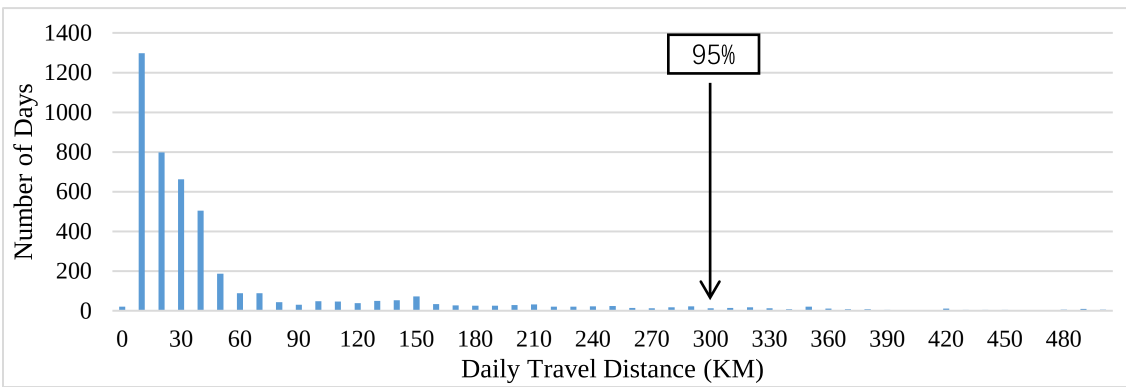


Figure 3.5 Histogram of daily travel distance during 4522 of the 4586 driving days*

*Because only 64 driving days are distributed between a DTD of 500 and 1600 km, the figure only shows the DTD within 500 km.

Figure 3.5 gives an overall image of the DTD in the carsharing system. The total driving days are 4586 for 48 vehicles, but since 98.6% of them are less than 500km, thus the figure only shows the trips within 500 km. As shown in Figure 3.5, the trips reach to a peak at 10 km, and another slight peak at 150 km. More than 82% of the trips are actually within 100km, which implies a battery size of larger than 100 km could cover about 80% of the travel demand in this carsharing system.

3.2 Distribution analysis

The distribution functions used in this chapter are normal, lognormal, gamma, exponential and Weibull. The probability density function for each can be represented as:

Normal: $$f(x|\mu,\sigma^2)=\frac{1}{\sqrt{2\pi\sigma^2}}\,e^{-\frac{(x-\mu)}{2\sigma^2}^2} \tag{3.1}$$

Lognormal: $$f(x)=\frac{1}{x}\cdot\frac{1}{\sigma\sqrt{2\pi}}\,\exp\left(-\frac{(\ln x-\mu)^2}{2\sigma^2}\right) \tag{3.2}$$

Gamma: $$f(x)=\frac{(\frac{x-\mu}{\beta})^{k-1}\exp\left(-\frac{x-\mu}{\beta}\right)}{\beta\Gamma(k)} \quad x\geq\mu;\ \ k,\beta\ \geq 0 \tag{3.3}$$

Exponential: $$f(x;\ \lambda)=\begin{cases}\lambda e^{-\lambda x} & x\geq 0,\\ 0 & x<0.\end{cases} \tag{3.4}$$

Weibull: $$f(x;\ \lambda,k)=\begin{cases}\frac{k}{\lambda}(\frac{x}{\lambda})^{k-1}e^{-(x/\lambda)^k} & x\geq 0,\\ 0 & x<0.\end{cases} \tag{3.5}$$

where,

μ is the location parameter;

σ is the standard deviation;

β is the scale parameter;

$k > 0$ is the shape parameter;

$\lambda > 0$ is the rate parameter.

The distribution functions are used to test with the DTD data of each vehicle, each vehicle may fit with one or more distributions. P-value estimated by Kolmogorov-Smirnov test (K-S test) (Simard et al., 2011) is used here to determine whether the DTD of a certain vehicle is subject to a certain distribution form with a 95% confidence level. The result of all vehicles for fitting each distribution is shown in Table 3.2, and an example of vehicle 3810 is given in Figure 3.6.

Table 3.2 All combinations of fitting distribution in terms of p-value*

normal	**lognormal**	**gamma**	**exponential**	**Weibull**	**case**
8	**21**	**13**	**4**	**20**	
×	×	×	×	×	**20**
○	×	×	×	×	**1**
×	○	×	×	×	**7**
○	×	×	×	○	**1**
×	○	×	×	○	**6**
×	×	○	×	○	**2**
○	×	○	×	○	**2**
×	○	○	×	○	**4**
×	×	○	○	○	**1**
○	○	○	×	○	**1**
○	○	○	○	○	**3**

*○ represents certain vehicles can be subject to this distribution,

× represents certain vehicles cannot be subject to this distribution.

The lognormal distribution performs best among 5 functions; 21 vehicles could fit this distribution with more than 95% of confident level. The Weibull comes the second best, only 1 vehicle less than lognormal. Exponential distribution fits the DTD of carsharing system the worst, only four vehicles are found to be suitable for this distribution. Additionally, there are three vehicles could fit all the distributions. However, there are 20 out of 48 vehicles cannot be fitted by any distribution function. Thus, the further study of distribution fitting could be conducted.

To improve the distribution fitting of DTD for each vehicle, mixture model used in this study as a combination of two lognormal distribution functions, and its probability density function (PDF) for a certain vehicle can be explained as followed:

$$f(r_t) = \alpha \cdot \frac{exp\left\{-\frac{[\,ln(r_t) - \mu_1]^2}{2\sigma_1^2}\right\}}{r_t\sqrt{2\pi\sigma_1^2}} + \frac{(1-\alpha)exp\left\{-\frac{[\,ln(r_t) - \mu_2]^2}{2\sigma_2^2}\right\}}{r\sqrt{2\pi\sigma_2^2}} \tag{3.6}$$

where r_t is the daily travel distance for day t;

α is the mixing proportion of component $\alpha \in [0,1]$;

σ_i is the standard deviation of i-th mixture component;

μ_i is the mean of i-th mixture component.

The Akaike information criterion (AIC), where AIC = − 2LL+2(p+1), p is the number of the model parameters, and LL is the log-likelihood function, and can be delivered as follows:

$$\mathrm{LL} = \sum_{t=1}^{T} \log f(r_t) \tag{3.7}$$

The best fitted form among five distribution functions is selected for each vehicle based on

AIC, and the result is shown in Table 3.3. The mixture model does fit better than other single distribution forms, 39 out of 48 vehicles are best fitted by the mixture model. Yet, there are still 6 vehicles fit the Weibull distribution best among 6 alternatives. In this way, we could select one best fitted form for each vehicle, and the best fitted form is used in the following study, which can help in determine the suitable EV for substitution, and therefore, the emission and cost change could be estimated as well as the electricity saving potential.

Table 3.3 Summary of goodness of fit according to AIC

normal	lognormal	gamma	exponential	Weibull	mixture
0%	4.17%	0%	2.08%	12.50%	81.25%

3.3 EV adoption

The result of distribution analysis is used here to determine the travel demand for each vehicle, in order to select a type of EV with a suitable driving range which can satisfy the driving demand. This study does not require that all conventional vehicles must be replaced with EV. Taking into account the needs of different driving distances, some of the vehicles in the original carsharing system can be retained and used especially for long-distance driving.

There is a definite difference between the observed data and best fitted form on the driving demand, it is shown in Figure 3.6. The best fitted form is showing a quite similar trend with observed data within 150 km, but the two dispersion after 200 km. As shown in Figure 3.6, an EV with a 150 km driving range could meet the need of 50% vehicles according to the observed data, but based on the best fitted form, it requires a 165 km driving range to meet the driving need of 50% vehicles. Therefore, the number of vehicles that can be replaced would differ based on the battery size of EV.

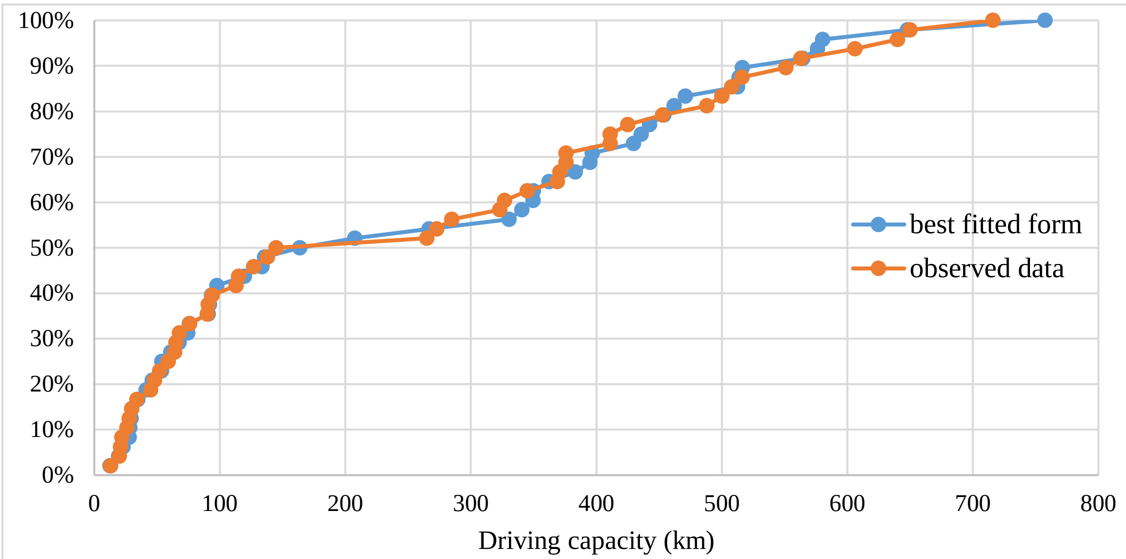


Figure 3.6 The percentage of replacement by the vehicle with different driving capacity in 95% satisfaction level according to the best fitted form and observed data

Two different types of EV are used here, the MITSUBISHI i-MiEV (Japanese cycle) (Type 1) and Tesla Model 3 (Type 2). The basic information and the number of replacement is shown in Table 3.4. Type 1 with a 160 km driving range can replace almost 48% of the vehicles, and with the larger battery capacity, Type 2 can replace more than 60% of the vehicles with a 350 km driving range.

However, the larger battery capacity doesn't stand for a better performance on driving considering the electric consuming. As mentioned in Table 3.4, Type 1 can drive 10 km when every kWh of electricity is consumed. Based on the electricity price of Nagoya University, Type 1 has lower driving cost than Type 2. Therefore, the cost of substitution should be re-considered based on not only the vehicle price, but also the driving price.

Table 3.4 EVs as alternatives for substitution

	Driving performance (km/kWh)	Driving cost (yen/km)	Substitution rate
Type 1	10	1.690	47.92% (23)
Type 2	7	2.414	62.50% (30)

3.4 Cost change for substitution

The two scenarios of substitution plan with Type 1 and Type 2, could lead to different cost. The Scenario 3 consists of 23 Type 1 EV and 7 Type 2 EV. The change of cost include the travel cost and purchase cost, and is shown in Table 3.5. The travel cost of EV is calculated based on the driving performance (km/kWh) in Table 3.4 as well as the electricity price (yen/kWh). The driving cost and purchase cost of EV in Scenario 3 is weighted average of 30 EV. The electricity price is provided on the Nagoya University's website of energy use.

As Table 3.5 shown, 23 conventional vehicles can be replaced by Type 1, these vehicles may have different fuel efficiency, thus the average travel cost of these vehicles is calculated based on their gasoline price and different fuel efficiency. The average travel cost of conventional vehicles is 10.2 yen/km, while Type 1 only cost 1.69 yen for every kilometer.

Table 3.5 Cost Change for Two Substitution Scenarios

Items	Scenario 1	Scenario 2	Scenario 3
Number of substition conventional vehicles	23	30	30
Average travel cost of conventional vehicles (yen/km)	10.193	10.167	10.167
Travel cost of EV (yen/km)	1.690	2.414	1.859
Average cost of conventional vehicles (10,000 yen)	295.08	279.30	279.30
Cost of each EV (10,000 yen)	300.03	380.00	318.69
Average DTD on observed data (km)	27.067	36.678	36.678
Average traveled days in a year on observed data	128.609	115.033	115.033

However, since Type 2 could replace more conventional vehicles, the average travel cost is calculated based on more conventional vehicles. As shown in Table 3.5, the average travel cost in Scenario 2 is cheaper than Scenario 1, but the travel cost of EV is more expensive in Scenario 2, so as the purchase cost. Both the purchase cost of conventional vehicles and EV are listed in Table 3.5, and the average DTD for each vehicle as well as the traveled days are also shown in the table. As for Scenario 3, the first 23 conventional vehicles with shorter DTD is replaced by Type 1, the rest 7 vehicles are replaced by Type 2. Therefore, the replaceable conventional vehicles are same with in Scenario 2, but the statistics for EV are calculated as weighted average of all EV.

Even though the purchase cost for both types of EV is more expensive than conventional vehicles, it would only take approximately 1.67 years for the travel cost to be even with the extra cost for purchasing in Scenario 1. However, since the purchase for EV in Scenario 2 cost more than in Scenario 1, it would take 30.79 years to reach the same goal. In this way, Scenario 1 is commercially more benefit efficient than Scenario 2. In the case of Scenario 3, the purchase cost would be higher than Scenario 1 since 7 Type 2 EV are added in this scenario. It would take 11.37 years for the travel cost to be even with the extra purchase cost.

3.5 Available electricity for peak-shaving

As shown in Table 3.5, the vehicles that could be replaced are only in use for about 1/3 days in a year, the rest of time, they were just parked in university. Therefore, it is possible to use them as electricity supply when they are parked. The electricity for charging EV is calculated based on the DTD observed data of the replaceable conventional vehicles, the result is shown in Figure 3.7. Here, we assume every EV would be charged immediately after check-in.

As shown in Figure 3.7, both types require the most of electricity for charging at17:00, and the electricity need reaches a slight peak at 12:00. From 2:00 to 7:00, the both types hardly need to be charged. This is because most EVs are already fully charged during this period. Both types require five hours to go from dead to fully charged. Once the electricity is charged to the EV, it could be discharged through the Vehicle-to-Grid (V2G) system. The discharging speed is 10 kWh per hour for both types (Erdogan et al., 2018).

The amount of consumed electricity is recorded every half hour, and is displayed on the university website. We collected 20 days (from Jun 20th 2017 to Jul 9th 2017) of electricity usage record from the website, and took the average of each hour’s electricity consumption data for these

20 days as shown in Figure 3.8. The hour-average electricity consumption reached a peak at 14:00 with 13561.25 kWh.

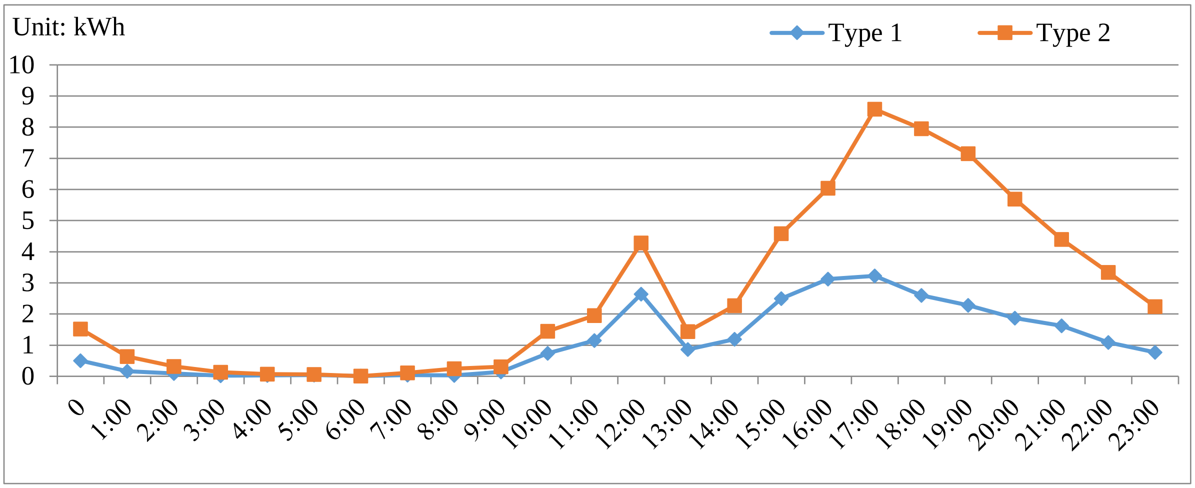


Figure 3.7 The average electricity for charging EV after substitution in every hour of a day.

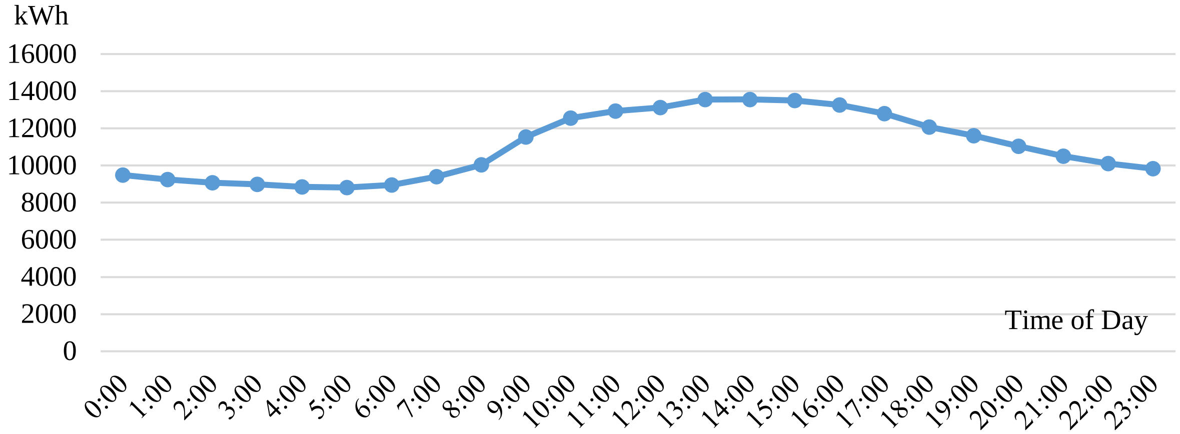


Figure 3.8 Hourly average electricity consumption during observed 20 days.

Since our goal of utilizing V2G with EV is peak-shaving, thus, we investigated the electricity providing potential at 14:00 and is shown in Table 3.6. Nagoya University (NU) is trying to reduce the electricity use, especially during the peak time, and it has made some progress. According to NU announcement, it has reduced 52 kWh of electricity, which is 0.3% and the 0.3% reduction of electricity use is already helpful of peak-shaving. In our scenarios, both types could provide more than 150 kWh of electricity during the peak hour, which is a big step on peak-shaving. Even though only 7 Type 2 EV are added into the substitution plan, the available electricity could reach to almost same amount as in Scenario 2. In this way, considering the purchase cost, using both type of EV would be more cost-benefit than Scenario 2.

Table 3.6 The average available electricity provided by EV at peak-hour (14:00) in each month (unit: kWh)

Month	Scenario 1	Scenario 2	Scenario 3
JAN	186.76	250.97	250.95
FEB	178.93	246.07	246.07
MAR	179.46	241.61	241.40
APR	175.77	238.00	237.44
MAY	181.53	246.77	246.36
JUN	170.52	232.00	231.86
JUL	170.97	230.00	230.00
AUG	183.71	243.23	242.74
SEP	174.00	230.67	230.67
OCT	171.61	228.39	228.39
NOV	182.00	238.67	238.67
DEC	186.64	247.74	247.61

3.6 Reduction of carbon dioxide

EV is not really zero emissions, it consumes electricity, and carbon dioxide emissions are generated during the production of electricity. As mentioned in Tettehfio et al. (2014), every liter of petrol produces 2.3 kg of CO_2 when burnt. Additionally, the Ministry of Environment, Chubu Electric Power, a Japanese electric utilities provider, for every kilowatt-hour of electricity produced, 0.496 kg of carbon dioxide is produced.

In this way, the emission could be calculated based on the observed data, and could be compared with two scenarios. The original carsharing system emitted 46133 kg of CO_2 emission over a year. In Scenario 1, after 23 conventional vehicles are replaced by Type 1 EV, the carsharing system could reduce 19% of the emission. As for the Scenario 2, it can reduce emissions by 24%. The Scenario 3 could reach to the highest reduction in the CO_2 emission by 27.6%. This is because the emission of the remaining conventional vehicles is the same, so the reduction in the replaceable conventional vehicles is same with Scenario 2. However, the 23 vehicles with shorter DTD would emit lower CO_2 than using Type 2 in Scenario 2, so the Scenario 3 is the most environmental benefit.

3.7 Conclusion and limitation

In this chapter, we first tested the DTD for each vehicle with five distribution functions, and determined the lognormal distribution is the best fitted among 5 alternatives. However, there are still 20 vehicles cannot fit with any distribution function, so we applied a mixture model with 2 lognormal components. The result shows the mixture model performed the best overall, but it is not the best fitted form for all the vehicles. The result of AIC implies 39 vehicles performed the best with mixture model, but there are still 9 vehicles performed better with other single distribution functions.

The determined best fitted form for each vehicle is used to identify whether a conventional vehicle in the carsharing system could be replaced by EV. Two types of EV is used here as the alternative for conventional vehicles. Type 1 could replace 23 vehicles as Scenario 1, and Type 2 could replace 30 conventional vehicles as Scenario 2. However, the Scenario 3 used both types of EV, and also can replace 30 vehicles. Therefore, the travel cost and purchase cost would be different, so as the electricity providing potential. Type 1 is found to be more cost beneficent compared to Type 2, it would only take approximately 1.67 years for the travel cost to be even with purchase cost. However, if the university wants to put more effort on environmental benefit, Scenario 3 can actually reach the most amount of reduction in the emission. Additionally, even though the Scenario 3 is not economically better than Scenario 1, the purchase cost would be made even by the driving cost for 11.37 years, which is 1/3 time as in Scenario 2. In this way, Scenario 3 could be a better option if the university wish to accomplish more reduction in the emission and cost less in the purchase.

Based on the electricity usage data, the electricity amount provided by EV is determined for both type of EV. With the help of V2G system, both type could reach the goal of peak-shaving. The larger amount of EV would definitely lead to more available electricity, but the amount is quite close to each other as in Scenario 2 and Scenario 3.

This chapter explores the possibility of replacing the conventional vehicles with EV in a carsharing system. The benefit of substitution is discussed on various aspects including cost-benefit, peak-shaving and emission reduction. In order to better understand the reason of drivers' preference toward driving distance, we also applied regression model to link the parameters of mixture model with other explanatory variables. However, the result didn't reach out expectation, this may be due to the vehicles are shared by multiple users, the driving characteristics in terms of distance cannot be explained uniformly. The result of regression is shown in Appendix A. Driving distance is not the only factor that prevents people from using EV. The promotion of EV requires more studies of people's driving behavior, and their adaptability of EV should be discussed on more individual level.

CHAPTER 4 Characterization of DTD for private vehicles: a case study in Toyota City

4.1 Introduction

As mentioned in the last chapter, the promotion of EV requires more understanding on driving behavior. The study of people's driving habits especially in terms of distance, and the reason to such certain habit could help us to better promote EV. The certain type of EV with limited driving range could be perfectly meet the daily driving demand of some people. However, the DTD of shared vehicles maybe difficult to be explained uniformly since the drivers are various.

In this way, this chapter utilized a data set collected from private vehicles, and the DTD of each vehicle could be better analyzed with other explanatory variables.

This chapter first tests the DTD of private vehicles with various types of mixture model. To better understand the characteristics of drivers' behavior, we applied survival model to link the DTD with other explanatory variables. The result shows vehicle and personal information play important roles in driving distance. The panel survival model is also applied to the data set in order to check the individual difference, and is confirmed by significant scale parameter for constant. The result could be utilized to determine the characteristics of target customers of EV.

4.2 Data descriptive analysis

The data set is collected from individuals who work or live in Toyota City, it is the largest city in the Aichi prefecture in terms of area. Base on the Toyota City website, the city is located in Aichi prefecture (137°09′E, 35°05′N), it occupies 17.8% (918 km^2) of the geographic area of Aichi prefecture, 70% of the city area is occupied by forest. By November 2020, Toyota City has a population of 422,858, of which the male to female ratio is 1.09:1, more than 20% of the population is elderly people (aged more than 65) the total household number is 182,600. Compare to the largest city Nagoya, it is the second largest in the Chukyo metropolitan area in terms of population, the ownership of ordinary motor cars is relatively large, and the number of the railway stations is relatively small (Yang et al., 2015). The city is characterized by a relatively low population density and highly dependent on private vehicles since the railway system is not sufficient (Yang et al., 2018).

This data set collected the driving record from 131 individuals who live or work in Toyota City. The device is equipped on their vehicle to collect the real-time GPS data. Thus, we believe the device would record the trip automatically during driving. Additionally, we also collected basic personal information and vehicle information as shown in Table 3.2.

The data is collected from April to September in 2011, the total observation period is 183 days. The data holds 15,118 observed driving days for 131 individuals in total, of which 182 observation belong to the same individual, and the least observation for one user holds only 8 driving days.

The weather information is collected based on the date of GPS data, and matched with the data on Japan Meteorological Agency.

Table 4.1 Descriptive statistics of the selected variables *.

Variables	Mean (or %)	Minimum	Maximum
Daily average temperature (°C)	22.05	7.7	29.9
Daily precipitation (mm)	6.78	0	97
Daily average wind speed (m/s)	1.56	0.6	3.8
Weekday dummy (1 if weekday, 0 otherwise)	69.95%	0	1
Engine size (100 cc)	19.19	9.9	34.5
Fuel efficiency (jc08-mode, km/L)	18.53	8.8	29.6
Price of vehicle (100,000 yen)	23.42	10.6	33.5
Vehicle type (1 if hybrid vehicle, 0 otherwise)	32.37%	0	1
Driver's age	45.70	23	72
Gender (1 if male, 0 otherwise)	90.84%	0	1
Job description (1 if working in Toyota City government, 0 otherwise)	55.73%	0	1
Job description (1 if working for car manufacturer, 0 otherwise)	20.61%	0	1
Job description (1 if working for public facility, 0 otherwise)	8.40%	0	1
Job description (1 if working as company staff, 0 otherwise)	6.11%	0	1
Job description (1 if working for driving school, 0 otherwise)	3.82%	0	1
Job description (1 if working as association staff, 0 otherwise)	3.82%	0	1
Job description (1 if unemployed, 0 otherwise)	1.53%	0	1

* The weather information and weekday dummy are based on 183 observation days; others are based on 131 individuals.

The personal information includes age, gender and occupation. The ages of the participants range from 23 to 67, and only 12 are female. Among the participants, 98.5% had a fixed job, and

70.8% of the trips were during the weekday and usually considered as commuting trips. Thus, unlike the vehicles in the first data set, which are shared by multiple users, we believe the trips in the second data set are made by themselves. As the trips made during weekdays are considered roughly as commuting, and the weekend trips are considered as leisure trips. Additionally, more than half of the participants work for government office, and other 8% participants work for public facilities, which implies their driving pattern especially during the weekdays are quite fixed. Even though the commuting trips could be fixed since they have certain origin and destination, but small changes in the route choice during to the traffic and weather condition are very common.

The vehicles used in this data set includes hybrid and conventional gasoline vehicle. There are only 7 different engine sizes in this data set, and ranged from 990 to 3450 cc. The fuel efficiency for each vehicle is measured by the Japanese Fuel Economy Standard JC08 test.

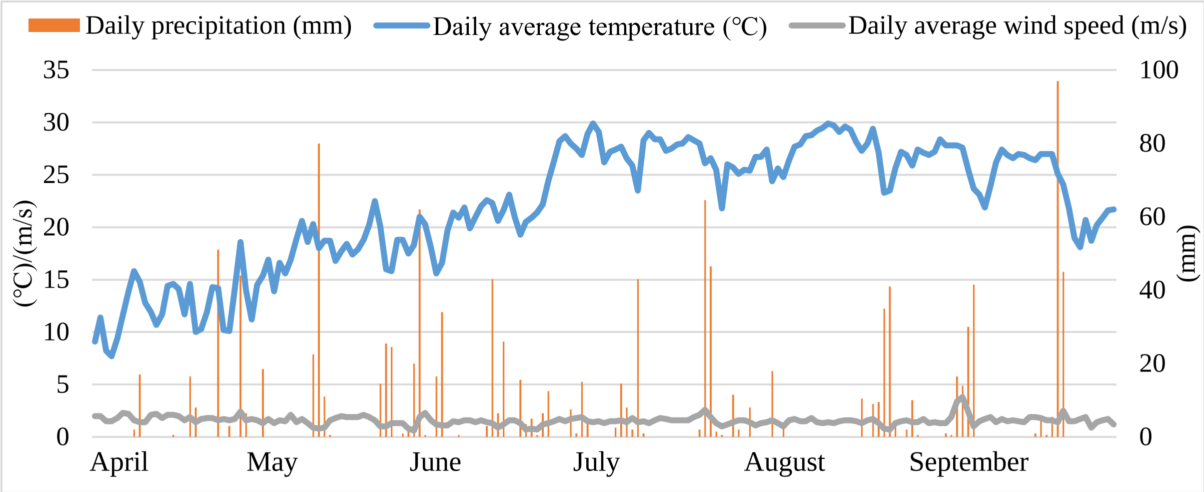


Figure 4.1 Daily weather information during the observation period.

The weather information is shown in Figure 4.1. As shown in Figure 4.1, the wind speed is generally quite stable during the observation period, but there is an obvious growing up in the daily average temperature, the daily total precipitation is quite scattered. Toyota City has four distinct seasons and obvious weather changes. Based on the weather data (from 1981 to 2010) released by the Japan Meteorology Agency (JMA), September is both the second hottest and the wettest month of a year. The observation period spans the spring and summer, and includes September. This could help us in determining the impact of hot and humid weather on driving habits.

4.3 Mixture model of DTD

The mixture model in the last chapter is proved to be better performed for the DTD than other single distributions. Here, we still apply the mixture lognormal model first to the DTD data. However, the number of component is of limited to two components. The number of component is n, and the probability density function can be represented as:

$$f(d_t) = \sum_{i=1}^{n} \alpha_i exp\left\{-\frac{[\,ln(d_t) - \mu_i]^2}{2\sigma_i^2}\right\} / d_t\sqrt{2\pi\sigma_i^2} \tag{4.1}$$

where,

d_t is the daily travel distance for day t;

α_i is the mixing coefficient, $\sum \alpha_i = 1$, and $\alpha_i \epsilon (0,1)$;

μ_{i1} is the mean of i-th mixture component;

σ_i is the standard deviation of i-th mixture component;

In order to evaluate the goodness of fit, the Akaike information criterion (AIC) is used here, where AIC = − 2LL+2(p+1), p is the number of the model parameters, and LL is the log-likelihood function, and can be delivered as follows:

$$\mathrm{LL} = \sum_{t=1}^{T} \log f(d_t) \tag{4.2}$$

We tested the data with mixture model from 2 components to 9 components, the total AIC for 131 vehicles is keep decreasing until the model with 7 components, the AIC for all vehicles with 8 and 9 components became larger than 7 components. Based on the AIC, the best fitted form could be selected for each vehicle. The result is show in Figure 4.2. Both 5 and 6 components share 18% (23 vehicles) as the best fitted form. There are 28 out of 131 vehicles fit the mixture model with 7 components best, which made the mixture model as the best fitted form. One reasonable explanation is that people's driving pattern may differ with the different day in a week.

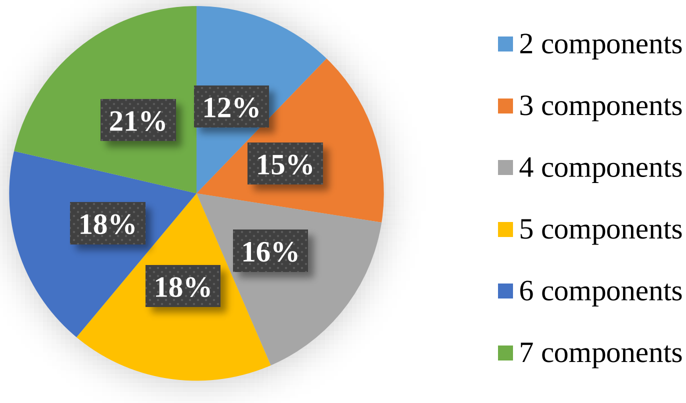


Figure 4.2 The percentile of best fitted form for each vehicle

The result implies the driving habit may be quite mixture on the distance, but it fails to give more detail information on the reason simply by the analysis of distribution. To look into the reason of different driving pattern, we must link the DTD with other explanatory variables.

4.4 Survival model

As we tried with regression model in Chapter 4 to link the DTD with explanatory variables, but the result shows the model is not working efficiently on the data. Therefore, we applied survival model in this chapter.

As mentioned in Chapter 2, the survival model can be classified as nonparametric, semiparametric and fully parametric. Here, in order to link the distribution of DTD with other explanatory variables, fully parametric duration model is applied. However, as mentioned in Qi (2009), the fully parametric model has two different ways to link the explanatory variables with the dependent variable, one is the fully parametric proportional hazard (PH) model, and the other is the accelerate failure time (AFT) model. The former measures the effect of explanatory variables on the hazard, while the latter utilizes a log-linear form to measure the direct effect on the distance in our case. The log-linear form of the AFT model could be represented as:

$$log(d) = \mu + \boldsymbol{\alpha X} + \sigma\varepsilon \tag{4.3}$$

where d is the daily travel distance (DTD) in our study, μ is constant, $\boldsymbol{\alpha}$ is a vector of estimable parameters, $\boldsymbol{X}$ is a vector of explanatory variables, σ is scale parameter, ε is a random variable and assumed to be distributed with a certain distribution. Here, if ε is normally distributed, which means d is log-normally distributed. The relationship of distribution of ε and d is shown in Table 4.2.

Table 4.2 The distribution of $\boldsymbol{\varepsilon}$ and $\boldsymbol{d}$

The distribution of ε	The distribution of d
Logistic	Log-logistic
Normal	Lognormal
Extreme value (2 parameters)	Weibull

In this study, we applied log-logistic, lognormal and Weibull duration model to the DTD data, and since the data is collected from multiple users, which made it possible to test the individual difference as panel model. The intercept μ as mentioned in equation 5.2 is assumed to be normally distributed in the panel model to simulate the individual difference.

4.5 Model result and discussion

The model is conducted by NLOGIT 6.0 (Econometric Software, Inc.) is used in this study. To measure the goodness of fit, here we applied AIC and likelihood ratio (X^2), and the likelihood ratio can be expressed as:

$$X^2 = -2[LL(\boldsymbol{\alpha}) - LL(0)] \tag{4.4}$$

where, $\boldsymbol{\alpha}$ is a vector of estimable variables, $LL(\boldsymbol{\alpha})$ is the log-likelihood of the model at convergence, and $LL(0)$ is the log-likelihood of the model when all the estimable coefficient $\boldsymbol{\alpha}$ is equal to 0.

The Akaike Information Criterion (AIC) is used here, and can be expressed as $AIC = 2k - 2LL(\boldsymbol{\alpha})$, where k is the number of parameters.

We first tested the DTD data with log-logistic, lognormal and Weibull distribution function. The parameters of distributions are shown in Table 4.3, and Figure 4.2 illustrates the shape of probability density function of three distributions.

Table 4.3 Estimated parameters for the three distributions.

Dependent Variable	**Logarithm of Daily Travel Distance**		
Distribution	**Location Parameter**	**Scale Parameter (σ)**	**Log-Likelihood $LL(0)$**
Lognormal	3.06	1.130	−23,322.8
Log-logistic	3.12	0.580	−22,154.5
Weibull	3.57	0.965	−22,539.7

As shown in Table 4.3, the log-logistic model fit the DTD best among three distributions. In Figure 4.3, the distance within 200 km contains 98.62% of the total DTD data. The log-normal has the highest peak while Weibull model has the lowest. From the diagram, log-logistic also seems to be better fitted with the observed DTD data.

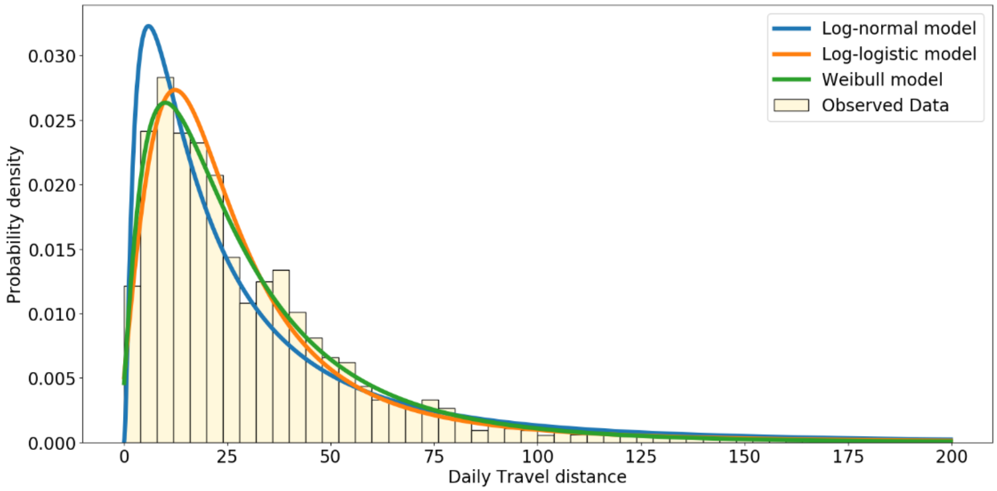


Figure 4.3 The probability density for the three distributions.

The 95% quantile of DTD for each distribution is 90 km for Weibull, 103 km for log-logistic, and 129 km for lognormal. Both types of EV mentioned in last chapter could meet the need of 95% of the driving demand for this data set, which makes it possible to promote EV to the citizen of Toyota City.

However, the adaptability could be different among various groups of people. The preference towards EV adaptable driving distance requires further study with other explanatory variables.

Table 4.4 illustrates the result of pooled survival model with log-logistic, lognormal and Weibull duration. The pooled survival model results follow the same pattern of distribution result. The log-logistic duration model performed the best, followed by Weibull duration model. All the variables in log-logistic duration model reach 95% of confident level. However, there are four insignificant variables in the lognormal duration model, and five in the Weibull duration model.

All of the variables for weather condition are significant in three duration models. The consistent positive daily average temperature implies the higher temperature could drive people to longer distance trips. On the contrary, the daily precipitation and daily average wind speed are playing consistent negative effect on the DTD, which implies drivers in Toyota City tend to drive less during the heavy rain and wind condition. This is understandable since people may cancel their driving plan during terrible weather, or switch to an alternative destination nearby. The weekday dummy is another variable with negative effect on the DTD, and is significant in three pooled models. It indicates the drivers' preference for longer distance trip during weekend, since the commuting trips during weekday are quite fixed, the weekend trip could be widely spread not only limited in Toyota City.

Engine size and vehicle price are also significant in all three distribution duration models. The larger engine size lead to shorter DTD may due to the consideration of environment and driving cost. On the other hand, people who drive more expensive vehicles tend to driving longer distance based on the result in Table 4.4. Both fuel efficiency and vehicle type are insignificant in one of the three distribution duration models. Fuel efficiency is insignificant only in lognormal duration model, while vehicle type is insignificant only in Weibull duration model. The positive effect of fuel efficiency in the other two duration models implies Toyota citizen do consider the environmental effect when driving, people tend to drive longer if their vehicles have better efficiency. So as the vehicle type, hybrid users would drive longer than other vehicle types users.

Table 4.4 Estimation results for pooled survival model

Dependent Variable: Natural Logarithm of Daily Travel Distance (km)	Lognormal		Weibull		Log-Logistic	
Explanatory Variables	**Coef.**	**P-value**	**Coef.**	**P-value**	**Coef.**	**P-value**
Constant	3.143	0.000	3.321	0.000	3.289	0.000
Daily average temperature (°C)	0.004	0.014	0.003	0.002	0.004	0.002
Daily precipitation (mm)	−0.002	0.002	−0.003	0.000	−0.002	0.002
Daily average wind speed (m/s)	−0.060	0.003	−0.058	0.000	−0.041	0.041
Weekday dummy (1 if weekday, 0 otherwise)	−0.053	0.004	−0.255	0.000	−0.093	0.000
Engine size (100 cc)	−0.021	0.000	−0.019	0.000	−0.027	0.000
Fuel efficiency (jc08-mode, km/L)	0.009	0.084	0.021	0.000	0.010	0.027
Price of vehicle (100,000 yen)	0.015	0.000	0.027	0.000	0.017	0.000
Vehicle type (1 if hybrid vehicle, 0 otherwise)	0.221	0.001	0.037	0.448	0.236	0.000
Age	−0.006	0.000	−0.008	0.000	−0.007	0.000
Gender (1 if male, 0 otherwise)	0.098	0.005	0.177	0.000	0.082	0.012
Job description (1 if working for car manufacturer, 0 otherwise)	−0.091	0.000	−0.002	0.900	−0.123	0.000
Job description (1 if working for public facility, 0 otherwise)	−0.031	0.353	0.090	0.000	−0.096	0.001
Job description (1 if working as company staff, 0 otherwise)	0.210	0.000	0.180	0.000	0.215	0.000
Job description (1 if working for driving school, 0 otherwise)	0.053	0.259	−0.030	0.526	0.101	0.028
Job description (1 if working as association staff, 0 otherwise)	−0.087	0.104	0.020	0.618	−0.137	0.002
Job description (1 if unemployed, 0 otherwise)	−0.252	0.000	0.033	0.385	−0.343	0.000
Scale parameter for survival distribution (p)	1.112	0.000	0.935	0.000	0.563	0.000
Initial log-likelihood LL(0)	−23,322.81		−22,539.75		−22,154.52	
Log-likelihood at convergence LL(β)	−23,090.43		−22,129.83		−21,785.89	
Likelihood ratios	464.76		819.84		737.26	
Akaike Information Criterion (AIC)	46,216.86		44,295.66		43,607.78	

Both age and gender is significant in three distribution duration models. Elder drivers would drive shorter than young drivers. This could be caused by the decreasing in the driving performance as well as driving inclination. The positive effect of gender implies male tend to drive longer distance than female, considering more than 90% of the participants are male, whether this is a regular pattern requires more studies.

As for the job description, people who work for private company and driving school tend to make longer trip than other occupations. This may due to the location of driving school is usually remote. The job for private company may requires more trip to visit their clients. However, the job description for driving school plays different effect among three distribution duration models.

The pooled duration model could partially explain the relationship between explanatory variables with DTD. However, it didn’t consider the individual difference. Therefore, the following part explained the result of panel duration model with three distribution assumptions. The individual difference is simulated by the normally distributed constant in the model. The result is shown in Table 4.5.

As mentioned above, in the pooled duration model, log-logistic distribution performed best and have the most number of significant variables. However, in the panel duration model, all the variables are significant in both lognormal and Weibull models. The panel log-logistic duration model is still the best fitted based on the AIC and log-likelihood, but five variables are insignificant in the model. The insignificant variables in panel log-logistic model are daily average temperature, vehicle type and three occupation dummy.

Table 4.5 Estimation results for panel survival model

Dependent Variable: Natural Logarithm of Daily Travel Distance (km)	Lognormal		Weibull		Log-Logistic	
Explanatory Variables	**Coef.**	**P-value**	**Coef.**	**P-value**	**Coef.**	**P-value**
Daily average temperature (°C)	0.004	0.001	0.001	0.045	0.000	0.986
Daily precipitation (mm)	−0.002	0.005	−0.003	0.000	−0.001	0.001
Daily average wind speed (m/s)	−0.059	0.015	−0.053	0.000	−0.042	0.018
Weekday dummy (1 if weekday, 0 otherwise)	−0.052	0.000	−0.287	0.000	−0.115	0.000
Engine size (100 cc)	−0.020	0.000	0.020	0.000	−0.020	0.000
Fuel efficiency (jc08-mode, km/L)	0.009	0.000	0.064	0.000	0.034	0.000
Price of vehicle (100,000 yen)	0.015	0.000	0.033	0.000	0.031	0.000
Vehicle type (1 if hybrid vehicle, 0 otherwise)	0.218	0.000	−0.593	0.000	−0.070	0.147
Age	−0.005	0.000	−0.005	0.000	−0.008	0.000
Gender (1 if male, 0 otherwise)	0.097	0.000	0.197	0.000	0.285	0.000
Job description (1 if working for car manufacturer, 0 otherwise)	−0.090	0.000	0.211	0.000	−0.002	0.921
Job description (1 if working for public facility, 0 otherwise)	−0.030	0.000	0.165	0.000	−0.290	0.000
Job description (1 if working as company staff, 0 otherwise)	0.207	0.000	0.107	0.001	−0.036	0.254
Job description (1 if working for driving school, 0 otherwise)	0.052	0.000	0.395	0.000	0.037	0.302
Job description (1 if working as association staff, 0 otherwise)	−0.085	0.000	0.145	0.001	0.459	0.000
Job description (1 if unemployed, 0 otherwise)	−0.245	0.000	0.559	0.000	0.721	0.000
Constant (means for random parameters)	3.100	0.000	1.611	0.000	2.317	0.000
Constant (scale parameter for random parameters)	0.009	0.000	0.505	0.000	0.683	0.000
Scale parameter for survival distribution (p)	1.111	0.000	0.848	0.000	0.454	0.000
Initial log-likelihood LL(0)	−23,322.81		−22,539.75		−22,154.52	
Log-likelihood at convergence LL(β)	−23,077.00		−20,714.03		−19,353.08	
Likelihood ratios	491.62		3651.44		5602.88	
Akaike Information Criterion (AIC)	46192.00		41466.06		38744.16	

Similar as pooled duration model, daily precipitation, daily average wind speed and weekday dummy are significant and play negative effect on DTD in three panel distribution duration models. The engine size, fuel efficiency and vehicle price are also all significant in all the panel models. Both age and gender are significant in all panel duration models, and they play similar effect as pooled model.

The only two occupation dummies with positive effect in pooled log-logistic duration model, are both insignificant here in panel log-logistic model. Additionally, except for the occupation dummy for driving school, all the dummy variables for job description are playing the opposite effect in different panel distribution duration models.

The log-likelihood and AIC for panel model is improved compare to pooled model for all three distribution assumptions. The significant scale parameter of constant implies the existence of individual difference, and is simulated by the random variable.

4.6 Conclusion and limitation

The mixture model provided information about various driving pattern maybe formed into the DTD, the detailed reason for different driving pattern requires consideration with other explanatory variables.

The AIC of single distribution, pooled duration model and panel model illustrates the best fitted form for this data set is log-logistic model. The EV types used in previous chapter could fit with more than 95% of the demand in this data set, which made it possible for the promotion of EV to individual buyers.

The significant scale parameter of constant and smaller AIC indicate the consideration of individual difference could help in improving the duration model. The significant variables of weather condition in both pooled and panel model imply people's preference of driving during different weather condition. Drivers would search for alternative destination nearby during the terrible weather, especially for leisure trips since the destination is more flexible. Those people who live in a city with frequent rainy weather could be more adoptable for EV. The effect of fuel efficiency and vehicle type indicate the drivers' consideration on the environmental factors. These drivers maybe could be more prefer with EV since the driving cost is less than gasoline vehicles. The elderly female drivers could be more focus as the target customers of EV based on the result.

Here, as an improvement to last chapter, we utilized duration model to link the DTD with other explanatory variables, which makes it more detailed about the characteristics of potential users for EV. However, the explanatory variables are very limited in this study. The participants have a large age span, and the ratio of men to women is very imbalanced.

CHAPTER 5 Characterization of DTD for elderly drivers

This chapter still utilize the duration model to test DTD data with other explanatory variables. However, here we focused on the elderly drivers. The elderly drivers, as mentioned in the Chapter 2, is a serious problem considering traffic safety, since their driving ability is decreasing with their age. As the world's population is aging rapidly, elderly drivers are getting more and more attention on the driving safety issues. The survival analysis applied in this chapter considers not only the personal information and weather condition, but also the psychological factors in the model as well as the aptitude test for driving performance.

5.1 Data description

The third data set is collected from the elderly drivers' data base of Nagoya University Center Of Innovation (COI) project, it is supported by the Ministry of Education, Culture, Sports, Science and Technology (MEXT), Japan and Japan Science and Technology Agency (JST). The participants mainly live around Nagoya City. The city is located in the northwest of Aichi prefecture, shown in Figure 3.1. It is the 4^{th} largest city in terms of population and 27^{th} in terms of area in Achi prefecture. More than 300 drivers aged from 50s to 80s joined this project since 2014, and the driving record is also collected from 85 participants. The device is equipped to their vehicle to collect the real-time Global Positioning System (GPS) data. Additionally, the participants are required to join the aptitude test every year to evaluate their driving ability. The psychological questionnaire survey is conducted to the participants in 2020. Both the aptitude test result and survey data are used in the study.

The observation period is different for each individual, some may quit the project less than one year, and some may continue for 4 years. The GPS record can trace back as early as 2015, and the latest is in 2019. The data for 2019 only records January and February, so we used the data ranged from 2015 to 2018. In this study, we used the most recent two years' data for the participants who join the project for more than two years, and all data for the rest. In addition to collecting basic personal information, the project managed to apply the aptitude test to the participants, so that we could evaluate their performance of driving. Additionally, when conducting the questionnaire survey to the participants in 2020, some may quit the project already. Thus, the total observation in terms of the driving days is 21839, belong to 73 participants.

The personal information used in this study includes gender, age, driving experience and education experience. The study divided the participants into 3 age group, young drivers (aged less than 65), young-old drivers (aged from 65 to 74), and old-old drivers (aged from 75). Only 14 participants aged less than 65, 80.8% of the participants could be referred as elderly driver.

Similar as in the second data set, the weather information is also collected from Japan

Meteorological Agency, the weather data is matched based on the start GPS of that day, and it includes the minimum temperature and total precipitation of that day.

Table 5.1 Descriptive statistics of the selected variables

Variables	Mean (or %)	Minimum	Maximum
Driving experience (year)	46.9	22	59
Education experience (year)	13.5	8	18
Gender (1 for male, 0 for otherwise)	63%	0	1
Young-old group (1 for aged from 65 to 74, 0 for otherwise)	61.6%	0	1
Old-old group (1 for aged from 75, 0 for otherwise)	19.2%	0	1
Minimum temperature (°C)	13.0	-4.8	29
Precipitation (mm)	4.4	0	170
Trail Making Test Score	2.8	1.2	5.5
Mini-Mental State Examination	28.6	22	30
Visual acuity during daytime	0.8	0.1	1.6

The aptitude test is applied to all the participants every year during the observation period. It contains Trail Making Test (TMT), Mini-Mental State Examination (MMSE) and Visual Acuity during the daytime. Visual acuity test, as mentioned in the previous chapter, is commonly used when obtaining the driving license. The TMT-test include part A and B, here we used the ratio of TMT-B to TMT-A as the Trail Making Test Score(TMTS). In the previous study of MMSE, the score of 23 or less is used to distinguish the person who has cognitive impairment (DePaulo et al., 1980), but here we used the MMSE score as a continuous variable.

As mentioned above, the questionnaire survey is conducted in the third data set. The questionnaire mainly consists of two parts, the Impulsive Sensation Seeking (ImpSS) and the Psychosocial Purpose of Driving Scale (PSPDS).

The questionnaire is applied in Japanese, the English translation of question items of ImpSS is shown in Table 5.2, the answer type is scaled from 1 to 4 (1 for strongly disagree, 4 for strongly agree). The Parallel Analysis is applied to the ImpSS, and the 19 question items are divided into 2 groups, the Impulsive group (Imp) and Sensation Seeking group (SS). As the previous study explained, the Imp scale evaluates the preference for change and uncertainty, while the SS evaluates the tendency to act without thinking or planning (Fernández-Artamendi et al., 2016). The coefficients of each question item is estimated by principle component analysis with varimax rotation. As shown in Table 5.2, only five question items belong to the Imp, and two of them play negative role in the sub-scale. Compared to other study, items 10 and 18 belong to the Imp group in Fernández-Artamendi et al. (2016), but they are recognized as SS group in our study. This may due to the different answer type, since in previous study the questionnaire uses a Y/N answer, but we use a 4 level scale answer. Additionally, the coefficients and classification may change among different groups of respondent. Fernández-Artamendi et al. (2016) applied the questionnaire to teenagers aged from 12 to 14, but our respondents are mainly elderly drivers.

The second part of the questionnaire is used here to summarize the driving purpose. The PSPDS in this study used a scale (1 strongly disagree, 4 strongly agree) consistent with contemporary psychological practice. The Parallel Analysis is also applied to the questionnaire which extracted only one component, and then the coefficient of each item is estimated. As shown in Table 5.3, both item 2 and 5 have the largest coefficient, indicate the elderly drivers driving purpose have a tendency towards the feeling of independent and powerful.

Table 5.2 Summary of the Impulsive Sensation Seeking Survey

Questions items	SS/Imp	mean	Std.	coefficient
(1) I tend to begin a new job without much advance planning on how I will do it	Imp	1.97	0.67	0.71
(2) I usually think about what I am going to do before doing it	Imp	2.88	0.64	-0.70
(3) I often do things on impulse	Imp	2.29	0.70	0.72
(4) I very seldom spend much time on the details of planning ahead	Imp	2.49	0.63	0.42
(5) I like to have new and exciting experiences and sensations even if they are a little frightening	SS	2.55	0.65	0.56
(6) Before I begin a complicated job, I make careful plans	Imp	2.68	0.70	-0.62
(7) I would like to take off on a trip with no preplanned or defining routes or timetable	SS	2.11	0.79	0.48
(8) I enjoy getting into new situations where you can't predict how things will turn out	SS	1.85	0.54	0.64
(9) I like doing things just for the thrill of it	SS	1.99	0.66	0.77
(10) I tend to change interests frequently	SS	1.96	0.73	0.54
(11) I sometimes like to do things that are a little frightening	SS	1.88	0.64	0.65
(12) I'll try anything once	SS	2.49	0.75	0.66
(13) I would like the kind of life where one is on the move and traveling a lot with lots of change and excitement	SS	2.33	0.78	0.64
(14) I sometimes do 'crazy' things just for fun	SS	1.77	0.70	0.71
(15) I like to explore a strange city or section of town by myself, even if it means getting lost	SS	1.99	0.79	0.70
(16) I prefer friends who are excitingly unpredictable	SS	1.88	0.69	0.60
(17) I often get so carried away by new and exciting things and ideas that I never think of possible complications	SS	2.10	0.65	0.61
(18) I am an impulsive person	SS	2.10	0.65	0.54

(19) I like 'wild' uninhibited parties	SS	1.74	0.75	0.54

Table 5.3 Summary of the Psychosocial Purpose of Driving Scale

Question items (you drove)	mean	Std.	coefficient
(1) For a sense of freedom	2.56	0.78	0.77
(2) So you could feel independent	2.38	0.72	0.80
(3) To show you are still young	2.25	0.68	0.75
(4) To relax	2.59	0.74	0.77
(5) To feel powerful	2.71	0.68	0.80
(6) So you could gain status amongst your friends	2.12	0.69	0.65
(7) So you could see your friends easily	3.14	0.67	0.23

5.2 Basic analysis

As the participants are divided into three groups by age, the driving distance for each age group could be different. Figure 5.1 illustrates the daily driving distance within 100 km for different age groups. The old-old group (aged from 75) has an obvious higher peak compared to other 2 groups, and the percentile of this group also fades quickly within 30 to 40 km. In general, 96.2% of the total observation on DTD is within 100 km, and this distance can be easily covered with EVs such as Nissan Leaf. Male participants accounted for 62% of the total.

As mentioned in last chapter, the unbalanced and the ratio of men to women in previous data set, made us question about the female's preference on the driving distance. Here, in this data set, 28 female driver made it possible to compare the driving distance between genders.

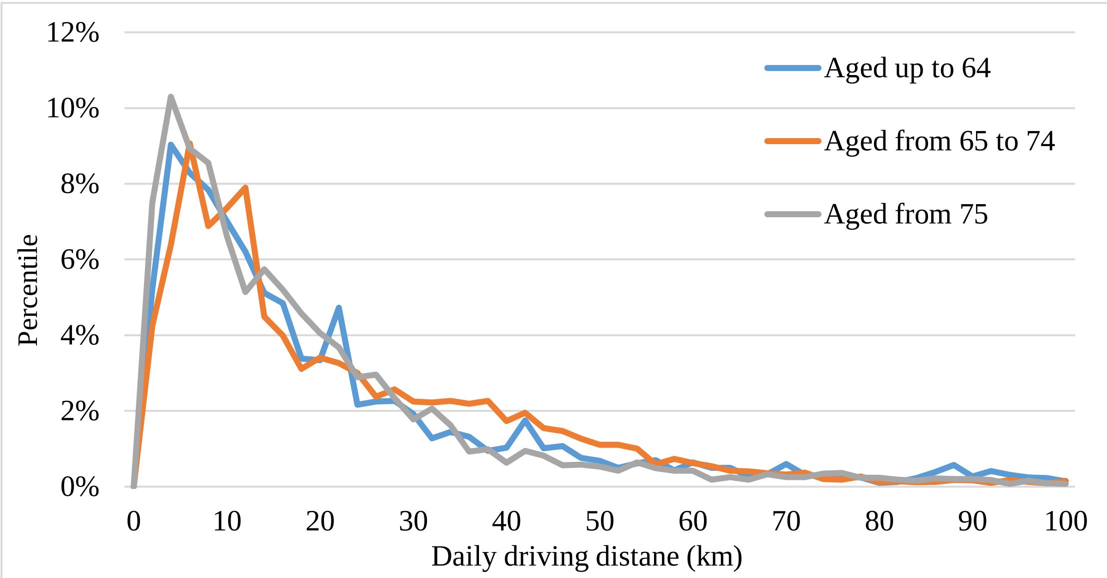


Figure 5.1 The daily driving distance within 100 km for different age groups (100 km covers 94.1% of the daily driving distance of drivers aged up to 64, 96.9% of the drivers aged from 65 to 74, 96.5% of the drivers aged from 75).

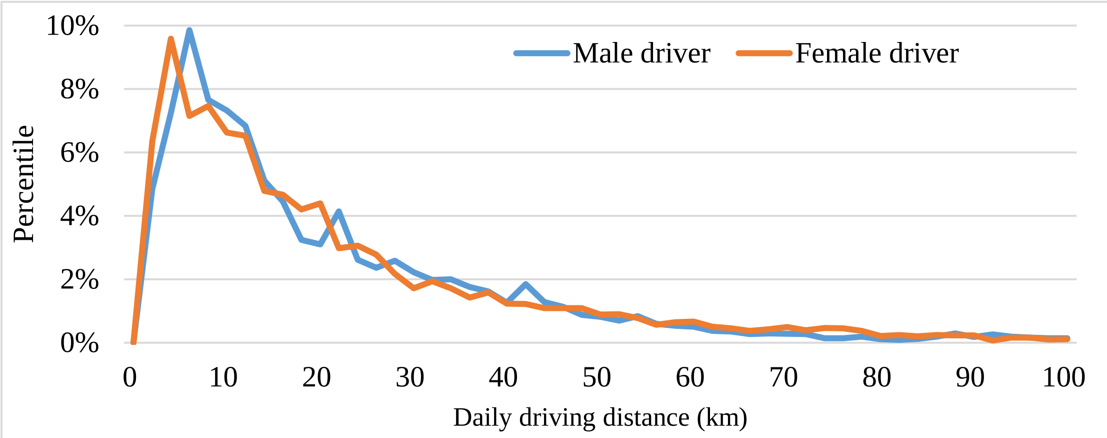


Figure 5.2 The daily driving distance within 100 km for male and female (100 km covers 95.6% of male drivers' daily driving distance, 97.2% of female drivers).

Figure 5.2 illustrates the percentile of daily driving distance for male and female drivers within

100 km. Even though the first peak of male and female drivers is different, the shape of percentile shows consistency over all.

Table 5.4 The average score for SS and Imp in each age group

The subscale	Young driver	Young-old	Old-old
Sensation seeking	18.44	17.92	18.08
Impulsive	-0.30	0.37	-0.05

The average score for SS and Imp subscale in different age groups is shown in Table 5.4. The young age group gets the highest average score in SS, which implies they may tend to act without thinking or planning. The young-old group has the highest average score in Imp, which implies they may prefer in changes and uncertainty. Even though the driving safety issue with elderly drivers has been discussed in many studies (Skyving et al., 2009; Jian and Shi., 2020). However, compare to other age groups, the ImpSS score shows the old-old drivers are less psychologically dangerous toward risky driving behavior.

The average score of each item in PSPDS for different age groups is shown in Table 5.5. As can be seen, the most driving purpose for all the age groups is the same, which is to meet friends easily. The average score over all is 2.5. For young-old drivers, they also have the driving purpose as for a sense of freedom, to relax, and to feel powerful that are beyond the average score. As for the old-old divers, they are also reported with the driving purpose of for a sense of freedom, feel independent, to feel powerful which are beyond the average score. In general, the driving purpose of elderly drivers is often determined by their psychological needs, and they hope to gain a sense of ability through driving.

Table 5.5 The average score of items in PSPDS in each age group

Question items (you drove)	Young driver	Young-old	Old-old
(1) For a sense of freedom	2.28	2.64	2.57
(2) So you could feel independent	2.14	2.38	2.64
(3) To show you are still young	2.00	2.31	2.29
(4) To relax	2.50	2.64	2.50
(5) To feel powerful	2.36	2.76	2.93
(6) So you could gain status amongst your friends	2.14	2.11	2.14
(7) So you could see your friends easily	3.21	3.08	3.21

5.3 Survival model result

To evaluate the goodness of fit, the Akaike Information Criterion (AIC) is used here, and can be expressed as $AIC = 2k - 2LL(\boldsymbol{\alpha})$, where k is the number of parameters, $LL(\boldsymbol{\alpha})$ is the log-likelihood of the model at convergence, $\boldsymbol{\alpha}$ is a vector of estimable variables. In our assumption, it is believed that the different age group may result in different attitude towards driving distance. This is interpreted by interaction terms of age groups and psychosocial scales in the regression model. The confident level is 95% in this study. Table 5.6 illustrates the result of pooled survival model.

Table 5.6 Model estimation results for pooled regression

Distribution assumptions for duration model	Log-logistic		Log-normal		Weibull	
Explanatory variables	Coef.	P-value	Coef.	P-value	Coef.	P-value
Driving experience	-0.0240	0.00	-0.0228	0.00	-0.0173	0.00
Education experience	-0.0061	0.14	0.0009	0.83	0.0025	0.46
Gender	0.0858	0.00	0.0974	0.00	0.0541	0.00
Young-old group (aged from 65 to 74)	0.9217	0.00	0.8639	0.00	0.2213	0.04
Old-old group (aged above 75)	-1.1838	0.00	-1.2073	0.00	-1.0352	0.00
Trail Making Test Score (TMTS)	-0.0488	0.00	-0.0452	0.00	-0.0564	0.00
Mini-Mental State Examination score (MMSE)	0.0898	0.00	0.0890	0.00	0.0767	0.00
Visual acuity during daytime	0.2053	0.00	0.2718	0.00	0.3019	0.00
Minimum temperature	0.0029	0.00	0.0029	0.00	0.0052	0.00
Precipitation	-0.0017	0.00	-0.0019	0.00	-0.0022	0.00
SS for young (aged less than 65)	-0.0565	0.00	-0.0594	0.00	-0.0643	0.00
IMP for young (aged less than 65)	-0.1513	0.00	-0.1390	0.00	-0.1348	0.00
PSPDS for young (aged less than 65)	0.1149	0.00	0.1169	0.00	0.1198	0.00
SS for young-old	-0.0017	0.60	0.0006	0.86	0.0128	0.00
IMP for young-old	0.0467	0.00	0.0435	0.00	0.0029	0.61
PSPDS for young-old	-0.0186	0.00	-0.0217	0.00	-0.0054	0.26
SS for old-old	0.0345	0.00	0.0368	0.00	0.0039	0.46
IMP for old-old	0.1286	0.00	0.1331	0.00	0.1213	0.00
PSPDS for old-old	0.1015	0.00	0.0966	0.00	0.1156	0.00
Constant (mean)	0.6254	0.01	0.4521	0.07	1.2884	0.00
Scale parameter for survival distribution (σ)	0.6388	0.00	1.1352	0.00	1.0982	0.00
Log-likelihood at convergence $LL(\alpha)$	-33732.5		-33758.0		-34995.7	
Akaike Information Criterion (AIC)	67507.0		67557.9		70033.5	

The pooled log-logistic survival model performed the best based on the log-likelihood and AIC among the three alternative distribution assumptions. The result of pooled models shows a consistency on many explanatory variables, the education experience is insignificant in all pooled models, and interaction item of SS and young-old group is insignificant for both log-logistic and lognormal model. The pooled Weibull model holds the largest AIC and least number of significant variables, which made it as the least fitted model among three distribution assumptions for pooled model. The scale parameter for pooled Weibull model and is larger than 1, which states that the hazard increases with the DTD.

Table 5.7 The log-likelihood of different assumptions with model and constant

Distribution assumptions for constant	Lognormal duration	Log-logistic duration	Weibull duration
Normal	-27970.9	-28511.4	-28917.1
Uniform	-28484.0	-28511.4	-28917.1
Triangular	-28586.0 ($\sigma_\mu = 0$)	-28511.5	-28917.1 ($\sigma_\mu = 0$)
Negative half normal	-28586.0 ($\sigma_\mu = 0$)	-28511.6	-28917.0
Centered lognormal	-28129.5	-28035.8	-28917.1
Lognormal	-28679.8	-28082.3	-28988.5

As previously discussed in Chapter 5, the individual difference could be represented by the normally distributed constant μ. Here, we also analyzed different distributions of constant μ, in order to check not only the better distribution for DTD, but also the better distribution for constant. The result is shown in Table 5.7. The scale parameter for constant (σ_μ) in Weibull duration with uniformly distributed constant, lognormal duration with triangularly or negative half normally distributed constant are equal to zero. This implies these three assumptions do not fit with the panel duration model. The log-likelihood values of log-logistic duration model with different distribution assumptions of constant are quite stable, except for centered lognormal and lognormal. The Weibull duration model with different distribution assumptions of constant is also quite stabilized in the log-likelihood function except for the lognormal assumption for the constant. Unlike pooled model, the log-likelihood of panel duration model implies the best fitted form is the lognormal duration model with normally distributed constant, and the result is shown in Table 5.8.

The education experience, different from pooled model, is significant in the lognormal panel model. The insignificant scale parameter for random effect of constant, σ_μ in other panel models demonstrates that it is not effective to consider the individual difference when considering log-logistic or Weibull duration. In lognormal panel model, the interaction item of IMP and young-old group is the only insignificant variable, but it still reached 85% of confident level. The marginal effect is calculated as $e^{\alpha} - 1$, could be referred in Koop and Christopher (1993), the result is shown in Table 5.8.

Table 5.8. Model estimation results for lognormal panel regression

Explanatory variables	Coef.	P-value	Marginal effect
Driving experience	-0.0264	0.00	-2.61%
Education experience	-0.0077	0.00	-0.77%
Gender	0.0970	0.00	10.19%
Young-old group	0.8350	0.00	130.48%
Old-old group	-1.1677	0.00	-68.89%
Trail Making Test Score (TMTS)	-0.0567	0.00	-5.51%
Mini-Mental State Examination score (MMSE)	0.1021	0.00	10.75%
Visual acuity during daytime	0.2671	0.00	30.62%
Minimum temperature	0.0027	0.00	0.27%
Precipitation	-0.0019	0.00	-0.19%
SS for young	-0.0656	0.00	-6.35%
IMP for young	-0.1301	0.00	-12.20%
PSPD for young	0.1170	0.00	12.41%
SS for young-old	0.0040	0.00	0.40%
IMP for young-old	-0.0033	0.15	-0.33%
PSPD for young-old	-0.0237	0.00	-2.34%
SS for old-old	0.0324	0.00	3.29%
IMP for old-old	0.1435	0.00	15.43%
PSPD for old-old	0.1002	0.00	10.54%
Constant (mean)	0.4379	0.00	-
Constant (standard deviation)	0.2072	0.00	-
Scale parameter for survival distribution (σ)	1.0987	0.00	-
Log-likelihood at convergence $LL(\alpha)$		-27970.9	
Akaike Information Criterion (AIC)		55985.8	

5.4 Discussion

The coefficients of explanatory variables for weather condition are consistent with last chapter. The minimum temperature has a positive effect on the DTD, which means people may prefer warmer weather for trips. The negative effect caused by precipitation proves that rain prevents people from traveling.

The individual information does affect the driving distance. Both the driving and education experience are showing significant negative effect on DTD, but compare to other variables, the marginal effect of driving and education experience played relatively small influence on the DTD, especially the education experience. The driving distance maybe affected by other personal information, but the education background plays a minor effect on it. Even though Figure 5.2 demonstrates a similar driving distance percentile for male and female, the results of model shows male drivers tend to drive longer than female and this result is consistent with both pooled and panel model with all distributions as well as previous study (Hakamies-Blomqvist and Wahlström, 1998).

Based on the marginal effect, the indicator variable for young-old group is playing the most positive effect on the DTD. On the contrary, the indicator variable for old-old group is playing the most negative effect on DTD. This indicates people’s driving distance are largely affected by different age groups. The previous studies divided drivers into 2 age groups as over or under 65 years old (Anastasopoulos et al., 2012, Yee et al., 2006). However, as the division of people older than 65 into young-old and old-old group, we found out the elderly drivers are not showing consistent tendency on shorter driving distance. The driving pattern of elderly drivers is consistent with Figure 5.1, the old-old group has an obvious preference for shorter distance, while the young-old group prefer longer driving distance. The young-old group tend to travel longer than others, which may be because the retirement allows them to have more spare time to travel, and compared to the old-old group, they are in general physically supported for longer distance driving. The old-old group plays a significant negative effect on DTD for all the models, since the decreasing physical abilities with increasing age could affect the driving performance (Delhomme et al., 2013). However, as mentioned in Table 5.4, the old-old drivers are not psychologically dangerous, this may because that they are aware of the changes in the driving ability. Similar idea is mentioned in Milleville-Pennel and Marquez (2020), although young drivers may perform better on driving, elderly drivers have other compensatory strategies for safety consideration. Overall, the indicator variables for different age group played the most effect on the DTD than any other explanatory variables.

The lower TMT score implies better performance on visual search, scanning, mental flexibility, executive functions and faster speed of processing. Thus, the negative coefficient of TMT score in model suggests the fading abilities with age could prevent drivers from longer driving. On the contrast, the higher MMSE score indicates the better performance of cognitive mental status. The coefficient of MMSE remains positive among all duration models for both pooled and panel, which may indicate the better cognitive metal status gives driver confidence on long-distance driving. Visual acuity is a significant variable in both pooled and panel model, it shows a positive relation on DTD. Changes in visual acuity are easily noticeable by drivers themselves, since it not only has effect on driving performance, but also affects other aspects of life. The confidence in their visual acuity could lead to more willing to drive. The comparison among three aptitude variables implies the TMT score has the least influence on the driving distance, while visual acuity has the most. This confirmed the importance of visual acuity test when obtaining or renew the driving license for elderly. As reported in Onishi (2020), the decline in visual functions and cognitive abilities are related with age. This could confirm the earlier mentioned idea that the old-old drivers are aware of their decline in driving abilities, they tend to drive less because of their awareness for declining driving abilities. To drive less could be one of their compensatory strategies of avoiding risky driving behavior.

Even though both variables for weather condition are showing significant in the model, but the marginal effect implies they have very little effect on the DTD compare to other variables. The variables for weather information have the least marginal effect, which implies even they are significant in the model, but people’s driving distance does not affect by weather condition as we expected.

The explanatory variables for psychological understanding of driving are almost all significant in the lognormal panel model. As mentioned above, IMP for young-old group as the only insignificant variable reached 85% of confident level. The SS, IMP and PSPDS played different effect among different age groups. Comparing the marginal effect of the interaction items in each age group, the driving distance of young-old group is not largely affected by their psychology status. On the other hand, both young and the old-old drivers are largely affected by the psychology elements.

The SS scale evaluates the preference for change and uncertainty, while the Imp scale evaluates the tendency to act without thinking or planning. For the young drivers (aged less than 65), both SS and IMP are showing negative effect, but they played both positive effect for old-old drivers.

As mentioned in table 5.4, young drivers would be more exposed to risky driving behavior based on the highest average SS score compare to other age groups. However, their tendency towards risky driving behavior actually may lead them to shorter distance, since they may be aware of their risky tendency. On the other hand, the old-old drivers are proved to be more cautious based on the scores of ImpSS, they are more willing to travel longer.

The PSPDS was related with risky driving behavior in Scott-Parker et al. (2015), and is also significantly related with driving distance for all age groups, but still with the least effect for young-old drivers. The PSPDS showed positive effect for both the young and old-old drivers, their psychosocial purposes drive them to longer distance, but PSPDS played a negative effect for young-old drivers. As shown in Table 5.5, the most driving purpose of young drivers is visiting their friends, but the old-old drivers have various driving purposes higher than average score and most are related with psychology thinking. Their psychological need to prove their ability urge them to travel more.

In general, the variables for psychological considering are not playing strong effect among the young-old drivers compare to other age groups. Even though the young-old drivers have fairy strong tendency to driver longer distance than any other age group, but they don’t have strong preference for driving without planning or seeking for changes. On the contrary, the young drivers are psychologically riskier in this way.

5.5 Conclusion and limitation

This study applies both pooled and panel hazard duration model with log-logistic, log-normal and Weibull distributions to reveal the influence of various variables on daily travel distance conducted by elderly drivers. Aptitude test result as TMT score, MMSE and visual acuity are considered to be factors that affect the driving performance of elderly people. Even though the existing EV has enough driving range to cover most daily driving demand of our participants. EV with longer driving range would be preferred for those who have better performance in their aptitude test especially for the young-old drivers.

Different from last chapter, as the elderly driver divided into 2 groups, only the old-old drivers have strong tendency of shorter distance. The young-old drivers, on the contrary has the most positive effect on the driving distance. Compared to other variables such as gender or psychological elements, the situation naturally brought by age would cause more spare time for driving.

The psychological understanding of drivers is also believed to be affective on driving behavior, but has not been tested on elderly driver yet. This study applied ImpSS and PSPDS on the elderly drivers, and made it as interaction item with different age groups. The result shows the interaction item of different age groups with same psychological considering is showing different effect on DTD, and the difference is more clearly displayed by the age groups at both ends. Even though the old-old group are identified as easier adopter for EV considering their tendency towards shorter DTD, but it would be better to provide them EV with autonomous function considering the decline in driving ability may cause safety issues.

The proposed study may contribute to the driving evaluation of elderly drivers, the psychological understanding of elderly driving behavior, especially considering driving safety for elderly drivers.

However, the evaluation of elderly drivers' driving ability and driving psychology is incomplete, especially the understanding of driving psychology is very superficial. The utilization of the ImpSS and PSPDS questionnaire could be improved.

CHAPTER 6 Conclusion and limitation

6.1 Conclusion

This dissertation mainly focuses on the study of daily travel distance (DTD). The distribution functions are used here to simulate the driving pattern for both carsharing users and private vehicle users. However, the more understanding of driving habits requires studies that could link the DTD with other explanatory variables. In this way, we applied Accelerate Failure Time (AFT) model which retains the distribution assumptions for DTD along with a parametric assumption on the covariates which have direct effect on the DTD. The determined characteristic of DTD with distribution functions could be used to identify the suitable battery size for EV. The AFT model results help the EV manufacturer to understand the features of their potential target customer. Besides, the AFT model applied to the elderly drivers could also contribute the driving safety problems with elderly people, especially in the psychological understanding.

The first part of this study utilized the five single distribution functions and a mixture model with 2 lognormal components to test the DTD of a sharing system. The test of different distribution functions implied the driving pattern in terms of distance cannot be simulated simply by the single distribution function. The mixture distribution with two lognormal components is the best fitted among all the alternatives. In this way, the driving pattern in terms of distance could be determined with each vehicle by its best fitted form, and is used here to quantify the benefit of vehicle electrification. Two types of EV are used here as reference, to evaluate the emission reduction and available electricity amount. The two EV types could replace 23 and 30 conventional vehicles respectively, and the emission could be reduced by 19% and 24% respectively. The driving cost could make even with the purchase cost of EV after 1.67 years for Type 1 but it's more than 30 years for Type 2. However, if we use both type in the substitution plan, the 30 replaced EV could reach the emission reduction by 27.6%, and the purchase cost would be made even by the driving cost for 11.37 years. This scenario could be adopted if the university wish to accomplish more reduction in the emission.

Even though it might be difficult for each household to have a V2G system, the electrification of private vehicles could still lead to environmental benefit by individually. However, not every driver would be willing to use EV since they have their own preference on their driving habit. Additionally, the existing EV with limited driving range may not be suitable for all the drivers.

In this way, the second part of this study focused on the driving behavior in terms of daily driving distance of private vehicles, the hazard duration model made it possible to consider the effect of other explanatory variables on the driving distance. The driving preference, and the reason of that preference is revealed in this part. The drivers in this part mainly live in Toyota City, and most of them have fixed job, which implies their driving pattern could be quite fixed. However, the result shows they still have their own preference such as turn to alternative destination nearby due to the terrible weather.

The expanded mixture model from 2 components to 7 components implies the complicated driving behavior. These complicated driving habit could not be explained simply by the distribution function of driving distance. In this way, AFT model is here to measure the effect of variables on driving distance. Compared to the pooled model, the panel AFT model considers the individual difference by using a normally distributed constant. The log-logistic assumption for duration data is the best fitted model among alternatives.

The result determined the factors that affect daily driving distance. As the results suggest that the travel distances achieved by people in Toyota City, Japan, is highly dependent on the weather conditions, specifically the precipitation and wind speed. Drivers in Toyota City would prefer an alternative destination nearby during the terrible weather. Socioeconomic indicators, such as age and gender, and vehicle characteristics, such as engine size and vehicle price, also significantly affect the car travel distance. For those who are currently using vehicles with less fuel consumption, they may become the earlier adopter for EV.

Male drivers tend to drive longer than female drivers, and this could be explained by the traditional Japanese family style as women are required to be more focused on families. However, since less than 10% of the participants are female, which made it difficult to be a universal pattern. The situation is same for age difference, even though the result implies elderly drivers may tend to drive less, but the data set only contains 2 elderly drivers (aged over 65), which made it difficult to summarized the different driving habits between different age groups.

Therefore, the third part of this study mainly focus on the driving behavior of elderly drivers. The data set is divided into 3 different age group as young drivers (aged less than 65), young-old drivers (aged from 65 to 74), and the old-old drivers (aged from 75). The aptitude test result is used to evaluate the driving ability, and the variables for psychological consider are used as interaction items with different age group. In this way, the interaction items could help us in understanding their driving attitude among different age groups. The application of panel survival model with log-logistic, log-normal and Weibull duration on daily travel distance (DTD) and different distribution assumptions on the constant shows the lognormal duration model with normally distributed constant is the best fitted form.

The result implies young-old driver (aged from 65 to 74) and old-old drivers (aged from 75) hold opposite effect on DTD. The young-old group shows the largest positive marginal effect on the DTD while the old-old groups shows the largest negative effect, which implies the driving distance is largely dependent on the driver’s age. The effect of gender is similar with in the second part, female drivers who prefer less driving distance could be more adoptable for EV.

The variables of aptitude test affect the driving distance especially the visual acuity. The shorter DTD conducted by old-old drivers could be caused by the decline in their driving ability. The result of psychology survey implies that they become cautious driver than other age groups.

The old-old drivers may not perform as well as young drivers considering their decreasing driving ability, but they will consciously avoid dangerous behavior compare to other age groups. On the contrary, the younger drivers have higher tendency towards risky driving behavior and more willing to drive.

In general, the promotion of EV, especially for the EV producer, it requires them to understand their potential customers. The characterization of daily travel distance could clarify the market direction for EV manufacturers. As determined in this study, for individual customers, the existing EV already has a driving range which can meet about 95% of their daily travel demand, especially for elderly drivers. Considering the decline in their driving ability, the EV with more autonomous functions could be more preferred for safety reason.

6.2 Limitation and future works

The personal characteristics of drivers are determined in this study, but as mentioned in Chapter 3, if the vehicle is shared by multiple users, the daily driving distance of a certain vehicle could be difficult to be determined simply by some explanatory variables. The utilization of EV in carsharing system could be better studied if the system is open up to the public. The data of university wide sharing system is very limited. Additionally, the basic analysis of the data shows there are at most 21 vehicles are in use at the same time, which implies the fleet number could be reduced. The optimization of the fleet size for the car sharing system could be one of the future topics.

The Chapter 4 and 5 determined the characteristics of driver that affects driving distance, but there are many other variables that have not been considered in the model. The impact of residential situation such as population density was not tested in the model. Both chapter utilized mixture model with multiple lognormal components, but the mixture model is not applied as the distribution assumption for duration data in the hazard model.

The substitution of EV for conventional vehicles in a carsharing system would be more dependent simply on the driving range, since users don't own the vehicle. They only need to consider whether the EV they choose from the carsharing system can meet their needs for this trip. However, to cater the driving demand of various users, it requires more flexibility in the carsharing system. The use of charging facility or provide another EV at a location midway could encourage users to use the EV despite the limited driving range. This could be another future research topic when considering using EV in a carsharing system.

As a matter of fact, the individual consumers would not only consider the most situation of their driving demand when purchasing an EV. Individual buyers would still tend to choose the EV with larger battery capacity in order to deal with infrequent situation of longer driving demand. Their acceptance towards EV cannot be simply summarized by daily travel distance, other features such as the size of vehicle and purchase cost.

APPENDIX A Regression model for parameters in mixture model

Table A.1 Regression model of α (the mixing coefficient)

Adjusted R-squared: -0.08763, Sample size: 48					
Coefficient					
		Estimate	Std. Error	t value	Pr(>|t|)
Intercept		0.8434	0.405	2.084	0.044
Vehicle type (truck as base)	SUV	0.0048	0.418	0.012	0.991
	Sedan	-0.0166	0.352	-0.047	0.963
	Van	0.0034	0.364	0.009	0.993
	Minivan	-0.0875	0.343	-0.255	0.800
Engine size (cc)		-0.0135	0.011	-1.193	0.240
Faculty members per vehicle		0.0009	0.001	0.632	0.531
Engine type	Diesel	-0.2473	0.488	-0.506	0.615
	Hybrid	0.1841	0.195	0.942	0.352

Table A.2 Regression model of μ_1 (the first peak)

Adjusted R-squared: -0.04972, Sample size: 48					
Coefficient					
		Estimate	Std. Error	t value	Pr(>|t|)
Intercept		4.1331	1.526	2.709	0.010
Vehicle type (truck as base)	SUV	0.4267	1.577	0.271	0.788
	Sedan	-1.4005	1.326	-1.056	0.297
	Van	-0.9410	1.373	-0.685	0.497
	Minivan	-1.3193	1.293	-1.020	0.314
Engine size (cc)		-0.0188	0.043	-0.442	0.661
Faculty members per vehicle		-0.0013	0.005	-0.247	0.806
Engine type	Diesel	-1.3314	1.841	-0.723	0.474
	Hybrid	-0.1773	0.737	-0.241	0.811

Table A.3 Regression model of σ_1 (the first standard deviation)

Adjusted R-squared: -0.1578, Sample size: 48					
Coefficient:					
		Estimate	Std. Error	t value	Pr(>|t|)
Intercept		0.8374	0.551	1.519	0.137
Vehicle type (truck as base)	SUV	-0.2534	0.570	-0.445	0.659
	Sedan	-0.0046	0.479	-0.010	0.992
	Van	0.0057	0.496	0.012	0.991
	Minivan	-0.1122	0.467	-0.240	0.812
Engine size (cc)		-0.0005	0.015	-0.032	0.975
Faculty members per vehicle		0.0012	0.002	0.629	0.533
Engine type	Diesel	-0.0856	0.665	-0.129	0.898
	Hybrid	0.0679	0.266	0.255	0.800

Table A.4 Regression model of μ_2 (the second peak)

Adjusted R-squared: -0.005368, Sample size: 48					
Coefficient:					
		Estimate	Std. Error	t value	Pr(>|t|)
Intercept		-0.1707	1.700	-0.100	0.921
Vehicle type (truck as base)	SUV	2.8436	1.757	1.618	0.114
	Sedan	2.9682	1.477	2.010	0.051
	Van*	3.2960	1.530	2.155	0.037
	Minivan*	3.2815	1.441	2.278	0.028
Engine size (cc)		0.0521	0.047	1.101	0.278
Faculty members per vehicle		0.0041	0.006	0.707	0.484
Engine type	Diesel	1.2259	2.051	0.598	0.553
	Hybrid	-0.6502	0.821	-0.792	0.433

Table A.5 Regression model of σ_2 (the second standard deviation)

		Estimate	Std. Error	t value	Pr(>|t|)
Adjusted R-squared: 0.005851, Sample size: 48					
Coefficient:					
		Estimate	Std. Error	t value	Pr(>|t|)
Intercept		0.8631	0.576	1.498	0.142
Vehicle type (truck as base)	SUV	0.0507	0.595	0.085	0.933
	Sedan	-0.2838	0.500	-0.567	0.574
	Van	-0.4096	0.518	-0.790	0.434
	Minivan	0.0506	0.488	0.104	0.918
Engine size (cc)		-0.0036	0.016	-0.227	0.822
Faculty members per vehicle		-0.0004	0.002	-0.211	0.834
Engine type	Diesel	-0.5292	0.695	-0.761	0.451
	Hybrid	-0.0877	0.278	-0.315	0.754

APPENDIX B The result of distribution panel duration model with different distribution assumptions for constant

Table B.1 The lognormal duration with uniformly distributed constant

Model: Lognormal	Constant: Uniform		Log-likelihood: -28484.0	
Variables	Coefficient	Prob |z|>Z	95% Confidence Interval	
Driving experience	-0.021	0.000	-0.022	-0.021
Education experience	0.001	0.231	-0.001	0.003
Gender	0.095	0.000	0.086	0.104
Young-old group	0.840	0.000	0.763	0.918
Old-old group	-1.175	0.000	-1.281	-1.068
Trail Making Test Score (TMTS)	-0.044	0.000	-0.049	-0.039
Mini-Mental State Examination score (MMSE)	0.087	0.000	0.083	0.091
Visual acuity during daytime	0.264	0.000	0.251	0.278
Minimum temperature	0.003	0.000	0.002	0.004
Precipitation	-0.002	0.016	-0.003	0.000
SS for young	-0.058	0.000	-0.063	-0.052
IMP for young	-0.135	0.000	-0.142	-0.128
PSPD for young	0.114	0.000	0.108	0.119
SS for young-old	0.001	0.115	0.000	0.002
IMP for young-old	0.042	0.000	0.039	0.046
PSPD for young-old	-0.021	0.000	-0.023	-0.019
SS for old-old	0.036	0.000	0.031	0.041
IMP for old-old	0.130	0.000	0.117	0.142
PSPD for old-old	0.094	0.000	0.088	0.100
Constant (mean)	0.440	0.000	0.302	0.578
Constant (standard deviation)	0.064	0.000	0.061	0.068
Scale parameter for survival distribution (σ)	1.105	0.000	1.102	1.108

Table B.2 The lognormal duration with triangularly distributed constant

Model: Lognormal	Constant: Triangular		Log-likelihood: -28586.0	
Variables	Coefficient	Prob |z|>Z	95% Confidence Interval	
Driving experience	-0.023	0.000	-0.024	-0.022
Education experience	0.001	0.340	-0.001	0.003
Gender	0.097	0.000	0.088	0.107
Young-old group	0.864	0.000	0.785	0.943
Old-old group	-1.207	0.000	-1.314	-1.101
Trail Making Test Score (TMTS)	-0.045	0.000	-0.050	-0.040
Mini-Mental State Examination score (MMSE)	0.089	0.000	0.085	0.093
Visual acuity during daytime	0.272	0.000	0.258	0.285
Minimum temperature	0.003	0.000	0.002	0.004
Precipitation	-0.002	0.013	-0.003	0.000
SS for young	-0.059	0.000	-0.066	-0.053
IMP for young	-0.139	0.000	-0.146	-0.132
PSPD for young	0.117	0.000	0.111	0.123
SS for young-old	0.001	0.211	0.000	0.002
IMP for young-old	0.044	0.000	0.040	0.047
PSPD for young-old	-0.022	0.000	-0.024	-0.020
SS for old-old	0.037	0.000	0.031	0.042
IMP for old-old	0.133	0.000	0.120	0.146
PSPD for old-old	0.097	0.000	0.091	0.103
Constant (mean)	0.452	0.000	0.314	0.590
Constant (standard deviation)	0.000	-1.000	0.000	0.000
Scale parameter for survival distribution (σ)	1.136	0.000	1.133	1.139

Table B.3 The lognormal duration with negative half normally distributed constant

Model: Lognormal	Constant: Negative half normal		Log-likelihood: -28586.0	
Variables	Coefficient	Prob |z|>Z	95% Confidence Interval	
Driving experience	-0.023	0.000	-0.024	-0.022
Education experience	0.001	0.340	-0.001	0.003
Gender	0.097	0.000	0.088	0.107
Young-old group	0.864	0.000	0.785	0.943
Old-old group	-1.207	0.000	-1.314	-1.101
Trail Making Test Score (TMTS)	-0.045	0.000	-0.050	-0.040
Mini-Mental State Examination score (MMSE)	0.089	0.000	0.085	0.093
Visual acuity during daytime	0.272	0.000	0.258	0.285
Minimum temperature	0.003	0.000	0.002	0.004
Precipitation	-0.002	0.013	-0.003	0.000
SS for young	-0.059	0.000	-0.066	-0.053
IMP for young	-0.139	0.000	-0.146	-0.132
PSPD for young	0.117	0.000	0.111	0.123
SS for young-old	0.001	0.211	0.000	0.002
IMP for young-old	0.044	0.000	0.040	0.047
PSPD for young-old	-0.022	0.000	-0.024	-0.020
SS for old-old	0.037	0.000	0.031	0.042
IMP for old-old	0.133	0.000	0.120	0.146
PSPD for old-old	0.097	0.000	0.091	0.103
Constant (mean)	0.452	0.000	0.314	0.590
Constant (standard deviation)	0.000	-1.000	0.000	0.000
Scale parameter for survival distribution (σ)	1.136	0.000	1.133	1.139

Table B.4 The lognormal duration with centered log-normally distributed constant

Model: Lognormal	Constant: Centered lognormal		Log-likelihood: -28129.5	
Variables	Coefficient	Prob |z|>Z	95% Confidence Interval	
Driving experience	-0.023	0.000	-0.024	-0.023
Education experience	0.001	0.426	-0.001	0.003
Gender	0.097	0.000	0.084	0.110
Young-old group	0.858	0.000	0.769	0.946
Old-old group	-1.199	0.000	-1.310	-1.087
Trail Making Test Score (TMTS)	-0.045	0.000	-0.051	-0.039
Mini-Mental State Examination score (MMSE)	0.088	0.000	0.083	0.093
Visual acuity during daytime	0.270	0.000	0.249	0.291
Minimum temperature	0.003	0.000	0.001	0.004
Precipitation	-0.002	0.007	-0.003	-0.001
SS for young	-0.059	0.000	-0.063	-0.055
IMP for young	-0.138	0.000	-0.146	-0.130
PSPD for young	0.116	0.000	0.111	0.121
SS for young-old	0.000	0.587	-0.001	0.002
IMP for young-old	0.043	0.000	0.039	0.047
PSPD for young-old	-0.022	0.000	-0.025	-0.019
SS for old-old	0.037	0.000	0.031	0.042
IMP for old-old	0.132	0.000	0.119	0.146
PSPD for old-old	0.096	0.000	0.089	0.103
Constant (mean)	0.449	0.000	0.282	0.616
Constant (standard deviation)	0.061	0.000	0.061	0.062
Scale parameter for survival distribution (σ)	1.128	0.000	1.125	1.130

Table B.5 The lognormal duration with log-normally distributed constant

Model: Lognormal	Constant: Lognormal		Log-likelihood: -28679.8	
Variables	Coefficient	Prob |z|>Z	95% Confidence Interval	
Driving experience	-0.038	0.000	-0.039	-0.038
Education experience	-0.004	0.000	-0.005	-0.002
Gender	0.097	0.000	0.089	0.105
Young-old group	0.863	0.000	0.800	0.926
Old-old group	-1.206	0.000	-1.275	-1.137
Trail Making Test Score (TMTS)	-0.046	0.000	-0.051	-0.041
Mini-Mental State Examination score (MMSE)	0.079	0.000	0.076	0.083
Visual acuity during daytime	0.271	0.000	0.259	0.283
Minimum temperature	-0.001	0.107	-0.002	0.000
Precipitation	-0.003	0.000	-0.005	-0.002
SS for young	-0.061	0.000	-0.065	-0.057
IMP for young	-0.139	0.000	-0.143	-0.135
PSPD for young	0.116	0.000	0.111	0.120
SS for young-old	-0.002	0.000	-0.003	-0.001
IMP for young-old	0.043	0.000	0.040	0.047
PSPD for young-old	-0.023	0.000	-0.025	-0.021
SS for old-old	0.035	0.000	0.030	0.040
IMP for old-old	0.133	0.000	0.123	0.143
PSPD for old-old	0.096	0.000	0.090	0.101
Constant (mean)	0.451	0.000	0.366	0.536
Constant (standard deviation)	0.000	-0.976	0.000	0.000
Scale parameter for survival distribution (σ)	1.135	0.000	1.132	1.138

Table B.6 The log-logistic duration with normally distributed constant

Model: Log-logistic	Constant: Normal		Log-likelihood: -28511.4	
Variables	Coefficient	Prob |z|>Z	95% Confidence Interval	
Driving experience	-0.013	0.000	-0.014	-0.013
Education experience	0.009	0.000	0.007	0.011
Gender	0.057	0.000	0.048	0.067
Young-old group	0.512	0.000	0.435	0.590
Old-old group	-0.715	0.000	-0.813	-0.617
Trail Making Test Score (TMTS)	-0.025	0.000	-0.029	-0.021
Mini-Mental State Examination score (MMSE)	0.084	0.000	0.081	0.087
Visual acuity during daytime	0.161	0.000	0.147	0.175
Minimum temperature	0.003	0.000	0.001	0.004
Precipitation	-0.003	0.000	-0.004	-0.001
SS for young	-0.030	0.000	-0.035	-0.024
IMP for young	-0.083	0.000	-0.089	-0.076
PSPD for young	0.073	0.000	0.068	0.078
SS for young-old	0.006	0.000	0.005	0.007
IMP for young-old	0.030	0.000	0.026	0.033
PSPD for young-old	-0.005	0.000	-0.007	-0.003
SS for old-old	0.023	0.000	0.018	0.027
IMP for old-old	0.079	0.000	0.070	0.088
PSPD for old-old	0.059	0.000	0.053	0.064
Constant (mean)	0.269	0.000	0.143	0.394
Constant (standard deviation)	0.001	0.258	-0.001	0.003
Scale parameter for survival distribution (σ)	0.672	0.000	0.670	0.675

Table B.7 The log-logistic duration with uniformly distributed constant

Model: Log-logistic	Constant: Uniform		Log-likelihood: -28511.4	
Variables	Coefficient	Prob |z|>Z	95% Confidence Interval	
Driving experience	-0.013	0.000	-0.014	-0.013
Education experience	0.009	0.000	0.007	0.011
Gender	0.057	0.000	0.048	0.067
Young-old group	0.512	0.000	0.435	0.590
Old-old group	-0.715	0.000	-0.813	-0.617
Trail Making Test Score (TMTS)	-0.025	0.000	-0.029	-0.021
Mini-Mental State Examination score (MMSE)	0.084	0.000	0.081	0.087
Visual acuity during daytime	0.161	0.000	0.147	0.175
Minimum temperature	0.003	0.000	0.001	0.004
Precipitation	-0.003	0.000	-0.004	-0.001
SS for young	-0.030	0.000	-0.035	-0.024
IMP for young	-0.083	0.000	-0.089	-0.077
PSPD for young	0.073	0.000	0.068	0.078
SS for young-old	0.006	0.000	0.005	0.007
IMP for young-old	0.030	0.000	0.026	0.033
PSPD for young-old	-0.005	0.000	-0.007	-0.003
SS for old-old	0.023	0.000	0.018	0.027
IMP for old-old	0.079	0.000	0.070	0.088
PSPD for old-old	0.059	0.000	0.053	0.064
Constant (mean)	0.269	0.000	0.143	0.394
Constant (standard deviation)	0.002	0.307	-0.002	0.005
Scale parameter for survival distribution (σ)	0.672	0.000	0.670	0.675

Table B.8 The log-logistic duration with triangularly distributed constant

Model: Log-logistic	Constant: Triangular		Log-likelihood: -28511.5	
Variables	Coefficient	Prob |z|>Z	95% Confidence Interval	
Driving experience	-0.013	0.000	-0.014	-0.013
Education experience	0.009	0.000	0.007	0.011
Gender	0.057	0.000	0.048	0.067
Young-old group	0.512	0.000	0.435	0.590
Old-old group	-0.715	0.000	-0.813	-0.617
Trail Making Test Score (TMTS)	-0.025	0.000	-0.029	-0.021
Mini-Mental State Examination score (MMSE)	0.084	0.000	0.081	0.087
Visual acuity during daytime	0.161	0.000	0.147	0.175
Minimum temperature	0.003	0.000	0.001	0.004
Precipitation	-0.003	0.000	-0.004	-0.001
SS for young	-0.030	0.000	-0.035	-0.024
IMP for young	-0.083	0.000	-0.089	-0.077
PSPD for young	0.073	0.000	0.068	0.078
SS for young-old	0.006	0.000	0.005	0.007
IMP for young-old	0.030	0.000	0.026	0.033
PSPD for young-old	-0.005	0.000	-0.007	-0.003
SS for old-old	0.023	0.000	0.018	0.027
IMP for old-old	0.079	0.000	0.070	0.088
PSPD for old-old	0.059	0.000	0.053	0.064
Constant (mean)	0.269	0.000	0.143	0.394
Constant (standard deviation)	0.001	0.692	-0.004	0.006
Scale parameter for survival distribution (σ)	0.672	0.000	0.670	0.675

Table B.9 The log-logistic duration with negative half normally distributed constant

Model: Log-logistic	Constant: Negative half normal		Log-likelihood: -28511.6	
Variables	Coefficient	Prob |z|>Z	95% Confidence Interval	
Driving experience	-0.013	0.000	-0.014	-0.013
Education experience	0.009	0.000	0.007	0.011
Gender	0.057	0.000	0.048	0.067
Young-old group	0.512	0.000	0.435	0.590
Old-old group	-0.715	0.000	-0.813	-0.617
Trail Making Test Score (TMTS)	-0.025	0.000	-0.029	-0.021
Mini-Mental State Examination score (MMSE)	0.084	0.000	0.081	0.087
Visual acuity during daytime	0.161	0.000	0.147	0.175
Minimum temperature	0.003	0.000	0.001	0.004
Precipitation	-0.003	0.000	-0.004	-0.001
SS for young	-0.030	0.000	-0.035	-0.024
IMP for young	-0.083	0.000	-0.089	-0.076
PSPD for young	0.073	0.000	0.068	0.078
SS for young-old	0.006	0.000	0.005	0.007
IMP for young-old	0.030	0.000	0.026	0.033
PSPD for young-old	-0.005	0.000	-0.007	-0.003
SS for old-old	0.022	0.000	0.018	0.027
IMP for old-old	0.079	0.000	0.070	0.088
PSPD for old-old	0.059	0.000	0.053	0.064
Constant (mean)	0.269	0.000	0.143	0.394
Constant (standard deviation)	0.000	-0.997	0.000	0.000
Scale parameter for survival distribution (σ)	0.672	0.000	0.670	0.675

Table B.10 The log-logistic duration with centered log-normally distributed constant

Model: Log-logistic	Constant: Centered lognormal		Log-likelihood: -28035.8	
Variables	Coefficient	Prob |z|>Z	95% Confidence Interval	
Driving experience	-0.035	0.000	-0.036	-0.035
Education experience	0.013	0.000	0.011	0.014
Gender	0.057	0.000	0.047	0.066
Young-old group	0.496	0.000	0.428	0.563
Old-old group	-0.691	0.000	-0.786	-0.595
Trail Making Test Score (TMTS)	-0.023	0.000	-0.028	-0.018
Mini-Mental State Examination score (MMSE)	0.117	0.000	0.113	0.121
Visual acuity during daytime	0.157	0.000	0.143	0.172
Minimum temperature	0.000	0.660	-0.001	0.002
Precipitation	-0.004	0.000	-0.005	-0.003
SS for young	-0.028	0.000	-0.033	-0.024
IMP for young	-0.086	0.000	-0.091	-0.081
PSPD for young	0.073	0.000	0.067	0.078
SS for young-old	0.006	0.000	0.006	0.007
IMP for young-old	0.031	0.000	0.027	0.034
PSPD for young-old	0.001	0.447	-0.002	0.004
SS for old-old	0.033	0.000	0.027	0.039
IMP for old-old	0.079	0.000	0.067	0.091
PSPD for old-old	0.065	0.000	0.057	0.072
Constant (mean)	0.261	0.000	0.139	0.383
Constant (standard deviation)	0.075	0.000	0.075	0.076
Scale parameter for survival distribution (σ)	0.650	0.000	0.648	0.652

Table B.11 The log-logistic duration with log-normally constant

Model: Log-logistic	Constant: Lognormal		Log-likelihood: -28082.3	
Variables	Coefficient	Prob |z|>Z	95% Confidence Interval	
Driving experience	-0.047	0.000	-0.047	-0.046
Education experience	0.011	0.000	0.010	0.013
Gender	0.059	0.000	0.049	0.069
Young-old group	0.506	0.000	0.436	0.576
Old-old group	-0.705	0.000	-0.778	-0.631
Trail Making Test Score (TMTS)	-0.030	0.000	-0.035	-0.025
Mini-Mental State Examination score (MMSE)	0.107	0.000	0.104	0.110
Visual acuity during daytime	0.160	0.000	0.143	0.176
Minimum temperature	0.001	0.415	-0.001	0.002
Precipitation	-0.006	0.000	-0.007	-0.005
SS for young	-0.043	0.000	-0.048	-0.039
IMP for young	-0.089	0.000	-0.095	-0.084
PSPD for young	0.076	0.000	0.070	0.082
SS for young-old	0.015	0.000	0.014	0.017
IMP for young-old	0.036	0.000	0.032	0.040
PSPD for young-old	-0.004	0.003	-0.007	-0.002
SS for old-old	0.035	0.000	0.030	0.040
IMP for old-old	0.086	0.000	0.076	0.096
PSPD for old-old	0.069	0.000	0.061	0.077
Constant (mean)	0.271	0.000	0.220	0.321
Constant (standard deviation)	0.107	0.000	0.099	0.114
Scale parameter for survival distribution (σ)	0.662	0.000	0.660	0.664

Table B.12 The Weibull duration with normally distributed constant

Model: Weibull	Constant: Normal		Log-likelihood: -28917.5	
Variables	Coefficient	Prob |z|>Z	95% Confidence Interval	
Driving experience	-0.015	0.000	-0.016	-0.015
Education experience	0.003	0.008	0.001	0.005
Gender	0.098	0.000	0.089	0.107
Young-old group	0.864	0.000	0.787	0.942
Old-old group	1.208	0.000	-1.288	-1.127
Trail Making Test Score (TMTS)	-0.045	0.000	-0.050	-0.040
Mini-Mental State Examination score (MMSE)	0.093	0.000	0.090	0.096
Visual acuity during daytime	0.272	0.000	0.257	0.287
Minimum temperature	0.005	0.000	0.004	0.006
Precipitation	-0.001	0.007	-0.002	0.000
SS for young	-0.059	0.000	-0.064	-0.054
IMP for young	-0.139	0.000	-0.144	-0.134
PSPD for young	0.117	0.000	0.112	0.122
SS for young-old	0.002	0.004	0.001	0.003
IMP for young-old	0.044	0.000	0.040	0.047
PSPD for young-old	-0.021	0.000	-0.023	-0.019
SS for old-old	0.038	0.000	0.035	0.041
IMP for old-old	0.133	0.000	0.123	0.144
PSPD for old-old	0.097	0.000	0.094	0.101
Constant (mean)	0.452	0.000	0.345	0.560
Constant (standard deviation)	0.000	-0.996	0.000	0.000
Scale parameter for survival distribution (σ)	1.136	0.000	1.134	1.139

Table B.13 The Weibull duration with uniformly distributed constant

Model: Weibull	Constant: Uniform		Log-likelihood: -28917.5	
Variables	Coefficient	Prob |z|>Z	95% Confidence Interval	
Driving experience	-0.015	0.000	-0.016	-0.015
Education experience	0.003	0.008	0.001	0.005
Gender	0.098	0.000	0.089	0.107
Young-old group	0.864	0.000	0.787	0.942
Old-old group	1.208	0.000	-1.288	-1.127
Trail Making Test Score (TMTS)	-0.045	0.000	-0.050	-0.040
Mini-Mental State Examination score (MMSE)	0.093	0.000	0.090	0.096
Visual acuity during daytime	0.272	0.000	0.257	0.287
Minimum temperature	0.005	0.000	0.004	0.006
Precipitation	-0.001	0.007	-0.002	0.000
SS for young	-0.059	0.000	-0.064	-0.054
IMP for young	-0.139	0.000	-0.144	-0.134
PSPD for young	0.117	0.000	0.112	0.122
SS for young-old	0.002	0.004	0.001	0.003
IMP for young-old	0.044	0.000	0.040	0.047
PSPD for young-old	-0.021	0.000	-0.023	-0.019
SS for old-old	0.038	0.000	0.035	0.041
IMP for old-old	0.133	0.000	0.123	0.144
PSPD for old-old	0.097	0.000	0.094	0.101
Constant (mean)	0.452	0.000	0.345	0.560
Constant (standard deviation)	0.000	-0.999	0.000	0.000
Scale parameter for survival distribution (σ)	1.136	0.000	1.134	1.139

Table B.14 The Weibull duration with triangularly distributed constant

Model: Weibull	Constant: Triangular		Log-likelihood: -28917.5	
Variables	Coefficient	Prob |z|>Z	95% Confidence Interval	
Driving experience	-0.015	0.000	-0.016	-0.015
Education experience	0.003	0.008	0.001	0.005
Gender	0.098	0.000	0.089	0.107
Young-old group	0.864	0.000	0.787	0.942
Old-old group	1.208	0.000	-1.288	-1.127
Trail Making Test Score (TMTS)	-0.045	0.000	-0.050	-0.040
Mini-Mental State Examination score (MMSE)	0.093	0.000	0.090	0.096
Visual acuity during daytime	0.272	0.000	0.257	0.287
Minimum temperature	0.005	0.000	0.004	0.006
Precipitation	-0.001	0.007	-0.002	0.000
SS for young	-0.059	0.000	-0.064	-0.054
IMP for young	-0.139	0.000	-0.144	-0.134
PSPD for young	0.117	0.000	0.112	0.122
SS for young-old	0.002	0.004	0.001	0.003
IMP for young-old	0.044	0.000	0.040	0.047
PSPD for young-old	-0.021	0.000	-0.023	-0.019
SS for old-old	0.038	0.000	0.035	0.041
IMP for old-old	0.133	0.000	0.123	0.144
PSPD for old-old	0.097	0.000	0.094	0.101
Constant (mean)	0.452	0.000	0.345	0.560
Constant (standard deviation)	0.000	-1.000	0.000	0.000
Scale parameter for survival distribution (σ)	1.136	0.000	1.134	1.139

Table B.15 The Weibull duration with negative half normally distributed constant

Model: Weibull	Constant: Negative half normal		Log-likelihood: -28917.5	
Variables	Coefficient	Prob |z|>Z	95% Confidence Interval	
Driving experience	-0.015	0.000	-0.016	-0.015
Education experience	0.003	0.008	0.001	0.005
Gender	0.098	0.000	0.089	0.107
Young-old group	0.864	0.000	0.787	0.942
Old-old group	1.208	0.000	-1.288	-1.127
Trail Making Test Score (TMTS)	-0.045	0.000	-0.050	-0.040
Mini-Mental State Examination score (MMSE)	0.093	0.000	0.090	0.096
Visual acuity during daytime	0.272	0.000	0.257	0.287
Minimum temperature	0.005	0.000	0.004	0.006
Precipitation	-0.001	0.007	-0.002	0.000
SS for young	-0.059	0.000	-0.064	-0.054
IMP for young	-0.139	0.000	-0.144	-0.134
PSPD for young	0.117	0.000	0.112	0.122
SS for young-old	0.002	0.004	0.001	0.003
IMP for young-old	0.044	0.000	0.040	0.047
PSPD for young-old	-0.021	0.000	-0.023	-0.019
SS for old-old	0.038	0.000	0.035	0.041
IMP for old-old	0.133	0.000	0.123	0.144
PSPD for old-old	0.097	0.000	0.094	0.101
Constant (mean)	0.452	0.000	0.345	0.560
Constant (standard deviation)	0.000	0.950	-0.004	0.004
Scale parameter for survival distribution (σ)	1.136	0.000	1.134	1.139

Table B.16 The Weibull duration with centered log-normally distributed constant

Model: Weibull	Constant: Centered lognormal		Log-likelihood: -28917.5	
Variables	Coefficient	Prob |z|>Z	95% Confidence Interval	
Driving experience	-0.015	0.000	-0.016	-0.015
Education experience	0.003	0.008	0.001	0.005
Gender	0.098	0.000	0.089	0.107
Young-old group	0.864	0.000	0.787	0.942
Old-old group	1.208	0.000	-1.288	-1.127
Trail Making Test Score (TMTS)	-0.045	0.000	-0.050	-0.040
Mini-Mental State Examination score (MMSE)	0.093	0.000	0.090	0.096
Visual acuity during daytime	0.272	0.000	0.257	0.287
Minimum temperature	0.005	0.000	0.004	0.006
Precipitation	-0.001	0.007	-0.002	0.000
SS for young	-0.059	0.000	-0.064	-0.054
IMP for young	-0.139	0.000	-0.144	-0.134
PSPD for young	0.117	0.000	0.112	0.122
SS for young-old	0.002	0.004	0.001	0.003
IMP for young-old	0.044	0.000	0.040	0.047
PSPD for young-old	-0.021	0.000	-0.023	-0.019
SS for old-old	0.038	0.000	0.035	0.041
IMP for old-old	0.133	0.000	0.123	0.144
PSPD for old-old	0.097	0.000	0.094	0.101
Constant (mean)	0.452	0.000	0.345	0.560
Constant (standard deviation)	0.000	-0.997	0.000	0.000
Scale parameter for survival distribution (σ)	1.136	0.000	1.134	1.139

Table B.17 The Weibull duration with log-normally distributed constant

Model: Weibull	Constant: Lognormal		Log-likelihood: -28988.5	
Variables	Coefficient	Prob |z|>Z	95% Confidence Interval	
Driving experience	-0.031	0.000	-0.032	-0.031
Education experience	-0.001	0.151	-0.003	0.001
Gender	0.097	0.000	0.089	0.106
Young-old group	0.863	0.000	0.799	0.928
Old-old group	1.207	0.000	-1.272	-1.141
Trail Making Test Score (TMTS)	-0.046	0.000	-0.051	-0.041
Mini-Mental State Examination score (MMSE)	0.084	0.000	0.081	0.087
Visual acuity during daytime	0.271	0.000	0.258	0.285
Minimum temperature	0.001	0.210	0.000	0.002
Precipitation	-0.003	0.000	-0.004	-0.002
SS for young	-0.060	0.000	-0.065	-0.055
IMP for young	-0.139	0.000	-0.148	-0.130
PSPD for young	0.116	0.000	0.110	0.123
SS for young-old	-0.001	0.095	-0.002	0.000
IMP for young-old	0.043	0.000	0.041	0.046
PSPD for young-old	-0.023	0.000	-0.025	-0.021
SS for old-old	0.036	0.000	0.033	0.038
IMP for old-old	0.133	0.000	0.124	0.142
PSPD for old-old	0.096	0.000	0.093	0.099
Constant (mean)	0.452	0.000	0.379	0.524
Constant (standard deviation)	0.000	-0.996	0.000	0.000
Scale parameter for survival distribution (σ)	1.135	0.000	1.133	1.137

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