Doctoral Dissertation

Analysis of Multi-faceted Driving Risks on Expressways and Drivers' Responses to Information Provision

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Abstract

Background and motivations

In practice, even though various traffic safety countermeasures have been taken, it is still considerably far away from a zero-accident society. It seems that voluntary changes in driving behaviors should be further encouraged in a more effective and sustainable way, especially considering that most traffic accidents are caused by human errors.

From the human perspective, it is necessary to not only prevent the occurrence of traffic accidents by mitigating various driving risks, but also mitigate the impacts of traffic accidents on human being once they occurred. In this regard, this study emphasizes the roles of information provision in helping drivers to develop a better understanding of their daily driving risks and to voluntarily modify their driving behaviors for reducing driving risks and adapting to the occurrence of traffic accidents. Literature review suggests that efforts along this direction have significantly ignored individual drivers' decision-making mechanisms. On the other hand, even though using smartphones or other mobile phones during driving is prohibited in many countries, in recent years, various smartphone apps have been developed and deployed in market. It remains unclear whether such smartphone apps should be promoted in traffic safety practices or not.

Research purposes

The purposes of this study are twofold. The first purpose is to mitigate driving risks by focusing on the role of contradictory use of smartphones, and the second is to mitigate the impacts of traffic accidents on drivers' travel choices. Both purposes further focus on dynamic traffic information provision on expressways in Japan. Concretely speaking, for the first purpose, this

study examines whether smartphone apps with diagnosis functions of driving risks and dynamic information provision should be promoted or not by targeting drivers' internal driving risks. As for the second purpose, this study clarifies drivers' adaptation and avoidance behaviors under the influence of dynamic information provision by targeting drivers' external driving risks. This study was done mainly based on primary data and econometric modeling approaches.

Data

Focusing on the first research purpose, a GSP-enabled smartphone app was first developed with *simplified* functions of driving risk diagnosis and dynamic information provision, and then a three-month driving experiment by inviting 100 drivers was implemented together with a series of questionnaire surveys for capturing actual behavioral changes due to the use of the app. Note that the purpose of the app development is not to develop an app with most advanced functions for improving driving safety. Targeting the second research purpose, a large-scale stated preference (SP) survey with 30,000 samples collected from 2,500 drivers was first conducted, where SP attributes were given by reflecting each driver's heterogeneous preference for information provision. And then, one more survey was carried out by focusing on truck drivers' route choices under the influence of potential traffic accidents, where truck drivers' employers' preferences are reflected (525 SP observations from 58 company managers and 186 drivers).

Modeling approaches

As for the first research purpose, driving risks are first measured in terms of over-speeding and compliance of speed limit, acceleration and deceleration, and driving stability at second-by-second and trip levels. And then driving risks are represented by a zero-inflated negative binomial regression (ZINBR) model, a multilevel ordered probit (MOP) model, a bivariate ordered probit (BOP) model, and a seemingly uncorrelated regression (SUR) model. With these models, discreteness and continuity, nonlinearity, and multiple correlations (with respect to driving risks and multitasking behaviors during driving, and subjective well-being indicators) existing in data measuring multi-faceted driving risks are explicitly incorporated.

Concerning the second research purpose, a nested logit (NL) model is first adopted to describe drivers' adaptation behavior changes under the influence of dynamic accident-related information provision. Second, a K-means cluster analysis is utilized to identify drivers' heterogeneous travel information styles relating to adaptation behavior. Third, a bivariate probit (BP) model is employed to investigate joint choices of truck company managers and drivers with respect to driving routes under the influence of potential occurrence of traffic accidents.

Contents of Chapters

Chapter 1 provides introductory information related to this research, including research background and motivations, research purposes, terminology, research features, and contributions. Literature review is given in Chapter 2, and data are explained in Chapter 3, where the smartphone app *Safety Supporter* is also described. Here, other chapters are briefly illustrated.

Chapters 4 – 6 are prepared for the first research purpose, and Chapters 6 – 7 for the second research purpose, where Chapter 6 connects the two research purposes via avoidance behavior analysis.

Chapter 4 focuses on short-term effects of the smartphone app on second-by-second driving risks, where various functions of the app are emphasized. First, effects of the app *Safety Supporter* on driver's over-speeding behavior are evaluated based on the ZINBR model, where heterogeneity across drivers is reflected in terms of behavioral change stages related to driving safety. Second, drivers' compliance of speed limit and control behavior of acceleration and deceleration are jointly estimated by employing the BOP model to explicitly accommodate the influence of correlations between the two driving behaviors. Totally, 187,549 epochs (calculated every two seconds) were extracted from 201 trips made by 15 drivers. Model estimation results suggest that in the short term, the *Safety Supporter* may encourage most drivers to be in compliance with speed limit, but its effect on acceleration/deceleration and driving stability are limited. The effects of some additional functions of the app on improvement in driving risks are mixed. It is further revealed that drivers' heterogeneous driving propensity should be properly considered when deploying individualized traffic safety measures in practice.

Chapter 5 deals with drivers' safe driving performance at the trip level. Here, an extensive set of behaviors related to driving safety are targeted, including driving risks measured by violation rates of speed limit compliance, acceleration/deceleration control, and driving stability, multitasking behaviors and affective experiences (measured in terms of different moods) during driving. To reflect potential correlations and behavioral dependencies existing in the above behaviors, the SURE model is adopted. As a result of data matching and cleaning, 353 trips made by 13 drivers were extracted for this analysis. Analysis results confirm the significant long-term influencing impact of the *Safety Supporter*. The importance of driving safety self-recognition is confirmed. It is necessary to incorporate subjective well-being factors and multitasking behavior during driving in driving risk studies.

With the results from Chapters 4 and 5, it is further revealed that some of the effects on driving performance are not consistent with the two measurement scales: i.e., second-by-second and trip levels. This suggests the necessity of paying sufficient attention to the measurement scale in evaluating traffic safety measures for avoiding any misleading policies. Nevertheless, it is found that the developed app is surely effective to improve driving safety, especially in terms of speed limit compliance, and a relatively high level of acceptance of using such apps in future is also confirmed.

Chapter 6 focuses on drivers' avoidance behaviors from two perspectives by responding to their internal risks (measured in terms of speed limit compliance, acceleration/deceleration control, and driving stability) and external risks (measured in terms of uncertain travel time on different driving routes caused by the potential occurrence of traffic accidents).

- As for drivers' internal risks, four types of driving avoidance behaviors, including punishment avoidance behavior, weather-related avoidance, traffic-related avoidance, and riding avoidance are targeted and their associations with affective experiences and multitasking behavior during driving, and three driving risk indicators are jointly estimated by using the SURE model. Results show that driving avoidance behaviors are statistically affected by speed limit compliance, driving stability, bad moods during driving, and multitasking behaviors in terms of mental distraction and radio operation. It is further revealed that the four types of driving avoidance behaviors also significantly influence driving risks, especially speed limit compliance level.
- Concerning drivers' external risks, a case study is conducted regarding choices of truck driving routes in the Chugoku Region of Japan, called Chugoku Expressway and Sanyo Expressway, which have different levels of both traffic accidents and the resulting congestion. Based on a combined revealed preference (RP) and SP questionnaire survey conducted in 2014 and 2015, totally, 525 valid observations on choices of truck driving routes obtained from 54 companies (a manager of truck operation and several truck drivers from each company) with respect to different SP scenarios. The BP model is employed to jointly estimate the potential factors that would significantly influence both company managers' and drivers' decisions on choosing expressway routes for avoiding risks caused by uncertain travel time. Model estimation results indicate that for truck drivers who frequently use expressways, avoidance behavior are significantly influenced by types of insurances purchased by

their companies, and their experiences of encountering serious traffic congestion and traffic accidents. In contrast, the avoidance behavior of company managers is more likely to be influenced by the factors of road congestion information, characteristics of delivery goods (especially, fragile goods), and incentives of avoiding use of congested routes.

Chapter 7 provides evidence on drivers' travel choice behaviors by adapting to the occurrence of traffic accidents for mitigating the resulting impacts. Here, the adaptation behavior is classified into no change in behavior; changes with respect to departure time, driving route, travel mode, and/or wait and see behavior on expressway; and trip cancelation, depending on three major decision contexts: before departure, on the way to expressway, and on expressway. The following dynamic traffic-related information attributes are defined by reflecting each driver's personal tastes: accident condition factors (relative location and severity of traffic accidents), accident impact factors (queue length and changes due to accident-induced congestion), alternative routes or travel modes, and traffic management factors (traffic regulation, estimated clearance time of congestion, estimation accuracy of clearance time, probability of clearing away the congestion at a certain length of clearance time, and clearance time provision method). For this part of this thesis study, an SP survey was implemented by collecting 30,000 SP responses from 2,500 expressway drivers. Analyses based on the NL model first found that interval values (rather than point-based values) of clearance time of traffic congestion play a considerably larger role in influencing drivers' adaptation behavior than other information contents and especially, the influences become larger and larger moving from "before departure" to "on the way to expressway" and to "on expressway". To further confirm the effectiveness of provided information by reflecting drivers' heterogeneous responses, a new concept of travel information style was proposed. As a result of the K-means cluster analysis, three types of travel information styles are derived: high dependence on information for relatively inflexible trip-making, high dependence on experience for risky trips, and least information users by investigating an extensive set of travel information search and usage items collected from the RP survey. Analysis results show that driver's behavioral responses among three information styles are considerably different under different decision contexts. Context-sensitive travel information targeting drivers with different travel information styles should be provided in the traffic management practice.

Chapter 8 summarizes the findings, implications, limitations of this thesis, and directions for future research.

Major findings

(1) Findings related to the first research purpose

Data and modeling analysis results have revealed both positive and negative evidence on promoting use of smartphone apps in traffic safety practices, where positive evidence is more prevalent. More evidence supporting the use of smartphone apps is found with respect to improving drivers' compliance of speed limits, by comparing with acceleration/deceleration and stable driving control behaviors. Furthermore, it is revealed that there are complicated associations between driving risks, affective experience and multitasking during driving as well as driving avoidance behaviors. However, evidence is mixed depending on different types of driving propensities and measurement scales of driving risks. All the above results re-confirm the importance and necessity of as well as difficulties in reflecting drivers' various heterogeneities (measured in terms of both objective attributes and subjective attributes) in traffic safety measures. Such findings implies that policy makers may need to encourage more risky drivers in traffic safety practices by considering drivers' values perceived in participating in policymaking via effective communication means.

(2) Findings related to the second research purpose

Drivers' adaptation behaviors to the occurrence of traffic accidents on expressways are context-sensitive in terms of drivers' decision timings. The adaptations further vary with drivers' travel information styles measured by the dependence level on information and types of trips. It is revealed that interval values (rather than point-based values) of clearance time of traffic congestion play a much larger role in influencing drivers' adaptation behavior to abnormal driving situations caused by traffic accidents than other information contents. Especially, the role grows before departure to on expressway. The distance to the accident, information of no fatal accident, queue length, information of no traffic regulation, clearance time accuracy, and queue decreasing trend are found to commonly affect adaptation behaviors, and influences of fatal accident information, clearance time, trip purpose, and clearance time interval information are significantly different across drivers' decision timings.

Major contributions

This is the first empirical research in literature to explore the roles of information provision in mitigating multi-faceted driving risks and the impacts of traffic accidents on travel choices in a consistent and comprehensive way. Major contributions are summarized as follows.

- Methodological contributions
  - Methodology of driving risk analysis: This study proposes a conceptual framework of various driving risks and relevant factors (both objective and subjective factors) over the whole driving decision-making process (i.e., before driving, during driving, and after driving), where the whole process of behavioral changes related to safe driving is also incorporated. This is the first study in literature to explore the role of subjective well-being factors in traffic safety studies.

- Methodology of truck driving route choices with group decision-making mechanisms: As avoidance behavior in the context of truck driving route choice, different from passenger drivers, truck driving route choices might be decided by truck drivers and/or their company managers. Therefore, it is necessary to properly reflect such group decision-making mechanisms in the analysis. For this, a bivariate probit model is employed to capture correlations existing in choice decisions by truck drivers and managers.
- Methodology of adaptation behavior analysis under the influence of dynamic information: Under the occurrence of traffic accidents on expressways, drivers may show heterogeneous responses in terms of their adaptation behavior. Such heterogeneities should be reflected not only in modeling analyses, but also in behavior surveys. In line with such considerations, this study first designed a large-scale stated preference (SP) survey by setting SP attributes based on each driver's diverse preferences for different types of travel information and his/her actual expressway usage experiences. And then, a new concept of travel information style is proposed and three information types are empirically derived: high dependence on information for relatively inflexible trip-making, high dependence on experience for risky trips, and least information users.

· Contributions to policymaking
  - Smartphone apps with driving risk diagnosis and information provision functions may contribute to the improvement of traffic safety, especially in terms of speed limit compliance, if drivers' various heterogeneities can be properly reflected in practical deployment and if use of smartphone during driving can be effectively prohibited. This is the first study in literature to examine whether smartphone apps should be promoted in traffic safety practices.

- There is no need to fully stop all multitasking behaviors during driving, because some tasks during driving (e.g., listening to music, talking with passengers) may be helpful for some drivers to mitigate the boringness of driving.
- Information assisting truck driving route choices should be provided to not only drivers, but also company managers. It is further revealed that insurance for covering wrecker fees in case of traffic accidents occurring on an inconvenient (or less favored by most drivers) route shows a significantly larger influence on driving route choices than other factors. This implies that traffic management for making full use of different routes should take the potential occurrence of traffic accidents on inconvenient routes into account.
- Information provision for assisting drivers' adaptation behavior under the occurrence of traffic accidents on expressways should also take drivers' heterogeneities and decision timings into account. As for detailed information contents, interval-based information about clearance time of traffic congestion caused by accidents is more preferred by drivers than the point-based information with prediction probability.
- Even though ICT technologies and services are expected as the next-generation of traffic safety measures, the role of traditional enforcement of traffic rules (here, punishments of traffic rule violations) should not be ignored.

· Data collection
  - This study has collected a series of original survey data for better understanding drivers' behavioral changes in response to dynamic information provision in the context of driving risk analysis in a comprehensive way by developing a GPS-enabled smartphone app and implementing a three-month driving experiment on expressways.

- This is the first study in literature to reflect each driver's heterogeneous preference in a large-scale stated preference survey in the context of drivers' adaptation behavior to the occurrence of traffic accidents on expressways.

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Chapter 1

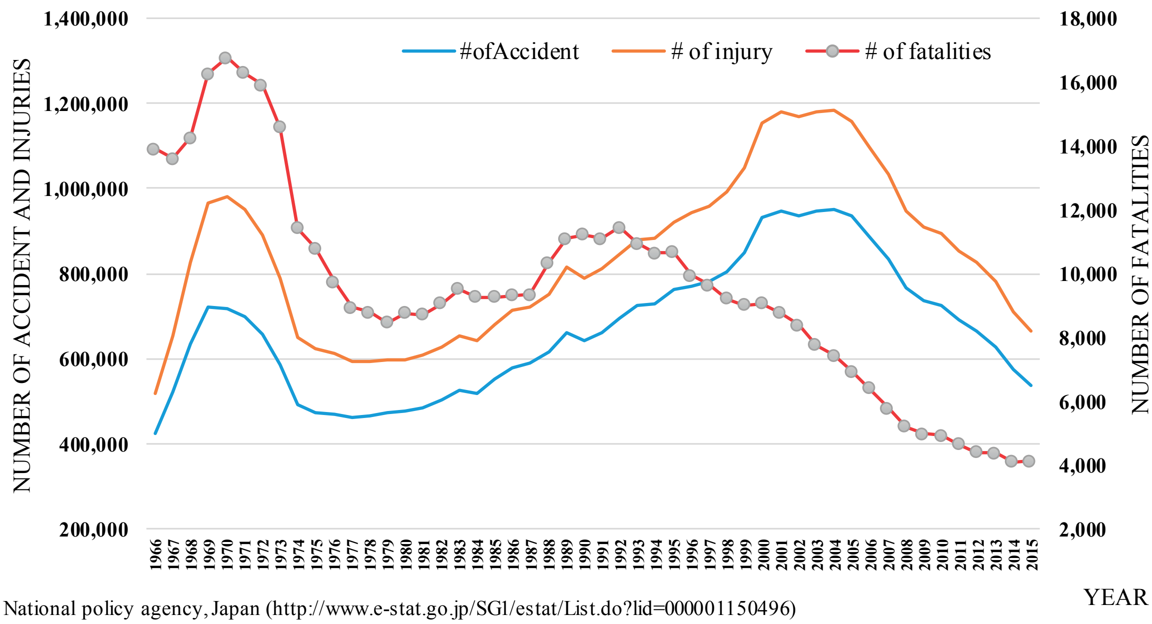
Introduction

1.1 Background

According to WHO (2015), traffic fatalities have exceeded 1.2 million per year since 2007, resulting in huge impacts on human health and economic development. Traffic fatalities are the leading cause of death among young people aged between 15 and 29 years. Economic losses due to traffic fatalities account for 3% of GDP on average at the global level, but 5% in low- and middle-income countries. Moreover, the world population increased by 4% between 2010 and 2013, and the global vehicle registrations increased by 16%. The plateaued road traffic deaths since 2007 has shown a comparative improvement in road safety status; however, actions to combat this global challenge are still insufficient and the pace of change is too slow.

Focusing on traffic accidents in Japan (see Figure 1-1), the highest number of traffic fatalities (16,765) was observed in 1970. Since then, the fatalities have declined gradually and the number of fatalities decreased to 4,117 in 2015, which is 25% of the highest number in 1970. This level is almost equal to that in 1950 (i.e., 4,202). This means that increase from the 4,000 scale of fatalities to the highest number of 16,765 took about 20 years; however, decrease from the highest number to the same 4,000 scale took more than 45 years. This illustrates the difficulties in reducing traffic accidents in reality vividly.

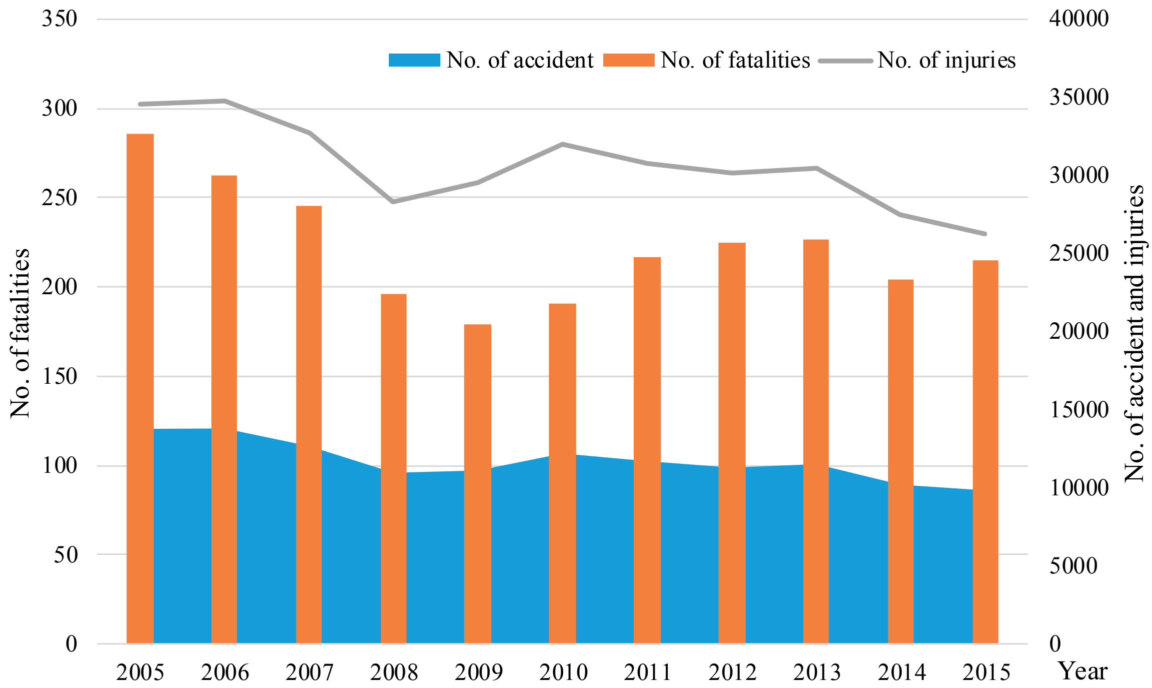
By taking a panoramic view of the evolution process of accidents and injuries, two significant decreasing points were achieved in the history of traffic safety measures in Japan. The first remarkable improvement was identified during the period 1970-1977 through substantial construction of safety infrastructure. The second significant decline of traffic fatalities have been observed, especially since the late 1990s when various ITS technologies have been actively developed and deployed together with enforcement of traffic safety laws and rules.



National policy agency, Japan (http://www.e-stat.go.jp/SG1/estat/List.do?lid=000001150496)

Figure 1-1 Traffic accidents in Japan (1966-2015)

Different from the above trend, traffic fatalities on expressways in Japan have increased since 2010, as shown in Figure 1-2. Once a traffic accident occurs on expressway, it often results in not only damages to human lives and properties, but also serious congestion and the resulting huge amount of travel time losses of many drivers (e.g., Jiang et al., 2013a). The accident sometimes causes secondary accidents, which may further worsen the congestion.



National policy agency, Japan (http://www.e-stat.go.jp/SG1/estat/List.do?lid=000001150496)

Figure 1-2 Traffic accidents on expressways in Japan (2005-2015)

Traffic accidents are mainly caused by human errors (e.g., Parker et al., 1995; Verschuur and Hurts, 2008), which may differ across divers. A driver may cause different types of accidents due to the same error. Different errors may lead to the same type of accidents. These suggests the existence of heterogeneity in the causes and outcomes of traffic accidents and consequently the necessity of taking individualized traffic safety measures (by reflecting each driver's specific characteristics). Moreover, one can see that what public sectors, firms, and communities and so on can assist drivers to improve their driving safety is limited. Policy makers should shift their policies directed toward individual drivers, rather than general drivers. It is essential how to reflect individual drivers' heterogeneity into traffic safety policy decisions from both outcomes and causes. Therefore, it becomes important to explore what kinds of individualized measures to prevent the occurrence of accidents are more effective. Especially, it has been a considerably difficult challenge how to effectively implement these measures, considering temporally decaying effects of the measures and drivers' willingness to accept and follow the measures.

Unfortunately, efforts of individualized traffic accidents prevention measures are still very limited. For example, in Japan, traffic safety education starts from elementary schools, meaning that almost all Japanese people have been educated. Drivers are also required to update their driving licenses regularly (every 3 – 5 years, depending on the type of driving license and experience of causing traffic accidents), where traffic safety training (video-based and guidance by instructors) is provided with general information about traffic accidents and safety measures with respect to an arbitrary group of drivers for about 30 – 120 minutes each time. However, the effects of such undifferentiated education on the prevention of traffic accidents are questionable. Community-based traffic safety education initiated by local police agencies and/or local residents is popular, especially for children, young people and elderly people, but the problems are that participants are limited and really risky drivers do not participate, as expected. Traffic safety campaigns have been deployed in spring and fall every year with respect to the general public, not each individual driver. As for road-related traffic safety measures, road-side and on-road traffic signs and variable message signs shown on road-side electronic boards are dominating, but once drivers become familiar with them, the effects of preventing the occurrence of traffic accidents decay. Again, these measures are provided to the general public, not each individual driver. Effects of all the above measures may be further worsened by the fact that drivers' safety consciousness may change as time passes due to a variety of reasons from both internal and external environments.

1.2 Motivations

In reality, even though various traffic safety countermeasures have been taken, we are still considerably far away from a zero-accident society. This is mainly because most traffic accidents are caused by human errors, which are difficult to be eliminated. It is therefore becoming more and more important how to reduce traffic accidents, focusing on drivers' internal driving behaviors towards various potential driving risks. Drivers' voluntary behavioral changes are essential for further reducing traffic accidents; however, even for such voluntary behavioral changes, external interventions are indispensable, such as safety education, punishment to traffic rule violation, and information provision via road signs and ICT (information and communication technologies) devices.

Especially, it is expected that effective countermeasures of ITS-based equipped with function of real-time accident information provision may play extremely important roles in mitigating the potential negative impacts by warning drivers about dangerous situations in advance, assisting them to shift to an alternative route, and/or modifying their experienced-based travel decisions (Bonsall, 2000; Ali et al., 2008; Ambak et al., 2009). Levinson (2003) argued that the greatest contributing effect of travel information in time-savings can be expected when non-recurring congestion occurs due to incidents. Recently, impacts of information provision on driver's adaptation behaviors under uncertain situations caused by traffic accidents have received an increasing attention (Zhang et al., 2009; Kusakabe et al., 2012; Chien et al., 2013; Jou and Cheng, 2013). Jou et al. (2005) confirmed that dynamic travel time prediction is the main type of information requested for non-recurring conditions. It is revealed that improper information provision could deteriorate the traffic situation and lead to additional problems such as oversaturation, overreaction, and concentration (Wahle et al., 2002). Therefore, studies on how to provide valuable information in a proper way and whether or not to display the reliability information to drivers become more and more important (Ramos et al., 2012). Moreover, it is still an unresolved issue how to meet drivers' personal information styles (searching and usage preference) for their decisions on safe driving and time delay avoiding, since drivers may show heterogeneous responses to the information provided (Kiefera et al., 2005; Maltz and Shinar, 2007; Zhang et al., 2013).

Mobile phone, a rapidly-growing ICT device, can be directly connected to individuals via GPS, social media (e.g., Facebook, SNS, LINE), and voice function etc., which may be used to assist a driver to improve his/her risk recognition, judgment, and/or vehicle operation. Especially, GPS equipped smartphones have provided a low-cost means to measure travel time, acquire instantaneous vehicle speeds, and estimate safety performance on the road (Astarita et al., 2014). High proportion of the GPS based smartphone usage has provide another data sensing technique with better coverage of the transportation network than current sensor technology (Herrera and Bayen, 2010; Kafi et al., 2013; Steen-Bruggen et al., 2013). In this sense, policy makers are interested in using mobile devices, including smartphones, to collect information for traffic control and management as well as road maintenance, e.g., travel time measurement and prediction, measurement of road roughness for maintenance (Zhang et al., 2014).

The role of information in human decision-making is well-known. However, the same information does not necessarily influence human decision in a same (or similar) way across various information provision context. Just like the role of the concept of lifestyle in various human decisions, it is expected that travel information style may play a significant role in the context of this study, i.e., drivers' behavioral responses to the occurrence of traffic accidents on expressways. However, the role of travel information style in drivers' choice behaviors has been under-researched in literature. In line with this consideration, it is very important to identify typical travel information styles and to clarify how drivers with different information styles adapt differently to uncertain situations caused by traffic accidents on expressways.

1.3 Research purposes

The purposes of this study are twofold. The first purpose is to mitigate driving risks by focusing on the role of contradictory use of smartphones, and the second is to mitigate the impacts of traffic accidents on drivers' travel choices. Both purposes further focus on dynamic traffic information provision on expressways in Japan.

For the first purpose, this study examines whether smartphone apps with diagnosis functions of driving risks and dynamic information provision should be promoted or not by targeting drivers' internal driving risks. Concretely speaking, a simplified GPS-enabled smartphone app was first developed with functions of second-by-second driving risk diagnosis and dynamic information provision about blackspots on expressways. In order to identify better functions of such apps, additional functions were further developed. With this app, a three-month driving experiment was implemented on expressways in the Chugoku region of Japan in February ~ May, 2014 by inviting 100 drivers who frequently used the target expressways. During the experiment, a series of questionnaires were also conducted to collect information for evaluating the effectiveness of the developed app as a cost-effective individualized traffic safety measure. To the best of the author's knowledge, this study makes the first initial in literature from the above perspective.

As for the second purpose, this study clarifies drivers' adaptation and avoidance behaviors under the influence of dynamic information provision by targeting drivers' external driving risks. Concretely speaking, here, this study investigates how drivers adapt their behavior to the traffic accidents in different decision scenes with the help of dynamic travel information.

For this purpose, a large-scale stated preference (SP) survey (2,500 persons, 30,000 SP responses) was conducted in 2012 with respect to expressway users in a part of the western Japan. Especially, reflecting each driver's heterogeneous information tastes in such a large-scale SP survey is rare in literature.

To connect the above two research purposes, avoidance behavior analyses are further given. Here, two types of avoidance behaviors are defined: one from drivers' internal aspects and the other from their external aspects. The first type is further classified into punishment avoidance behavior, weather avoidance, traffic avoidance, and riding avoidance, and avoidance of driving on expressways. The second type is captured in two ways: one as a part of general adaptation behavior against the occurrence of traffic accidents on expressways, and the other as a choice strategy to avoid driving risks caused by drivers' external factors.

1.4 Terminology

1.4.1 Multi-faceted driving risks

Driving risks include both internal and external risks, which may all lead drivers to be involved into a traffic accident/incident.

Internal driving risks refer to driving risks that are directly associated with a driver. The risks may be directly caused by the driver him/herself, or triggered by the surrounding traffic, where the vehicle is under control of the drivers. These risks include both objective and subjective risks. In this study, objective risks are measured directly from driver's behaviors while driving in terms of speed control, multitasking, and avoidance of driving, etc. In this study, speed control behaviors refer to compliance to the speed limit, acceleration and deceleration, and speed stability within a certain period. Subjective driving risks are associated with driver's safety awareness, attitudes, norms, and driving habits. Driving propensity, and affective experience while driving are two examples of subjective risks, targeted in this study. It is expected that objective and subjective driving risks may be interrelated. Their correlations should be properly reflected in traffic safety studies.

External driving risks refer to those risks mainly coming from traffic accidents (black spots) or near-miss incidents (this may be called grey spots) occurring in the past. These risks may lead drivers to be involved in accidents passively. In this study, black spots are defined as those locations (e.g., sharp curves, steep slopes, and complicated intersections) where traffic accidents had occurred often in the past. As for near-miss incidents, for example, maps of near-miss incidents have been provided to the general public in many areas of Japan, where information about various types of near-miss incidents identified from various data sources is available[1]. In this study, only black spots are focused on, which are provided to drivers as traffic warning information via the developed smartphone app.

1.4.2 Temporal effects

In this study, temporal effects are evaluated with respect to the developed app in terms of potential driving safety improvements. The developed app may first affect drivers' second-by-second judgments about driving because of feedback of driving safety diagnosis results and the corresponding driving safety advices. As a result of accumulation of such influences over time, the app may further affect driving behavior at a trip level and even ultimately affect driving habits over a much longer period. This study classifies such temporal effects into short-term and long-term effects. Short-term effects refer to those at a second-by-second level, while long-

[1] The following are some examples (Accessed July 26, 2016):
https://www.cgr.mlit.go.jp/hirokoku/pdf/HiyariMAP_Hiroshimaken_ver/hirokoku_H20_4area.PDF;
http://www.cgr.mlit.go.jp/okakoku/hiyari/okayama-tamano/area-a.html
http://www.adclub.jp/aichi/hiyarihatto_nagoya_2015.html

term effects indicate those observed at a trip level, considering that data available to this study only cover information about driving behavior over three months. Long-term effects over a longer period are left as a future research issues.

1.4.3 Subjective well-being

OECD (2013) introduced a relative broad definition of subjective well-being (SWB) as "good mental states, including all of the various evaluations, positive and negative, that people make of their lives and the affective reactions of people to their experiences". SWB is a broad concept to understand human behavior and life (Kahneman and Krueger, 2006; Diener, 2009).

Zhang (2009) argued the importance of studying the subjective well-being in transportation from the perspectives of both activity-travel behavior analysis and policy-making, as follows:

> *"In the activity-travel behavior analysis, travelers' actual choices are often represented based on the assumption of utility maximization. However, travelers' actual choices do not necessarily reflect their true preference. It has also been arbitrarily assumed that travelers derive negative utility from trip-making and positive utility from activity participation. Such assumption has its rationality considering the fact that the utility is a relative concept; however, it has not been empirically verified. It is expected that the concept of subjective well-being could provide some hints to support or relax the above assumptions in the activity-travel behavior analysis. On the other hand, policy makers are interested in knowing how policies could improve the people's quality of life (QOL), which can be measured by the subjective well-being to reflect the overall self-appraisal about various aspects of lives."*

In case of SWB while driving, in this thesis, it is measured by driver's affective experiences. Based on the method proposed by Kahneman et al. (2004), affective experience while driving is captured with shares of different moods during the whole drive, including good mood, pleasant, low, and bad mood (sum up to 100% totally). This measurement is a part of day reconstruction method (DRM) proposed by Kahneman et al. (2004), and it is detailed as follows in a questionnaire form.

We would like to know how you feel and what mood you are in when you are at doing ….	
When you are doing …, what percentage of the time are you	
in a bad mood	____%
a little low or irritable	____%
in a mildly pleasant mood	____%
in a very good mood	____%
	Sum 100%

1.4.4 Driving propensity

In Japan, driving propensity diagnosis and advice on safe driving are standard components of driver education programs that drivers are required to undertake when they renew their driving license (every 3–5 years, depending on the type of driving license and their traffic accident record). Besides the objective driving performances, different drivers may have different driving propensities and consequently respond differently to traffic measures. Driving propensity indicates a peculiar latent attitude or a kind of habit that are inherent to drivers (Kusuhashi et al., 2012). According to Japan Traffic Safety Association (2006), driving propensities can be classified into 6 types based on 27 question items as follows:

(1) Irritable driving: Drivers tend to be annoyed with other vehicles or pedestrians and drive with high stress. It is the case if four or more out of eight items targeted are selected.

(2) Careless driving: Drivers tend to frequently encounter dangerous driving experience during driving. It refers to the case that three or more out of nine items are selected.

(3) Aggressive driving: Drivers tend to make unnecessary lane changes during driving. If one or more out of three items targeted are selected, the driving is judged to be aggressive.

(4) Excessively-confident driving: Drivers tend to drive with excessive self-confidence. If none of targeted seven items are selected, the driving is judged to excessively confident.

(5) Indecisive driving: Drivers tend to drive with hesitation and insufficient confidence. If four or more out of the target items in the above (4) are fitted, the driving is indecisive.

(6) Safe driving nature: Drivers tend to drive calmly in a balanced way. None of the above types are identified.

1.4.5 Avoidance behaviors

In Mosby's Dental Dictionary (2008), avoidance behavior is defined as a conscious or unconscious defense mechanism by which a person tries to escape from unpleasant situations or feelings, such as anxiety and pain. In reality, drivers may sometimes avoid driving. For example, some less-confidential drivers may avoid driving on expressways. Concretely speaking, two types of avoidance behaviors have been discussed in this thesis with regard to drivers' avoidance behaviors from drivers' internal and external aspects (Liourta and Empelen, 2008; Scott-Parker et al., 2014; Motak et al., 2014). The first type from drivers internal aspects is further classified into punishment avoidance behavior, weather avoidance, traffic avoidance, and riding avoidance (Stewart and Peter, 2004). Driving avoidance from the external aspects is captured in two ways: one as a part of general adaptation behavior against the occurrence of traffic accidents on expressways, and the other as a choice strategy to avoid driving risks caused by drivers' external factors. (Motak et al., 2014; Naumann et al., 2011) The latter is called situational avoidance.

1.4.6 Context dependence

Drivers' travel decisions usually involve a number of choices made under different contexts over time and across space. Consideration of individual's locational contexts and time pressures or constrains are very important from the viewpoint of effective information provision. Here, focusing on accident-related information provision on expressway, impacts of time pressure (Xu et al., 2011) derived from different trip purposes on drivers' adaption behaviors should not ignored. In this study, such context dependence is reflected by targeting two types of trips: one with strong time constraint and the other without strong time constraints. In terms of the location context when drivers are going to receive the provided information, three different locations are considered: before departure of a trip, on the way to expressway, and on expressway.

1.4.7 Adaptation behaviors

Under the information provision of accident occurrence and/or related assistant information (e.g. substitute travel mode and travel route, and accident severity and impact information), drivers may change their original planed behavior and adapt to the information provided.

Related to adaptation behaviors, this study focuses on accident-related information provision on expressway. Different locational contexts are considered for representing driver's behavioral adaptations, where three decision-making scenes are targeted: before departure of a trip, on the way to expressway, and on expressway. For scenes of "before departure" and "on the way to expressway", a same choice set of adaptation alternatives is considered. Drivers can choose to change departure time, change to ordinary road, change to other travel mode, cancel the trip, or insist on original trip plane. As for the "on expressway" scene, beside the original trip plan insisting, more adaptation alternatives are optional for drivers under this context, including wait & see at nearby SA/PA, change to alternative expressway, detour via ordinary road, change to ordinary road, change to other travel mode, or cancel the trip.

1.4.8 Travel information style

This study examines the roles of travel information in changing people's driving behavior from a safety perspective. Information is essential to all human decisions, while human decisions are not the same across individuals. Different people may treat the same information differently. A same person may use the same information for making different decisions. Related to this study, even same information is provided to drivers under the same context, drivers' decision making may not exactly the same.

For information searching, decision makers may search from various sources via various tools. In the transportation field, various ITS technologies have been developed and provided users with more and more options, such as public information sources from radio, road-side variable message signs (VMS), and mobile ICT devices. In reality, there are too many information sources, which contain similar and/or different contents. Because of limited information processing ability, people cannot treat a large set of information from a large number of sources and usually have to simplify information processing. For this, different people have different ways for such simplification by considering their personal interests in information, accessibility to information, information processing experiences and habits, attitudes toward different types and sources of information, etc. Just like the role of lifestyle concept in various human decisions, it can be assumed that travel information style may also exist and play various significant roles in the context of this study.

This study examines the concept of travel information style in the context of drivers' behavioral adaptations to the occurrence of traffic accidents on expressways. Moreover, in reality, it is more useful to represent individual driver's heterogeneous behavioral responses captured from typical patterns of information needs and preference. With this consideration, the concept of travel information style is proposed in this study. Detail definition and proposal of the travel information style concept is introduced in the later part of Subsection 7.3.1.

1.4.9 Heterogeneity

Human behaviors are not the same, i.e., heterogeneous. Heterogeneity is an essential behavioral phenomenon in human decisions. Different persons may not behave in the same way. A same person may make a same decision differently from time to time or from context to context. In this sense, heterogeneity may exist across individuals on one hand, while it may also exist with respect to a same person on the other. This is also true to driving behaviors. Such heterogeneity is usually divided into observed and unobserved heterogeneities.

Observed heterogeneity can be captured by using, for example, individual attributes (e.g., age, gender, income, and job type). Observed heterogeneity may also exist with regard to decision/behavior itself. For example, if a person commutes by different modes on different days, observed heterogeneity exists.

Unobserved heterogeneity is caused by factors that are not observed or cannot be observed via surveys. The existence of unobserved heterogeneity usually makes the representation of human decisions difficult, because unobserved heterogeneity is generally captured using error terms. In many cases, the existence of unobserved heterogeneity usually leads to complicated structures of error terms, making decision models difficult to be operationalized.

1.4.10 Traffic Information

Traffic information includes both dynamic and static information, which are expected to affect driving behavior differently.

Dynamic information targeted in this thesis refers to,

- Information for mitigating internal driving risks: Blackspot warning information (via both voice and image) provided to drivers during driving when approaching each blackspot, and information of service area (SA) or parking area (PA) when driving for a certain length of time
- Information for adapting to the occurrence of traffic accidents (i.e., external driving risks): Accident condition information (e.g. location of accident spot and accident severity), accident impact information (e.g. queue length and queue changing trend), availability of alternative route or travel mode information, as well as traffic measurement information, e.g. traffic regulation, congestion clearance time with probability.

Static information includes,

- Information for mitigating internal driving risks: Advices for safer driving based on diagnosis results via the app after each trip, online traffic safety education campaign information, etc.
- Information for avoidance of driving: Different levels of travel time and frequency of traffic congestion associated with the potential occurrence of traffic accident

1.5 Features of this study

1.5.1 Data collection

Focusing on the first research purpose, a GSP-enabled smartphone app was first developed with simplified functions of driving risk diagnosis and dynamic information provision, and then a three-month driving experiment by inviting 100 drivers was implemented together with a series of questionnaire surveys for capturing actual behavioral changes due to the use of the app. Targeting the second research purpose, a large-scale stated preference (SP) survey with 30,000 samples collected from 2,500 drivers was first conducted, where SP attributes were given by reflecting each driver's heterogeneous preference for information provision. And then, one more survey was carried out by focusing on truck drivers' route choices under the influence of potential traffic accidents, where truck drivers' employers' preferences are reflected (525 SP observations from 58 company managers and 186 drivers).

1.5.2 Modeling analysis

As for the first research purpose, driving risks are first measured in terms of over-speeding and compliance of speed limit, acceleration and deceleration, and driving stability at second-by-second and trip levels. And then driving risks are represented by a zero-inflated negative binomial regression (ZINBR) model, a bivariate ordered probit (BOP) model, a multilevel ordered probit (MOP) model, and a seemingly uncorrelated regression (SUR) model. With these models, discreteness and continuity, nonlinearity, and multiple correlations (with respect to driving risks and multitasking behaviors during driving, and subjective well-being indicators) existing in data measuring multi-faceted driving risks are explicitly incorporated.

Concerning the second research purpose, a nested logit (NL) model is first adopted to describe drivers' adaptation behavior changes under the influence of dynamic accident-related information provision. Second, a K-means cluster analysis is utilized to identify drivers' heterogeneous travel information styles relating to adaptation behavior. Third, a bivariate probit (BP) model is employed to investigate joint choices of truck company managers and drivers with respect to driving routes under the influence of potential occurrence of traffic accidents.

1.6 Contributions

This is the first empirical research in literature to explore the roles of information provision in mitigating multi-faceted driving risks and the impacts of traffic accidents on travel choices in a consistent and comprehensive way. Major contributions are summarized from the perspectives of methodologies and policies.

1.6.1. Methodological contributions

There are various methodological challenges related to this study. Methodological contributions of this thesis can be summarized below.

(1) Methodology of driving risk analysis

This study proposes a conceptual framework of various driving risks and relevant factors (both objective and subjective factors) over the whole driving decision-making process (i.e., before driving, during driving, and after driving), where the whole process of behavioral changes related to safe driving is also incorporated. All the above attributes are captured in a series of questionnaires answered by same respondents at different points in time over the whole period of the three-month driving experiment.

- Before-driving attributes include aberrant driving behavior, driving tasks, driving skills, driving avoidance behavior, experiences of traffic accidents and fatigue driving, attributes about the whole process of behavioral changes (e.g., social norms, attitudes, intention to drive safely, and behavioral change stages of safe driving), and self-evaluation of driving safety before using the app.
- During-driving attributes include three driving risks measured using the app, multitasking behavior and affective experience (captured within the theory of subjective well-being) during driving. Especially, this is the first study in literature to explore the role of subjective well-being factors in traffic safety studies.
- After-driving attributes include self-evaluation of driving safety, ranking of driving safety among drivers participating in the experiment, avoidance behavior, driving tasks, driving skills, and attributes about the whole process of behavioral changes (e.g., social norms, attitudes, intention to drive safely, and behavioral change stages of safe driving).

(2) Methodology of truck driving route choices with group decision-making mechanisms

As avoidance behavior in the context of truck driving route choice, different from passenger drivers, truck driving route choices might be decided by truck drivers and/or their company managers. Therefore, it is necessary to properly reflect such group decision-making mechanisms in the analysis. For this, a bivariate probit model is employed to capture correlations existing in choice decisions by truck drivers and managers.

(3) Methodology of adaptation behavior analysis under the influence of dynamic information

Under the occurrence of traffic accidents on expressways, drivers may show heterogeneous responses in terms of their adaptation behavior. Such heterogeneities should be reflected not only in modeling analyses, but also in behavior surveys. In line with such considerations, this study first designed a large-scale stated preference (SP) survey by setting SP attributes based on each driver's diverse preferences for different types of travel information and his/her actual expressway usage experiences. And then, a new concept of travel information style is proposed by three categories of factors: (1) situations under which information search on expressways had to be done, (2) time use and frequency of information search, and (3) travel information preference.

1.6.2. Policy contributions

This is the first study in literature to examine whether smartphone apps should be promoted in traffic safety practices by investigating not only driving performance indicators and their influential factors, but also drivers' acceptance of such apps as both a driving risk diagnosis tool and a Big Data collection tool for traffic management.

Contributions via the development of the smartphone app

For this study, a GPS-enabled smartphone app (i.e., *Safety Supporter*) was developed. The basic functions in the app include driving risk diagnosis, information provision of blackspots on expressways, and feedbacks of advices about safer driving by reflecting diagnosis results. Additional functions further contain SA/PA information, ranking of driving safety level among drivers participating in the driving experiment, traffic safety campaign information, and driving propensity diagnosis. The app was designed not only as a tool of driving risk diagnosis and information provision, but also as a Big Data collection tool for traffic management, in a cost-effective and sustainable way. As a diagnosis tool, drivers can measure their driving risks at any time and at any place. Easily accessible feedbacks of diagnosis and advices allow the app to also serve as a driving safety education tool. The good feature of such a Big Data collection tool is that it is designed based on a “give & take” (i.e., win-win) mechanism between information service providers and receivers.

Contributions to policymaking

- Smartphone apps with driving risk diagnosis and information provision functions may contribute to the improvement of traffic safety, especially in terms of speed limit compliance, if drivers’ various heterogeneities can be properly reflected in practical deployment and if use of smartphone during driving can be effectively prohibited. One implication might be to develop more advanced technologies that allow drivers to choose the app functions based on their own preference, and to operate phone, radio, and/or navigation system more safely via voice control.
- There is no need to fully stop all multitasking behaviors during driving, because some tasks during driving (e.g., listening to music, talking with passengers) may be helpful for some drivers to mitigate the boringness of driving. However, operation of phone, radio, and/or navigation system without enough attention to surrounding traffic is clearly dangerous.
- In recent years, developments of autonomous vehicles have attracting an increasing attention of auto makers and ICT companies and so on. These new developments should be promoted; however, it is still far from actual deployment in the mass market. Finally, reducing dependence on car in people’s daily life is more essential to dramatically reduce traffic accidents.

- Revealed joint decisions between truck company managers and drivers suggest that information assisting truck driving route choices should be provided to not only drivers, but also company managers. This is clearly different from information provision to passenger drivers. It is further revealed that insurance for covering wrecker fees in case of traffic accidents occurring on an inconvenient (or less favored by most drivers) route shows a significantly larger influence on driving route choices than other factors. This implies that traffic management for making full use of different routes should take the potential occurrence of traffic accidents on inconvenient routes into account. Finally, incentives of insurance compensation to companies are more effective than direct refund of toll fee for encouraging drivers to use Chugoku expressway, which has less traffic than Sanyo expressway.
- Information provision for assisting drivers' adaptation behavior under the occurrence of traffic accidents on expressways should also take drivers' heterogeneities and decision timings into account. As for detailed information contents, interval-based information about clearance time of traffic congestion caused by accidents is more preferred by drivers than the point-based information with prediction probability.
- Even though ICT technologies and services are expected as the next-generation of traffic safety measures, our analyses show that the role of traditional enforcement of traffic rules (here, punishments of traffic rule violations) should not be ignored. In other words, the enforcement should be practiced together with ICT-based traffic safety measures. However, due to the privacy issue, it is difficult to enforce traffic rules via the use of smartphone.

1.7 Outline of the thesis

This thesis is composed of eight chapters, each of which is summarized as follows.

Chapter 2 provides a literature review for supporting the importance, the necessity, and the originalities of this study, and clarifying unresolved research issues in literature. The above literature review revealed the following unresolved research issues related to the two research purposes of this study.

- It is unclear whether smartphone apps should be promoted in traffic safety practices or not. Concretely speaking, the effects of the apps on driving safety improvement have not been confirmed in a consistent way.
- Driving risks and safety research have been widely conducted by focusing on limited numbers of factors in the context of particular aspects of driving behavior and traffic safety measures. Little has been done from a comprehensive viewpoint.
- Driving avoidance behaviors may differ depending on drivers' internal risks and external risks. Literature review suggests that such behaviors under the influence of travel information provision have not well been examined.
- As for drivers' adaptation behaviors against the occurrence of traffic accidents on expressways, it remains unclear how the adaptation behaviors vary with decision timings and across drivers. It is not clear, either, what types of travel information are more effective to assist decisions on adaptations than other factors.

The above unresolved issues will be investigated via both surveys and modeling analyses.

Chapter 3 describes efforts of data collections for achieving the research purposes of this study. Three different types of data were originally collected for this study.

- The first data set comes from a three-month driving experiment by recruiting 100 drivers to experience the use of the developed smartphone app on expressways in the Chugoku Region of Japan in February ~ May, 2014. Six versions of the app (combinations of different functions: driving risk diagnosis, information provision, feedback of advice for safer driving, SA/PA information, self-evaluation, ranking of diagnosis scores, online safety campaign) were experienced by drivers at different points in time of the whole experiment. After each driving, drivers were also asked to report their multitasking behaviors and affective experience during driving. Furthermore, a series of questionnaires with the following items were conducted, including behavioral change stages of safe driving, daily aberrant driving behavior, driving avoidance behavior, driving skill evaluation, driver social desirability scale, and questions based on theory of planned behavior, etc.
- The second data set was collected from a web-based questionnaire survey, which was conducted to capture drivers' adaptation behavior changes under the dynamic information provision related to traffic accidents on expressways. A large-scale SP survey was conducted in March 2012, based on another large-scale revealed preference (RP) survey conducted in December 2011, by reflecting personal preferences of expressway users in the Chugoku Region of Japan.
- The third data set was collected from a paper-based RP and SP survey during 2014~2015. Freight forwarder companies, located in Kansai, Kyushu, and Chugoku regions were selected as potential users of expressways in the Chugoku Region. Data collected in this survey is used for identifying the factors influencing route avoidance driving behaviors against the occurrence of external risks.

Chapter 4 evaluates the short-term effects of a GPS-enabled smartphone App, called *Safety Supporter,* on driving risk mitigation. Second-by-second data analysis is conducted in this chapter to find out the significant factors influencing driving performance. Firstly, effects of the app on driver's over-speeding behavior were analyzed based on the ZINBR model. Especially, heterogeneity across drivers have also been considered by taking drivers' behavioral change stages into account. And then, rationality for distinguishing between three driving risk indicators have been examined through the MOP models. Finally, individual's speed limit compliance and abrupt acceleration/deceleration control behavior were estimated jointly by employing the BOP model to investigate the correlation between two driving performance indicators.

Chapter 5 deals with individual's safe driving performances at a trip level. Analysis in this chapter assumes that driver's actual driving performance (here, refers to violation rates of speed limit compliance, acceleration/deceleration control, and driving stability) might also be influenced by individual's psychological states (here, affective experiences) and actions (here, multitasking behaviors) while driving. Mutual correlations among the five indicators are jointly estimated based on the SURE model. Significant long-term effects of the *Safety Supporter* on driving risk performance as well as other two indicators are confirmed, together with other useful findings for traffic safety practices.

Chapter 6 focuses on driving avoidance behavior from two perspectives. Firstly, in order to help drivers relief from the potential driving risks of accident involvement, additional consideration of driving avoidance behavior have been analyzed together with drivers' affective experience, multitasking behavior, and three driving performance indicators. Four types of driving avoidance behaviors, including general avoidance, weather avoidance, traffic avoidance, and riding avoidance, have been discussed. Again, the SURE model is employed in this part of analysis. Secondly, emphasizing driver's situational avoidance behavior while driving, a specific case study of truck driver's route avoidance behavior have been discussed. Case study is conducted with regarding to two substitutable expressways in Chugoku area of Japan, called

Chugoku Expressway and Sanyo Expressway. Even though two expressways are substitutable, Sanyo Expressway has been facing up with serious traffic congestion issues. In contrast, Chugoku Expressway has been experiencing a decreasing traffic demand, and due to such decline of traffic demand, some SAs/PAs had to be closed. A bivariate probit model is employed to jointly estimate the potential factors that would significantly influence not only truck drivers, but also their company managers.

Chapter 7 focuses on the dynamic information provision of traffic accident. Context-sensitive adaptation behaviors influenced by accident related information provision have been analyzed, with considering of three decision contexts of before departure, on the way to expressway, and on expressway driving. A nested logit (NL) model have been employed for data analysis. Moreover, heterogeneous responds across drivers' adaptation behavior under the provided information have been further investigated based on the proposed concept of travel information styles. Three types of travel information styles have been identified from a K-means cluster analysis through a series of information search and usage related variables.

Chapter 8 summarizes the findings, implications, limitations of this thesis, and directions for future research are discussed.

Chapter 2

Literature Review

As stated by Jiang and Zhang (2016a), people experience and/or perform various risky behaviors in their daily life, e.g., driving while intoxicated, speeding, angry driving, illegal drug use, smoking, unsafe use of the Internet, bungee jumping, going on a jungle safari, skiing, and skating. Risky behaviors compromise health, quality of life, or life itself. Risky driving is one of the most serious risky behaviors in people's daily life. Here, existing smartphone apps for driving safety diagnosis are first reviewed, followed by review about studies on driving speed control and Big Data in transportation. Next, review is given with respect to subjective well-being and driving risks. Finally, studies on avoidance and adaptation behaviors are reviewed.

2.1 Existing smartphone apps for driving safety diagnosis

Over the many years, various studies have been conducted with respect to driving safety enforcement and intervention developments. Starting from roadside infrastructure investment of traffic signs and signals to dynamic traffic information provision devices (e.g., variable message sign (VMS)), further to the introduction of ICT devices and services, importance of individualized driving inventions have been well-recognized in the current traffic safety research (Böhm and Jonsson, 2011; Lu, 2006; Zhang et al., 2013).

Especially, mobile ITS devices, like GPS equipped smartphones, have provided a low-cost means to measure travel time, acquire instantaneous vehicle speeds, and estimate safety performance on the road (Astarita et al., 2014). High proportion of the GPS based smartphone (about 80% among young people) usage has provide another data sensing technique with better coverage of the transportation network than current sensor technology (Herrera and Bayen, 2010; Kafi et al., 2013; Steenbruggen et al., 2013). In this sense, policy makers are interested in using mobile devices, including smartphones, to collect information for traffic control and management as well as road maintenance, e.g., travel time measurement and prediction, measurement of road roughness for maintenance (Zhang et al., 2014). To date, various iOS and Android systems based Apps have been developed and utilized in the study of accident detection (White et al., 2011; Zaldivar et al., 2011), safe driving diagnosis (Zhang et al., 2014; Jiang et al., 2015), and over-speeding management and control systems (Sarowar and Shende, 2015). In this sense, smartphone based Apps have become not just a simple entertainment software, but also important driving safety management tools for both drivers and traffic managers as well as policy makers.

In line with this trend of prevalence of smartphone app, our developed smartphone App *Safety Supporter* makes use of GPS information to diagnose driving risks and provide traffic warning information. As stated by Charlton et al. (2014), literature review suggests that drivers modify their driving behaviors according to the risk they perceive. And driving risks vary substantially across drivers (Guo and Fang, 2013). These support the development of the *Safety Supporter* that measures driving risks. The *Safety Supporter* provides second-by-second data for the measurement. The accumulation of such data from various drivers can become a new type of so-called “Big data”. There are similar Apps developed, but the *Safety Supporter* is well differentiated from others, especially without any needs to add new algorithms and sensors, etc.

Probably because the development of such Apps is quite new, similar studies in literature are very limited. For example, Fazeen et al. (2012) tried to assist drivers to improve their safety awareness by employing an Android smartphone based “Nexus One” App to record and analyze the potentially dangerous driving behavior, where road conditions can also be detected. Charlton et al. (2014) suggest that drivers modify their driving behavior based on the risk they perceive. In the study by Newnam et al. (2014), a GPS-enabled on-board diagnosis tool, called OBDII, was used to explore the effectiveness of designed behavior modification interventions, where drivers received weekly feedback on their speeding performance and goal setting exercises, with an aim to reduce over-speeding violations. Vaiana et al. (2014) developed a prototype mobile application that can measure driving safety level based on accelerations (longitudinal and lateral), where the aggressiveness of driving is measured and evaluated by plotting vehicle's acceleration on a g-g diagram.

In case of Japan, since 2013, five insurance companies in Japan have started services of diagnosing driving safety based on their developed smartphone Apps. All these Apps were developed under the iOS and Android environment and can be downloaded for free. Details are shown in Table 2-1. Major shortcomings of these existing safety diagnosis tools are shown below.

The measurement mainly focuses on driving skills, but not directly on driving safety. The scoring of safety level is arbitrary and does not reflect actual safety level. To avoid any worse influence of excessive confidence for driving, developers purposely lowered the safety level (NEXCO RI, 2013). The purpose of the development is understandable; however, that may lead to unrealistic diagnosis, which may hinder the active use of the Apps. The Apps do not reflect road-specific features related to traffic accidents. Some road attributes tend to increase the possibility of traffic accidents, which should be properly informed to drivers. There are no Apps developed for expressways. Once an accident occurs on an expressway, it is much more likely to result in a serious accident than on an ordinary road. Therefore, special attentions should be paid to the development of relevant Apps for expressways.

Based on the above brief literature review, this study tries to evaluate the effects of the developed App, *Safety Supporter*, on driver's safe driving behaviors. Different from existing studies, this study further focuses on different individuals' driving heterogeneity, especially from the perspective of driving propensity and behavioral changes. Driving propensity means a peculiar latent attitude or a kind of habit that may be hard to be recognized by drivers (Kusuhashi et al., 2012). Behavioral changes in the context of driving safety are captured based on the stage model of change (Glanz and Rimer, 2005). Furthermore, this study simultaneously investigate the influences of various factors on driver's over-speeding behavior, including both drivers' internal and external factors. Internal factors contain personal characteristics, driving propensity, self-evaluation of driving safety, behavioral stage of safe driving. External factors include the App functions, driving contextual factors, time-dependent trip attributes, and drivers' experiential factors.

Table 2-1 Smartphone apps with diagnosis functions of driving safety in Japan

Company	Name of App	Main functions
Sony Assurance Inc.	Japanese name: ドライバーズナビ (DriversNAVI)	・Scoring for brake, stop, steering, right turn and left turn, and smoothness (full points: 20 for each; in total, 100) ・Trajectories of driving routes and speeds ・Driving recorder ・Fuel efficiency display ・Maintenance information
Sompo Japan Insurance Inc. Nipponkoa Insurance Co., Ltd.	Japanese name: セーフティサイト (Safety Sight)	・Scoring for inter-vehicle distance, steering, accelerator, brake, and continuous driving (full points: five stars for each) ・Trajectories of driving routes and speeds ・Driving recorder ・Alarm of collision to the vehicle ahead ・Contact information in case of emergence
Mitsui Sumitomo Insurance Co., Ltd.	Japanese name: スマ保 (SumaHo)	・Scoring for stability of acceleration, stability of deceleration, stability of cornering, stability of steering, and eco-driving (full points: 20 for each; in total, 100) ・Driving propensity based on back-forth, right-left and up-down jolting ・Driving recorder ・Driving suitability test ・Navigation under emergent troubles
Aioi Nissay Dowa Insurance Co., Ltd.	Japanese name: サポ NAVI (SaPoNAVI)	・Scoring for brake, stop, steering, right turn and left turn, and smoothness (full points: 20 for each; in total, 100) ・Cognition of driving dangerousness by showing videos of actual driving ・Hazard map of traffic accidents ・Alarm of snoozing ・Guidance of responses to emergent situations

Source: Revised based on NEXCO RI (2013) and the websites of the above companies

2.2 Studies on driving speed control

Driving is a dangerous task, for which speed control is important (e.g., Summala, 1988; Wilmots et al., 2016). As stated by Summala (1988), speed and time control directly determine mobility. Driving faster allows a driver to reach a destination earlier, resulting in a higher efficiency of traffic operation. On the other hand, driving faster needs the driver to overtake some vehicles under the influence of legal speed limit, to keep proper distances from the preceding car and neighboring cars under the influence of heavy traffic mixed with different types of vehicles, and/or to decide whether to drive cross an intersection or not when the traffic light is yellow, and so on. These operations involves not only second-by-second physical control of a vehicle by keeping eyes on the surrounding traffic, road structure and surface conditions, and other driving environment, but also various psychological processing (e.g., attention control, risk perception, and mood control). Thus, speed control is essential to all the above-mentioned operations.

Various studies have been done with respect to the association between driving speed and safety. Examples of some early studies are given below. Based on an analysis of 10,000 accident records of rural highways, Solomon (1964) found a U-shaped curve, where crash rates were lowest for driving speeds near the mean speed, while the rates increased with greater deviations from the mean. Solomon's U-shape curve was further replicated using traffic accidents data (2,000 vehicles) of interstate freeways (Cirillo, 1968) and data of urban roadways (Harkey et al., 1990). Similarly, Kloeden et al. (1997) found that the risk related to injury crashes was lowest when drivers travel with near or below the median speed (60 km/h) and increased exponentially with higher speeds. Joksch (1993) revealed that the risk of a driver being killed in a crash increased with the change in speed to the fourth power. Examples of recent studies on the link between speed and traffic accidents include Bener et al. (2008), Li et al. (2011), and Møller and Haustein (2016). Related to driving speed, GPS-enabled smartphones can record vehicles' locations second-by-second over time from various types of drivers in a much easier and more cost-effective way than existing data collection tools.

Under such circumstances, by employing the developed app, individual's driving risks are measured based on three types of driving speed controls of compliance with the speed limit, abrupt acceleration and deceleration, and driving stability (variation in driving speed over a given time period), second by second.

2.3 Studies on Big Data in transportation

Related to "Big Data", in recent years, massive amounts of driving data in high resolution have been accumulated and also become available to the public from various devices based on information and communication technologies (ICT) (Wang et al., 2015). Using data with 51,370 trips and 36 million seconds of speed data collected from in-vehicle GPS devices in Atlanta, USA in 2011, Wang et al. (2015) examined volatility in driving decisions, captured by jerky movements during the whole trip, which are categorized into vehicular jerk reversals (acceleration followed by deceleration), jerk enhancements (increasing accelerations or decelerations), and jerk mitigations (decreasing accelerations or decelerations). It was found that "overall 14% of the travel time spent on high vehicular jerk; 7% of driving time was spent on idling or traveling at speeds below 5 mph, 47% of driving time was spent on acceleration, 41% of driving time was spent on deceleration and 5% of driving time was spent on maintaining constant speed". Maintaining speed is also a kind of instantaneous driving decision. The information derived from such instantaneous driving decisions can be useful not only for better emissions estimations, but also for better measurement of driving risks.

Smartphone based applications with simplified algorithms are more easily deployed in the real world. Applications developed based on better sensing techniques could surely provide more reliable measurement of driving risks. For example, Hong et al. (2014) developed an in-vehicle smartphone based sensing platform (an Android system), which can collect a variety of information from drivers' naturalistic driving, e.g., speed, acceleration, deceleration, engine RPM, throttle position, and steering wheel movement.

Different from existing studies, this research attempts to make use of the most common GPS information, which can be easily obtained from any type of smartphones, to measure driving risks and provide safer driving advices as well as traffic warning information, without any additional sensors. This is motivated by the needs of easy and widespread deployment of such driving safety diagnosis devices.

2.4 Studies on subjective well-being and driving risks

Recently, as stated by Mokhtarian (2015) in her keynote speech at the 14th International Conference on Travel Behaviour Research, an increasing number of studies on travel and well-being have been conducted in the field of transportation. Mokhtarian argued the role of subjective well-being (SWB) in transport policy, clarified terminologies and measurement methods of SWB, summarized three conceptual models of the impacts of transport on SWB, and discussed five ways in which transport influences SWB.

Relevant transport studies have investigated SWB mainly from the travel mode choice and transportation service evaluation. As an important daily life activity, many people drive a lot and encounter various traffic situations every day; however, little has been known about the role of SWB in the context of driving safety, especially the relationship between positive mood and safe driving. Actually, in case of risky driving, there are several efforts to explore the effects of anger on driving, for example, one study conducted by Beck et al. (2013), who found that driver's hurried driving behavior was significantly associated with one's lower levels of distress tolerance and suggested the necessity of developing driving safety campaigns that address drivers' affective coping abilities. However, limited attentions have been payed to the relationship between positive emotions on both perceptions of and experiences while driving. (e.g., Rhodes et al., 2015). According to the summary in the research by Rhodes et al. (2015), young male drivers tend to enjoy risky driving, moreover, people in happy moods tend to engage in less effortful information processing, therefore leading to engage in risky driving, while on the contrary side, individuals in negative moods are more likely to engage in effortful and systematic processing of information, resulting in better driving. The finding that faster driving speed is significantly associated with driving in a happy mood and with a passenger have been re-confirmed through a driving simulation experiment.

Various objective and subjective factors affecting driving behavior have been explored; however, efforts of incorporating these factors in a comprehensive way are quite limited. This research attempts to fill this gap.

2.5 Studies on avoidance behavior

Recent studies about avoidance behavior theory have mainly focused on two parts: punishment avoidance behaviors (Liourta and Empelen, 2008; Scott-Parker et al., 2014) and situational avoidance behaviors (Stewart and Peter, 2004; Motak et al., 2014). Punishment avoidance behavior indicates that drivers might evade the detection of police by avoiding to driving in police enforcement activity areas or avoid a potential traffic citation by speeding behavior due to substance-impaired driving behaviors, such as drunk driving and driving after drug consumption (Fleiter and Watson, 2005; Scott-Parker et al., 2011). Research conducted by

Fleiter and Watson (2005) pointed out that traffic rule violation behavior, especially speeding behavior, is strongly correlated to the prediction of individual's punishment avoidance behavior. This result is consistent with the findings in the research of Scott-Parker et al. (2011), who showed that more risky driving behavior in general have been conducted by the punishment-avoiders. Generally speaking, situational avoidance behavior is derived mainly from driver's after-driving experience, especially experience of crash involvement driving. Drivers tend to perform avoidance behaviors towards situations in which their impairments identified/obtained from previous crash involvement might expose them to an increased risk of accident (Motak et al., 2014). Ten situations were identified from study of Motak et al. (2014), including driving at night, at night in the rain, long distances, in the rain, in fog, during the rush hour, at roundabouts, left turns, in the snow, and on highways. In a more general avoidance driving research conducted by Stewart and Peter (2004), a questionnaire of Driving and Riding Avoidance Scales (DRAS) was developed. Four types of avoidance behavior, including general avoidance, traffic avoidance, weather avoidance, and riding avoidance, are generated from 20 related items. It is also revealed that greater avoidance behaviors could be identified from drivers who experienced medical treatments from crash-related injuries than those who were uninjured or injured and not medically treated.

Naumann et al. (2011) investigated drivers' self-restriction behaviors by focusing on three high-risk conditions of driving at night, driving in bad weather, and driving on highway or high-speed roads. Comparison among all ages drivers result show that self-restrictions are not only observed on older drivers, but also quite prevalent among young drivers. Moreover, higher percentage of bad weather self-restricting behaviors in bad weather among young women drivers than women in other age groups has also been found. Focusing on the measurement of harm avoidance behavior, Bas et al. (2015) used the Multidimensional Personality Questionnaire 28-item Harm Avoidance subscale (MPQ—Harm Avoidance)

(Tellegen and Waller, 1982) to predict young driver's driving risk together with a series of self-report items, and it's found that higher levels of driving risk were associated with lower levels of harm avoidance.

2.6 Studies on adaptation behavior

In the field of human being involved research, including both active involvement of decision making (e.g., purchasing and route changing behaviors) and passive incident involvement (e.g., accident and congestion involvement), human factors all impose a considerable influencing impact on the event development. Due to the great behavioral heterogeneity among individuals, various human being related studies have made various efforts in better exploring the heterogeneity in their targeted research issues, such as in the medical field (Dizney and Dearing, 2013), political field (Chiarella et al., 2012), marketing field (Plötz et al., 2014; Ponta et al., 2011), and transportation field (Lee et al., 2014; Ossen and Hoogendoorn, 2011).

In general, early research of drivers' behaviors exploring the influence of individual heterogeneity mostly limited their scopes in the examination of unobserved error terms or individual attributes (e.g., age, gender, and income) (Kim et al., 2013). However, as discussed by lots of recent studies, individual behavior patterns also show great variations among drivers and among decision-making contexts (Ossen and Hoogendoorn, 2011; Plötz et al., 2014). Ossen and Hoogendoorn (2011) revealed that two types of heterogeneity, i.e., driving style heterogeneity and heterogeneity within a driving style, were identified in the context of car-following behavior. The study by Plötz et al. (2014) explored the influence of user heterogeneity in driving behavior and different user groups in the context of market diffusion of electric vehicles based on real world driving data.

In terms of heterogeneity in traffic incident management, Karlaftis and Tarko (1998) estimated a model of accident crash numbers in various counties by introducing various infrastructure, socioeconomic, and traffic characteristics. Three distinctive clusters, including counties belonging to urban, suburban, and rural clusters are generated for separate model estimations, and results of this research verified the significant differences between clusters derived and the better performance of the model with heterogeneity consideration.

Focusing on the impacts of personalized travel information on individual's activity-travel behavioral changes, Parvaneh et al. (2014) pointed out that even though lots of applications have assessed the individual's activity-travel behavioral changes, research examining the heterogeneous influence of the provided information is still limited.

As discussed above, a large amount of research has been conducted with respect to driver's behavioral changes (Jiang and Zhang, 2014) and the individualized dynamic information provision (Jiang et al., 2013b; Jiang and Zhang, 2015a). However, efforts focusing on the expressway information provision and heterogeneous adaptation behaviors under different driving scenes are still very limited. Especially, little is known about the role of travel information style in literature.

Chapter 3

Data, Measurement and Evaluation of Driving Risks

Data employed in this study are originally collected from three ways, including a field driving experiment, a web-based questionnaire survey, and a paper-pencil questionnaire survey. Firstly, potential impacts of the developed app on individual's driving risk diagnosis and mitigation are evaluated through the field experiment together with the web-based questionnaire survey, simultaneously. Concretely speaking, in order to diagnose individual's driving risk on expressway, a GPS-based smartphone app was developed in this study. Effect of the designed smartphone app was evaluated through an objectively on-site experiment on expressway, 2014. In addition, besides individual's objective driving performances, changing impacts of driver's subjective safety awareness, e.g. driving safety stage change and safety self-evaluate, have also been inspected and captured from the corresponding web-based questionnaire survey measurement. This part of data will be used in Chapter 4, Chapter 5, and part of Chapter 6. Then, focusing on the situational risk avoidance behavior, a paper-pencil reference preference (RP) and stated preference (SP) questionnaire survey was conducted with respect to choice of truck routes on two substitutional expressways in the western region of Japan in 2014~2015. This data set will be analyzed in Chapter 6. Finally, focusing on the impact of real-time dynamic information provision on drivers' adaptation behaviors, again the web-based RP and SP questionnaire survey was conducted in the same research area Japan from 2012~2013. Important factors that under which specific contexts, e.g. before departure for expressway usage, on the way to the expressway, or driving on expressway, what type of specific information, e.g. accident injury, accident impact prediction, and substitute travel mode/route information, are required and essential for individual driver have been investigated, together with potential effective forms of information provision. Data of this part will be used in Chapter 7. Subsections 3.1 and 3.2 are written mainly based on the publication by Zhang et al. (2014).

3.1 Smartphone Application Development

3.1.1 Introduction

Individualized traffic safety measures need individualized tools. Mobile phones may become one of such tools considering their rapid diffusion in many countries, which may improve driver's risk recognition, judgment, and operation. Applications of mobile phones in transportation are becoming more and more popular, mainly in providing trip makers with previously unavailable information (e.g., Bonsall, 2000; Herrera et al., 2010). Policy makers are interested in using them to collect information for traffic control and management as well as road maintenance, e.g., travel time measurement and prediction, measurement of road roughness for maintenance. Especially, it is worth exploring the ability of smartphones. Smartphones do not have just telephone functions. They have been developed just like a mini note PC, where various PC functions, music and video play functions are contained. Especially, a variety of application software (simply called App) can be easily downloaded via the Internet. With these Apps, various convenient services become accessible. Because of such attractiveness, the number of smartphone users has been rapidly increasing year by year. As stated by Brazil and Caulfield (2013), the rise of smartphone applications within the transport sector has created new and exciting opportunities to provide users with a wide range of previously unavailable information services, and while these applications are becoming more readily available in the market place, little in terms of scientific research has been undertaken to examine their influence on users.

Motivated by the above-mentioned matters, one objective of this study is to develop a GPS-enabled smartphone App (called *Safety Supporter*: [2]) that diagnoses driving safety by making full use of GPS information and provides advices and traffic warning information to drivers for the prevention of traffic accidents. Note that the purpose of this app development is not to develop an app with the most advanced functions related to driving safety. Rather, the purpose is to develop an app with simplified functions for testing whether such apps can be used to improve driving safety or not and what kinds of functions are more effective to the improvement of driving safety.

In the remaining part of this section, first, we briefly introduce existing GPS-enabled smartphone Apps with functions of driving safety diagnosis. Second, we describe how to implement the diagnosis of driving safety in the *Safety Supporter*. Third, we explain the development of the app. Finally, details of a three-month driving experiment is introduced.

3.1.2 Diagnosis of Driving Safety

Traffic accidents occur with driving speed changes. If all vehicles were driven at the same speed, traffic accidents would not occur. If a driver does not drive under the speed limit, the probability of causing accidents may increase, as known by the fact that over-speeding is one of major causes of traffic accidents. If the driver makes a sudden stop or start, or does not drive smoothly, he/she may cause an accident with comparative higher probability than usual. In line with such considerations, observing changes in driving speed and informing drivers about the

[2] It can be downloaded for free from Google Play (Japanese site), named セーフティサポーター.

consequences of the changes may provide useful insights into the prevention of traffic accidents. Accordingly, we propose diagnosing the driving safety level from the following three perspectives: i.e., *compliance with speed limit*, *abrupt acceleration and deceleration*, and *driving stability*. We show details below. Vehicle locations can be captured every second. Considering the data processing speed and the capacity of data saving server, diagnoses are implemented every two seconds.

Threshold for the three proposed diagnosis indicators are shown as follows:

- *Compliance with speed limit* is set for safer driving. Obeying speed limit more likely results in safer driving and violating speed limit is more likely linked with the occurrence of an accident. In other words, the higher the over-speed the more dangerous. Therefore, here, the degree of over-speed can be used to measure the driving safety level. Here, we treat every two seconds as a sample and score the driving safety level. Concretely speaking, the safest level is given 100 points when driving speed is equal to or slower than speed limit plus 5 km/h (5 km/h is set considering the errors that a driver judge the speed) and the most dangerous level is given 0 point when driving speed exceeds speed limit for more than 50 km/h. Other driving speeds are scored depending on how much speed limit is violated, shown in Table 3-1. The scoring is measured by reflecting the fine levels determined by policy agencies in Japan.

Table 3-1 Scoring method of compliance with speed limit

Value of over-speeding (x)	Score of driving safety	Levels of fines (Yen)
$x - a \leq 5$	100	0
$5 < x - a < 15$	91	9,000
$15 \leq x - a < 20$	88	12,000
$20 \leq x - a < 25$	85	15,000
$25 \leq x - a < 30$	82	18,000
$30 \leq x - a < 35$	75	25,000
$35 \leq x - a < 40$	65	35,000
$40 \leq x - a < 50$	20	80,000
$50 \leq x - a$	0	100,000

- *Abrupt acceleration and deceleration.* If the absolute value of acceleration/deceleration is larger than 0.3 G or 2.94 m/s2, the safety level is judged to be the most dangerous level, i.e., the score is equal to 0. If the absolute value is 0.0 G, the score of safety level is 100 points, i.e., the safest level. Other instantaneous speed changes are scored depending on how large of the acceleration/deceleration.
- *Driving stability*: The larger the variation of driving speeds in a traffic flow, the more dangerous the driving in the flow. To measure the dangerousness of driving from such a perspective, we define a time period that covers four seconds before and after a second under study, and the second, i.e., the total time period is nine seconds. If the driving speed is 80 km/h, the nine seconds correspond to the distance of 200 m. If the driving speed at a second within the nine seconds is equal to the median (Y) of all the nine speed values, the score of safety level is set to 100 points, i.e., the safest level. If the driving speed is beyond the range of Y ± 2σ, where σ is the standard deviation, then the score of safety level is set to 0, i.e., the most dangerous level. Other speed values are scored between 0 and 100 points depending the deviation from the median.

Besides the objective driving performances, different drivers may have different driving propensities and consequently respond differently to traffic measures. Driving propensity indicates a peculiar latent attitude or a kind of habit that are inherent to drivers. According to Japan Traffic Safety Association (2006), driving propensities can be classified into 6 types based on 27 question items as follows:

1. Irritable driving: It is the case if four or more out of the following eight items are selected: (1) Do you feel ripped off when a car has run into the queue in front of your car in case of traffic congestion?; (2) Do you feel angry when a car is stopping on street on your way and taking time for dropping off/picking up?; (3)Do you feel unhappy when

your driving speed is influenced by other vehicles?; (4) Do you feel angry to the horning from rear cars; (5) Do you feel angry when a car jumping into the traffic in front of you?; (6) Do you feel unhappy when you encounter a red traffic light on your way?; (7) Do you often feel angry about other driver's driving?; (8) Do you purposely shorten the headway when a car is trying to run into the traffic in front of you?.

2. Careless driving: It refers to the case that three or more out of the following nine items are selected: (1) Have you ever scared yourself due to looking aside while driving?; (2) Have you scared yourself due to thinking other things while driving?; (3) Have you ever experienced any panic situation due to the late recognition of the rear light of the front car?; (4) Have you ever scared yourself due to drowsy driving?; (5) Have you ever been forced to make a sudden brake due to the late recognition red traffic light?; (6) Have you ever been scared by a pedestrian/cyclist when driving at night; (7) Have you ever noticed a pedestrian/bicycle when just driving into the crossway of a road?; (8) Have you ever experienced any multitasking while driving, e.g. eating and makeup?; (9) Have you ever picked up your phone when there is an incoming call while driving?.
3. Aggressive driving: If one or more out of the following three items targeted are selected, the driving is judged to be aggressive: (1) Do you often overtake other cars in front and change driving lane?; (2) Are you more likely to change driving lane unconsciously and without careful confirmation of traffic?; (3) Do you often operate radio, music player and TV while driving?.
4. Excessively-confident driving: If none of the following seven items are selected, the driving is judged to excessively confident: (1) Do you feel that you are not confident with your skill to back a car?; (2) Do you feel that you are more or less not good at driving?; (3) Do you often hesitate to drive or stop when approaching a merging point?; (4) Have you ever changed driving lane when the timing is not proper?; (5) Do you try

to avoid driving at night or during bad weather?; (6) Do you often make a brake even when it is not so necessary?; (7) Do you try to driver below the speed limit even under good road conditions?.

5. Indecisive driving: If four or more out of the seven items in the above “4” are selected, the driving is indecisive.
6. Safe driving nature: It refers to the case that none of the above types are identified.

The above 27 items are used to measure different types of driving propensities. However, it is not difficult to imagine that different respondents might respond to several item categories simultaneously in a different way, and as a result, it might become difficult to clearly distinguish a certain type of driving propensity from other types. In reality, drivers' driving propensities might differ across driving situations. In other words, a driver might belong to two or more types of driving propensities simultaneously. We score the driving propensity based on how many types that a driver is classified into. If a driver is classified into the type (6), the score for driving propensity is set to 100 points. If a driver is classified into four or more types, the score is set to be 0, meaning that he/she is the most dangerous driver potentially. The scorings for other numbers of the propensity types are given between 0 and 100 points.

3.1.3 The Development of *Safety Supporter*

We developed a GPS-enabled smartphone App, called *Safety Supporter*, under the Android environment, which can not only diagnose the driving safety level, but also provide advices to drivers about the improvement of driving safety as well as traffic warning information on expressways.

Function components of the *Safety Supporter*, including safety diagnosis, information provision, as well as information feedbacks.

1) Safety diagnosis (objective and subjective diagnosis)

(1) Objective safety diagnosis. It is given with respect to *compliance with speed limit*, *abrupt acceleration and deceleration*, and *driving stability*. For each of the three diagnosis indicators, the diagnosis result is explained and advices about how to improve the safety level are provided. (shown in Figure 3-1)

Figure 3-1 An example of objective safety diagnosis

(2) Subjective safety diagnosis. Two types of subjective diagnosis is provided, including diagnosis of driving propensity and self-diagnosis of driving. Self-diagnosis of driving is conducted before sending a request to the App *Safety Supporter* for the diagnosis, the driver can choose to diagnose the driving safety level by him/herself. This function is prepared for allowing drivers to understand the perception gap between their subjective evaluation and objective diagnosis. On the other hand, driving propensity diagnosis based on the self-

reported evaluation, each driver will be classified into one of the previous six types. Depending on the types, *Safety Supporter* provides advices about how to improve the safety level are provided. Example of the driving propensity diagnosis interface is shown in Figure 3-2.

(3) Information provision. Two types of warning information is provided only on expressways, including black spots, i.e., dangerous road sections, where traffic accidents occurred frequently, and SA/PA information. Driving safety diagnosis and warning information provision when passing through black spots or presenting of fatigue for long-distance driving. Moreover, automatic guidance of SA/PA is provided (Shown in Figure 3-3).

Figure 3-2 An example of driving propensity diagnosis interface

Figure 3-3 An example of warning information provision interface

2) Information feedback to drivers (Figure 3-4)

(1) Scores of driving safety. Each time, a driver can choose to first make a self-diagnosis about their actual driving safety level and then he/she will be provided with an average score of the total measurement over the whole driving course and scores of compliance level of speed limit, instantaneous change of speed, and stability of driving. Drivers can skip the self-diagnosis step.

(2) Trajectory of driving route with driving safety level. Each time, after providing drivers with scores of safety level, a driver will be provided with a trajectory of driving route, where the driving safety level at each moment is shown in the map. In addition, the average score in the previous time is also shown. The App also stores all the measurement results so that drivers can review their previous driving performance.

(3) Ranking over time among registered members. As a social agency, drivers tend to

compare with other drivers. The App prepares a function that show each driver's ranking among registered members.

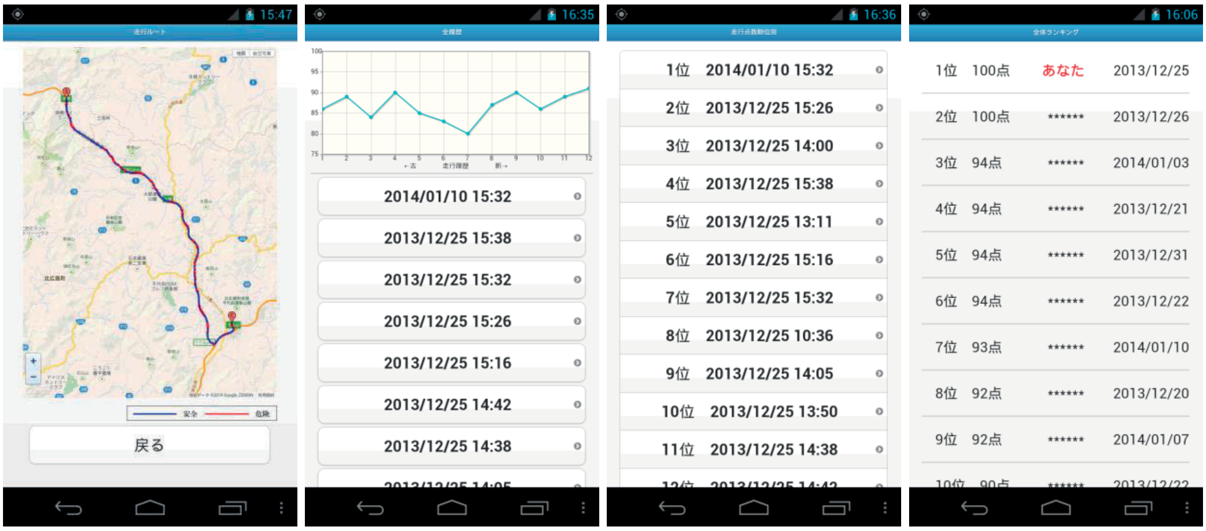


Figure 3-4 An example of information feedback interface

3.1.4 System Design Considerations of *Safety Supporter*

For the current version of *Safety Supporter*, it is developed under the Android environment. It is also possible to develop under the iOS environment. Because we need to revise the App through a field experiment by reflecting the opinions and requests from drivers, to avoid any delay for the improvement of the App due to the approval time, we just developed the App within the Android system. Especially, for the iOS Apps, they must be a completed version for obtaining the approval. The program codes are made using the Javascrip language under the smartphone development framework "Phonegap". The merit of using the Phonegap is that the program coded for the Android system can be directly applied to the iOS system.

Diagnosis by *Safety Supporter* can start at any time over the whole driving course. Both ordinary roads and expressways are targeted. However, only traffic warning information related to expressways is provided.

In terms of the app system design consideration, it could be summarized as below:

1) Basic information processing during driving. During driving, the longitude and latitude information is captured every second via GPS in order to identify the vehicle location. If the accuracy of GPS is extremely bad (e.g., when a vehicle is running into a tunnel), the App will not obtain the location information. Once the location is identified, the App searches for the relevant information within the 100 m radium and process the information, which includes dangerous road sections, IC, and SA/PA.
2) Privacy Protection. Measurements start after a certain length of time passes from the departure site and ends before arriving to destination.
3) Information processing after passing through the IC. In case of the measurement for expressway, it starts when the entry IC is approached and ends when the exit IC is approached. For avoiding wrong detections, IC points are pre-specified.
4) Information processing of dangerous road sections. If a dangerous road section, where traffic accidents have often occurred, is detected within a certain distance (can be defined by users; default: 2 km) from the current location of vehicle, the warning information will be announced. For each dangerous road section, the information of location, type of frequent traffic accident, road name, kilo-post, and down-stream and up-stream of road is stored.
5) Information processing of SA/PA. After a certain length of time (can be defined by users; default: 120 minutes) passes after the start of driving, the App will search for whether there is an SA/PA within the defined distance from the vehicle location. When the SA/PA is detected, it will be displayed.
6) Termination of measurement. Users can stop the measurement at any point in time. Formally, the App terminates the measurement once users push the button of "end of measurement". After that, users will be asked whether to send measurement results to the Web server of the App. Once the sending is done, the App will display the diagnosis results with scoring and

driving trajectories on map.

7) Data accumulation. Information measured is stored in a Web server. To send the information to the server, user's agreement is first required. In other words, only the information with users' agreement will be saved in the server.
8) Setting of User-specific values. Users can change values related to the provision of traffic information, which includes black spots and SA/PA. The default value driving time is 120 minutes. This value is used to diagnose driving fatigue. After the designated time passes, the APP will provide drivers with SA/PA information for taking a rest. The default timing of information provision relating to black spots is 2 km to the current location of vehicle.
9) Usability consideration. Design and interfaces of *Safety Supporter* are developed by attaching the most importance to the safety during driving. Concretely speaking, to start the measurement, only few touches are needed; and then, for the information of black spots and SA/PA, it is displayed with an icon and voice-based warning that driver do not need to watch the screen; moreover, users can use it without special setting.

3.1.5 How drivers were instructed to use the *Safety Supporter*?

In the experiment, *drivers were instructed NOT* to operate their phones for any reasons during driving. Because most of the results from the app are only accessible after driving and traffic warning information is announced via voice, drivers do not need to watch the phone during driving. Such a design can avoid any serious distraction. On the other hand, because many relevant apps in the market (in Japan) often show information via image for attracting more drivers to use apps, we also designed our app by showing traffic warning information on the phone screen via image. Note that *drivers were instructed NOT* to watch the phone during driving. It is illegal to use phones during driving in Japan; however, in reality, not all drivers strictly follow this traffic rule. Thus, we cannot strictly control the use of phones during driving.

Figure 3-5 An example of app setting position

In order to reduce distractions as much as possible, drivers are advised to install their phones into the phone holders provided, which are advised to put in a position within driver's sight (shown as in Figure 3-5 : on the middle of dashboard, similar to those in-vehicle navigation systems), in case that they have to watch their phones. In fact, 1.4% watched the app and 5.1% used their phones during driving, suggesting that distractions due to the use of the app are ignorable. Similarly, 4.4% operated their car navigation systems. The multitasking during driving with the highest share was radio operation (17.1%), followed by thinking about other things unrelated to driving (12.4%) and watching TV (10.7%). These values suggest that the app did not induce serious distraction from driving.

3.2 Field Experiment of driving risk mitigation with App *Safety Supporter*

3.2.1 Pilot experiment

The pilot field experiment was conducted in the middle of December 2013 by inviting five university student drivers. Each driver was asked to drive on five routes of expressways (Figure 3-6: pink, red, green, blue, and light blue routes), which are under the administration of the Chugoku Regional Branch, West Nippon Expressway Co. Ltd. (West NEXCO), Japan.

We further checked scores of all the three diagnosis indicators on the five routes. As for the indicator of *compliance with speed limit*, most of the scores were larger than 80 points. Because this was an experiment, it seems that student drivers tend to obey the speed limit. In contrast, the scores for *abrupt acceleration and deceleration* and *driving stability* show a considerably different trend. There are many moments when the scores were lower than 60 points. Especially, even under such an experimental situation, there were not few moments when scores were lower even than 10 points, suggesting that daily traffic flows on expressways may involve more risky driving actions. Such risky actions could be properly captured using the App developed.

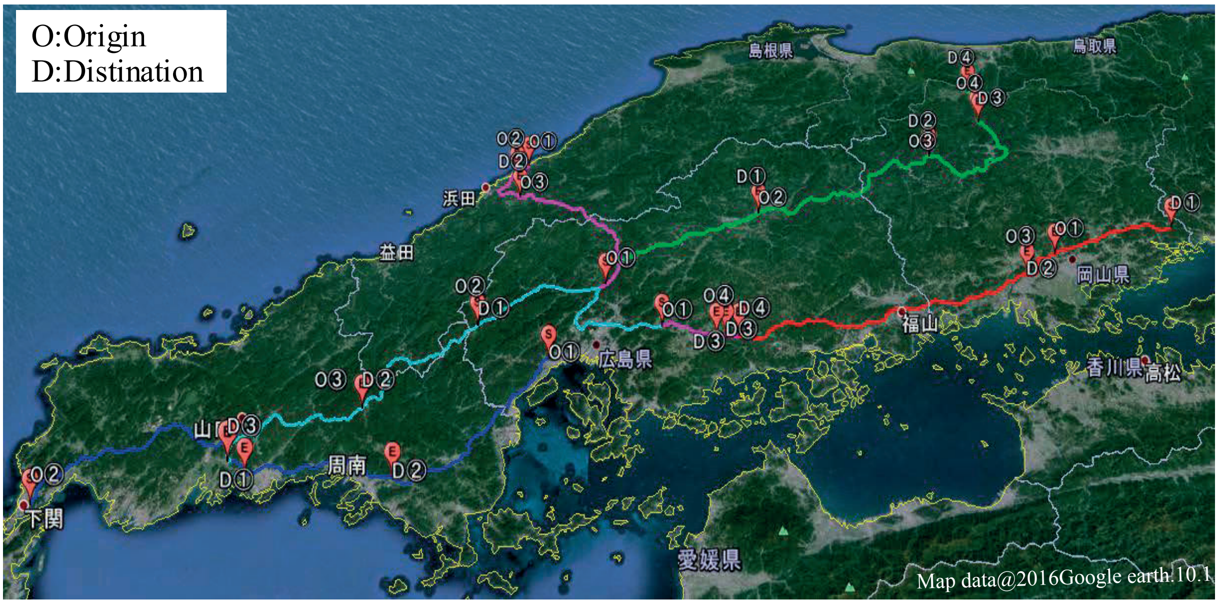


Figure 3-6 Driving routes in pilot experiment

Moreover, the correlations between the three indicators have been calculated and it's found that these indicators did not perform consistently and their correlations just ranged between 0.02 and 0.19. These results suggest that all of the three indicators are needed to measure the driving safety level because they reflect different aspects of driving safety. Existing measurements of driving risks rely on the occurrence of actual accidents, which occur at specific road sections and specific time points. On the other hand, accidents can occur at any place and at any time. Accidents occur within seconds. Such second-based measurement is useful to capture driving risk in a continuous way.

3.2.2 Full-scale experiment

Based on the results of the pilot experiment (Zhang et al., 2014), a full-scale driving experiment was conducted targeting expressway drivers in the Chugoku region of Japan in February ~ May, 2014. In the experiment, 100 drivers using expressways in the above region more than 4 times per month were recruited. In order to testify the impacts of different App functions, the three months were divided into six periods. In different periods, different combinations (experiment scenarios) of App functions were tested.

As shown in Table 3-2, in the first month (1st ~ 4th weeks), drivers were asked to drive as usual and driving data were collected using the App. Data in this period are used as a reference to identify changes in driving behaviors under different scenarios. In the second period (5th ~ 6th weeks), drivers made use of the App with basic functions: diagnose scores and corresponding advices about safe driving, trajectory of driving route, and traffic warning information of blackspots. In the third period (7th ~ 8th weeks), the function of SA/PA information provision was added (Function 1). The scenario in the next week (Function 2) contains ranking of scores among all the App users and self-evaluation of driving safety for each trip before being shown with the score by the App, where the self-evaluation score is designed to help drivers better recognize their own driving performance. After the above scenarios, the function of driving propensity diagnose (Function 3) was added in the fifth period (10th ~ 11th weeks). Finally, in the last period (12th ~ 13th weeks), the online traffic safety education campaign "Drive & Love" was introduced to the App (Function 4).

Table 3-2 Summary of the three-month driving experiment

Period	Experiment Scenarios & Purposes	Date of experiment	Drivers participated
1	*Business as usual*: Drivers were asked to drive as usual, and driving data were collected using the app. *Purpose*: To collect a set of reference data for clarifying whether and the app affects driving risks.	Feb 14 ~ Mar 13, 2014 (1st ~ 4th weeks)	85
2	*Basic functions*: diagnose results & advices, driving trajectory, black spot information. *Purpose*: To test whether and how basic functions affect driving risks.	Mar 14 ~ Mar 27, 2014 (5st ~ 6th weeks)	57
3	*Functions in Period 2 + Additional function (1)*: SA/PA information. *Purpose*: To test whether and how SA/PA information may further reduce driving risks.	Mar 28 ~ Apr 10, 2014 (7st ~ 8th weeks)	48
4	*Functions in Period 3 + Additional function (2)*: ranking among drivers and self-evaluated safety score after each trip before showing the diagnosed scores. *Purpose*: To test whether and how social comparison and driver's perception about their driving affect driving risks.	Apr 11 ~ Apr 17, 2014 (9th weeks)	37
5	*Functions in Period 4 + Additional function (3)*: driving propensity diagnosis *Purpose*: To test whether and how diagnosis of driving propensities are further beneficial to the improvement of driving risks.	Apr 18 ~ May 1, 2014 (10th ~ 11th weeks)	35
6	*Functions in Period 5 + Additional function (4)*: Traffic safety campaign "Drive & Love" † . *Purpose*: To test whether and how drivers additionally improve their driving after accessing various traffic safety related information in the Internet.	May 2 ~ May 15, 2014 (12th ~ 13th weeks)	31

† "Drive & Love" is a nation-wide online traffic safety campaign, supported by more than 240 firms and organizations, where various types of traffic safety information (e.g., driving safety knowledge, events, news, and new technologies) are available and updated frequently.

To encourage drivers to participate in the three-month experiment as much as possible, they were paid for 1,500 to 10,000 Japanese Yen, depending on the number of scenarios they experienced. They were further provided with a potable battery charger and a phone holder, which are all free of charge and unnecessary to return to us after the experiment.

We recruited 100 drivers, 91% of them are male. As for age, 10% are aged 21–30, 35% aged 31–40, 39% aged 41–50, and the remaining 16% aged 51–60. And, 36% worked in public sectors, 23% in manufacture, and 19% in service sector. Note that participation in the experiment was based on drivers' own will, without influence of any external forces, and drivers' private information (names, home address, phone and vehicles, etc.) were excluded from analyses. Participants were recruited with the help of a private company. The company obtained either written consent via e-mail or verbal consent via phone from participants and also took care of paying incentives to participants. Because these drivers lived in different parts of the target region, we instructed them via e-mail about how to download and use the app, the requirements to participate in the experiment (including participate in the questionnaire surveys), and incentives. As a result, 85 drivers actually participated from the first period of the experiment. Just like standard panel surveys, some participates dropped out because of various reasons, including fatigue. The actual number of participants in the following periods is 57 drivers in the second period, 48 in the third period, 37 in the fourth period, 35 in the fifth period, and 31 in the last period, respectively (shown in Table 3-2). Because of the budget constraints and limited project period supported by the West NEXCO, we could not refresh the dropout samples. As for the questionnaire surveys, the above different numbers of participants provided valid answers in the six periods.

Focusing on the 31 drivers who participate in the field experiment continuously, 55% are aged within 41–50 years old, 29% aged 31–40, and the remaining is 51–60 takes 16%. As for gender, 29 are male drivers (takes 94%). And 35% worked in public sectors, and 23% in manufacture. Figure 3-7 shows the average driving diagnosis score of 31 drivers across six different versions of three driving safety indicators.

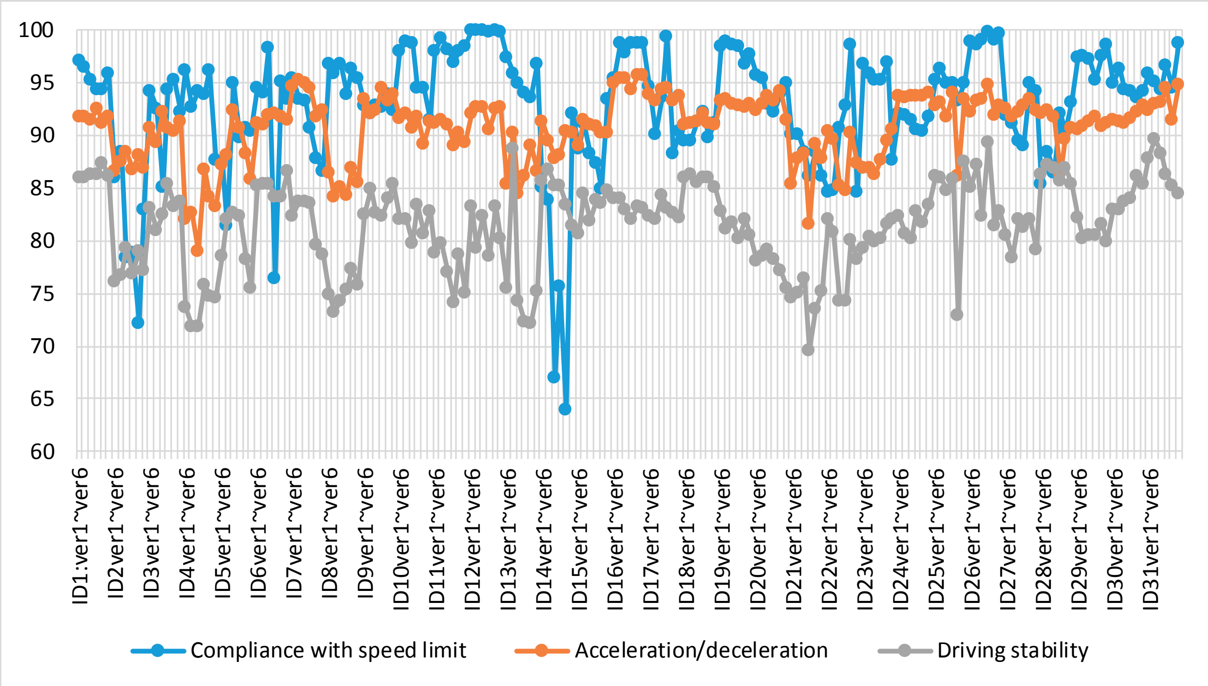


Figure 3-7 Distribution of individual's average diagnosis scores in six app versions

3.3 Questionnaire survey of driving risk mitigation, avoidance, and adaption

3.3.1 Subjective safety driving awareness questionnaire

During the three-month experiment, a series of questionnaire surveys were conducted to reveal influential factors in answering the question about whether and how the app is effective to promote driving safety.

Questionnaire items include drivers' various personal factors associated with driving safety and evaluation about the performance of the app. The former further contain driving skills, driving tasks, behavioral change stages of safe driving, aberrant driving behavior, driving avoidance behavior, factors based on the theory of planned behavior, and experiences of traffic accidents and fatigue driving as well as individual socio-demographic attributes (details of the questionnaire contents are shown in Appendix). The latter asks questions about drivers' satisfaction with the use of the app and opinions on how the app should be improved in future, intention of future use and recommendation to others, etc. To reduce answering burden, the above items were divided into different groups, which were answered in one or more periods during the experiment, respectively. Those items expected to change over the experiment period were answered twice or more.

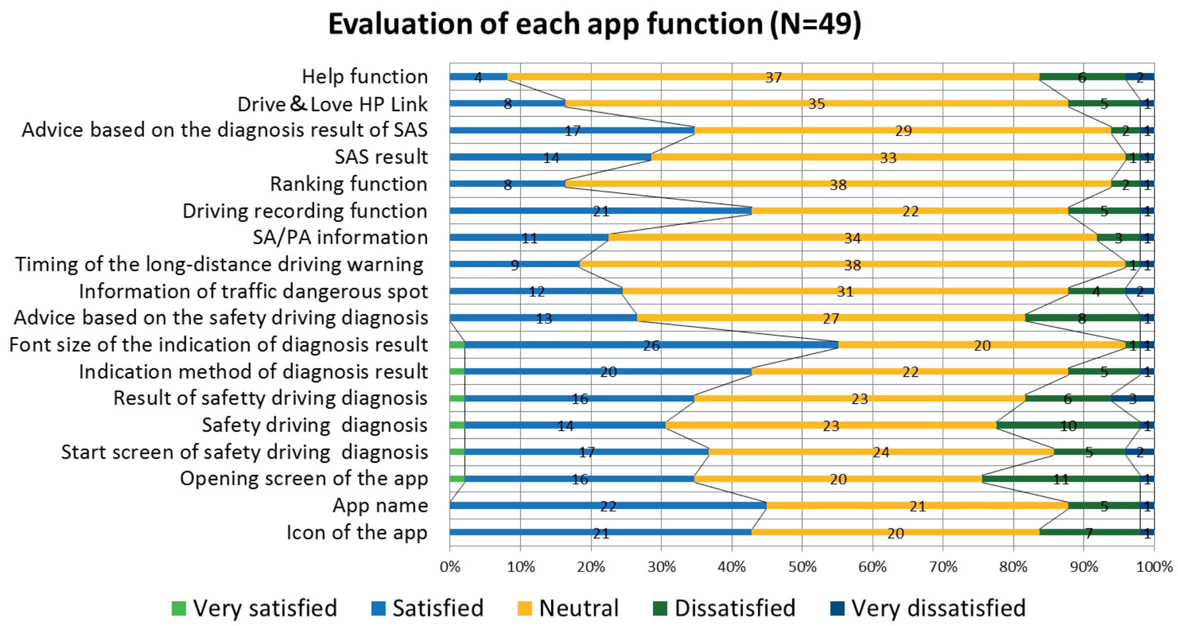


Figure 3-8 Evaluation of app functions

In terms of the developed app evaluation, a series of app related questions have been inquired to the respondents, with regarding to the effect of the functions provided, information provision method and timing issue, as well as the detail app interface design and ease to use, etc. Figure 3-8 shows the aggregated evaluation result obtained from 49 app users. The figure shown that only limited evaluation of "*very satisfied*" opinion could be identified from the functions of *"front size of the indication of diagnosis result," "indication method of diagnosis* *result", "result of safety driving diagnosis", "safety driving diagnosis", "starting screen of safety driving diagnosis, and "opening screen of the app".* About 40% of the users thought the app functions are "*neutral*", neither satisfied nor dissatisfied. Less than 20% of the users expressed negative evaluation opinion on the app function. The least three satisfied functions of the listed functions are *"safety driving diagnosis", "opening screen of the app",* and *"result of safety driving diagnosis".*

On the other side, user s' positive evaluation of the app function, especially the diagnosis functions, take more than 30% of the total evaluation, which imply that the app users are more sensitive with the safety diagnosis function, with less share of neutral comments, and there are still big space that should be done to improve the diagnosis function of the designed app. Aggregation result of each detail function satisfaction is inconsistent with the evaluation result of the app performance (Figure 3-9).

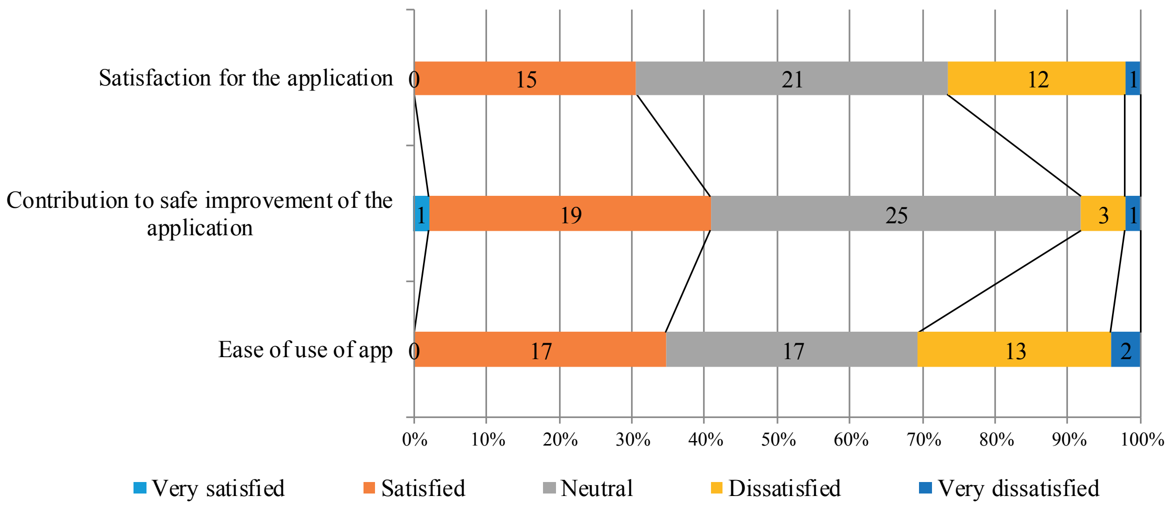


Figure 3-9 Overall satisfaction with the app

Figure 3-10 asked driver's their future app usage willingness, and it shown that those trial users are still hesitate to use this app, since there are no opinions of "*absolute no*" or "*absolute yes*" revealed. On the other hand. However, from the perspective of potential further app usage, about 54% of the users have responded without any negative opinions, including 16% of "*maybe yes*" and 39% of "*neutral*" selections.

In terms of driver's information provision willingness, the Figure 3-11 shows that about24% of the drivers are resistance to information sharing, including 18% of "*yes*" and 6% of "*absolute yes*" opinions. More than 50% of the app users, 37% of "*no*" and 18% of "*absolute no*" opinions, are willing to provide their information for analysis, which reinforced the possibility of employing the smartphone as a more simple, convenient, and elaborated data collection tool.

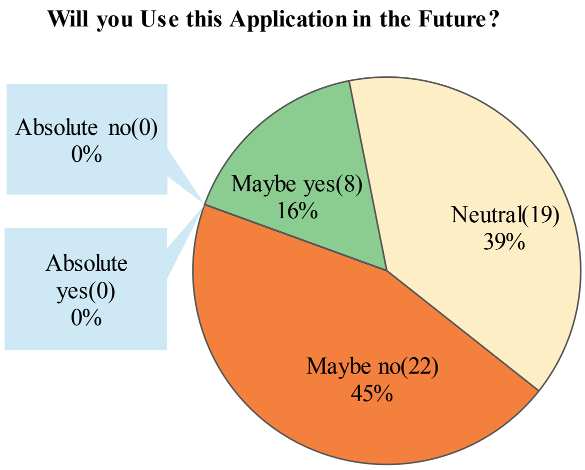


Figure 3-10 Future use of the app

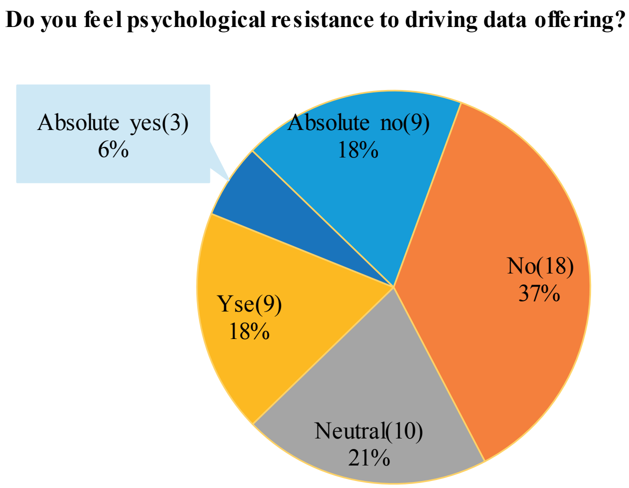


Figure 3-11 Psychological resistance to driving data offering

3.3.2 Case study: truck driving route avoidance questionnaire survey

In terms of driving safety, in addition to individual's objective driving risk mitigation before and during one's trip, drivers may purposely avoid driving on particular routes due to time, cost, and most importantly safety concerns, especially for those drivers from freight forwarders, where a large amount of trips are conducted for goods delivery. Potential driving risks due to long-distance fatigue driving, night driving, and even post-incident responses issues all significant influence and act on driving avoidance behaviors. In case of freight forwarders, company managers may directly and/or indirectly affect drivers' driving decisions from the perspective of safe business operation. Because of the business purpose, drivers may also need to make decisions on driving considering the requirement from the company. Therefore, in order to investigate driving avoidance behavior for mitigating driving risks from the perspective of both drivers and their companies, a questionnaire survey was conducted in the same research area in Chugoku Area, Japan. As shown in Figure 3-12, as for the expressway connecting Kansai area and Kyushu area, two substitute expressways exist: Chugoku expressway (blue line) and Sanyo expressway (red line), which are targeted in this survey.

Compared with regions along Chugoku expressway, more industrial functions and urban functions are concentrated in regions along Sanyo expressway. As a result, traffic volume on Sanyo expressway is much heavier than Chugoku expressway, and more traffic congestion and accidents have occurred on the Sanyo expressway. Moreover, according to NEXCO West[3], due to the pressure of heavy traffic volume on the Sanyo expressway (average daily traffic volume (ADT) on Sanyo expressway is 37787.1 vehicles/day, which is about 2 times of that on Chugoku expressway (15431.3 vehicles/day)), serious saturation of capacities has also been

[3] www.w-nexco.co.jp/

observed in many service areas (SA) and parking areas (PA) on Sanyo expressway. In contrast, about 9 parking areas on Chugoku expressway had to be closed down or already shortened their business hours due to decreasing traffic volume.

As a typical situational driving avoidance behavior, influential factors affecting why most drivers, especially truck drivers, choose to use Sanyo expressway but not Chugoku expressway is the main purpose of implementing this survey.

Figure 3-12 Map of Chugoku expressway (blue line) and Sanyo expressway (red line)

Prior to the implementation of the above questionnaire survey, a face-to-face hearing interview was conducted with several freight forwarder companies in the Kansai region and the Chugoku region in November, 2014. Main topic of the hearing interview focused on company route decision making mechanisms and route decision criteria under unexpected events, current transport status, and preferred incentives for further use of Chugoku expressway.

Based on the hearing interview, a RP/SP combined questionnaire survey was conducted in 2014~2015. Freight forwarder companies, located in Kansai, Kyushu, Sanin, and Sanyo regions in the Chugoku area were selected, by considering their potential use of both Sanyo and Chugoku expressways.

As for truck driving route decisions, three ways may exist. First, the company manger may decide before departure and the driver just follows. Second, the company driver may decide before department and adjust driving routes depending on actual driving situations. Third but not least, both the company manager and diver may make decisions on driving routes jointly. However, in literature, there is no research has been conducted to investigate such decision-making mechanisms of freight forwarders. Therefore, in this survey, the above matters were reflected as a driving avoidance behavior. This is because, for example, companies and /or drivers may purposely avoid driving on either Sanyo expressways or Chugoku expressway.

As for survey contents, the RP contents are different between company managers and drivers, while the SP contents are same for all the respondents (the manager and drivers) belonging to a same company. A maximum of five drivers were selected from each company. A brief summary of the survey contents is shown in Table 3-3.

Table 3-3 Summary of survey contents

Respondents	Company managers and drivers of freight forwarders in Kansai, Kyushu, Sanin, and Sanyo regions.
Survey contents	Company profile (e.g. vehicle ownership, number of employees, freight delivery cost), incentives for further use of Chugoku expressway, personal attributes of managers and drivers (e.g., age, gender, professional driving age), RP survey of previous driving experience evaluation of driving route and SA/PA services, image evaluation of Chugoku expressway, and SP survey contents

In terms of the RP survey, questions raised for company manager mainly include company profile, including vehicle ownership, number of employees, annual trade volume, insurance status, concerned factors for route decision making, as well as shares of expenses on expressway toll, vehicle maintenance and renewal cost, fuel consumption, safety measures, labor, and environmental preservation. Questions about drivers mostly focus on their previous target expressway usage experience, including detailed route information and SA/PA usage information of recent Sanyo and Chugoku expressway usage. Additionally, driver's evaluations of their experienced target expressways and services of SA/PA were also reported, together with general frequency information of driver's experiences related to expressway traffic congestion, accidents, and vehicle malfunctions.

As for SP survey, attributes identified from the previous hearing interview were utilized in the SP survey design. Detailed information of SP attributes and their levels are shown on Table 3-4. Totally, four important attributes were employed in the SP design, each of which has two or three levels. By employing an orthogonal design method (realized in SPSS16.0 software), nine SP profiles with different combinations of SP attributes and levels were obtained.

Table 3-4 Levels of SP attributes

Goods type	1. fragile goods
	2. general goods
Travel time on Sanyo expressway	1. same as normal travel time
	2. once in 10 times, 1.5 times of normal travel time
	3. once in 5 times, 1.5 times of normal travel time
Tow truck subsidy for incident/malfunction	1. No subsidy for both Sanyo and Chugoku expressway
	2. subsidy is provided for the part that is not covered by insurance, only for Chugoku expressway (must be insured)
	3. full subsidy is provided without any requiremnt of insurance insured on Chugoku expressway
Reduction	1. no reduction
	2. 2000 JPY point reduction for oneway Chugoku expressway use
	3. 3000 JPY point reduction for oneway Chugoku expressway use

In this survey, seven OD pairs (shown in Table 3-5) were pre-selected considering the locations of freight forwarders selected. In other words, a total of 63 SP profiles (seven OD pairs * nine SP profiles for each OD) were generated. Figure 3-13 shows an example of the SP profile (or card) provided to respondents. In the survey, each respondent was assigned three SP profiles (or cards) with respect to only one OD pair (or one driving route).

The survey was conducted during 2014 ~ 2015 by distributing questionnaires to 173 target companies via post mails. As a result, 58 companies returned questionnaires. A total of 232 valid questionnaires from 54 company managers and 178 drivers were obtained for this study.

Table 3-5 Seven OD route pairs

	Origin (O)	Destination(D)
OD1	Chugoku Suita	Mojiko
OD2	Matsue Tamatsukuri	Mojiko
OD3	Tottori	Mojiko
OD4	Okayama	Mojiko
OD5	Hiroshima	Mojiko
OD6	Kyoto	Shimane Tamatsukuri
OD7	Kyoto	Matsue Tamatsukuri

Assume there is one trip to deliver fragile goods according to the OD below:

Origin Destination

Chugoku Suita IC (Osaka) → Mojiko IC (Fukuoka Prefecture)

ETC night price 12600Yen (normal price 18700Yen)

	Chugoku Road	Sanyo Road
Travel Distance	544.2 km	520.4 km
Toll fee	ETC night price 12600 JPY (normal price 18700 JPY)	
Travel Time	About 7 hours (normal time)	About 6 hours (normally), but once in 10 times about 9 hours (1.5 times) due to accident caused congestion
Tow truck subsidy for incident/ malfunction	Full subsidy is provided without any requirement of insurance insured on Chugoku Road	No subsidy
Reduction	No reduction	No reduction

Based on those information, please circle out the route you want to choose.

Chugoku Road ・ Sanyo Road

Figure 3-13 An example of SP card for expressway route avoidance survey

3.3.3 Adaptive behavior under accident information provision questionnaire

To capture drivers' adaptation behavior to the occurrence of traffic accidents on expressways and dynamic travel information, we implemented two web-based questionnaire surveys: one was a large-scale revealed preference (RP) survey in December 2011 and the other was a large-scale stated preference (SP) survey in March 2012. Since in the SP survey, respondents were asked to make decisions based on hypothetical questions, efforts to generate realistic hypothetical scenarios should be made to guarantee the reliability of respondents' decisions. In line with such consideration, the SP survey was designed based on respondents' actual expressway usage experiences, travel information preference and usage, which were collected from the RP survey.

First, 2,500 respondents participated in the RP survey. After that, they were further asked to participate in the SP survey and as a result, 1,923 respondents remained in the SP survey. To meet the required sample size, the remaining 577 respondents were newly recruited. In the SP survey, three driving scenes were assumed: (1) before departure, (2) on the way to expressway, and (3) on expressway. Each respondent was asked to answer four SP cards for each scene. Therefore, 10,000 SP responses were obtained for each scene and 30,000 SP responses in total were obtained. In the following, the RP and SP surveys are briefly explained. Contents of the pilot survey are shown as follows:

1) Vehicle usage: vehicle usage frequency and usage purpose and so on;
2) Expressway usage: frequency, purpose, recent expressway usage information (e.g. entry and exit interchanges (ICs), trip purpose, travel time, and other detail conditions during the use of expressways);
3) Needs for travel information (22 types): vehicle type of primary party causing the

accident, accident severity, collision objects, clearance time (predicted value, prediction accuracy, provision of time interval value), queue length, time elapsed after the occurrence of accident, queue changing trend (increasing or decreasing), location of service area (SA) with smart IC (only vehicles equipped with ETC (electronic toll collection) functions are allowed to pass), neighboring SA & PA (parking area) (availability, distance to them), neighboring IC (availability, distance to its), lane regulation or closure, availability of alternative choices (expressways, ordinary roads, other travel modes), queuing nearby exit ramp, park & ride facilities;

4) Internet usage: ownership, usage frequency, usage time;
5) Tolerance levels of accident impacts: tolerance queuing time and queue length;
6) Acceptable information accuracy and willingness to pay for the information with the acceptable accuracy;
7) Individual attributes: age, gender, address, education background, occupation, and vehicle ownership, etc.

The objective of SP survey is to quantitatively measure the influence of dynamic travel information on driver's adaptation behavior responding to the occurrence of traffic accidents on expressways. It is expected that such adaptation behavior differs depending on where a driver is when the accident occurs and uncertain levels of available information. Drivers may face different levels of time pressure and experience a differing availability of various types of information depending on the location. Therefore, the driver location is divided into three scenes: before departure, on the way to expressway, and on expressway.

Based on the pilot survey, this study selected 12 attributes for the SP survey, each of which has two or three levels.

1) accident condition factors (two attributes): (1) distance from entrance IC ramp to the accident site (hereafter, distance to site), with two levels (far or close); (2) accident

severity information, including three levels of “have fatality”, “no fatality”, or “no information provided”

2) accident impact factors (two attributes): (3) queue length due to accident-induced congestion (long, short, or no information provided); (4) queue changing trend with three levels: increasing, decreasing, or no information provided

3) alternative route or travel mode factors (three attributes: each with three levels (with (or without) alternative route/mode, or no information provided)): (5) alternative ordinary road, (6) alternative expressway, (7) other travel modes

4) traffic management factors (five attributes): (8) traffic regulation (with/without regulation, or no information provided), (9) estimated clearance time of congestion (short, long, or no information provided), (10) estimation accuracy of clearance time (high or low), (11) probability of clearing away the congestion at a certain length of clearance time (high (80%), low (60%)), and (12) clearance time provision method (point-based information or time interval based information).

In total, 24 SP profiles were obtained from the 12 attributes by employing an orthogonal fractional factorial design. Except for the probability of clearing away the traffic congestion at a certain length of clearance time, the values of other attributes are all calculated by reflecting each respondent’s reported information from a recent trip of using an expressway route in the pilot survey. To enhance the reliability of the hypothesis scenarios in the SP survey, detail information processing and review tasks were conducted as follows:

1) Trip information (i.e., entry and exit IC ramps, IC distances): First, unclear and mistaken names of IC ramps were revised with referring to drivers’ address information and reported IC distance information. Next, in case that IC ramps are unknown, IC ramps located close to drivers’ homes or destination were adopted. In addition, IC distance reported less than 5 km were re-checked and modified by

comparing with the actual distance between given entry and exit IC ramps.

2) Tolerance level of the length (distance and time) of traffic congestion: Specific values of expected queue length and clearance time information were calculated based on the corresponding tolerance value reported by respondents in the pilot survey. Long and short levels of queue length were calculated to be 1.2 times and 0.7 times of tolerance queue length reported, respectively, while long and short levels of clearance time were set to be 1.2 times and 0.8 times of tolerance clearance time reported, respectively.

3) Acceptable level of time information accuracy: Two levels of low and high accuracy of interval clearance time were set to be 80% and 100% of the revealed acceptable time accuracy information in the pilot survey, respectively.

4) Distance to site: Long and short levels of "distance to site" were given by taking the 70% and 20% of the target IC distance. For cases that the IC distance is very short, a minimum distance to site value of 0.5 km was assumed.

The adaptation alternatives are assumed differently depending on drivers' locations, including before departure, on the way to expressway, and on expressway. Adaptive choice set in each decision scene (drivers' location) is assumed as follows:

1) Before departure and on the way to expressway: **a)** *no change* (use the expressway as original plan); **b)** *change departure time* (use the expressway as scheduled, but change the scheduled departure time); **c)** *ordinary road* (give up using the expressway, instead, shift to the ordinary road usage); **d)** o*ther travel mode* (give up using the car, instead, use other travel mode(s)); **e)** *Cancel the trip*.

2) On expressway: **a)** *no change* (use the expressway as original plan); **b)** *wait and see at SA/PA* (take a short rest at nearby service area (SA) or parking area (PA) for wait and see); **c)** *alternative expressway* (shift to other alternative expressway); **d)** *ordinary road detour* (get

out of the expressway at nearest exit ramp and then detour back to the expressway to avoid the accident affected area); **e)** *ordinary road* (give up using the expressway, and shift to ordinary road usage); **f)** *other travel mode* (give up using the car, instead, use other travel mode(s)); **g)** *Cancel the trip*.

Examples of the SP cards are shown below.

If you are now under the condition of "**on the way to the entrance IC**", the supposed trip information is shown as follows:

Trip purpose	Entrance IC	Exit IC	IC distance
Commuting	Shiwa IC	Hiroshima IC	20 Km

A traffic accident occurrence on the expressway which you pretend to use, distance from the entrance IC to the accident site is about **14 km**. Then, information provision of related information is shown as:

Traffic information	
Traffic accident information	
Accident severity	Have fatal accident
Lane regulation information	
Have lane regulation	
Traffic congestion information	
Queue length	2 km
Clearance time	Probability that the congestion will be cleared with 24minutes is 80%.
Queue changing trend	Decreasing
Substitute route & travel mode information	
Sub expressway	No substitute expressway
Sub ordinary road	No information
Sub other travel mode	Have substitute public transportation

If you are now under the condition of "**before departure**", the supposed trip information is shown as follows:

Trip purpose	Entrance IC	Exit IC	IC distance
Entertainment	Shiwa IC	Hiroshima IC	20 Km

A traffic accident occurrence on the expressway which you pretend to use, distance from the entrance IC to the accident site is about **4 km**. Then, information provision of related information is shown as:

Traffic information	
Traffic accident information	
Accident severity	No information
Lane regulation information	
No information	
Traffic congestion information	
Queue length	2 km
Clearance time	Congestion will be cleared in 25 ~ 47 mins.
Queue changing trend	Increasing
Substitute route & travel mode information	
Sub expressway	No information
Sub ordinary road	No information
Sub other travel mode	Have substitute public transportation

Figure 3-14 Examples of SP cards adaptation questionnaire survey

Chapter 4

Short-term Effects of *Safety Supporter* on Mitigation of Objective Driving Risks

In this chapter, short-term effect of a GPS-enabled smartphone App, called *Safety Supporter,* was examined on driving risks mitigation. "Short-term" effect mentioned in this part refers to the instant influencing impact of the app on drivers' objective driving performances, evaluated at second-by-second level. Concretely speaking, risk indicator of compliance with speed limit, which is the mostly conventional and direct indicator of driving risk, has been analyzed firstly to check the effect of the *Safety Supporter* on driving safety. Individual's over-speeding behavior performances under the real time information provision through various proposed functions have been investigated. Moreover, heterogeneous across drivers have also been considered with according to driver's belong to different driving behavioral safety change of stage. Secondly, the necessity of jointly using three types of driving risks indicators of speed limit compliance, abrupt acceleration/deceleration, and driving stability control have been investigated. Finally, performance of individual driver's speed limit compliance and acceleration/deceleration control behavior has been studied jointly, to investigate the inter-correlation between two driving safety indicators. Second-by-second data was utilized for data analysis in this chapter to also find out the significant short-term factors that influencing on drivers' second-by-second driving performance.

4.1 Descriptive statistics of second-by-second driving performance

In addition to the data obtained from experiment and questionnaire survey, some external environment data have also been collected, including traffic volume data (measured every five minutes based on drivers' temporal-space information), GIS based data of expressways types and lane use types along the expressway. The external data were matched with the second-by-second data from *Safety Supporter* along the whole driving route.

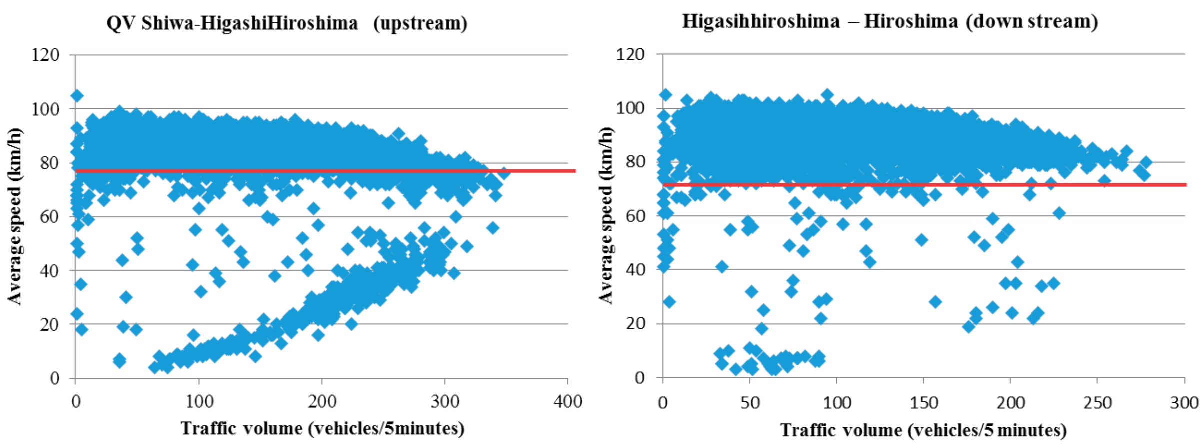


Figure 4-1 An example of the free traffic flow speed identification through QV curves

If a trip is too short, it might be difficult to observe the effects of the app on safety improvement. With this consideration, trips lasting for less than 10 minutes were excluded. In order to purely investigate individual drivers' behavioral changes influenced by Safety Supporter, only cases of free traffic flow and expressways with two or more lanes were selected. Under free traffic flow, drivers do not need to drive by reacting to other drivers in the surrounding traffic and the existence of two or more lanes allows drivers to make a free choice of driving lane. In other words, under these two cases, it is expected that drivers can choose their driving speed more freely than other cases. Based on our analysis, free traffic flow was observed when driving speed is faster than 70 km/h (Figure 4-1). Data with poor satellite signals and other errors were further excluded. Finally, after matching available data of the variables, 187,549 epochs (i.e., two seconds) from 201 trips made by 15 individuals were extracted for this study. Numbers of epochs collected from the 15 drivers by each of six period are shown in Table 4-1.

The 15 individuals are all male drivers and aged from 30 ~ 59 years old (the average age is 42 years old). Among the 15 individuals, 11 of them (73.3%) intend to improve their driving safety under the stages of contemplative, preparation, action, or maintenance. Average score of drivers' safety self-evaluation is 72 (ranging from 0~90). 53.3% of the drivers used to have traffic accident experiences, and about 73.3% of the driver have been punished due to the traffic rule violation behaviors. Looking at the driving environment, 26.2% of the driving is on holiday, and almost half (46.1%) of the driving is observed during the night time. Driving direction on both side (up and down stream) is equally distributed. Average speed limit on the expressway is 85km/h, with average traffic volume of 68 vehicles per 5 minutes, and 23.6% of large vehicles share rate in the traffic.

Table 4-1 Data collected from the 15 drivers by period

(Unit: epoch)

ID	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Total
1		1,021			1,264	3,966	6,251
2	525		1,026				1,551
3	11,272		2,938		3,072	3,754	21,036
4	9,672	3,676			10,749	14,232	38,329
5	13,325	5,056		473	12,494	3,937	35,285
6		4,010	620			779	5,409
7	494	7,329	9,876		8,286	12,019	38,004
8	4,379	1,311	399		925	1,823	8,837
9					1,001		1,001
10			2,058				2,058
11	1,354			1,039	983		3,376
12	1,875	1,217		1,171	1,276	2,363	7,902
13	3,474					3,723	7,197
14						525	525
15	4,092	1,018	3,458		1,112	1,108	10,788
Total	50,462	24,638	20,375	2,683	41,162	48,229	187,549

All factors collected from both the field experiment and questionnaire survey should be introduced to explain driving risks. However, especially for those subjective and objective factors collected from the questionnaire surveys, various complicated cause-effect relationships may exist, making analyses difficult. Because the purpose of this study is to clarify effects of driving safety diagnosis and traffic warning information, it is better to avoid any factors that might cause statistically correlated information as much as possible, in representing driving risks. With this consideration, we selected explanatory variables as shown in Table 4-2

(1) Because the basic functions (both diagnosis and traffic warning information provision) of *Safety Supporter* are most important in the development of *Safety Supporter*, to properly measure the effects on driving risks, drivers' heterogeneity is reflected in terms of driving propensity. For this analysis, irritable drivers (73.3%), careless drivers (60.0%), aggressive drivers (60.0%), and excessively confident drivers (60.0%) are identified. None of the 15 drivers was classified as either indecisive or safe drivers. It is obvious that some drivers belong to two or more types of driving propensities.

(2) Additional functions are evaluated separately by introducing a dummy variable for each function (0 or 1) with the aim of determining the best functions of *Safety Supporter*.

(3) Contextual factors are introduced, including driving on holiday, driving at night, speed limits, driving direction, and traffic factors (traffic volume and proportion of large vehicles), where traffic factors (measured every five minutes) were collected from external sources.

(4) Because many drivers in this case study are risky drivers, experiences of traffic accidents and punishments for traffic rule violations are selected.

(5) Because the analysis unit is epoch (i.e., two seconds) and many data involve continuous driving within a single trip, time-dependent factors should be introduced to explain epoch-by-epoch variations of driving risks. Here, driving time with respect to each epoch and trip

duration as a whole are selected. Driving time is specified as a percentage in the total trip duration, which can be used to represent the level of a driver's concentration to driving.

(6) Driving risks may change depending on the driving environment. Related to this, land use along expressways and types of expressways are employed.

(7) Driving risks may vary with drivers' individual attributes, which are therefore listed for accommodating any potential observed heterogeneities.

(8) Finally, as for the items included in the questionnaires, we selected two potentially influential factors reported before the experiment: one is self-evaluated score of daily driving safety (0–100 points) and the other is behavioral change stages. The self-evaluated safety score is used to represent drivers' inherent abilities of safe driving control. Behavioral change stages express the intention level for improving driving safety. Based on the theory of planned behavior, people's behavioral changes may never occur without intention in mind in advance.

Table 4-2 Explanatory variables and their average values

Basic functions (1: yes; 0: no) × driving propensity (1: yes; 0: no)	
Basic functions × Irritable driver	49.5%
Basic functions × Careless driver	41.8%
Basic functions × Aggressive driver	60.3%
Basic functions × Excessively confident driver	63.5%
Driving propensity (1: yes; 0: no)	
Irritable driver	73.3%
Careless driver	60.0%
Aggressive driver	60.0%
Self-confident driver	60.0%
Additional functions	
Function 1 (SA/PA information)	60.0%
Function 2 (Ranking and self-diagnose)	49.1%
Function 3 (Driving propensity & advice)	47.7%
Function 4 (Traffic safety campaign)	25.7%
Experiential factors	
Traffic accidents (1: yes; 0: no)	53.3%
Punishment of traffic rule violation (1: yes; 0: no)	73.3%
Trip attributes	
Driving time (%)	49.0%
Trip duration (second)	3,807
Self-evaluation factors	
Self-evaluated safety score (0~100)	72
Behavior change stage (1: Intend to improve safety; 0:otherwise)	73.3%
Driving contextual factors	
Drive on holiday (1: yes; 0: no)	26.2%
Driver at night (1: yes; 0: no)	46.1%
Speed limit (km/h)	85
Driving Direction (1: upstream; 0: downstream)	49.9%
Traffic volume (number of vehicles per 5 minutes)	68
Share of large vehicles in traffic (%)	23.6%
Driver attributes	
Age (years old)	41.6
Occupation (1: public sector; 0: others)	27.0%
Trip purpose (1: with time constraints; 0: without)	60.0%
Driving frequency (ordinal data)	2
Land use factors	
Driving along farm lands (1: yes; 0: no)	20.3%
Driving along forests (1: yes; 0: no)	51.2%
Driving along building areas (1: yes; 0: no)	10.9%
Types of expressways	
Chugoku (south-north direction) (1: yes; 0: no)	9.7%
Chugoku (west-east direction) (1: yes; 0: no)	39.6%
Sanyo (west-east direction) (1: yes; 0: no)	48.5%

4.2 Influence of behavioral change stages of safe driving on speed limit compliance

This subsection aims to clarify the influence of behavioral change stages (Rasouli and Timmermans, 2016; Zhang et al., 2016) of safe driving on speed limit compliance. It is written mainly based on the publication by Jiang and Zhang (2016b).

4.2.1 Introduction

It is expected that driving behavior might be heterogeneous across drivers, but it is unclear that under the influence of the developed App, what kinds of factors cause such a heterogeneity. In addition, the purpose of the developed App is to assist drivers to perform safer driving; however, whether drivers perform safer driving or not may depend on their behavioral change stages. To answer the above questions, we employ data collected from a three-month driving experiment implemented in Japan between February and May in 2014 with a purpose to examine the effects of this App on over-speeding violation behaviors on expressways, especially focusing on behavioral change stages. Six different behavior stage is shown in Table 4-3.

Table 4-3 Behavioral change stages of safe driving

1	Pre-contemplative	As the moment, I am happy with my current level of safe driving, and see no reason why I should change it.
2		As the moment, I would like to improve my level of safe driving, but feel at this moment it would be impossible for me to do so.
3	Contemplative	As the moment, I am thinking about improve my level of safe driving, but at this moment, I am unsure how I can.
4	Preparation(/testing)	As the moment, I still want to improve my level of safe driving, I already know methods that I could help me, but as yet have not actually put this into practice.
5	Action	As the moment, I still want to improve my level of safe driving, and now working on it.
6	Maintenance	As I am aware of many problems associated with safety driving, I already try to improve my driving safety level as much as possible. I will maintain or even improve my already high safe driving level in the future.

4.2.2 Methodology: A zero-inflated negative binomial regression (ZINBR) model

Focusing on individual's behavioral changes of safety stage, the second-by-second over-speeding violation behavior was selected as dependent variable with comparison analysis between two aggregated stages.

We estimated the models for drivers at a stage of trying to improve safe driving (Driver Type 1: 31) and stage of pre-contemplation to improve (Driver Type 2: 16). Analysis unit is observation of driving behavior by every two seconds. And the sample sizes are 152,666 (zero observations: 31,297) for Driver Type 1 and 34,883 (zero observations: 4,758) for Driver Type 2. Distribution of the over-speeding value is show in Figure 4-2.

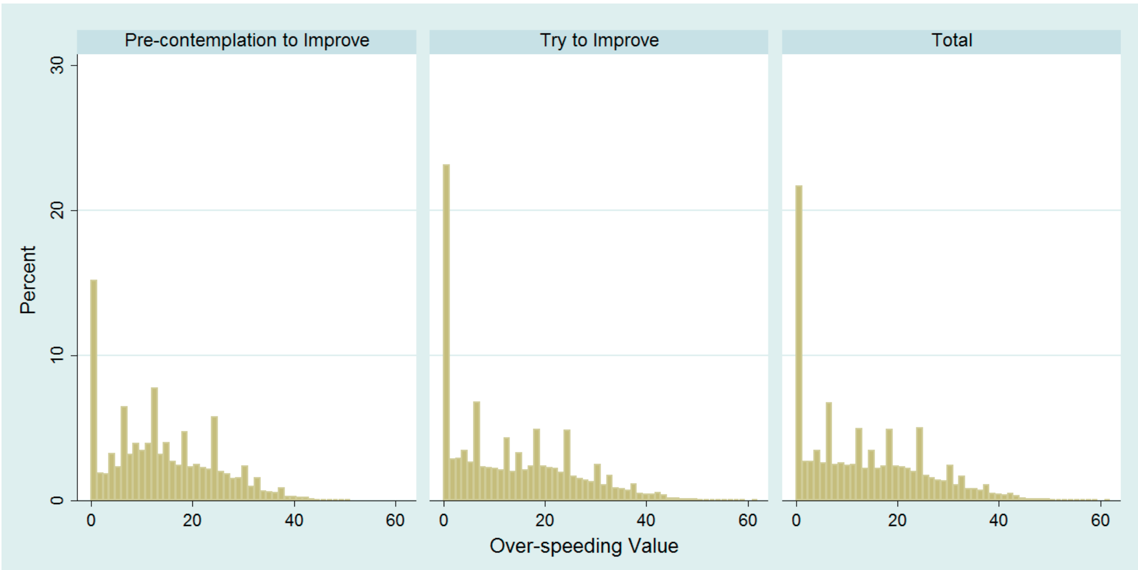


Figure 4-2 Distribution of over-speeding value among three group data

Aggregation result of three groups result shows that for drivers belong to pre-contemplation group, distribution of their overs-speeding value is different from the group of

Driver Types 1. Higher over-speeding rate (84.8%) could be identified for drivers belong to Driver Type1, comparing with rates of Driver Type 2 (76.9%) and full sample data (78.4%).

Due to the higher share rate of “0” value, which indicate no over-speeding violation behavior, a Zero-Inflated Negative Binomial (ZINBR) regression model was employed for the data analysis based on the distribution of our dependent variable. Equation of the ZINBR model is show as follows:

$$\Pr(Y = y) = \begin{cases} p + (1-p)e^{-\lambda}, & y = 0 \\ (1-p)\dfrac{e^{-\lambda}\lambda^{y}}{y!}, & y > 0 \end{cases} \qquad \textit{4-1}$$

$$\log it(p) = \log(\frac{p}{1-p}) = G\gamma \qquad \textit{4-2}$$

$$\log(\lambda) = B\beta \qquad \textit{4-3}$$

Where G and B are parameter matrix,β and γ are observed explanatory variables, and λ is over dispersion coefficient (if λ =0 indicates the model is better estimated using a Poisson regression model).

The ZINBR regression model assumes there are two distinct data generation processes. The result of a Bernoulli trial is used to determine which of the two processes is used. Logit model is employed for the inflation model to determine whether the observation is zero (equation 2). For observation i, with probability p the only possible response of the first process is zero counts, and with probability of $(1-p)$ the response of the second process is governed by a negative binomial with mean λ.

4.2.3 Model estimation results

Model estimation result is shown in Table 4-4, and the significant likelihood ratio test for lamada (λ) =0 indicates that the ZINBR model is preferred to the ZIP model (zero inflated probit regression) for the three model. Meanwhile, the significant z-test of the Vuong test indicate that the ZINBR is more suitable than the ordinary negative binomial regression model. The McFadden's Rho-squared (Adjusted Rho-squared) value are, 0.14 (0.14), 0.20 (0.19), and 0.14 (0.14) for the "try to improve" models of Driver Type 1, "pre-contemplation to improve" model for Driver Type 2, and whole sample model. Rho-squared values of the ZINBR models range from 0.14 to 0.20 indicate the model fit the data well.

Focusing on the inflation model, individual attribute was employed as the explanatory variables, including the age, occupation, trip purpose, and driving frequency. Among those individual attributes, significant negative impact of the "occupation" factors could be identified for drivers at pre-contemplation to improve (-1.06) and try to improve (-2.83) stages, which indicate the drivers in public sectors (27.0%) are more likely to perform over-speeding behaviors. While for other factors, opposite impacts between two types of drivers could be identified. Regarding to drivers under stage of try to improve, higher over-speeding performance probability could be identified from elderly drivers (-0.02) with lower driving frequency (0.53), and low time constrain trips (0.91). On the other hand, younger drivers (0.02) who are driving for a trip purpose without strict time constraints (60.0%) are less likely to follow the limited speed while their driving. In addition to individual attribute information, self-evaluation factors (self-evaluated safety scores (72 points on average, measured before the experiment) is also employed as explanatory variable. Significant positive sign (0.01) of the self-evaluated safety score indicate that driver with high self-evaluation scores are more likely to compliance with the speed limit, and therefore driving safer.

Table 4-4 Estimation results of ZINBR models

	the "Try to Improve" driver model (Driver Type 1)		the "Pre-contemplation to Improve" driver model (Driver Type 2)		the whole sample model	
	Coef.	sig.	Coef.	sig.	Coef.	sig.
Variables describing data generation process						
Driver attributes						
Age (years old)	-0.02	***	0.02	**	-0.01	***
Occupation (1: public sector; 0: others)	-2.83	***	-1.06	***	-0.85	***
Trip purpose (1: with time constrains; 0: without)	0.91	***	-3.35	***	0.75	***
Driving frequency (ordinal data)	0.53	***	/		0.53	***
Self-evaluate safety score (0~100)	0.01	***	/		0.01	***
Constant term	-3.33	***	-2.2	***	-3.71	***
Variables describing non-zero data generation process						
Basement function (1: yes; 0: no) x driving propensity (1: yes; 0: no)						
Irritable driver	-0.02	***	-0.31	***	0.002	
Careless driver	-0.35	***	-0.74	***	-0.37	***
Aggressive driver	0.22	***	/		0.14	***
Excessively confident driver	-0.11	***	0.29	***	-0.11	***
Additional functions (1: yes; 0: no)						
Function_1 (SA/PA information)	0.26	***	0.34	***	0.21	***
Function_2 (Ranking and self-diagnose)	-0.13	***	0.18	***	-0.09	***
Function_3 (Driving propensity & advice)	-0.07	***	/		0.0001	
Function_4 (Traffic safety campaign)	0.04	***	-0.05	***	0.05	***
Experiential factors						
Traffic accidents (1: yes; 0: no)	0.69	***	5.72	***	0.65	***
Punishment of traffic rule violation (1: yes; 0: no)	-0.77	***	-0.67	***	-0.6	***
Trip attributes						
Driving time (%)	-0.02	***	0.07	***	-0.01	
Trip duration (second)	-0.0001	***	0.0001	***	-0.0001	***
Driving contextual factors						
Drive on holiday (1: yes; 0: no)	0.23	***	-0.08	***	0.18	***
Driving at night (1: yes; 0: no)	0.11	***	-0.19	***	0.08	***
Speed limit (km/h)	-0.05	***	-0.04	***	-0.05	***
Driving Direction (1: upstream; 0: downstream)	0.05	***	0.01	**	0.04	***
Traffic volume (number of vehicles per 5 minutes)	-0.003	***	0.0001		-0.003	***
Share of large vehicles in traffic (%)	-0.86	***	0.21	***	-0.7	***
Land use factors (1: yes; 0: no)						
Driving along farm lands	0.03	***	0.04	***	0.03	***
Driving along forests	-0.02	***	0.03	***	-0.01	*
Driving along building areas	0.02	***	0.04	***	0.02	***
Types of expressways (1: yes; 0: no)						
Chugoku (south-north direction)	-0.39	***	4.82	***	-0.38	***
Chugoku (west-east direction)	-0.39	***	5.02	***	-0.35	***
Sanyo (west-east direction)	-0.03	***	0.1	***	-0.03	***
Constant term	7.61	***	1.27	**	7.27	***
ln(λ)	-1.39	***	-2.06	***	-1.41	***
λ	0.25 ***		0.13 ***		0.25 ***	
Converged log-likelihood	-491333.69		-111965.57		-610257.7	
Initial log-likelihood	-573996.59		-139105.49		-713046.41	
Rho-squared	0.14		0.2		0.14	
Adjusted Rho-squared	0.14		0.19		0.14	
Number of observations (sample size)	152666		34883		187549	
Number of zero observations	31297		4758		36055	
Log-likelihood ration (LR) χ2 (29)	70841.24		19690.19		79639.17	
Pr > c2	0		0		0	
Vuong test against standard negative binomial model	z = 93.02 Pr>z = 0.00		z = 52.79 Pr>z = 0.000		z = 105.98 Pr>z = 0.00	
Likelihood for testing "λ= 0"	chibar2(01) =2.1e+05 Pr>=chibar2 = 0.00		chibar2(01) = 2.1e+04 Pr>=chibar2 = 0.00		chibar2(01) = 2.6e+05 Pr>=chibar2 = 0.000	

Significant level: *** 99%, ** 95%, * 90%; "/" no data

Model estimation results show that effects of the App information provision on driver's over-speeding behavior are mixed. Especially, the opposite influencing impact of the same information on different driver types have also been observed. Focusing on the basic function of the App, influence of individual's driving propensity (i.e., irritable driving, careless driving, aggressive driving, and excessively confident driving) is incorporated into the analysis to reflect driver's heterogeneous responses to the App. For careless drivers (60.0% in total), the basic functions of the App contribute to lower over-speeding value because the corresponding parameters in driver type 1 sub-model (-0.35) and in the driver type 2 sub-model (-0.74) are all negative. Potential explanation of this result is that for careless driver, they are not sensitive enough to the driving speed change, therefore information provision of designed App could help to draw their attention and significantly contribute to driver's safe driving improvement with lower speed limit violation behavior. In terms of the irritable driver (73.3%), who tend to be annoyed with other vehicles (e.g., Kusuhashi et al., 2012), basic information provision of the App could help driver's to pay more attention on their speed control while they were trying to overtake the vehicles in front of them. In contrast, for aggressive driver (60.0%), significant positive sign of the basic function information provision indicate the basic function does not effectively help drivers on driver's over-speeding behavior. The reason why the basic function provision could not persuade drivers to driver more slowly is probably due to the fact that the purpose of aggressive drivers' lane changing behavior is to drive faster, making the diagnosis work in an unexpected way. In terms of the excessively confident driver (60.0%), impact of the basic information provision could only help to Driver Type 1 drivers, who intent to improve their safe driving status. Unfortunately, the over-speeding behavior by Driver Type 2 would be worsened.

As for effects of additional function, it is observed that impact of the "Function 1", e.g., SA/PA information provision, fail to improve driver's speeding control behavior. Because in the designed App, SA/PA information is only provided to drivers who drive a longer time (the default value is two hours and can be changed by drivers depending on their own preference). However, in the experiment long-distance drivers were not the majority, influence of the SA/PA information could not influence on driver's over-speeding behavior properly, above result cannot be properly interpreted. On the other side, three other additional functions surely help to improve driver's speeding control behavior conditionally. Focusing on the Driver Type 1 drivers, who are currently trying to improve their driving safety, App function of "Function 2" (ranking among other App user and self-diagnose by the end of each drive) and "Function 3" (driving propensity & advice) significant helps on the improvement of driver's over-speeding control behavior with significant negative parameters (-0.13 and -0.07 for "Function 2" and "Function 3"). While for the second type drivers, who are still under the contemplation to improve their safety stage, this two provided functions failed to meet our expectation. On the meanwhile, even though the aforementioned function failed to help on drivers under the pre-contemplation to improve stage, the significant and negative parameter (-0.05) of traffic safety campaign function (Function 4) suggests that those drivers who experienced the website of social campaign "Drive & Love" enhanced their over-speeding control behavior properly, which is consensus with our expectation of promote the drivers towards driver driving stages.

Regarding to driver's experiential factors, experiences of traffic accidents and punishments of traffic rule violations are expected to be influential to driving over-speeding behavior control. It is observed that drivers with experiences of traffic accidents (53.3%) are more likely to over-speeding (0.69, 5.72, and 0.65 for three model parameters), while in contrast, those with experiences of traffic rule violation punishments (73.3%) performed safer with significant negative parameter for three models (-0.77, -0.67, and -0.60). Result of the experiential factors on over-speeding behavior emphasis that experiencing the punishments may compel drivers to pay more attention to more mannered driving. This finding also confirms that enforcement of traffic rule violation punishment is important to the improvement of safer driving management.

As for trip attributes, the contradictory influencing impact of the two time-dependent variables, trip duration (the entire time of a trip with about 63 minutes on average)) and driving time (the time elapsed from the start of the trip, which is measured in terms of the percentage of the time elapsed in the trip duration) have been also identified. For drivers intend to improve their driving safety stage, better driving control behavior with lower over-speeding value could be achieved for longer trips driving and the later period of the trips. And then for driver belong to other safety stage, safer driving behavior mainly under the situations of short trips and early period of a trip.

Estimation results of driving contextual factors reveal that the App is more effective to the improvement of driving safety on high speed limit and downstream driving direction expressways for drivers under any of the safety stages. However, other driving contextual factors show a mixed effect on over-speeding driving reflecting from the opposite driving behaviors between two types driver. Concretely speaking, for drivers try to improve their safety stage, more large-sized vehicles in traffic (23.6% on average) and higher traffic volume in the traffic flow would increase the driving conflicts among vehicles and as a result, lower over-speeding behaviors will be identified. However, for drivers belong to other safety stages, they are less sensitive to the traffic volume situation and tend to perform more over-speeding behaviors when more large-sized vehicles are involved in the traffic low. In the meanwhile, they are more likely to be control of their over-speeding behaviors under night time (46.1%) and holidays (26.2%) driving. Potential explanation of this result is that for drivers under situation of holiday and night driving is quite different from the conventional driving environment, therefore, more contextual-specific features should be considered in the traffic safety studies.

Focusing on the land use factors, estimation result shows that for drivers driving along three land use types of farm lands, forests, and building areas are more likely to over-speeding, only one exception of lower over-speeding behavior could be identified for type 1 drivers along the forests land on expressway.

Concerning types of expressways, drivers who are trying to improve their safety stage are more likely to perform better on the three types of expressways with lower over-speeding behavior. While inversely, drivers belong to other stages are more likely to over-speeding on the three types of expressways. In terms of the difference of three expressway types, model estimation result shows that drivers on the two types of Chugoku expressways are tend to influence larger on driver's over-speeding behavior. Take type one drivers for example, significant parameters of -0.39 on Chugoku expressways and -0.03 on Sanyo expressway have been obtained. This result is reasonable, because geometric shape on the Chugoku expressways are more road with curves and slopes, therefore higher influencing impact of the Chugoku expressway in driver's over-speeding behavior could be observed.

4.3 Driving risk levels diagnosed from three driving speed controls

Using data collected from the three-month experiment, the purpose of this part's study is to capture changes in driving risks on expressways due to use of the Safety Supporter app, aiming to provide additional empirical evidence on whether such apps are effective in promoting road safety or not. The research questions are (1) whether it is necessary to jointly use the three types of driving risks, i.e., compliance with the speed limit, abrupt acceleration and deceleration, and driving stability, and (2) whether and how driving safety diagnosis and provision of traffic warning information affect driving risks by controlling the influence of other factors, such as drivers' sociodemographic attributes, contextual factors, and drivers' driving propensities. This subsection is mainly written based on the publication by Jiang and Zhang (2016c).

4.3.1 Rationale for distinguishing between three driving risk indicators

Figure 4-3 plots all three driving risk indicators measured every two seconds of all 15 drivers. The results show that for the indicator compliance with the speed limit, most scores were greater than 60 points, and variations were much smaller than those for the other two indicators. This is probably because speed is visible to drivers via the vehicle's speedometer, while the other two indicators are not visible. As a result, drivers can more easily control their driving speed over time, and consequently the drivers' speed limit compliance scores are more stable. Conversely, there were many instances, where the acceleration and deceleration and driving stability scores were less than 60 points.

The correlations between the three indicators are shown in Figure 4-3. The results indicate that they did not perform consistently in the sense that their Pearson's correlations ranged between 0.01 and 0.49. These results suggest that the three indicators measure different aspects of driving risks, and therefore should be used jointly, supporting the design concept of *Safety Supporter*.

More importantly, accidents can occur at any place and at any time. The app *Safety Supporter* can measure driving risks at any point on roads at the second level. Such measurement can allow traffic managers to capture driving risks continuously over time and across space.

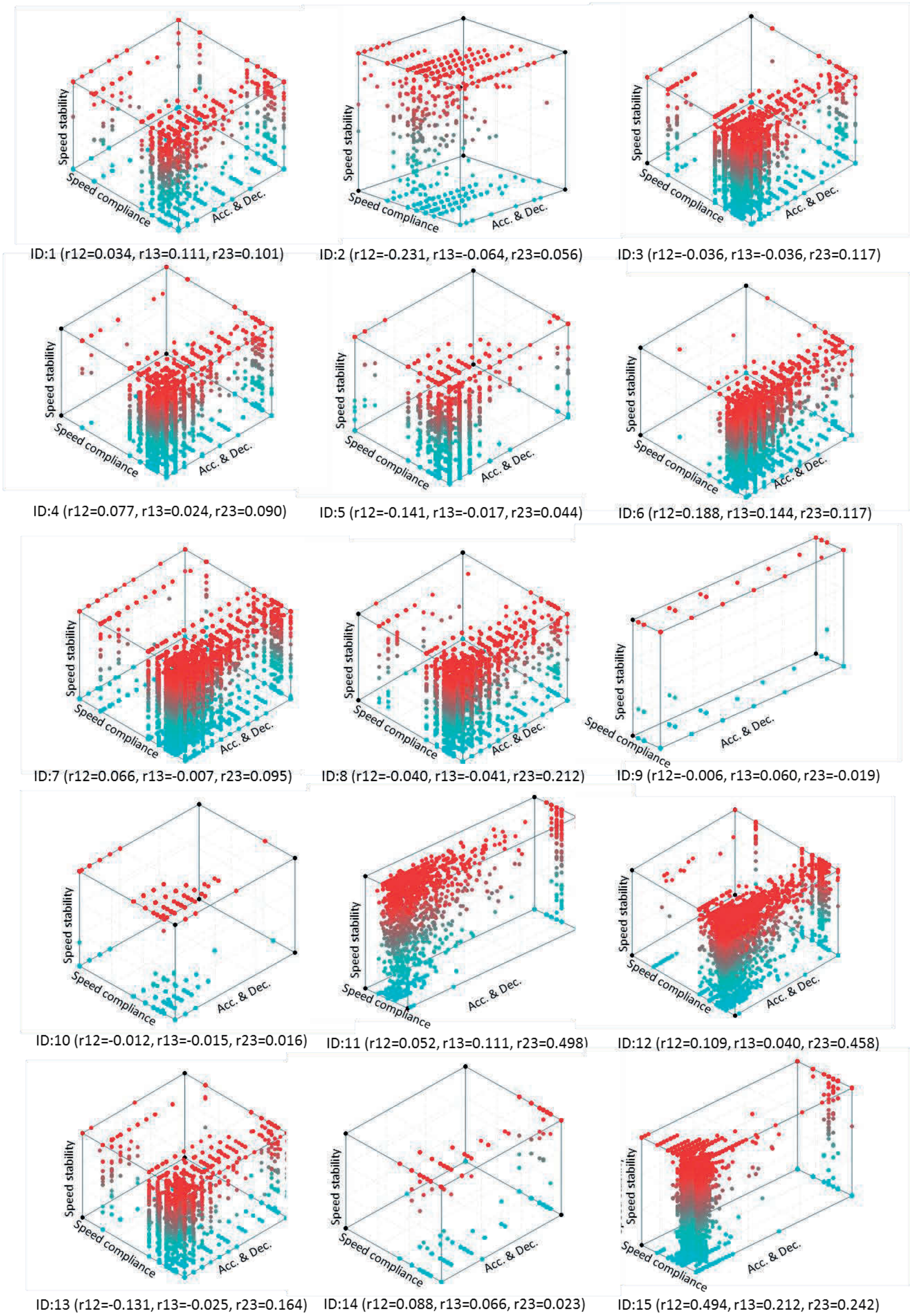


Figure 4-3 Distributions of driving risk scores and Pearson’s correlations

4.3.2 A multilevel ordered probit model for representing driving risks

In this section, for the sake of identifying factors affecting different levels of driving risks, the score for each of the three driving risks is categorized into three ordered scales: high risk (0–75 points), medium risk (76–90 points), and low risk (91–100 points), where the points are diagnosis scores calculated by the app, as described in Sub-section 3.1. Driver risks are categorized just for reflecting various nonlinear relationships involved in the analysis of actual driving risks detected from speed. For example Solomon (1964) found a U-shape relationship between crash rates and driving speeds, which was further replicated by Cirillo (1968) and Harkey et al. (1990). Such a U-shape curve was derived from comparison between vehicles. In this experiment, only driving data from a single vehicle are available and therefore the above categorization should be regarded as a proxy method to reflect the nonlinearity involved in driving safety.

Such unified categorizations are made based on an assumption that the same score corresponds to the same level of driving dangerousness. This means that, for example, the dangerousness of over-speeding by 50 km/h is the same as that of (the absolute value of) acceleration/deceleration being larger than 0.3G. It is desirable to validate this interpretation in a scientific way; however, it is not possible to validate it using the data collected in this experiment. Such a validation issue may also be applicable to the above thresholds for categorizing risk levels. In this sense, it is more reasonable to say that the above categorizations are just for ease of understanding. Shares of low, medium, and high risks are 44.76%, 40.88%, and 14.36%, respectively, for the speed limit compliance model, 59.04%, 11.17%, and 29.79%, respectively, for the acceleration and deceleration model, and 60.59%, 2.56%, and 36.84%, respectively, for the driving stability model. The above uneven distributions of three risk categories for each risk indicator also suggest that the three risk indicators may capture different aspects of driving risks. To describe such an ordered scale, a multilevel ordered probit (MOP) model was applied by introducing the explanatory variables shown in Table 4-2 where the average value of each variable is shown on the right-hand side. A multilevel modeling approach is applied because our samples come from a limited number of drivers who repeated their trips over the three-month period.

4.3.3 Model estimation results

The model estimation results are displayed in Table 4-5. Rho-squared values of the speed limit compliance model and acceleration and deceleration model are 0.25 and 0.18, respectively. The threshold parameters of the two models are statistically significant at the 1% level. Moreover, the random-effect parameters (variances) at the individual level are 1.23 in the speed limit compliance model and 3.19 in the acceleration and deceleration model, both of which are statistically significant at the 1% level. It is further confirmed that the MOP model is superior to the standard ordered probit model without random effects based on a likelihood-ratio test ($\chi 2$=14881.68 (p=0.00) for the speed limit compliance model and 688.78 (p=0.00) for the acceleration and deceleration model). All the above results support the use of the MOP model. The same type of MOP model was also estimated with respect to driving stability. However, probably due to the low share of medium risk, the rho-squared of the corresponding MOP model is only 0.004 and its threshold parameters are not significant. Therefore, a standard binary probit model was employed here, which works better because the rho-squared value is 0.19 (the dependent variable is equal to 1 (most dangerous: 24.68% in the total sample) when driving speed is beyond the range “medium speed $\pm 2\sigma$” within a certain time (see Section 2 for details), and 0 otherwise (75.32%)).

The model estimation results show that the effects of information provision on driving risks are mixed with regard to different types of driving risks. As the core part of the app development, the complex and heterogeneous influencing impacts of the basic functions were inspected together with driver's inherent driving propensity. For careless drivers (60.0% in total), the basic functions of *Safety Supporter* contribute to safer driving, as suggested by the corresponding parameters with negative values in the speed limit compliance model (–0.08), acceleration/deceleration model (–0.04), and driving stability model (–0.47). This result is acceptable because careless drivers may not tend to purposely drive unsafely, but merely to pay insufficient attention. In contrast, for irritable, aggressive, and excessively confident drivers, their driving risks as measured by speed limit compliance risks show a different result from those of acceleration/deceleration and stability risks. Concerning irritable drivers (73.3%) and excessively confident drivers (60.0%), the results show that even though use of *Safety Supporter* could contribute to a higher level of speed limit compliance, driving risks as measured by acceleration/deceleration and driving stability are increased. Irritable drivers tend to become annoyed with other vehicles (Kusuhashi et al., 2012). They may express their annoyance with more frequent speed changes, such as larger acceleration/deceleration and uneven driving, but such speed changes do not necessarily mean a serious violation of the speed limit. Similar to excessively confident drivers, they may self-evaluate themselves as good at driving with better control in terms of larger acceleration/deceleration and stability in potentially dangerous situations. Therefore, considering that acceleration and deceleration, as well as driving stability, are not visible to drivers (i.e., it is difficult for drivers to easily recognize the risks resulting from acceleration/deceleration and uneven driving), *Safety Supporter* may assist excessively confident drivers to pay more attention to controlling their driving speed. The opposite result is observed with respect to aggressive drivers (60.0%). In practical terms, the use of the app could improve their driving safety as measured by acceleration/deceleration and driving stability, while it could worsen driving safety as measured by speed limit compliance. Because aggressive drivers are more likely to make unnecessary lane changes (e.g., Kusuhashi et al., 2012), this is probably the main reason why aggressive drivers may improve their driving safety based on appropriate control of acceleration and deceleration under the diagnosis of driving risks. The reason why the diagnosis of speed limit compliance could not persuade drivers to drive more slowly is probably due to the fact that the purpose of aggressive drivers' lane changing behavior is to drive faster.

Regarding the effects of additional functions, it is observed that only "Function 3" (i.e., driving propensity diagnosis and advice for safe driving) contributes significantly to the improvement in driving safety because the corresponding parameters are negative and statistically significant (–0.47 for speed limit compliance and –0.41 for acceleration/deceleration). Meanwhile, the impact of "Function 3" on driving stability is positive, implying that the driving propensity diagnosis and advice functions failed to encourage drivers to drive smoothly. In Japan, driving propensity diagnosis and advice on safe driving are standard components of driver education programs that drivers are required to undertake when they renew their driving license (every 3–5 years, depending on the type of driving license and their traffic accident record). Our observation is consistent with the expectations of driver education practices in terms of speed limit compliance and acceleration/deceleration. To improve driving stability, the model estimation results suggest that "Function 2", which provides drivers with a ranking of their driving safety and self-diagnosis, in addition to the contents included in "Function 1," is effective.

Table 4-5 Estimation results of three driving risk models

	Model of speed limit compliance		*Model of acceleration / deceleration*		*Model of driving stability*	
	Para	z-value	Para	z -value	Para	z-value
Interaction between Basic Function (BF) and driving propensity						
BF * Irritable driver	-0.75	-49.65***	0.46	25.75***	0.28	14.56***
BF * Careless driver	-0.08	-6.38***	-0.04	-3.33***	-0.47	-33.31***
BF * Aggressive driver	1.44	82.05***	-0.32	-15.74***	-0.51	-21.63***
BF * Excessive confidence driver	-0.54	-36.50***	0.17	10.32***	0.20	9.60***
Additional app functions						
Function 1 (SA/PA information)	-0.005	-0.36	0.15	10.74***	1.72	100.46***
Function 2 (Ranking/self-diagnose)	0.52	18.17***	1.55	37.72***	-0.12	-3.85***
Function 3 (Propensity/advice)	-0.47	-16.73***	-0.41	-10.13***	0.07	2.41 **
Function 4 (Traffic safety campaign)	-0.10	-10.82***	0.05	5.06***	-0.01	-0.66
Experiential factors						
Traffic accident	0.43	33.70***	0.82	51.21***	0.28	18.75***
Punishment of traffic rule violation	-1.01	-62.84***	-0.54	-26.29***	-0.10	-5.29***
Trip attributes						
Driving time	-0.05	-4.36***	0.08	7.26***	0.08	6.67***
Trip duration	-0.0001	-26.45***	-0.00002	-10.24***	-0.000005	-2.34**
Self-evaluation factors						
Self-evaluated safety score	-0.02	-63.56***	-0.01	-20.62***	-0.002	-5.55***
Behavioral change stage	-1.19	-65.00***	0.45	22.24***	0.49	20.22***
Driving contextual factors						
Drive on holiday	0.49	59.71***	-0.13	-14.97***	-0.14	-14.56***
Drive at night	-0.27	-29.18***	0.01	0.89	0.004	0.32
Speed limit	0.005	12.67***	0.002	4.61***	0.001	1.84*
Driving direction	0.14	20.73***	-0.03	-3.98***	0.01	1.90*
Traffic volume	-0.01	-68.31***	0.001	9.76***	0.001	6.50***
Share of large vehicles in traffic	-0.96	-34.24***	-0.10	-3.55***	-0.14	-4.34***
Land use factors						
Driving long farm lands	0.08	8.11***	-0.01	-1.28	0.01	1.19
Driving along forests	0.02	2.18**	-0.01	-1.23	0.03	3.48***
Driving along building areas	-0.03	-2.56***	-0.005	-0.42	-0.02	-1.73*
Types of expressways						
Chugoku (south-north direction)	-0.83	-34.76***	0.01	0.39	0.13	4.57***
Chugoku (west-east direction)	-0.72	-33.24***	-0.04	-1.81*	0.07	2.81***
Sanyo (west-east direction)	-0.04	-2.07***	-0.05	-2.66***	0.01	0.33
Driver attributes						
Age	-0.06	-53.99***	-0.03	-21.28***	0.02	11.27***
Occupation	-1.45	-77.57***	0.97	40.43***	0.53	22.92***
Trip purpose	-0.23	-15.53***	0.10	5.41***	-0.04	-2.17**
Driving frequency	-0.89	-65.97***	0.23	15.26***	0.23	13.31***
Threshold value(1)	-8.96	-85.88***	0.46	4.27***		
Threshold value(2)	-7.35	-70.82***	0.86	7.89***		
Random-effect (variance)	1.23	59.56***	3.19	13.46***		
Constant term					-3.29	-24.28***
Rho-squared	0.25		0.18		0.19	
Initial log-likelihood	-188,331.32		-171,936.86		-104,809.00	
Converged log-likelihood	-141,522.12		-141,223.17		-84,975.16	

Significance level: * 10%, ** 5%, ***1%

The significant and negative parameter of "Function 4" suggests that those drivers who visited the website of the social campaign "Drive & Love" enhanced their driving safety level as measured by speed limit compliance. Unfortunately, such improvement could not be observed with respect to acceleration/deceleration and driving stability. This is probably because one can easily find rich information on the "Drive & Love" website about speed-related safer driving, but less information about acceleration/deceleration. As for "Function 1" (SA/PA information provision), it influenced driving safety in a manner contrary to our expectations (i.e., improved safety levels). SA/PA information is only provided to drivers who drive for a long time (the default value is two hours, and it can be changed by drivers depending on their preferences). One more possible reason might be because long-distance drivers were not in the majority in the experiment.

Looking at self-evaluation factors (self-evaluated safety scores (72 points on average, measured before the experiment) and behavioral change stages of traffic safety engagement), drivers with a higher self-evaluated safety score before the experiment tend to drive more safely from the perspectives of all three driving risk control behaviors. Those drivers in the stage of trying to improve their safety level (73.3%) are more likely to improve their speed limit compliance level, but unlikely to improve their acceleration/deceleration and driving stability behavior.

Experience of traffic accidents or punishments for traffic rule violations are expected to be influential on driving risk. It is observed that drivers with experience of traffic accidents (53.3%) are more risky than those without such experience, but in contrast, those with experience of traffic rule violation punishments (73.3%) are safer. Experiencing such punishments may compel drivers to pay more attention to their driving. This finding also confirms that enforcement of punishments for traffic rule violations is effective in improving driving habits.

As for trip attributes (trip duration (about 63 minutes on average) and driving time (the time elapsed since the start of the trip, measured as a percentage of the trip duration)), longer trips tend to be safer in terms of speed limit compliance, acceleration/deceleration, and driving stability. Driving in the later period of a trip is safer than driving in the early period from the viewpoint of speed limit compliance, but more risky in terms of acceleration/deceleration and driving stability.

The estimation results for contextual factors show that the app is more effective in improving driving safety if there are more large vehicles among the traffic (23.6% on average). However, other contextual factors show mixed effects on driving risks. Under the free traffic flow situation in this case study, traffic volume shows a reasonable influence on driving risks: the greater the volume of traffic, the greater the number of conflicts among vehicles, and as a result, the higher the speed limit compliance level and the lower the driving safety level as measured by acceleration/deceleration and driving stability. Similarly, the influence of driving at night also seems logical. Practically speaking, drivers driving at night (46.1%) are more likely to obey the speed limit, but less likely to control acceleration/deceleration and driving stability. On holidays (26.2%), drivers tend to show better control of their acceleration/deceleration and driving stability, but are worse in terms of compliance with the speed limit. Normally, there is more traffic on holidays than on weekdays; however, the association with holidays is different from that with traffic volume. This may imply that driving has some holiday-specific features. As for driving direction, downstream driving is more in compliance with the speed limit, but more risky in terms of acceleration/deceleration and driving stability. The higher the speed limit, the lower the driving risks measured in terms of speed limit compliance, acceleration/deceleration, and driving stability. In recent years, there has been discussion about deregulating the speed limit in Japan. Our results suggest that deregulation may worsen the traffic safety level.

No significant influence of land use factors could be identified on drivers' acceleration/deceleration behavior. Driving through farmland (20.3%) is more likely to induce speeding. This can be interpreted as reflecting the fact that there is usually a lower level of traffic among farmland, and as a result, conflicts among vehicles are less likely to occur. On expressways through farmland, drivers may expect less enforcement from the police, and are therefore more likely to exceed the speed limit. In contrast, driving on expressways through built-up areas (10.9%) is safer in terms of speed limit compliance and driving stability. On the other hand, driving through forests (51.2%) is only of significant influence in relation to speed limit compliance and driving stability.

Regarding types of expressways, drivers on the Sanyo expressway (a major expressway in the target area of this study that has more traffic than other expressways) (48.5%) are more likely not only to comply with the speed limit, but also to drive safely by reducing their acceleration and deceleration. In contrast, drivers on the two Chugoku expressways tend to obey the speed limit, but fail to drive smoothly. Their failure to drive smoothly is probably because there are more curves and slopes on the Chugoku expressways. On the other hand, drivers traveling east on the Chugoku expressways are less risky because they try to reduce their use of acceleration and deceleration.

Different types of drivers are expected to show different levels of driving risk. Our results indicate that older drivers are more likely to comply with the speed limit and to control their acceleration/deceleration. Meanwhile, younger drivers are more likely to drive smoothly. Contrary to our expectations, driving on a trip with strict time constraints (60.0%) is safer in terms of speed limit compliance and driving stability. Frequent drivers are more likely to obey the speed limit, but less likely to control acceleration/deceleration and driving stability. Drivers in the public sector (27.0%) tend to be more likely to comply with the speed limit, but are more risky in terms of control of acceleration/deceleration and driving stability.

In order to clarify the degree of influence of the various explanatory variables introduced in the model estimation, the partial utility of each explanatory variable (i.e., the product of its parameter and its average value) is calculated, and its share of the overall utility is shown in Figure 4-4. The partial utility means that the larger its share in the overall utility, the bigger the influence of the corresponding factor on driving risks. Comparing the shares of the partial utilities, it can easily be seen that age is more influential on driving risks, followed by driving frequency. Self-evaluation factors, including both self-evaluated safety score and behavior change stages, also have a significant effect on driving risk levels. This is also true with respect to experience of traffic accidents and punishment for traffic rule violations. Unfortunately, land use and types of expressways are less influential. Among contextual factors, speed limit, traffic volume, and share of large vehicles in traffic are most influential. Relatively speaking, the app functions show a noticeable influence compared with other factors.

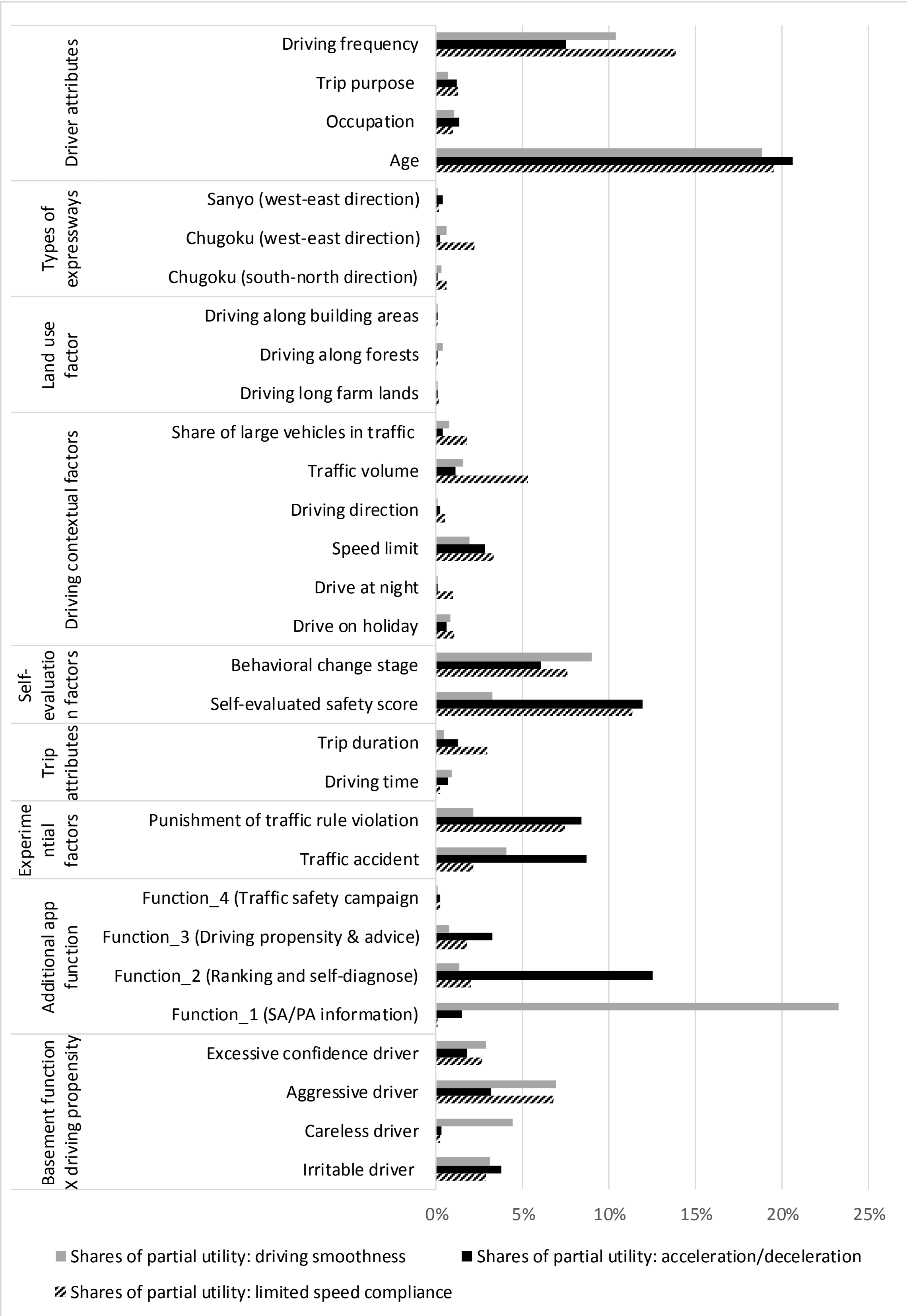


Figure 4-4 Partial utility of explanatory variables in MOP model

4.4 Joint modeling of speed limit compliance and acceleration/deceleration behavior

This subsection aims to confirm whether different driving risks should be modeled jointly or not. As a case study, only speed limit compliance and acceleration/deceleration behavior are targeted. It is written based on the publication by Jiang and Zhang (2016d).

4.4.1 Necessity for joint estimation of driving risks

In the app described previously, three types of driving risks were measured: speed limit compliance, acceleration/deceleration, and driving stability. Regarding driving stability, since variations across drivers are low, it is excluded from this joint analysis. One of the reasons why such low variations were observed is probably because the target of this study is the use of expressways. Variations in driving stability are expected to be larger in the case of ordinary roads. This is left for future study. Therefore, this study only treats the first two indicators, i.e., speed limit compliance and acceleration/deceleration as dependent variables.

For these two dependent variables, three risk levels (high, medium, and low) were categories same as rules in last section 4.3, where scores corresponding to the three risk levels are 0–75 points (high risk), 76–90 points (medium risk), and 91–100 points (low risk). Note that all diagnosis results were shown to drivers after each trip in the experiment and driver cannot review the results during driving, unless they stop their cars in, for example, a parking area. In this sense, the above categorization does not reflect drivers' actual perceptions about their real-time driving safety level. Shares of low, medium and high risks with respect to speed limit compliance and acceleration/deceleration are shown in Table 4-6. Obviously, driving risks measured by speed limit compliance and acceleration/deceleration have a much higher level of consistency (30%) with respect to the low risk category than the other two categories, which consistency levels are not ignorable, either. Thus, it seems that the two driving risk indicators might be correlated.

Table 4-6 Shares of speed limit compliance and acceleration/deceleration indicators

Speed limit compliance \ Acceleration/Deceleration	Low risk	Medium risk	High risk	Subtotal
Low risk	30%	4%	10%	45%
Medium risk	21%	5%	15%	41%
High risk	8%	2%	5%	14%
Subtotal	59%	11%	30%	100%

To accommodate such potential correlations, a bivariate ordered probit model (Greene, 2008; Dawson and Dobson, 2010) is applied, where each indicator is represented by an ordered probit model and the correction between error terms of the functions of two dependent variables of driving risks is explicitly incorporated. The model was estimated based on maximum likelihood estimation method, using the software Stata (Version 13.1). Explanatory variables used in this study are shown in Table 4-2, where average value of each variable is shown in the right side. And model estimation results can be found in Table 4-7.

4.4.2 Methodology: A bivariate ordered probit (BOP) model

BOP model is a hierarchical system of two equations that can be used to model a simultaneous relationship of two response variables, and addresses possible endogeneity problems, such that the severity levels of injuries to two or more participants involved in the same accident are typically correlated (Savolainen et al., 2011). Equation of the BOP model is shown as:

$$y_{i,1}^{*}=\beta_1' x_{i,1}+\varepsilon_{i,1}, \quad y_{i,1}=j \quad if\ \mu_{j-1} < y_{i,1}^{*} < \mu_j, \quad j=0,...,J_1 \qquad 4\text{-}4$$

$$y_{i,2}{*}=\beta_1' x_{i,2}+\varepsilon_{i,2},\ \ y_{i,2}=j \quad if\, \delta_{j-1} < y_{i,2}^{\ *} < \delta_j, \quad j=0,\ldots,J_2 \tag{4-5}$$

where $y_{i,1}$ and $y_{i,2}$ are dependent variables of individual i's speed violation level and acceleration/deceleration violation level, respectively; β_1 and β_2 are vectors of unknown parameters; μ and δ are cutoff values for ordered risk levels; and $\varepsilon_{i,1}$ and $\varepsilon_{i,2}$ are error terms that follow a bivariate normal distribution with correlation of ρ.

$$\begin{pmatrix}\varepsilon_{i,1}\\ \varepsilon_{i,2}\end{pmatrix} \sim N\left[\begin{pmatrix}0\\0\end{pmatrix},\begin{pmatrix}1 & \rho\\ \rho & 1\end{pmatrix}\right] \tag{4-6}$$

The joint probability for $y_{i,1}=j$ and $y_{i,2}=k$ is:

$$\begin{gathered}\Pr\mathrm{ob}(y_{i,1}=j, y_{i,2}=k \,|\, x_{i,1}, x_{i,2}) = \\ \begin{bmatrix}\Phi_2[(\mu_j-\beta_1' x_{i,1}),(\delta_k-\beta_2' x_{i,2}),\rho] \\ -\Phi_2[(\mu_{j-1}-\beta_1' x_{i,1}),(\delta_k-\beta_2' x_{i,2}),\rho]\end{bmatrix} - \begin{bmatrix}\Phi_2[(\mu_j-\beta_1' x_{i,1}),(\delta_{k-1}-\beta_2' x_{i,2}),\rho] \\ -\Phi_2[(\mu_{j-1}-\beta_1' x_{i,1}),(\delta_{k-1}-\beta_2' x_{i,2}),\rho]\end{bmatrix}\end{gathered} \tag{4-7}$$

4.4.3 Model estimation results

As shown in Table 4-7, the results of the likelihood ratio test of the independence of the two driving risk indicators speed limit compliance and acceleration/deceleration indicate that independence is rejected. The correlation (“rho” value) between the two indicators is statistically significant, which also supports the rejection of independence, even though the correlation itself is quite low (0.04). In other words, it can be said that the two indicators measure different aspects of driving risk and are interrelated. The positive correlation implies that the higher the compliance with speed limits, the lower the driving risk in terms of acceleration/deceleration, and vice versa. Furthermore, as for the threshold parameters distinguishing between different levels of driving risks, they are all statistically significant, implying that the adoption of the ordered probit model to represent driving risk is acceptable. Moreover, most of the explanatory variables introduced in the model are statistically significant.

Table 4-7 Estimation results of the BOP model of driving risks

Explanatory variables	*Driving risk in terms of speed limit compliance*			*Driving risks by acceleration/deceleration*		
	Para	Std. Err.	sig.	Para	Std. Err.	sig.
Basic Functions (1: yes; 0: no) × driving propensity (1: yes; 0: no)						
Basic Functions × Irritable driver: 49.5%	-0.42	0.01	***	0.27	0.02	***
Basic Functions × Careless driver: 41.8%	-0.44	0.01	***	-0.14	0.01	***
Basic Functions × Aggressive driver: 60.3%	1.06	0.02	***	-0.24	0.02	***
Basic Functions × Excessively confident driver: 63.5%	-0.47	0.01	***	0.15	0.02	***
Additional functions						
Function 1 (SA/PA information): 60.0%	0.40	0.01	***	0.18	0.01	***
Function 2 (Ranking and self-diagnose): 49.1%	0.12	0.03	***	1.63	0.04	***
Function 3 (Driving propensity & advice): 47.7%	-0.25	0.03	***	-0.42	0.04	***
Function 4 (Traffic safety campaign): 25.7%	-0.03	0.01	***	0.02	0.01	***
Self-evaluation factors						
Self-evaluated safety score: 72 points	-0.01	0.00	***	-0.01	0.00	***
Behavioral change stage: 73.3%	-0.48	0.02	***	0.46	0.02	***
Factors changing over time during the trip						
Driving time: 49.0%	-0.05	0.01	***	0.08	0.01	***
Trip duration: 3,807 seconds	-0.0001	0.00	***	-0.00002	0.00	***
Experiential factors						
Traffic accidents: 53.3%	0.99	0.01	***	0.59	0.01	***
Punishment of traffic rule violation: 73.3%	-0.98	0.02	***	-0.30	0.02	***
Contextual factors						
Driving on holiday (1: yes; 0: no): 26.2%	0.46	0.01	***	-0.13	0.01	***
Driving at night (1: yes; 0: no): 46.1%	-0.05	0.01	***	0.08	0.01	***
Speed limit: 85 km/h	0.005	0.00	***	0.002	0.00	***
Trip purpose (1: with time constraints; 0: without): 60.0%	-0.51	0.01	***	-0.10	0.02	***
Driving frequency (ordinal data)	-0.44	0.01	***	0.10	0.01	***
Driving Direction (1: upstream; 0: downstream): 49.9%	0.11	0.01	***	-0.02	0.01	***
Traffic volume (number of vehicles per 5 minutes): 68	-0.01	0.00	***	0.001	0.00	***
Share of large vehicles in traffic (%): 23.6%	-1.26	0.03	***	-0.13	0.03	***
Driving along farm lands: 20.3%	0.09	0.01	***	-0.01	0.01	
Driving along forests: 51.2%	0.005	0.01		-0.01	0.01	
Driving within urban areas: 10.9%	-0.03	0.01	***	-0.01	0.01	
Driving on Chugoku (south-north direction): 9.7%	-0.79	0.02	***	0.06	0.03	**
Driving on Chugoku (west-east direction): 39.6%	-0.72	0.02	***	0.02	0.02	
Driving on Sanyo (west-east direction): 48.5%	-0.06	0.02	***	-0.01	0.02	
Individual attributes						
Age: 42 years old	-0.04	0.00	***	-0.02	0.00	***
Occupation (1: public sector; 0: others): 27.0%	-0.95	0.02	***	0.68	0.02	***
Parameters characterizing the ordered probit model structure						
Threshold value (1)	-5.11	0.10	***	0.49	0.11	***
Threshold value (2)	-3.56	0.10	***	0.88	0.11	***
rho (correlation between error terms of two driving risk models)	0.04	0.00	**			
Likelihood ratio test: $\chi^2 = 127.88$ ($p = 0.0000$) (against the independence between two driving risk models)						
Value after ":" of each variable is its average value; Significance level (sig.): ** 5%, *** 1%.						
Chugoku: Chugoku expressway; Sanyo: Sanyo expressway						

All the above factors indicate that the bivariate ordered probit model is suitable for analyzing driving risks in this case study. As for the influence of an explanatory variable on driving risk, if its parameter is positive, then increase in its value leads to a higher level of driving risk.

4.4.3.1 Comparison between MOP and BOP model estimation results

As shown in Table 4-5 and Table 4-7, model estimation results of two models are mainly consistent with each other, with regarding to the estimation result of speed limit compliance and acceleration/deceleration sub-model. Here, the small differences existence between to model results are summarized as below:

Firstly, influencing impact of additional "Function 1" (SA/PA information provision) become significant with jointly consideration of driver's control behavior of "speed limit" and "acceleration /deceleration". Then, the second difference comes from driver's trip purpose of expressway usage, jointly estimation of two driving performance behavior shows that drivers in "timely trip" are more likely to behavior safer with lower violation level of the speed limit compliance and acceleration/deceleration control behaviors. Moreover, road factor of Chugoku expressway (south-north direction) also impose a significant influencing impact on acceleration/deceleration behavior in case of joint model estimation. On the contrary, significant influencing impact from land use factor of forest, and road use factor of Chugoku expressway (west-east direction) become insignificant.

4.4.3.2 Effects of basic functions of the app

Model estimation results show that effects of information provision on driving risks are mixed. Because the basic functions of the app are the core of its development, we explicitly incorporate the influence of driving propensity (i.e., irritable driver, careless driver, aggressive driver, and excessively confident driver) into the measurement of the effects of the basic functions in order to reflect the drivers' heterogeneity.

Improving both speed limit compliance and acceleration/deceleration: Careless drivers

For careless drivers (60.0% in total), the basic functions of the app contribute to safer driving because the corresponding parameters in the speed limit-based driving risk submodel (–0.44) and in the acceleration/deceleration-based submodel (–0.14) are both negative. According to Japan Traffic Safety Association (2006), drivers who often perform multitasking while driving and pay insufficient attention to driving because of getting accustomed to driving and so on are more likely to be classified into careless drivers. Feedbacks of diagnosis results to drivers may help them to better recognize how dangerous of their careless driving and consequently are more likely to comply with the speed limit and better control of speed changes. Provision of black spots information to may be effective to attract these drivers' attention to driving.

Improving only speed limit compliance: Irritable and excessively confident drivers

Irritable and excessively confident drivers received different influences of the basic functions of the app from the above careless drivers. As for irritable drivers (73.3%) and excessively confident drivers (60.0%), the results show that even though use of the app could contribute to a higher level of speed limit compliance, unfortunately, the driving risk measured by acceleration/deceleration increases. Irritable drivers tend to become annoyed with other vehicles (Japan Traffic Safety Association, 2006). In this case study, we extracted data under the free traffic flow and on expressways with two or more lanes. This means that drivers may feel less annoyed because they can easily overtake the vehicles in front of them, if they wish. Note that overtaking behavior does not necessarily mean a serious violation of the speed limit. Warning information of black spots announces what types of black spots have been often observed. Knowing such information in advance may also mitigate the level of irritable drivers' being annoyed. Concerning excessively confident drivers, their driving is likely to be rude and they may often unconsciously bet a nuisance to others or more easily violate traffic rules (Japan Traffic Safety Association, 2006). The app may assist excessively confident drivers to better obey the speed limit, but may not necessarily lead to better control of acceleration/deceleration, because these drivers may think they can manage potentially dangerous situations caused by excessive acceleration/deceleration.

Improving only control of acceleration/deceleration

The opposite result is observed with respect to aggressive drivers (60.0%). It is observed that the use of the app could improve their driving safety as measured by acceleration/deceleration, while it could worsen driving safety as measured by speed limit compliance. Aggressive drivers are more likely to often make unnecessary lane changes, perform radio operation, and/or drive in a manner that is reflected as a threat to other drivers (Japan Traffic Safety Association, 2006). Information provision of black spots may encourage drivers to avoid unnecessary land changes or to make smoother lane-changing by comparing to cases without information. Feedbacks of diagnosis results may help these drivers to well recognize their misperceived driving safety caused by multitasking during driving and improper driving behavior. The reason why the diagnosis of speed limit compliance could not persuade drivers to drive more slowly is probably due to the fact that the purpose of aggressive drivers' lane changing behavior is to drive faster and the app cannot sufficiently assist these drivers to comply with the speed limit.

4.4.3.2 Effects of additional functions of the app

Driving propensity diagnosis and advice for safe driving

Regarding the effects of additional functions, it is observed that only “Function 3” (i.e., driving propensity diagnosis and advice for safe driving) contributes significantly to the improvement in driving safety because the corresponding parameters are negative and statistically significant (–0.25 for speed limit compliance and –0.42 for acceleration/deceleration). In Japan, driving propensity diagnosis and advice on safe driving are standard components of driver education programs that drivers are required to undertake when they renew their driving license (every 3–5 years, depending on the type of driving license and their traffic accident record). Our observation is consistent with the expectations of driver education practices. Even though drivers participating in the experiment already experienced the diagnosis about their driving propensities when updating their driving licenses, they may already forget those diagnosis results. The above findings suggest that diagnosis of driving propensity is important to driving safety and should be implemented more frequently.

Online traffic education campaign

The significant and negative parameter of “Function 4” suggests that those drivers who visited the website of the social campaign “Drive & Love” enhanced their driving safety level as measured by speed limit compliance. Unfortunately, such improvement could not be observed with respect to acceleration/deceleration. This is probably because one can easily find rich information on the “Drive & Love” website about speed-related driver education, but less information about acceleration/deceleration. This suggests that it is necessary to make more efforts to clarify how to properly provide information about the dangerousness caused by improper acceleration/deceleration for better enhancing drivers' perceptions.

Unclear effects of SA/PA information provision and social comparison

As for "Function 1" (SA/PA information provision) and "Function 2" (ranking of diagnosis results and self-diagnosis), they both influence driving safety in ways contrary to our expectations (i.e., an improvement in safety levels). SA/PA information is only provided to drivers who drive for a long time (the default value is two hours, and it can be changed by drivers depending on their preferences). Because long-distance drivers were not in the majority in the experiment, the above result cannot be properly interpreted. This should be further confirmed in future by inviting more long-distance drivers to use the app. The unexpected influence of the ranking may indicate that drivers dislike such social comparisons, and that of the self-diagnosis may indicate that drivers are not satisfied with the gap between self-diagnosis and objective diagnosis, and as a result purposely drive in a more risky way. Generally speaking, human decisions are context-dependent, where reference points are crucial to describe their decisions (Kahneman et al., 1991; Tversky and Simonson, 1993). Both the ranking and the self-diagnosis may serve as reference points in driving decisions. Kahneman et al. (1991) and Tversky and Kahneman (1991) argued that change of reference point might lead to preference reversal. Providing the ranking information and allowing drivers to self-diagnose their driving safety levels may change drivers' reference points in their driving decisions and consequently induce such preference reversal.

4.4.3.3 Importance of behavioral change stages and traffic rule violation punishments

Looking at self-evaluation factors (self-evaluated safety scores (72 points on average, measured before the experiment) and behavioral change stages of traffic safety engagement), drivers with a higher self-evaluated safety score before the experiment tend to drive more safely from the perspectives of both speed limit compliance and better acceleration/deceleration control. Those drivers in the stage of trying to improve their safety level (73.3%) are more likely to improve their speed limit compliance, but unlikely to improve their acceleration/deceleration control. Existing studies suggest that the theory of planned behavior (Ajzen, 1988 and 1991) is applicable to driving safety studies (e.g., Castanier et al., 2013; Rowe et al., 2016). Then it is natural to assume that if a driver is trying to improve his/her driving safety, his/her driving risks should be lower than other drivers. In the questionnaire surveys, we asked drivers to report their behavioral change stages regarding general driving safety, without explaining driving safety in details. Such an unexpected deterioration of driving risks in terms of acceleration/deceleration control may imply that when drivers reported their behavior change stages, they may not perceive driving safety by considering their daily acceleration/deceleration control behavior.

It is observed that drivers with experience of traffic accidents (53.3%) are more risky (in terms of speed limit compliance and acceleration/deceleration) than those without such experience. This may suggest that many drivers do not learn lessons in case of driving safety, re-confirming the difficulty of preventing/reducing traffic accidents. At the same time, we cannot deny that this result may be special just in this case study, considering a remarkably larger share of drivers experiencing traffic accidents. In contrast, those with experience of traffic rule violation punishments (73.3%) are safer. Experiencing such punishments may compel drivers to pay more attention to their driving. This finding also confirms that enforcement of punishments for traffic rule violations is still effective in improving driving habits in Japan.

Concerning the differences of driving risks caused by individual attributes, our results indicate that older drivers are more likely to comply with the speed limit and to control their acceleration/deceleration. Contrary to our expectations, driving on a trip with strict time constraints is safer in terms of both speed limit compliance and acceleration/deceleration. Frequent expressway drivers are more likely to obey the speed limit, but less likely to better control acceleration/deceleration. As for occupation, public sector is emphasized in this analysis based on the fact that traffic rule violations by public servants are more easily criticized by mass media in Japan, probably forcing drivers working in the public sector to drive more carefully than other drivers. Analysis results suggest that drivers in the public sector (27.0%) tend to comply with the speed limit, which is consistent with our expectation; however, they are more risky in terms of control of acceleration/deceleration.

4.4.3.4 Influences of contextual factors

The estimation results for contextual factors show that the app is more effective in improving driving safety if there are more large vehicles among the traffic (23.6% on average). However, other contextual factors show mixed effects on driving risks. Traffic volume shows a reasonable influence on driving risks: the greater the volume of traffic, the greater the number of conflicts among vehicles, and as a result, the higher the speed limit compliance level and the lower the driving safety level as measured by acceleration/deceleration. Even though data in this study were collected under the free traffic flow situations, the above results are probably applicable to the congestion situations, too. Similarly, the influence of driving at night also seems logical in the sense that drivers driving at night (46.1%) are more likely to obey the speed limit, but less likely to show control in terms of acceleration/deceleration. The darkness is directly attributable to this observation on one hand, while features of traffic flow at night may explain it to some extent on the other. On holidays (26.2%), drivers tend to show better control of their acceleration/deceleration, but are worse in terms of compliance with the speed limit. Normally, there is more traffic on holidays than on weekdays; however, the influence of holidays is different from that of traffic volume. This may imply that driving has some holiday-specific features. As for driving direction, downstream driving is more in compliance with the speed limit, but more risky in terms of acceleration/deceleration. The higher the speed limit, the lower the driving risks measured in terms of both speed limit compliance and acceleration/deceleration. In recent years, there has been discussion about deregulating the speed limit in Japan. Our results suggest that deregulation may worsen the traffic safety level.

No significant influence of land use factors could be identified on drivers' acceleration/deceleration behavior. Driving through farm lands (20.3%) is more likely to induce speeding, but it is less risky in terms of acceleration/deceleration. This can be interpreted as reflecting the fact that there is usually a lower level of traffic among farm lands, and as a result, conflicts among vehicles are less likely to occur. On expressways through farm lands, drivers may expect less enforcement from the police, and are therefore more likely to exceed the speed limit. In contrast, driving on expressways through built-up areas (10.9%) is safer in terms of speed limit compliance. On the other hand, driving through forests (51.2%) has no influence on driving risk.

Regarding types of expressways, drivers on the Sanyo expressway (a major expressway in the target area of this study that has more traffic than other expressways) (48.5%) are more likely not only to comply with the speed limit, but also to drive safely by reducing their acceleration/deceleration. In contrast, drivers on the two Chugoku expressways tend to obey the speed limit, but their acceleration/deceleration seems more risky, probably because there are more curves and slopes on the Chugoku expressways.

As for trip attributes (trip duration (about 63 minutes on average) and driving time (the time elapsed since the start of the trip, measured as a percentage of the trip duration)), longer trips tend to be safer in terms of both speed limit compliance and acceleration/deceleration. Driving in the later period of a trip is safer than driving in the early period from the viewpoint of speed limit compliance, but more risky in terms of acceleration/deceleration.

4.4.3.5 Relative contributions of influential factors and implications

Relative contribution of the various explanatory variables are discussed again based on the calculation result of partial utility of each explanatory variables, and the share of partial utility in the overall utility is shown in Figure 4-5. Comparing the shares about all explanatory variables, the influence of age on driving risks is still the largest with respect to both speed limit compliance and acceleration/deceleration. Such derived importance of age in driving safety is consistent with the observations from existing studies (e.g., Conner and Smith, 2014; Arai and Arai, 2015). We expected that driving risks may vary largely between public servants and others; however, the partial utility results suggest that their influence is ignorable (shares: -0.8% and 1.2%).

Relatively speaking, the app functions show a noticeable influence in comparison with other factors. Totally, the basic functions and additional functions can explain 18.8% of the total variation of speed limit compliance utility and 32.2% of acceleration/deceleration utility. Especially, the app with basic functions is more effective to assist drivers to comply with speed limit than to better control of acceleration/deceleration. This suggests the importance of exploring the use of smartphones in improving driving safety, especially considering low costs of smartphone apps and the popularity of smartphones in the market. On the other hand, analysis results also indicate that more functions do not necessarily contribute more to the improvement of driving safety, as shown by the shares and signs of Function 1 (SA/PA information) and Function 2 (ranking and self-diagnose). Considering the influence of drivers' heterogeneous driving propensities, the above results may imply that it is better to prepare a set of driving safety assistance functions and allow drivers to choose depending on their own preference when deploying relevant smartphone apps in practice.

Another group of factors showing larger influences on driving risks is self-evaluation factors, which can explain 10.7% of the total utility of speed limit compliance and 20.2% of that of acceleration/deceleration. Therefore, external interventions should properly reflect the influence of such drivers' self-perceptions about their driving safety (i.e., self-evaluated safety score and behavioral change stage). One more group is related to one of popular traditional traffic safety measures, i.e., enforcement of punishment of traffic rule violations, because the corresponding share of partial utility is 9.8% for speed limit compliance and 5.9% for acceleration/deceleration, respectively. This result suggests that deploying relevant smartphone apps to improve traffic safety cannot ignore the role of some traditional measures.

Looking at factors changing over time during the trip, the corresponding shares of partial utility are very small (ranging just between 0.3% and 4.0%). In addition, values of land use factors and types of expressways also vary over time across the whole trip. Their influences are also not remarkable, either. Among contextual factors, larger influences on driving risks are observed with respect to driving frequency, traffic volume, speed limit, and share of large vehicles in traffic.

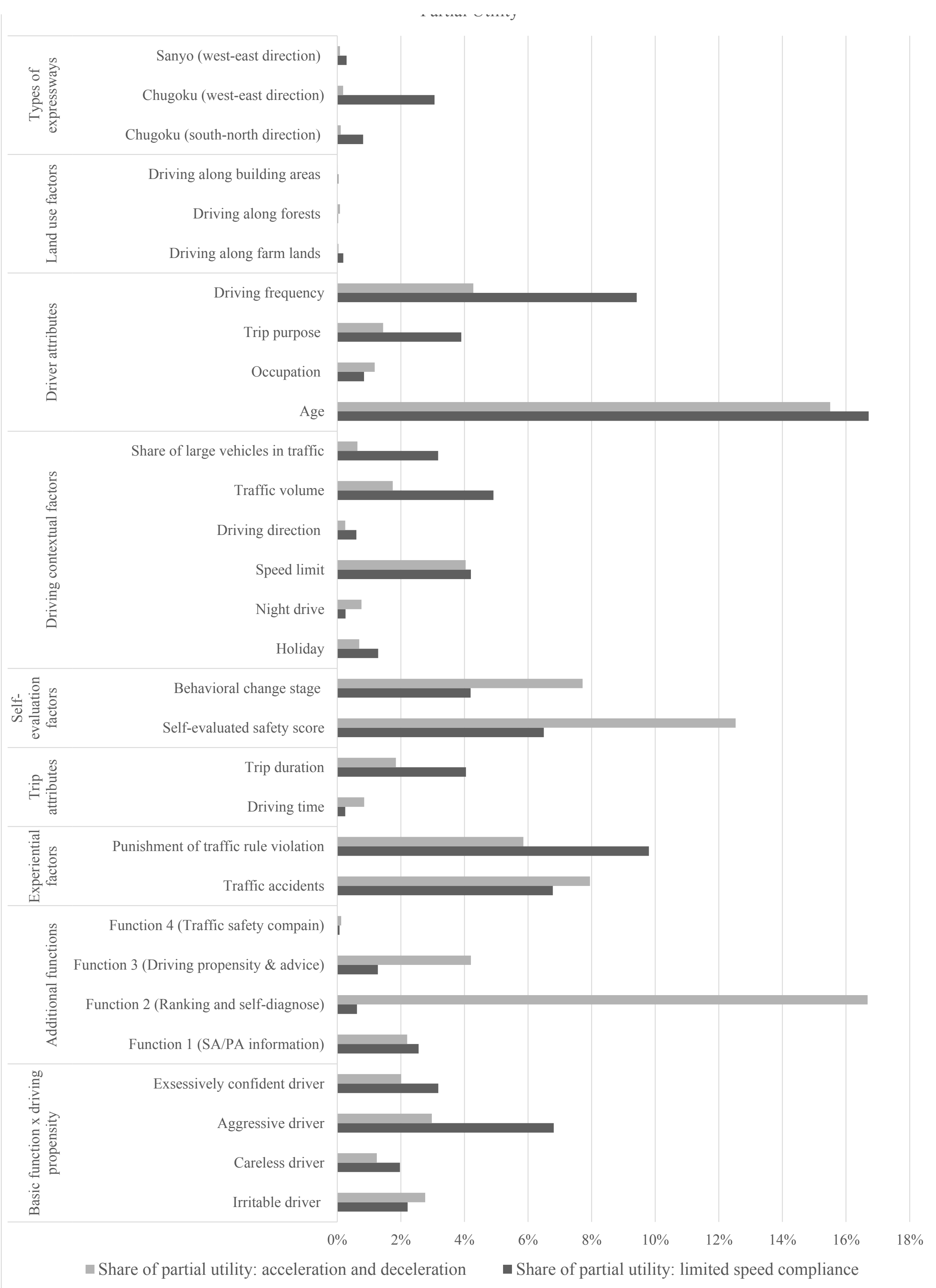


Figure 4-5 Partial utility of explanatory variables in BOP model

4.5 **Summary**

Motivated by the importance of capturing heterogeneous driving behavior in the context of traffic safety, this study examined the short-term effects of a GPS-enabled smartphone App, called *Safety Supporter*, on individual driver's second-by-second objective driving performance, in terms of over-speeding violation behavior and acceleration/deceleration control behavior. The function design of app is to capture driving safety performance second by second, and to provide drivers with real-time blackspot warning information, post-driving safety advices, as well as other safety-related information (including SA/PA information). Data in this study were collected from a three-month driving experiment (February to May in 2014), where a series of questionnaire surveys were simultaneously conducted. Additional driving contextual factors, e.g., traffic volume, driving direction, speed limit, land use along expressways, and types of expressways, have also been collected and utilized in the model analysis.

Four main conclusions can be derived from three model estimation results.

Firstly, according to the respondents' app usage responses, it is conclude that the *Safety Supporter* could encourage most drivers to be in compliance with speed limit, but its improvement of acceleration/deceleration control behavior is limited at the second-based level. Basic functions of the *Safety Supporter* are surely effective to improve the safety level of 60.0% of drivers (i.e., careless drivers) in terms of both speed limit compliance and acceleration/deceleration. Focusing on the speed limit compliance, use of the *Safety Supporter* with basic functions leads to the improvement of driving safety of 60.0% ~ 73.3% of drivers (i.e., irritable drivers and excessively confident drivers). As for aggressive drivers (60.0%), their control behavior of acceleration/deceleration could become better after use of the App. Similarly, additional functions of driving propensity diagnosis and advice feedback are also contributable to speed limit compliance and better control of acceleration/deceleration. Traffic safety campaign via smartphones is influential to speed limit compliance, but the influencing power is almost ignorable. Unfortunately, SA/PA information provision, ranking of diagnosis results among drivers and self-diagnosis were not helpful to improve driving safety. Meanwhile, similar influencing impacts of the aforementioned factors could be identified on driver's over-speeding driving behavior only by drivers who tried to improve their safety level. However, relevant effectiveness cannot be observed with respect to drivers in the pre-contemplation behavioral change stage.

Secondly, effect of the app basic function on careless drivers' driving behavior improvement are quite significant. Concretely speaking, the analysis confirmed that basic functions (safety diagnosis and blackspot information provision) of the *Safety Supporter* do helps driver with careless driving propensity to improve their safety level from the perspective of lower level violation of speed limit compliance and acceleration/deceleration control. As for driver's over-speeding behavior, the significant contributing effect of the App on driver's lower speed violation behavior could be identified through driver's belong to all the safety stages.

Thirdly, it is re-confirmed that traditional enforcement of traffic rules (here, punishments of traffic rule violations) is still very powerful to force drivers to drive safely. In addition, age is considerably influential to driving risks. Moreover, behavioral change stages of driving safety do affect driving risks, but only those who intended to improve their driving safety are more likely to obey the speed limit.

Finally, influence of drivers' heterogeneity implying that drivers' heterogeneity (especially their varied driving propensities and different safety stage of changes) should be properly reflected in the deployment of such individualized traffic safety measures. Careful combination of various information provision could significantly improve the driving safety level, but drivers in different behavioral change stages may show heterogeneous responses to the App.

Chapter 5

Long-term Effects of *Safety Supporter* on Mitigation of Objective Driving Risks

5.1 Introduction

Significant influencing impacts of the developed smartphone app on driving safety performance have been verified from the level of second-by-second diagnosis in Chapter 4. In this chapter, individual's safe driving performance is diagnosed at a trip level for capturing the long-term effects of the app. Definition of the "long-term" in this chapter is a relative concept simply in comparison with the short-term effects mentioned in Chapter 4.

Concretely speaking, firstly, data analysis for driving risks in terms of three diagnosis indicators were aggregated as the violation rates of speed limit compliance at the trip level (percentage of epochs that driving speed is larger than speed limit for more than 5 km/h), abrupt acceleration/deceleration (percentage of epochs that absolute acceleration/deceleration values are larger than 0.3g ≈ 2.94 m/s^2), and driving stability (percentage of epochs that is different from median speed of adjacent 9 seconds above 2 times the corresponding standard deviation). Secondly, after each trip during the three-month driving experiment, drivers were also asked to report their affective experience and multitasking during driving, which are expected to be influential to individual's driving risks measured at the trip level. Multitasking behaviors (e.g., Jiang and Zhang, 2012) are captured in association with a series of activities unrelated to driving conducted while driving, including app watching, phone operation, looking around, turn-back talk, watching TV, eating, smoking, thinking, dozing, pick up items, radio operation, and navigation system operation. Affective experience is reported by shares of different moods (good, pleasant, low, and bad moods) during a whole drive, to capture driver's subjective well-being (SWB) experiences.

Analyses in this chapter assume that driver's objective driving risks (i.e., speed limit compliance, acceleration/deceleration control, and driving stability), multitasking behaviors and affective experience during driving might be influenced by the developed app, where correlations between them at the trip level may not ignorable.

The writing of this chapter is partially based on the publication by Jiang and Zhang (2015b).

5.2 Driving risks at trip level

As a result of data matching and cleaning, 353 trips made by 13 drivers were extracted for this study. The 13 individuals are all male drivers aged 33 ~ 59 years old (the average age is 41 years old). Average driving age of these drivers are 22 years, ranging from 12 ~41 years.

Violation rates of the three risk indicators among the 353 trips are shown in Figure 5-1 (where, the horizontal axis is the trip number), in an increasing order of the driving stability violation rate value. Plots of three driving risk indicators reveal that different from driver's violation rates of "driving stability", which are more centralized at the 20%~60%, driver's violation rates of speed limit compliance are more scattered over in a larger range of 0% ~ 100%. Moreover, lower violation rates of acceleration and deceleration could also be identified from observations with low violation rates of "driving stability" (less than 30%). Meanwhile, in terms of higher violation rates of "driving stability" (more than 40%), violation rates of acceleration and deceleration become less concentrated and scattered from 0%~100%.

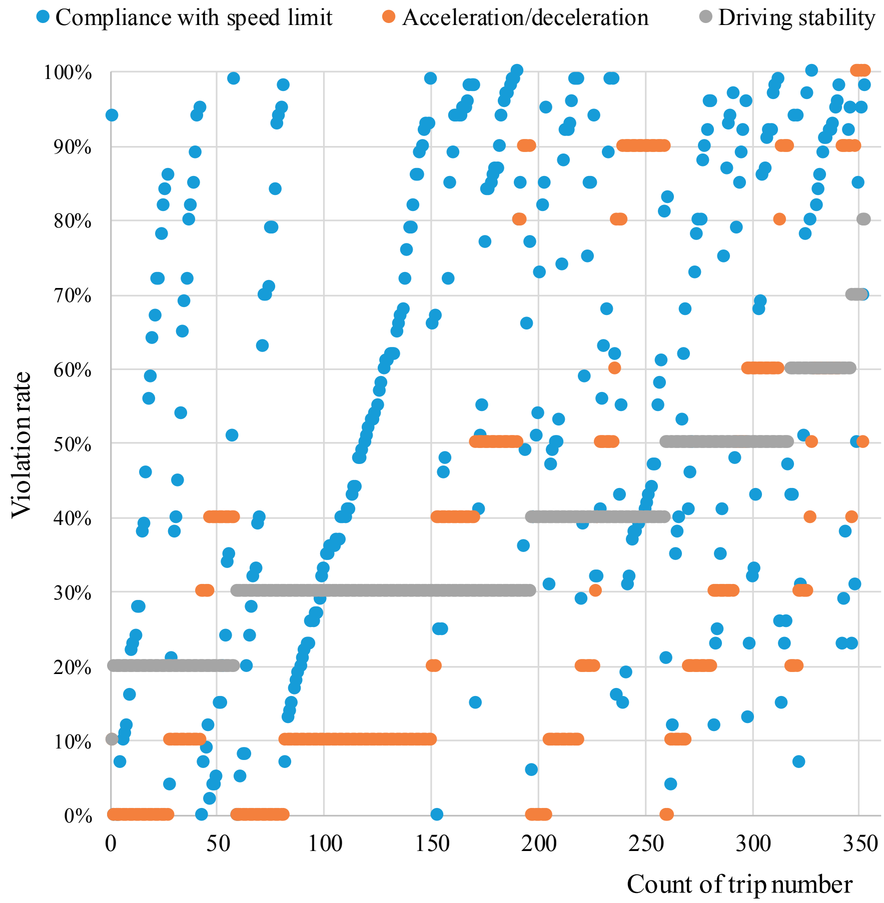


Figure 5-1 Violation rates of three diagnosis indicators of driving risks

As for multitasking behaviors, they are reclassified into five types: Multitasking Type (MT) 1 - eye sight distraction (looking around, turn-back talk, and watching TV), MT 2 - mental distraction (thinking and dozing), MT 3 - handling distraction (eating and smoking), MT 4 - phone operation (app watching, and phone operation), and MT 5 - mixed distraction (pick up items, radio operation, and navigation system operation). These multitasking behaviors are shown in Figure 5-2, where the horizontal axis is the app version number and the vertical axis is the average rate of multitasking. It is obvious that multitasking rates first varied largely from Versions 2 ~ 4, and then become stable at a lower level in Versions 5 and 6. An overall decreasing trend of the multitasking rates from MT1 to MT4 can be identified.

Regarding affective experience, instead of the original shares of four distinct moods (very good, pleasant, low, and bad mood), three dummy variables are generated for capturing dominate moods during driving: 1 indicates that a dominate mode is identified if the share of that mood is the largest among the four moods, 0 otherwise. Moreover, one "happy" dummy is further generated. It equals to 1 if a driver experienced more than 50% of pleasant or good mood during driving, and 0 otherwise. Figure 5-3 shows the changing trend of the dominate moods, together with "*happy mood*" throughout the six app versions. As a whole, more drivers experienced happy mood through the whole experiment (45%~95%), and the lowest share of the happy mood (45%) was observed in App Version 6.

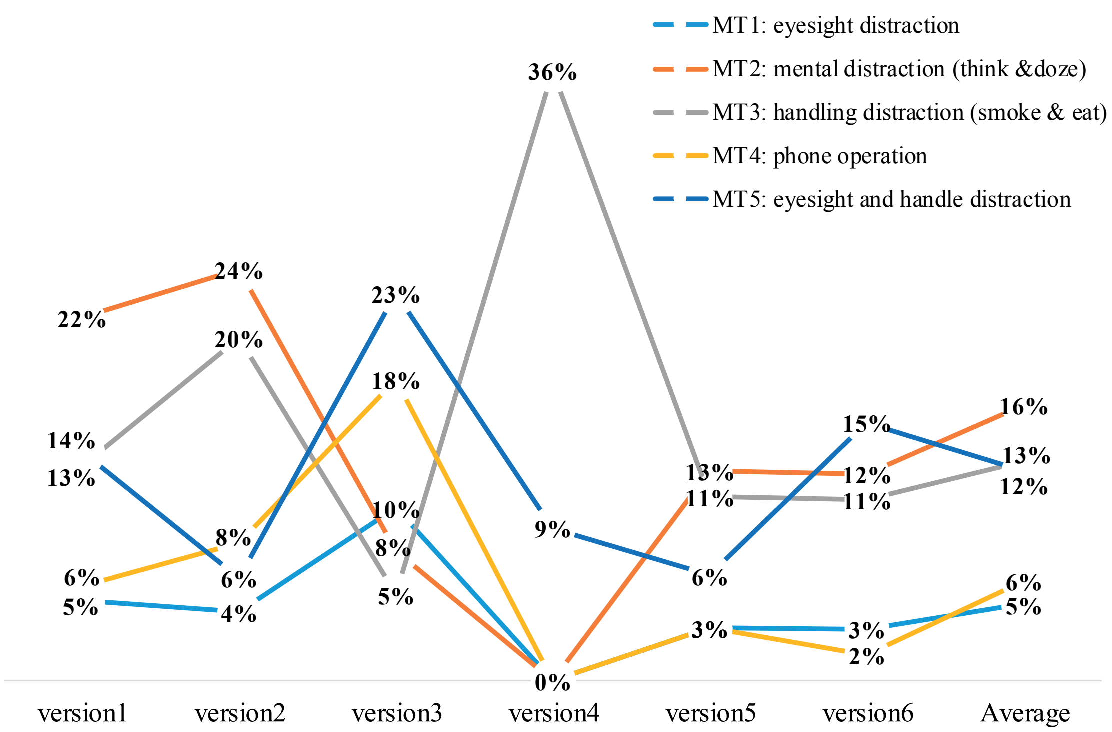


Figure 5-2 Multitasking behaviors under six app versions

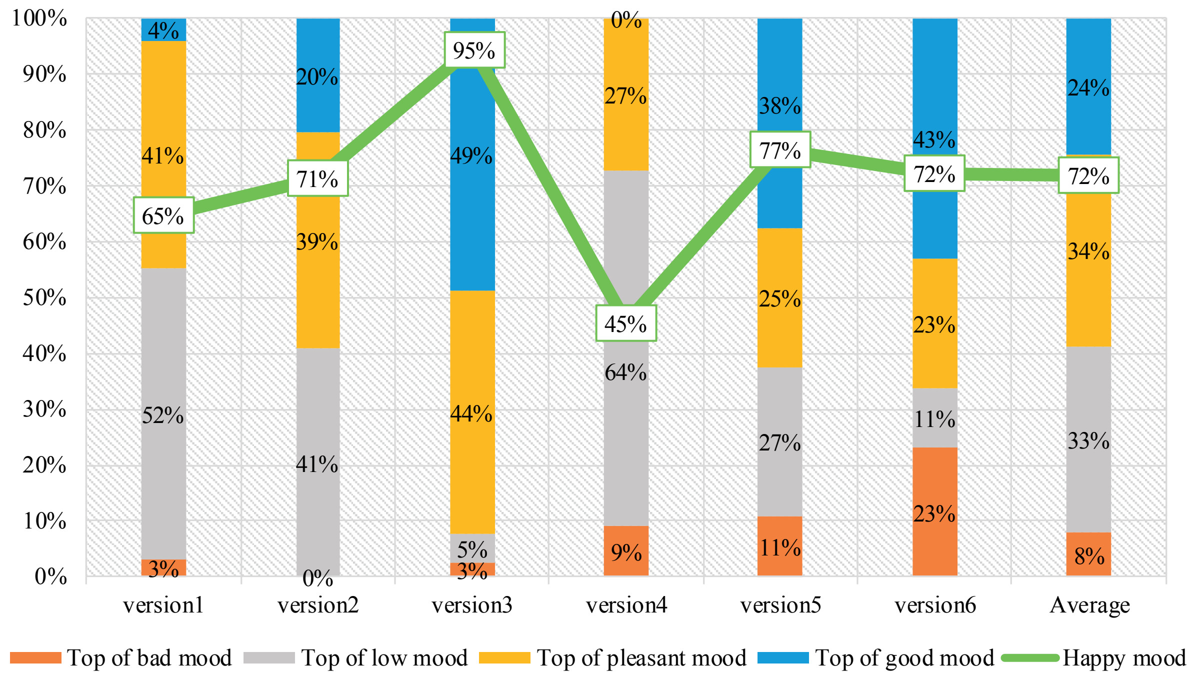


Figure 5-3 Affective experience under six app versions

Interestingly, same as drivers' multitasking behaviors and affective experience, larger variations also first appeared in Versions 2~4 and then became stable in Versions 5 and 6. Sharp change identified from Version 3 to Version 4 may be due to the short experiment duration (one week) and fewer trips experienced (11 trips) in comparison with other versions (see Table 5-1).

Table 5-1 Total trips in each experiment scenario

	Duration	Trip Numbers
Version 1	4 weeks	125
Version 2	2 weeks	49
Version 3	2 weeks	39
Version 4	1 week	11

5.3 Methodology: A seemingly unrelated regression model

In this study, five dependent variables are targeted: three driving risk indicators (violation rates of speed limit compliance, dangerous driving measured by acceleration and deceleration, and dangerous driving measured by driving stability), multitasking behavior during driving, and affective experience while driving. These five variables might be correlated with each other. To account for such correlations, a Seemingly Unrelated Regression (SUR) model is built, as shown in Figure 5-4.

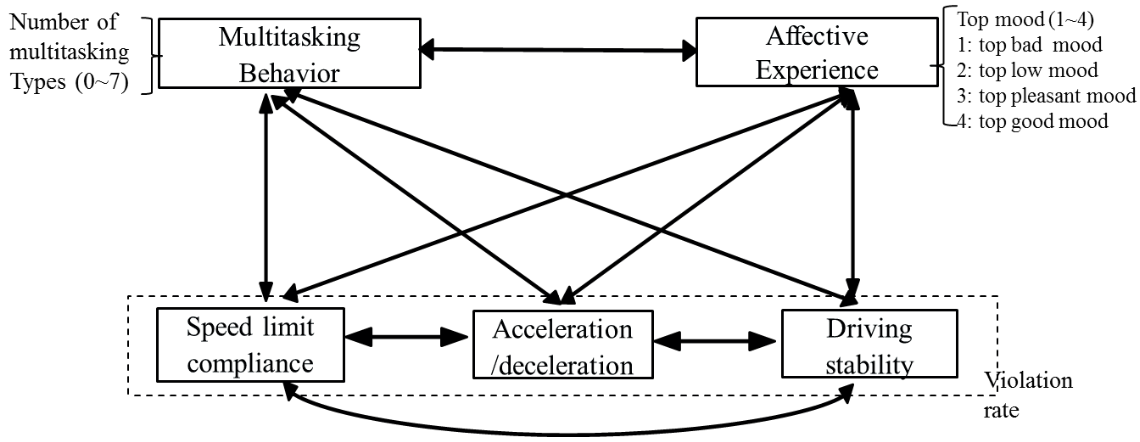


Figure 5-4 Interrelated dependent variables and assumed correlation structure

The SUR model estimates a set of separate regression equations allowing for the contemporaneous cross-equation error correlations. Such correlated error terms reduce standard errors of the estimated parameters, consequently improve the reliability level of estimations, by comparing with those from separate regressions (Zellner, 1962; Anastasopoulos and Mannering, 2016). Moreover, the correlations among dependent variables can also be captured by introducing a dependent variable to explain other dependent variables. Thus, the above five dependent variables are estimated simultaneously. In addition to mutual explanations across dependent variables, drivers' internal factors (e.g., psychological factors, driving propensity, experiences of traffic accidents and traffic rule violation penalty), external interventions (diagnosis and information provision via the app), and driving environmental factors (e.g., road structure, traffic volume, and weather) are introduced to explain these dependent variables.

Introduced as a dependent variable, affective experiences represent the driving mood that took the largest share among four types of emotions during a drive. Ordered value of 1 ~ 4 corresponds to the top mood of bad, low, pleasant, and very good. Meanwhile, when utilizing affective experience as an explanatory variable in other regression equations, four dummy variables (1: yes; 0: no) of "top good mood", "top low mood", "top bad mood", and "happy mood" are utilized, where "top of pleasant mood" is used as a reference. Similarly, dependent variable of multitasking behavior is counted as number of the corresponding tasks performed during driving. Independent variables of multitasking behavior is represented by subcategories of 5 types multitasking behavior (MT1~MT5) (1: yes; 0: no).

5.4 Model estimation results

As shown in Table 5-2, the R-squared value for each sub-regression model is 0.64 for the sub-model of speed limit compliance, 0.91 for (abrupt) acceleration/deceleration, 0.74 for driving stability, 0.59 for affective experiences, and 0.47 for multitasking behavior, respectively. The model performance measured from R-squared value improved a little bit compared with estimation of three driving risks indicators solely (Table 5-3), where R-squared values are 0.62, 0.91, 0.73 for sub-models of speed limit compliance, acceleration/deceleration, and driving stability control behavior. Even though the R-squared value of the multitasking behavior sub-model is low (0.47), the overall performance of the SUR model is still acceptable.

Focusing on the influencing impacts of the five dependent variables on each other, firstly, statistically significant and positive signs among three driving risk indicators imply that one of driver's higher violation behavior of three risk indicators will significantly contribute to higher violation rate of the other two indicators. As for influences from the individual's affective experiences, it is found that driver's *"happy mood"* and *"top low mood"* are significantly influential to driver's violation behavior of speed limit compliance. Negative and significant influence from *"top of low mood"* on acceleration/deceleration violation, and from *"top of good mood"* on driving stability violation behaviors have also been identified. Effects of affective experience factors imply that large share of positive moods, e.g., happy mood and good mood, are more likely to contribute to driver's safer driving performance with lower violation rate of speed limit compliance and driving stability control. While, large share of the *"low mood"* during the trip is more likely to result in lower violation rate of acceleration/deceleration control behavior.

The performance of multitasking behavior while driving significantly influences driver's violation behaviors measured by speed limit compliance and acceleration/deceleration. However, significantly opposite impacts of multitasking behaviors on the two driving behaviors imply that performing multitasking behaviors may cause more abrupt acceleration/deceleration behaviors (significantly influenced by "MT1: *eyesight distraction*", and "MT2: *mental distraction"*), but less over-speeding behaviors (significantly influenced by "MT2: *mental distraction*", "MT4: *phone operation*", and "MT5: *eyesight and handling distraction*"). The impact of multitasking behaviors on driver's violation behavior is logical, as with the increasing recognitions of potential risks while multitasking driving, drivers tend to slow down for complying more with the speed limit; however, distractions caused by the multitasking behaviors still induce more abrupt acceleration/deceleration behaviors.

Focusing on factors affecting driver's affective experiences while driving, it is shown that drivers would obtain more happy emotions through the performance of over-speeding and abrupt acceleration/deceleration behaviors. In contrast more upset emotions would be obtained with the influence of driver's multitasking behaviors, especially behaviors of "MT1: *eyesight distraction*", "MT2: *mental distraction*", "MT3: *handle distraction*", and "MT4: *phone operation*").

Concerning factors affecting multitasking behaviors, it is showed that three types of objective driving risk indicators all impose significant influence on driver's multitasking behaviors. More multitasking behaviors could be identified from drivers who performed higher violation rate of acceleration/deceleration and lower violation rates of speed limit compliance and driving stability. Affective experiences also significantly contribute to driver's multitasking behaviors, with larger shares of good mood and low mood.

Focusing on the effects of the app functions, it is found that basic function of the app significantly influences driver's objective and subjective driving performance, except for multitasking behavior. However, such influences show diversities across different driving propensities of irritable drivers, careless drivers, and aggressive drivers as well as excessively confident drivers. In terms of four types of additional app functions, Function 2 (ranking/self-diagnose) and Function 3 (propensity and advice) show a higher influencing power over the six driving scenarios. However, driver's speed limit compliance behavior was only significantly influenced by Function 4 (online traffic safety campaign).

In terms of experiential factors, experience of traffic accidents shows significant a positive influence on violation of acceleration/deceleration control behavior and multitasking behaviors. This indicates that drivers with experience of traffic accident involvement may perform more violation behavior of acceleration/deceleration control and multitasking behaviors while driving. In contrast, significantly negative impact of accident experience on affective experience means that more negative driving moods might be experienced for drivers who experienced traffic accidents. Focusing on factor of punishment of traffic rule violation, significant influence only imposed on driver's violation behavior of acceleration/deceleration and stability control. And the opposite influencing impact implies that drivers who experienced the punishment of traffic rule violation are more likely to perform better driving stability control, but more violation behavior of acceleration/deceleration control. In terms of factors revealed from driver's self-evaluation, it is found that drivers who are self-evaluated themselves with higher score and want to improve their current driving safety performances are more likely to perform less violation behavior of acceleration/deceleration, but more risky performance of driving stability control.

Comparison with model estimation result with only three driving performance indicators (Figure 5-3), significant factors identified for three sub-regression models are mostly consistent with model estimation results together with affective experience and multitasking sub-models, except for influences of app basic function on excessively confident drivers, which become significantly positive in the estimation results of the model with five dependent variables.

Table 5-2 SUR model estimation results (5 dependent variables)

Independent Variable \ Dependent Variable		Speed limit		Acc. / dec.		Driving stability		Affective		Multitasking	
		Coef.	z-value	Coef.	z-value	Coef.	z-value	Coef.	z-value	Coef.	z-value
Violation behav.	speed limit compliance			0.05	1.86*	0.07	3.88***	0.29	1.73*	-0.77	-3.58***
	acceleration / deceleration	0.21	1.87*			0.55	16.91***	1.29	3.53***	1.74	3.69***
	driving stability	0.58	3.88***	0.95	16.92***			0.64	1.33	-1.15	-1.84*
Affective experience	Happy mood	-0.07	-1.79*	0.01	0.54	0.001	0.04			0.05	0.32
	Top of bad mood	0.08	2.05**	0.018	1.02	0.003	0.22			-0.33	-2.18**
	Top of low mood	-0.06	-1.08	-0.08	-2.98***	0.01	0.45			0.94	4.02***
	Top of good mood	-0.04	-1.27	-0.01	-0.61	-0.03	-2.08**			0.35	2.47**
Multitasking	Multitask type 1	0.03	0.55	0.06	2.17**	-0.02	-1.06	-0.39	-2.02**		
	Multitask type 2	-0.09	-2.84***	0.03	1.87*	-0.01	-0.55	-0.38	-3.76***		
	Multitask type 3	-0.03	-0.92	-0.001	-0.07	0.01	0.55	-0.46	-4.14***		
	Multitask type 4	-0.03	-0.57	0.04	1.55	-0.002	-0.12	-0.47	-2.89***		
	Multitask type 5	-0.11	-3.23***	0.03	1.63	-0.02	-1.69*	0.09	0.81		
Interaction between Basic Function (BF) and driving propensity											
BF * Irritable driver		-0.16	-3.8***	0.003	0.13	0.03	2.04**	0.76	5.76***	0.26	1.48
BF * Careless driver		-0.059	-1.44	0.07	3.57***	-0.02	-1.55	-0.65	-5.08***	-0.54	-3.2***
BF * Aggressive driver		-0.03	-0.70	-0.10	-5.63***	0.06	4***	-0.12	-0.87	0.06	0.37
BF * Excessive confidence driver		0.08	1.73*	0.004	0.20	-0.04	-2.57**	0.01	0.07	0.15	0.8
Additional app functions											
Function 1 (SA/PA information)		-0.033	-0.72	-0.06	-2.76***	0.07	4.76***	0.07	0.46	0.19	1.00
Function 2 (Ranking/self-diagnose)		-0.11	-1.07	0.64	19.74***	-0.37	-11.96***	-1.25	-3.94***	-1.44	-3.54***
Function 3 (Propensity/advice)		0.01	0.16	-0.11	-3.59***	0.07	2.9***	0.65	2.93***	0.35	1.2
Function 4 (Traffic safety campaign)		0.08	2.5**	-0.02	-1.38	0.01	0.49	0.01	0.09	0.19	1.42
Experiential factors											
Traffic accident		0.08	1.30	0.06	2.14**	-0.01	-0.47	-0.73	-4.08***	0.69	2.95***
Punishment of traffic rule violation		-0.09	-0.81	0.15	3***	-0.19	-4.98***	-0.20	-0.56	-0.72	-1.60
Self-evaluation factors											
Self-evaluated safety score		0.001	0.42	-0.0025	-2.04**	0.002	2.46**	0.005	0.56	-0.05	-4.77***
Behavioral change stage		-0.09	-1.00	-0.19	-4.72***	0.21	7.54***	0.23	0.81	0.34	1.01
Driving contextual factors											
Drive on holiday		0.06	1.79*	-0.02	-1.29	-0.004	-0.33	0.05	0.49	-0.11	-0.84
Drive at night		0.05	1.8*	-0.01	-0.99	0.005	0.43	0.17	1.73*	0.15	1.21
Speed limit		-0.0012	-0.35	0.0022	1.45	-0.0004	-0.38	-0.01	-1.25	-0.01	-0.68
Driving direction		-0.009	-0.34	0.0008	0.07	-0.0033	-0.35	-0.06	-0.73	-0.06	-0.58
Traffic volume		-0.0018	-3.16***	0.0001	0.34	0.0002	0.73	0.0028	1.48	0.0001	0.03
Share of large vehicles in traffic		0.22	1.72*	-0.05	-0.91	0.05	1.10	-0.84	-2.07**	-0.41	-0.78
Landuse factors											
Driving long farm lands		-0.65	-2.32**	-0.11	-0.87	0.33	3.34***	-0.96	-1.05	-0.89	-0.76
Driving along forests		-0.80	-3.73***	0.04	0.39	0.21	2.82***	-1.08	-1.54	-0.52	-0.57
Driving along building areas		-1.00	-3.31***	0.17	1.21	0.11	1.00	-0.18	-0.18	0.99	0.78
Type of expressways											
Chugoku (south-north direction)		0.27	4.01***	-0.03	-1.01	0.002	0.09	-0.15	-0.65	-0.002	-0.01
Chugoku (west-east direction)		0.51	7.88***	-0.06	-1.88*	-0.01	-0.48	-0.2325	-1.03	0.42	1.45
Sanyo (west-east direction)		0.59	6.21***	-0.05	-1.05	-0.03	-0.88	-0.02	-0.06	0.33	0.78
Driver attributes											
Age		0.002	0.5	-0.001	-0.65	-0.002	-1.11	0.01	0.92	0.07	4.31***
Occupation		-0.05	-0.8	-0.02	-0.83	0.07	3.73***	-0.47	-2.64***	-0.39	-1.72*
Trip purpose		-0.11	-1.4	0.11	2.99***	-0.11	-4.14***	-0.09	-0.36	-0.57	-1.85*
Driving frequency		-0.01	-0.18	0.06	2.84***	-0.04	-2.61***	-0.50	-3.35***	0.46	2.39**
Constant term		1.04	2.56**	-0.39	-2.05**	0.15	1.02	4.67	3.64***	2.49	1.49
R squared		0.64		0.91		0.74		0.59		0.47	

Table 5-3 SUR model estimation results (3 dependent variables)

Independent Variable \ Dependent Variable	Speed limit compliance		Acc. / dec.		Driving stability	
	Coef.	z-value	Coef.	z-value	Coef.	z-value
Violation behavior						
Speed limit compliance			0.04	1.72*	0.09	5.15***
Acceleration / deceleration	0.20	1.72*			0.57	17.68***
Driving stability	0.76	5.15***	0.98	17.68***		
Interaction between Basic Function (BF) and driving propensity						
BF * Irritable driver	-0.14	-3.48***	0.02	1.1	0.04	2.68***
BF * Careless driver	-0.07	-1.63	0.05	2.64***	-0.02	-1.55
BF * Aggressive driver	-0.03	-0.74	-0.11	-5.96***	0.06	4.02***
BF * Excessive confidence driver	0.06	1.3	0.01	0.64	-0.05	-2.94***
Additional app function						
Function 1 (SA/PA information)	-0.03	-0.67	-0.06	-2.97***	0.08	5.16***
Function 2 (Ranking/self-diagnose)	-0.09	-0.93	0.63	19.08***	-0.38	-12.64***
Function 3 (Propensity/advice)	0.02	0.21	-0.11	-3.28***	0.08	3.27***
Function 4 (Traffic safety campaign)	0.07	2.12**	-0.02	-1.47	0.01	0.66
Experiential factors						
Traffic accident	0.05	0.99	0.05	1.89*	-0.02	-1.16
Punishment of traffic rule violation	-0.03	-0.27	0.15	2.92***	-0.19	-5.4***
Self-evaluation factors						
Self-evaluated safety score	0.004	1.44	-0.004	-3***	0.003	3.33***
Behavioral change stage	-0.18	-2.17**	-0.17	-4.52***	0.21	8.24***
Driving contextual factors						
Drive on holiday	0.08	2.54**	-0.02	-1.24	-0.004	-0.36
Drive at night	0.05	1.77*	-0.01	-0.82	0.01	0.5
Speed limit	-0.001	-0.25	0.002	1.36	-0.001	-0.58
Driving direction	-0.01	-0.27	0.003	0.23	-0.005	-0.5
Traffic volume	-0.002	-3.12***	0.0001	0.23	0.0002	1.12
Share of large vehicles in traffic	0.22	1.72*	-0.09	-1.46	0.04	0.82
Landuse factors						
Driving long farm lands	-0.57	-1.96**	-0.17	-1.25	0.34	3.49***
Driving along forests	-0.80	-3.66***	0.01	0.1	0.21	2.78***
Driving along building areas	-1.17	-3.8***	0.20	1.37	0.11	0.99
Type of expressways						
Chugoku (south-north direction)	0.27	3.85***	-0.04	-1.18	0.003	0.12
Chugoku (west-east direction)	0.49	7.36***	-0.07	-2.04**	-0.02	-0.65
Sanyo (west-east direction)	0.63	6.5***	-0.05	-1.02	-0.03	-0.93
Driver attributes						
Age	0.003	0.71	0.0001	0.05	-0.003	-1.86*
Occupation	-0.06	-1.11	-0.03	-1.35	0.07	3.98***
Trip purpose	-0.03	-0.43	0.09	2.73***	-0.11	-4.44***
Driving frequency	-0.05	-1.01	0.06	2.71***	-0.05	-3.21***
Constant term	0.66	1.64	-0.30	-1.62	0.15	1.07
R squared	0.62		0.91		0.73	

In this part of analysis, the partial utility for two model estimation results are also calculated to clarify the influencing degree of the various explanatory variables. Shares of each explanatory factors in the entire utility are shown in Figure 5-5 and Figure 5-6, for SURE model structure with three and five dependent variables, separately.

Comparing shares of partial utility, it is found that influencing power of driver's violation rate of speed limit compliance on their performance of acceleration/deceleration and stability control behavior is quite small. Whereas, influencing power of acceleration/deceleration on driving stability control (12% of total utility) and powers of driving stability on speed limit compliance and acceleration/deceleration control behavior take larger shares (9% and 20%). On the other hand, factors that impose large influencing power on driver's violation behavior speed limit compliance are driving long forest land (23%), driver's self-evaluation factor (4%), which reduced about 8% after introducing the affective experience and multitasking behaviors into the model.

Focusing on the factors that contribute to large share of the utility of driver's acceleration/deceleration behavior, Function 2 (ranking/self-diagnose), punishment experience of traffic rule violation, self-evaluated safety score, and speed limit factors could be identified. In terms of driver's violation behavior of driving stability, large shares of utility are observed with respect to factors of Function 2 (ranking/self-diagnose), punishment experience of traffic rule violation, self-evaluated safety score, safety stage change, and land use factor of driving along forest.

Large partial utilities identified from sub-model of affective experience regression are coming from factors of speed limit, driving along building area, and driving frequency. While, in terms of driver's multitasking behavior, the major contributions are generated from safety stage change and age factors. Focusing on the influencing power of the app functions, relatively speaking, the app functions surely show an unneglectable influence, by comparing with other driving contextual and environmental factors.

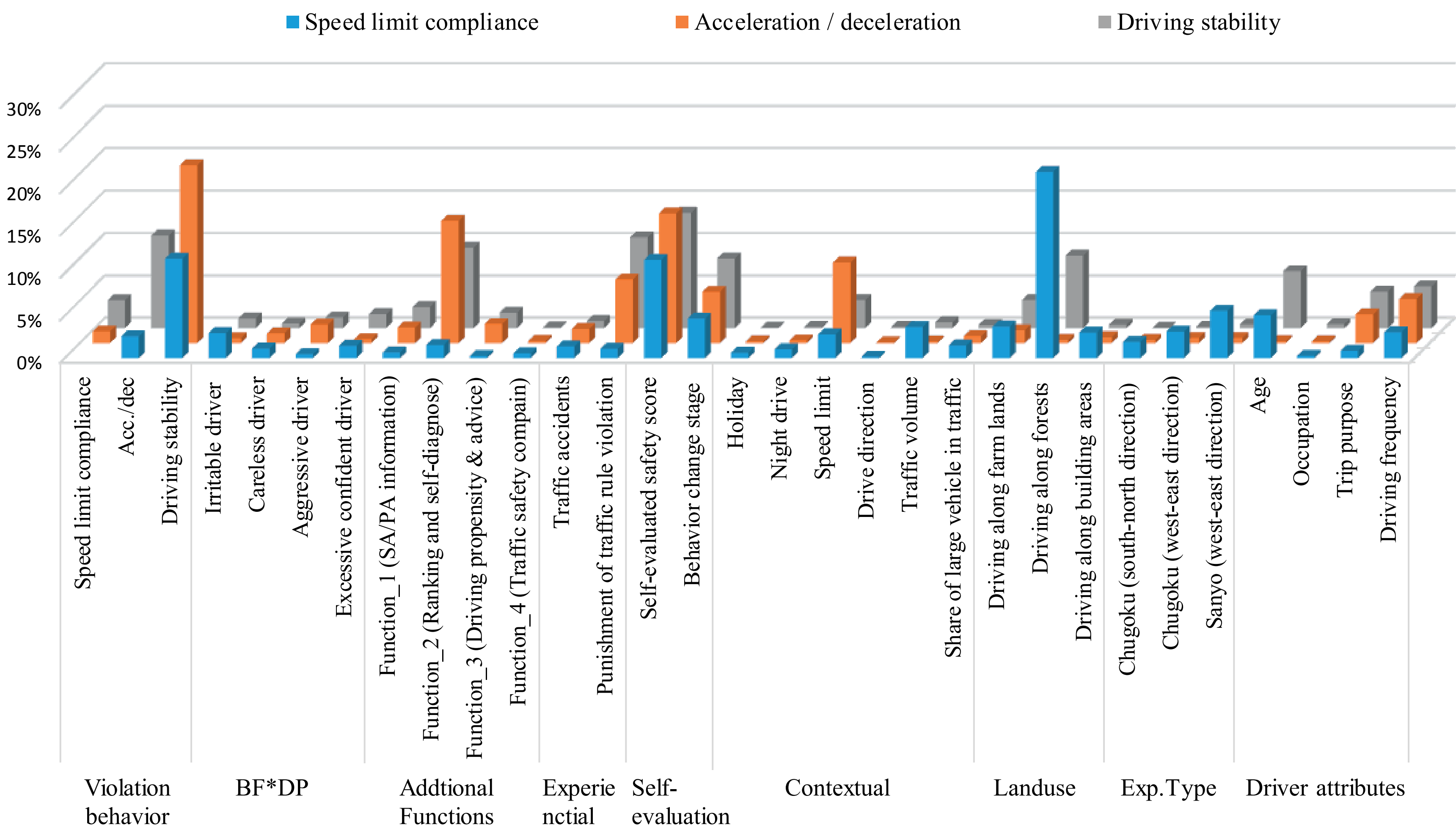


Figure 5-5 Partial utility of explanatory variables (3 dependent variables)

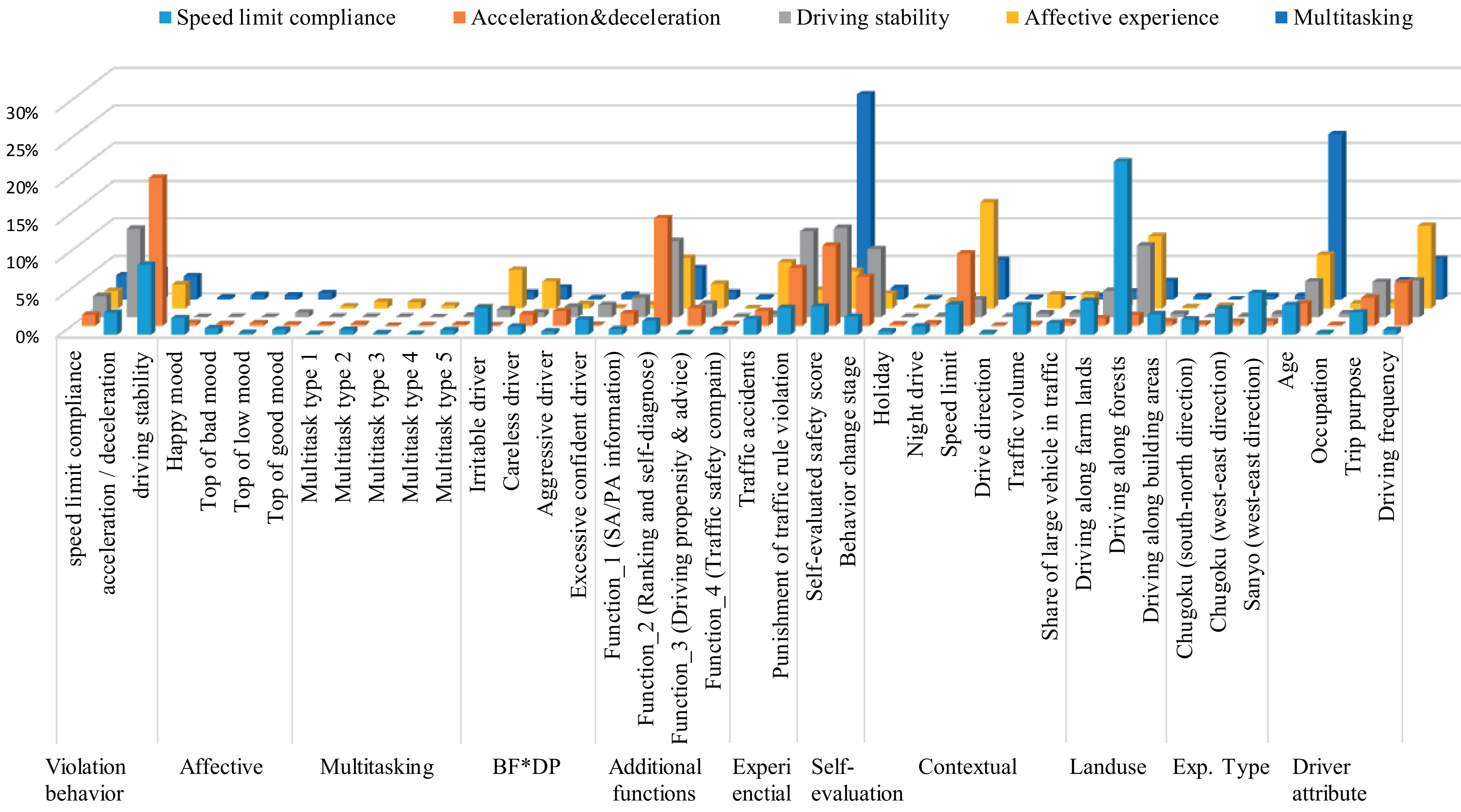


Figure 5-6 Partial utility of explanatory variables (5 dependent variables)

5.5 Summary

In the transportation field, subjective well-being (SWB) has been attracting more and more attention. However, SWB has been mainly treated as a factor to explain activity and travel choice and the reverse relationship has been ignored. Related to traffic safety under study, it is expected that drivers' psychological states (e.g., feeling or affect) and actions (vehicle operation behavior and multitasking during driving), which are further associated with driving risks, are not independent of each other. Unfortunately, little is known about such interdependences, not to mention their influencing factors. Considering that driving is an important behavior in people's daily lives, study on SWB and driving behavior has its own rationality and it is also important for further improving traffic safety. Therefore, in this chapter, based on the data collected from the GPS-enabled smartphone app, individual's driving risks, measured from three indicators of speed limit compliance, acceleration and deceleration, and driving stability control, have been analyzed together with individual's affective experience and multitasking behaviors while driving. Three driving performance indicators are measured at a trip level, where violation rates during one trip are targeted.

Four main conclusions can be derived from this chapter's model estimation results.

Firstly, significant long-term influencing impact of the additional app functions of Function 2 (ranking/self-diagnose) has been verified on driving performances of acceleration/deceleration and driving stability control, as well as affective experiences. Implication of this result could be realized in the further driving safety reinforcement policies with more efforts on introducing the ranking and self-diagnosis mechanisms to drivers. Moreover, importance of driving safety self-recognition have been reconfirmed from the significant contribution effect of the self-evaluation factors obtained from the model estimation results.

Secondly, significant mutual influences among driving performance indicators of speed limit compliance, acceleration/deceleration, and driving stability, have been confirmed at the trip level.

Thirdly, integration of the SWB and multitasking factors into the model estimation framework surely help to increase the model performance of two sub-models of speed limit compliance and driving stability. Even though the contribution power of those two factors are not as strong as our expectation from the perspective of partial utility analysis point of view.

Finally, focusing on the affective experience and multitasking behaviors, it is found that driver's multitasking behaviors are mainly influenced by driver's individual attributes (e.g. age and frequency) and self-evaluation of safety scores. Influencing impact of our designed app is quite limited on driver's multitasking behavior performances. Meanwhile, more factors have been identified to be significant influential to driver's affective experiences, with which the developed app performed better influencing impact with other driving environmental factors of speed limit, driving along forest, and driving frequency.

In summary, the above results show that data analysis from the trip based level might not be exactly the same as data analyzed from the second-by-second data analysis results. This emphasizes the necessity of impact evaluation of the app from the perspective of both long-term and short-term. Evaluation of various traffic safety measures should pay more attention to the measurement level of traffic safety for avoiding any misleading policy.

Chapter 6

Drivers' Avoidance Behavior to Potential Driving Risks

This chapter deals with two types of avoidance behaviors: one is about general driving avoidance behavior associated with drivers' internal risks and the other is about truck route avoidance behavior associated with external driving risks. The first part is written mainly based on the publication by Jiang and Zhang (2016e), and the second part mainly based on the publication by Jiang et al. (2016).

6.1 Introduction

In reality, drivers may sometimes avoid driving. Especially, avoid driving on expressway by some less-confidential drivers. According to the literature review, two types of avoidance behaviors have been introduced, including general punishment driving avoidance (Liourta and Empelen, 2008; Scott-Parker et al., 2014) and situational avoidance behavior from the perspectives of internal and external risks.

Punishment driving avoidance driving behavior emphasis more general driving avoidance awareness enforced by the rule and even punishment by the police management. In this sense, driving safety education program may help driver and encourage drivers to avoid driving in some cases. For example, driving safety education may encourage drivers to avoid driving in some cases. Questionnaire of Driving and Riding Avoidance Scales (DRAS) proposed by Stewart and Peter (2004) is employed in this paper to identified four types of avoidance behaviors, i.e., general avoidance, traffic avoidance, weather avoidance, and riding avoidance from 20 items as follows:

(1) general avoidance: put off a brief trip or errand that required driving a car; chose to walk or ride a bicycle someplace to avoid driving in a car; avoided driving a car if one could; put off a brief trip or errand that required riding in a car; chose to ride a bus someplace to avoid driving in a car; avoided activities that required using a car; and avoided driving a car after dark;

(2) traffic avoidance: avoided driving on residential streets; avoided driving on busy city streets; avoided driving on the freeway or interstate; avoided driving through busy intersections; traveled a longer distance to avoid driving through heavy traffic or busy; rescheduled making a drive in a car to avoid traffic; avoided riding in a car if the driver knew the traffic was heavy;

(3) weather avoidance: avoided driving a car because the weather was bad (e.g., fog, rain, and ice); avoided driving a car after dark; avoided riding in a car because the weather was bad (e.g., fog, rain, and ice); avoided riding in a car after dark; rescheduled making a drive in a car to avoid bad weather (e.g., fog, rain, and ice);

(4) riding avoidance behavior: avoided riding in a car if the driver could; avoided riding in a car because the weather was bad (e.g., fog, rain, and ice); avoided riding in a car after dark; avoided riding in a car if the driver knew the traffic was heavy; avoided riding in a car on the freeway or interstate.

As for situational avoidance behavior, drivers tend to perform avoid driving under specific situations, such as heavy snow, unfamiliar driving environment, feeling drowsy/tired, and fear of driving on expressways, in which their impairments identified/obtained from previous crash involvement experience might expose them to an increased risk of accident (Stewart and Peter, 2004; Motak et al., 2014). Thus, such avoidance behaviors may be influenced by not only drivers' internal factors, but also external environment and/or interventions.

Focusing on aforementioned two types of avoidance driving behavior, research conducted in this chapter are composed of two parts. The first part is to investigate relationship between drivers' avoidance driving perception and objective driving performance, inspired by the general punishment avoidance driving idea identified from driver's internal risks. The second part is targeting at external risks factors that would cause on driver's avoidance behavior, therefore, a case study of driver's specific expressway route avoidance issue, problem raised in Chugoku area, Japan.

6.2 Relationships between general punishment avoidance driving avoidance and objective driving behavior performance

6.2.1 Data introduction

In order to investigate the relationship between individual's driving avoidance behavior and their objective driving performance, data obtained from the three-month smartphone experiment have been utilized again in this part of analysis. Individual's driving avoidance behaviors are investigated based on the DRAS questionnaire from a subjective questionnaire survey, which is measured through the six experiment periods with different app versions provision.

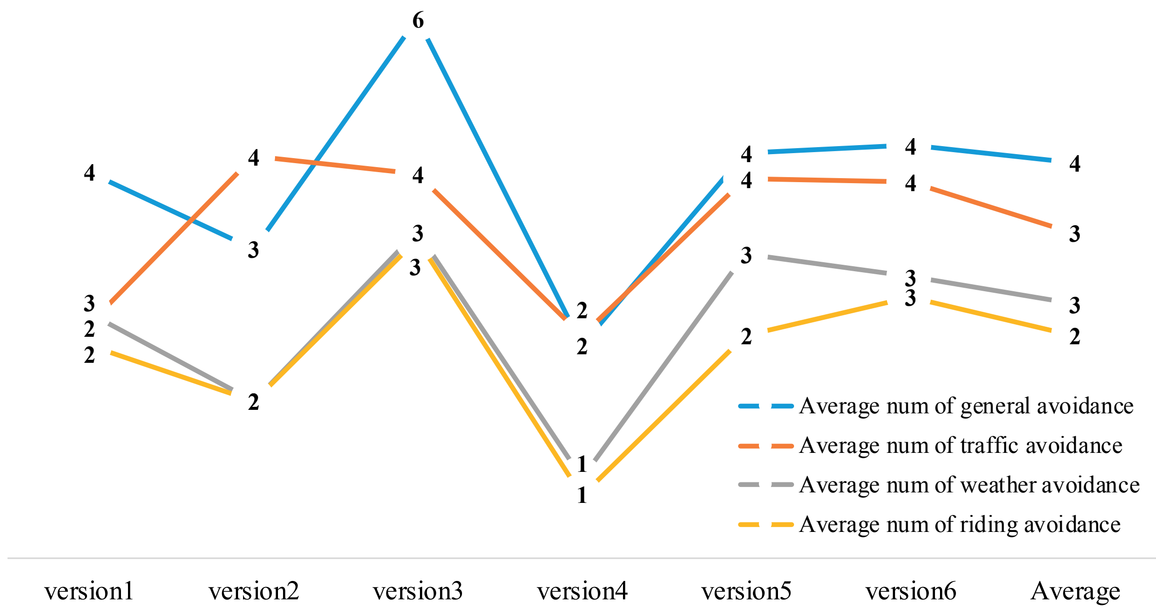


Figure 6-1 Avoidance behaviors under six app versions

Focusing on the avoidance driving behavior, deficiency of driver's avoidance behaviors are focused: which value is equal to 1 if the driver hardly has that kind of avoidance behavior, and 0 otherwise. Meanwhile, four types of avoidance behaviors (general avoidance, traffic avoidance, weather avoidance, and riding avoidance) are defined, which value is defined as the count of driver avoidance deficiency types. Average number of four type avoidance behaviors under six app versions are shown in Figure 6-1. Generally speaking, the average number of traffic avoidance behavior keep stable throughout the whole experiment period with six app versions. larger average number of general avoidance and less number of weather and riding avoidance behavior imply that drivers performed more weather and riding avoidance behaviors, in the meanwhile comparatively hardly perform general avoidance behavior.

6.2.2 Analysis framework

The trip based data employed in Chapter 5 have been utilized for data analysis here. In order to keep consistent with the previous analysis, in this section, the additional avoidance driving behavior is added to the analysis structure in Chapter 5. Therefore, the assumed inter-correlation structure can be modified as Figure 6-2.

In the new structures, six dependent variables are targeted: three driving performance indicators (violation rate of speed limit, dangerous driving measured by acceleration/deceleration, and dangerous driving measured by driving stability), multitasking behavior during driving, affective experience while driving, and avoidance behavior. These six variables are assumed to be correlated with each other. To account for such correlations, the Seemingly Unrelated Regression (SUR) model is employed again in the data analysis.

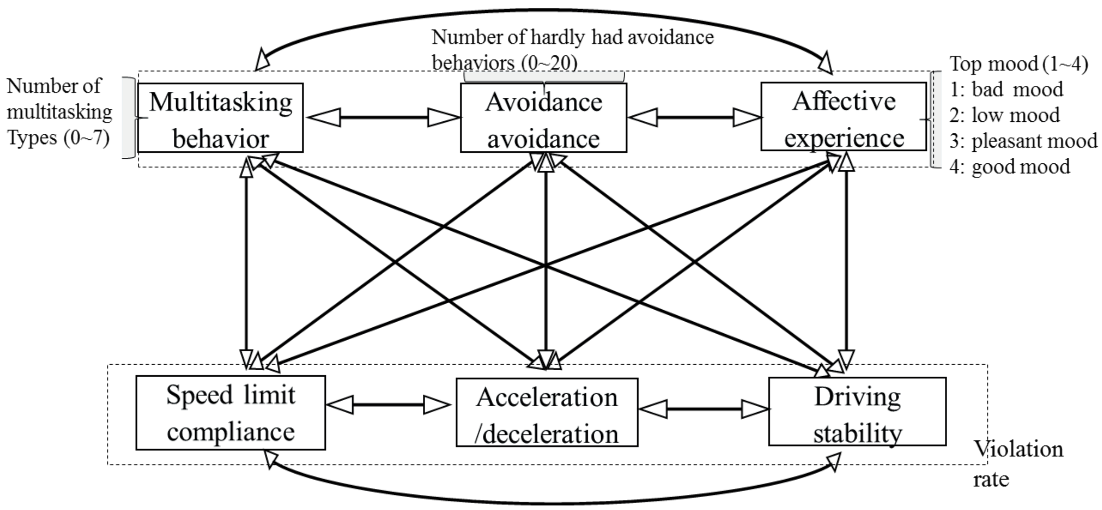


Figure 6-2 Interrelated dependent variables and assumed correlation structure

6.2.3 Model estimation results

As shown in Table 6-1, the R-squared value for each sub-regression model is 0.67 for the sub-model of speed limit compliance, 0.92 for acceleration/deceleration, 0.75 for driving stability, 0.61 for affective experiences, 0.47 for multitasking behavior, and 0.85 for driving avoidance behaviors, respectively. Model goodness of fit for four sub-regression models of speed limit compliance, acceleration/deceleration, driving stability, and affective experience, all improved with increased R-squared value by comparing with model structure without sub-model of avoidance behavior. Unfortunately, performance of multitasking sub-model keep stable.

Focusing on the influencing impacts of three driving performance indicators on each other, positive sign among three indicators could be identified. However, speed limit compliance and acceleration/deceleration behaviors are not significantly correlated to each other anymore, after the additional consideration of avoidance driving behavior, which is contrary to our previous observations (Jiang and Zhang, 2015b) based on same structure analysis but without driving avoidance behaviors.

As for influence from other variables, it is found that impacts of individual's affective experiences are insignificant, except for the significant impact of "*top of low mood*" on acceleration/deceleration violation behaviors. Factors of "*happy mood*" and "*top of bad mood*" become insignificant in this new structure analysis from the perspective of statistical analysis. The faint effect of affective experience imply that driver's risky driving behaviors are not seriously influenced by people's emotional factors while driving since avoidance behavior have been added for consideration. Similar to the five dependent variable SURE structure result (5DV_SURE), the performance of multitasking behavior while driving significantly influences on driver's violation behaviors measured by speed limit compliance and acceleration/deceleration. Moreover, one additional significant influencing impact from driver's multitasking behavior type 4: "MT4*: phone operation*" could be identified.

Interestingly, it is found that three types of violation driving behaviors are all significantly influenced by four types of avoidance behaviors. Significant and positive parameter of "*punishment avoidance*" implies that more "hardly have" avoidance (in other words, less performance) of the general punishment avoidance behavior (e.g., put off a brief trip or errand that required driving a car, and avoid activities that required using a car) will lead to less driving violation behaviors of speed limit compliance and abrupt acceleration/decelerations. In line with this interpretation, significant impact of "*traffic avoidance*" behaviors indicates that less performance of traffic avoidance behaviors (e.g., avoid driving on busy city street, residential streets, and freeway) will lead to more abrupt acceleration/deceleration behavior and less violation of speed limited and driving stability. "*Weather avoidance*" behavior only significantly affects driver's speed limit compliance behavior in a negative way. While, positive sign of "*riding avoidance*" behavior indicates that less performance of riding avoidance behaviors (e.g., avoid riding in a car after dark, and avoid riding in a car if possible) will lead to more over-speeding behavior and violation behaviors of driving stability.

Focusing on factors affecting driver's affective experiences while driving, driver's avoidance behaviors impose very limited influence on driver's affective experience: only one exception of significant negative impact of "*traffic avoidance*" could be identified. Moreover, it is observed that drivers would obtain more happy emotions through the performance of abrupt acceleration/deceleration behaviors, no significant influencing impact could be identified from other two performance indicators. On the other hand, more upset emotions would be obtained with the influence of driver's multitasking behaviors, especially behaviors of "MT2: *mental distraction*", "MT3: *handle distraction*", and "MT4: *phone operation*"). Concerning factors affecting multitasking behaviors, it is similar to model estimation result obtained in 5DV_SURE structure. Only one exception is that significant influencing impact of the experiential factor of traffic accident experience become insignificant in the new structure analysis result. In terms of influence comes from avoidance behavior, there was no significant influencing impacts could be identified on multitasking behaviors.

As for driving avoidance behavior, it is found that influential factors affecting driving avoidance behaviors include violation behaviors of speed compliance and driving stability, top of bad mood, multitasking type 2 (mental distraction), and multitasking type 4 (radio operation). Positive signs of parameters imply that higher driving stability rate and multitasking of mental distraction and radio operations will lead to more “hardly have” violation behaviors, which means the insufficient performance of many of those avoidance behaviors.

Furthermore, speed limit compliance behavior and avoidance behaviors are broadly influenced by factors such as driver’s internal factors, external intervention factors from the designed app, and driving environment factors.

Focusing on the effects of the app functions, it is found that basic function of the app significantly influences driver’s objective and subjective driving performance, except for multitasking behavior. On the other hand, various influencing impacts across different driving propensities of irritable driver, careless driver, aggressive driver, as well as excessive confidence driver, could be verified. In terms of four types of additional app functions, Function 2 (ranking/self-diagnose) and Function 3 (propensity and advice) show more influencing power among the six driving scenarios. However, no significant influencing impact could be observed on driver’s speed limit compliance behavior in this estimation result.

Table 6-1 SUR model estimation results (6 dependent variables)

Independent Variable	Dependent Variable	Speed limit compliance		Acc. / dec.		Driving stability		Affective experience		Multitasking		Avoidance behavior	
		Coef.	z-value	Coef.	z-value	Coef.	z-value	Coef.	z-value	Coef.	z-value	Coef.	z-value
violation behav.	*Speed limit compliance*			0.04	1.55	0.04	2.10**	0.07	0.42	-0.83	-3.75***	-5.32	-3.94***
	Acc. / dec.	0.18	1.55			0.55	16.21***	1.27	3.41***	2.05	4.23***	0.13	0.21
	Driving stability	0.31	2.09**	0.92	16.22***			0.34	0.7	-1.47	-2.32**	5.43	3.05***
Affective exper.	*Happy mood*	-0.05	-1.29	0.01	0.45	0.00	0.16			0.03	0.2	0.17	0.38
	Top of bad mood	0.06	1.6	0.00	-0.13	0.01	0.69			-0.28	-1.80*	-1.56	-3.52***
	Top of low mood	-0.04	-0.77	-0.10	-3.70***	0.02	1			1.04	4.39***	0.54	0.79
	Top of good mood	0.01	0.42	-0.01	-0.89	-0.01	-1.14			0.40	2.68***	0.47	1.13
Multi-tasking	*Multitask type 1*	0.06	1.1	0.06	2.21**	-0.02	-0.81	-0.27	-1.42			1.01	1.4
	Multitask type 2	-0.09	-2.99***	0.04	2.52**	-0.01	-1.26	-0.33	-3.31***			0.92	2.41**
	Multitask type 3	-0.04	-1.08	0.00	-0.07	0.01	0.45	-0.47	-4.33***			-0.29	-0.7
	Multitask type 4	-0.05	-0.95	0.05	2.23**	-0.01	-0.6	-0.44	-2.76***			1.32	2.20**
	Multitask type 5	-0.11	-3.30***	0.02	1.55	-0.02	-1.67*	-0.01	-0.08			-0.43	-1.04
Avoidance behavior	*Punishment avoidance*	-0.04	-1.66*	-0.03	-3.02***	0.01	1.37	-0.07	-0.84	-0.05	-0.5		
	Traffic avoidance	-0.05	-2.91***	0.02	2.36**	-0.01	-2.22**	-0.18	-3.14***	-0.10	-1.38		
	Weather avoidance	-0.03	-1.79*	0.00	-0.66	0.00	-0.67	-0.03	-0.56	0.08	1.13		
	Riding avoidance	0.14	4.78***	-0.01	-0.64	0.02	2.10**	0.13	1.49	0.12	0.93		
Interaction between Basic Function (BF) and driving propensity													
BF * Irritable driver		-0.09	-1.81*	-0.02	-1.01	0.05	3.10***	0.60	3.87***	0.21	1.03	-2.14	-4.18***
BF * Careless driver		0.00	-0.08	0.04	2.09**	-0.02	-0.9	-0.38	-2.52**	-0.25	-1.28	1.50	3.11***
BF * Aggressive driver		-0.09	-2.06**	-0.07	-3.97***	0.04	2.38**	-0.06	-0.39	-0.03	-0.18	1.92	3.93***
BF * Excessive confidence driver		0.10	1.99**	-0.02	-0.97	-0.02	-1.33	0.25	1.42	0.24	1.09	1.77	3.22***
Additional app functions													
Function 1 (SA/PA information)		0.00	0.01	-0.03	-1.48	0.07	4.14***	0.12	0.78	0.15	0.81	0.63	1.15
Function 2 (Ranking/self-diagnose)		-0.14	-1.45	0.65	20.58***	-0.38	-12.22***	-1.33	-4.17***	-1.69	-4.06***	2.93	2.50**
Function 3 (Propensity/advice)		0.07	0.98	-0.12	-3.85***	0.08	3.46***	0.67	3.00***	0.39	1.34	-0.76	-0.92
Function 4 (Traffic safety campaign)		0.05	1.33	-0.04	-2.40**	0.01	0.84	-0.01	-0.07	0.23	1.59	-0.72	-1.82*
Experiential factors													
Traffic accident		0.17	1.89*	-0.04	-1.01	0.06	1.82*	-1.29	-4.71***	0.60	1.6	-11.69	-16.76***
Punishment of traffic rule violation		-0.36	-2.52**	0.08	1.22	-0.18	-3.68***	-1.62	-3.50***	-0.98	-1.64	-16.93	-12.73***
Self-evaluation factors													
Self-evaluated safety score		0.00	0.4	0.00	1.24	0.00	0.18	0.02	2.27**	-0.05	-3.81***	0.41	13.01***
Behavioral change stage		0.10	0.89	-0.12	-2.43**	0.19	5.35***	1.24	3.57***	0.56	1.3	12.14	11.84***
Driving contextual factors													
Drive on holiday		0.04	1.35	-0.02	-1.04	-0.01	-0.55	0.06	0.53	-0.07	-0.53	-0.03	-0.07
Drive at night		0.06	2.04**	-0.02	-1.22	0.01	0.87	0.11	1.11	0.17	1.33	-1.09	-3.05***
Speed limit		0.00	0.13	0.00	1.29	0.00	-0.21	-0.01	-0.62	-0.01	-0.41	0.05	1.2
Driving direction		0.00	-0.06	0.00	0.15	0.00	-0.36	-0.01	-0.08	-0.06	-0.57	0.72	2.29**
Traffic volume		0.00	-2.34**	0.00	-0.35	0.00	1.2	0.00	1.03	0.00	0.29	-0.02	-2.71***
Share of large vehicles in traffic		0.23	1.88*	-0.06	-1.12	0.06	1.39	-0.81	-2.04**	-0.30	-0.58	-2.76	-1.85*
Landuse factors													
Driving long farm lands		-0.64	-2.31**	-0.02	-0.13	0.26	2.71***	-1.17	-1.28	-1.12	-0.95	1.12	0.33
Driving along forests		-0.69	-3.32***	0.06	0.57	0.18	2.45**	-0.72	-1.03	-0.33	-0.37	4.24	1.65*
Driving along building areas		-1.07	-3.64***	0.19	1.41	0.04	0.41	-0.11	-0.11	0.99	0.78	5.75	1.59
Type of expressways													
Chugoku (south-north direction)		0.27	4.02***	-0.02	-0.7	0.01	0.22	0.03	0.15	0.00	-0.01	1.60	1.93*
Chugoku (west-east direction)		0.54	8.56***	-0.05	-1.56	0.00	0.14	0.05	0.22	0.49	1.65	1.58	1.91*
Sanyo (west-east direction)		0.57	6.17***	-0.03	-0.66	-0.02	-0.6	0.22	0.68	0.30	0.71	2.40	2.02**
Driver attributes													
Age		-0.01	-0.76	0.01	2.09**	-0.01	-2.48**	-0.02	-1.08	0.05	1.88*	-0.16	-3.09***
Occupation		-0.06	-1	-0.03	-1.28	0.07	3.65***	-0.58	-3.18***	-0.32	-1.34	-2.49	-3.73***
Trip purpose		-0.18	-2.01**	0.02	0.53	-0.08	-2.48**	-0.77	-2.66***	-0.61	-1.65	-9.63	-10.53***
Driving frequency		0.01	0.18	-0.01	-0.25	-0.01	-0.27	-0.98	-4.98***	0.43	1.64	-8.50	-14.83***
Constant term		1.30	2.81***	-0.64	-3.02***	0.33	1.98**	6.75	4.46***	3.24	1.63	10.92	2.26**
R squared		0.67		0.92		0.75		0.61		0.47		0.85	

In terms of experiential factors, oppose to the previous 5DV_SURE model estimation result, the experiences of traffic accident show significant influencing impact on speed limit compliance and driving stability control behavior, which indicates that drivers with experiences of traffic accident involvement would perform more violation behavior of speed limit compliance and driving stability control while driving. However, no significant influencing impact could be observed on driver's abrupt acceleration/deceleration control behavior. On the other hand, significant negative impact of accident experience and traffic rule violation punishment on affective experience and avoidance behavior indicate that more negative driving moods and avoidance behaviors will be experienced for drivers who experienced traffic accident before. Furthermore, it is found that different from traffic accident involvement factor, drivers would behave less risky behaviors of speed limit and driving stability violation if they have been punished due to the traffic rule violations before.

6.3 Situational driving route avoidance behavior on expressways

6.3.1 Data

Situational driving avoidance behaviors are very common in practice, especially for truck drivers who work on driving, have rich experience about driving, and usually perform certain types of situational avoidance behaviors, for example, avoiding of using routes with more traffic, bad road conditions, or more traffic accidents.

In terms of route choice behaviors of freight forwarders, decision makers might differ across companies, depending on decisions contexts. Considering that transporting goods is a business involving contracts, both truck drivers and company managers may become actual decision makers. Based on data from the 54 companies participated in the questionnaire survey, company managers reported that about 53% of truck route decisions are made by managers, 16% by drivers, and 20% of the companies make route decisions according to actual situations. In case of drivers, they reported that 58% of trips were decided by managers and 37% by drivers.

To clarify similarities and dissimilarities between managers' and drivers' reports on truck route choice decisions, data with at least one pair of manager and driver who fully answered the questionnaires are generated. As a result, a total of 525 paired observations were obtained.

Figure 6-3 shows cross-aggregation results between managers' and drivers' reports on truck route choice decisions. Decisions by managers were consistently reported by both managers and drivers or drivers who account for 86% among the 525 paired observations. The consistent share for decisions by drivers is 85%. As for other types of decisions (mainly decisions depending on circumstances), the consistent share between managers and drivers is just 42%. The inconsistent shares for the above three types of decisions range between 14% and 58%. Such a large inconsistency may be caused by inconsistent understanding about the meaning of circumstances and the timing of decision, etc.

The above results suggest that decisions on truck routes may not be independent between drivers and managers. This indicates that modeling approaches should be carefully selected for clarifying influential factors in a convincing way.

Concerning choices of the two expressways, drivers' and managers' images about them may matter. For this, 12 items about images of expressways were prepared. Evaluations were given by asking respondents to compare the two expressways. In this sense, the evaluation value is conceptually relative. Image is evaluated based on 5-point scaling method: very bad, bad, neutral, good, and very good. Evaluation results are shown in Figure 6-4 and Figure 6-5.

Results show that as a whole, company managers reveal less preference for Chugoku expressway comparing with Sanyo expressway: on average only 11% showed a positive evaluation (*very good*: 2%; *good*: 9%) about Chugoku expressway. In contrast, about 19% of drivers provided a positive evaluation (*very good*: 9% and *good*: 10%), on average. "*Neutral*" opinions on images of Chugoku expressway were given by about half of the respondents (managers: 54%, drivers: 50%) across the 12 items. Focusing on shortcomings of the Chugoku expressway environment, revealed from individual's evaluations "*bad*" and "*very bad*", it is found that the top four factors are "brightness", "comfort", "road safety", and "willingness to drive on" factors for managers and drivers.

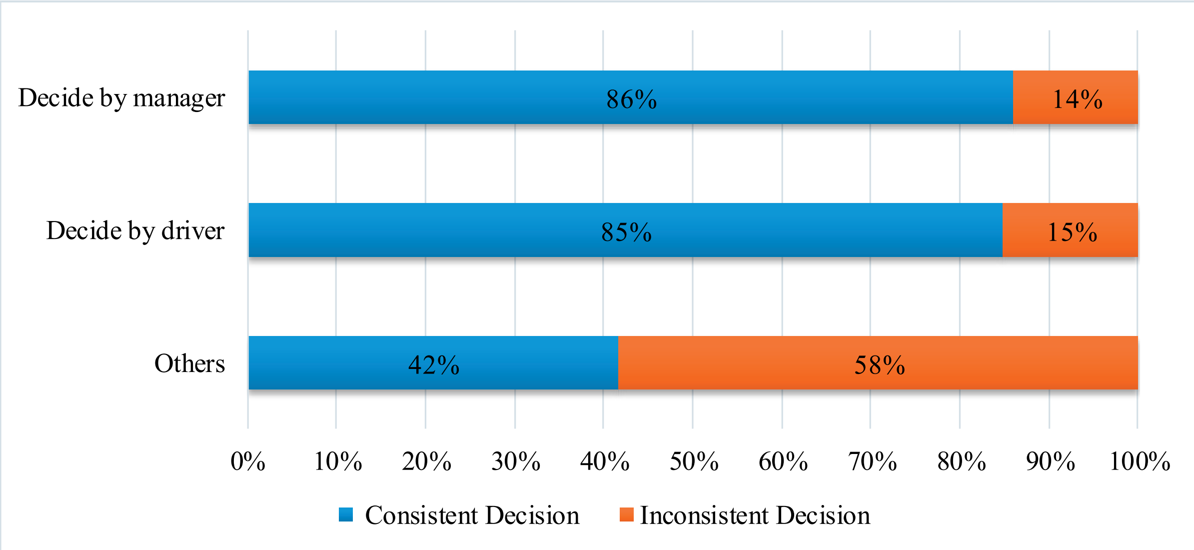


Figure 6-3 Consistencies of route decision-making rules reported by managers and drivers

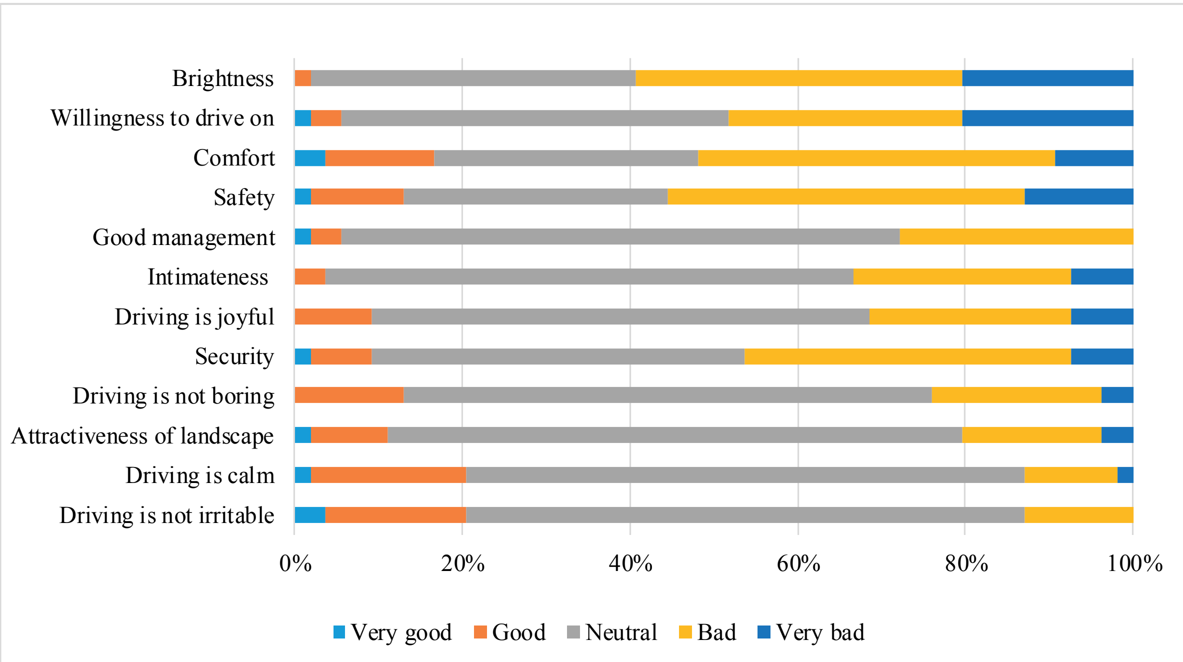


Figure 6-4 Managers' images of Chugoku expressway

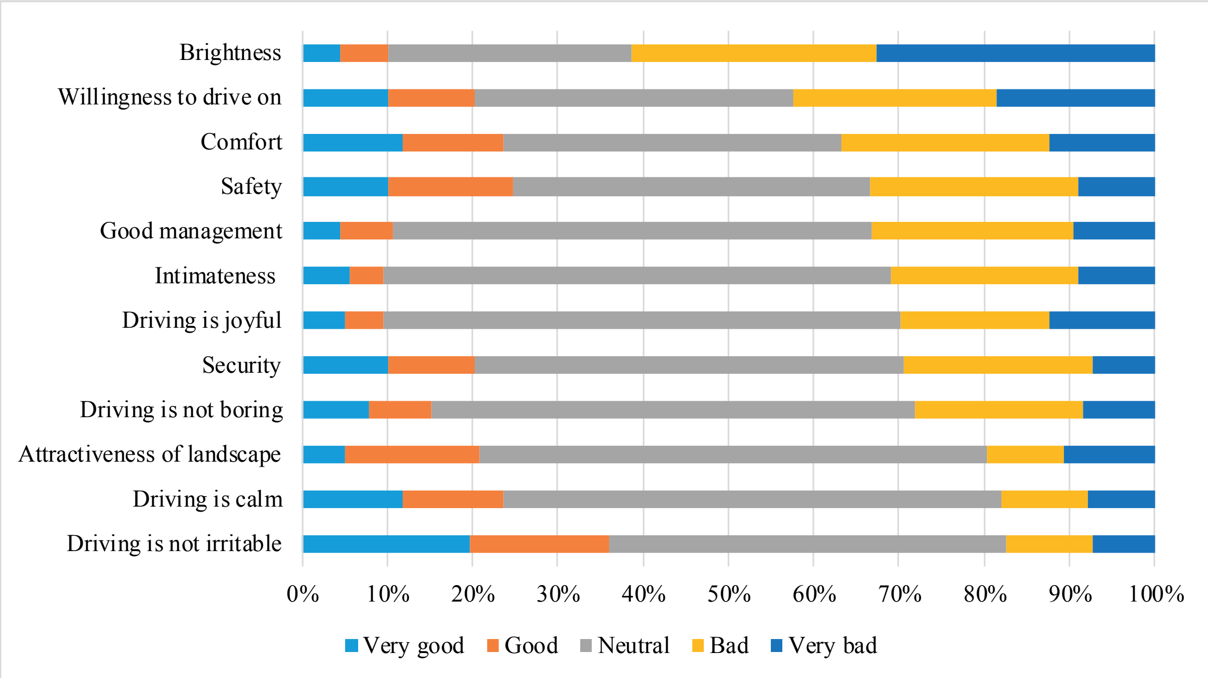


Figure 6-5 Drivers' images of Chugoku expressway

6.3.2 Methodology: A bivariate probit (BP) model

As shown in the previous subsection, decisions on truck route choices may involve not only drivers, but also company managers, and sometimes the decisions may vary with decision circumstances. In other words, decisions on truck route choices should be regarded as a group decision. In case of group decisions, decision functions should not ignore the influence of observed inter-agent interactions (e.g., in terms of joint decision function or altruism) and/or unobserved inter-agent interactions (i.e., correlations of error terms) (e.g., Bhat and Pendyala, 2005; Timmermans and Zhang, 2009). Here, as the first attempt in literature, the following bivariate probit (BP) model is adopted to represent joint choices of Sanyo and Choguku expressways by managers and drivers.

$$y_{i,1}{*}{=}\beta_1' x_{i,1}{+}\varepsilon_{i,1},\ \ y_{i,1}{=}1\ if\ y_{i,1}{*}{>}0;\quad y_{i,1}{=}0, otherwise \tag{6-1}$$

$$y_{i,2}{*}{=}\beta_2' x_{i,2}{+}\varepsilon_{i,2},\ \ y_{i,2}{=}1\ if\ y_{i,2}{*}{>}0;\quad y_{i,2}{=}0, otherwise \tag{6-2}$$

Here, $y_{i,1}$ and $y_{i,2}$ are dependent variables indicating expressway choices for individual observation i, where 1 and 2 indicate driver and manager, respectively. β_1 and β_2 are vectors of unknown parameters. $\varepsilon_{i,1}$ and $\varepsilon_{i,2}$ are error terms, which follow a bivariate normal distribution with correlation of ρ. And, ρ is used to represent unobserved interactions between managers and drivers. If ρ is positive, managers' and drivers' choices are more likely to be consistent, while, if ρ is negative, managers and drivers tend to make different choices. Insignificant value of ρ suggests that managers' and drivers' decisions are independent.

$$E(\varepsilon_{i1})\ = E(\varepsilon_{i2})\ = 0 \tag{6-3}$$

$$Var(\varepsilon_{i1})\ = Var(\varepsilon_{i2})\ = 1 \tag{6-4}$$

$$\mathrm{Cov}(\varepsilon_{i1},\varepsilon_{i2}) = \rho;\ i = 1,2,3,\ldots,n \tag{6-5}$$

Then, the log-likelihood function for the BP model can be calculated as follows:

$$\begin{aligned} logL &= \sum_{i=1}^{n} \log \Phi_2\left[(2y_{i1}-1)\beta_1' x_{i,1}, (2y_{i2}-1)\beta_2' x_{i,2}, (2y_{i1}-1)(2y_{i2}-1)\rho,\right] \\ &= \sum_{i=1}^{n} \log \Phi_2\left[q_{i1}\beta_1' x_{i,1}, q_{i2}\beta_2' x_{i2,}, q_{i1}q_{i2}\rho\right] \end{aligned} \tag{6-6}$$

Where $\Phi(\bullet)$ is the cumulative distribution function for the standard normal distribution, and q_{i1} and q_{i2} are defined below.

$$q_{i1} = (2y_{i1} - 1) = \begin{cases} -1, & if\, y_{i1} = 0, \\ +1, & if\, y_{i1} = 1, \end{cases} \qquad \text{6-7}$$

$$q_{i2} = (2y_{i2} - 1) = \begin{cases} \text{-}1, & if\, y_{i2} = 0, \\ +1 & if\, y_{i2} = 1, \end{cases} \qquad \text{6-8}$$

The above model can be estimated based on standard maximum likelihood method.

6.3.3 Model estimation results

Model estimation result are shown in Table 6-2. The likelihood ratio test against the independence of route choices between managers and drivers suggests that the independence is rejected, because the correlation (ρ) between managers' and drivers' models is statistically significant. In other words, this result supports joint estimation of managers' and drivers' route decisions.

Focusing on influences of SP attributes, it is observed that there is no significant influence of any attributes on route choices of drivers on one hand and significant influences are surely found with respect to five out of the seven SP attributes. One potential explanation of such results is that all factors extracted from the hearing interview are reported by company managers, not by truck drivers. The other explanation might be that truck drivers transport goods for customers required by companies, not for their own purpose, and as a result, they may not care about any factors identified by managers. Looking at those influential factors to managers' route choice decisions, managers tend to ask drivers to use Chugoku expressway,

- if full compensation of tow truck fee is provided only to those trucks with relevant insurance, and
- if more refund is provided to company when using Chugoku expressway.

Table 6-2 Model estimation results of joint truck route choice model by managers and drivers

y = 1: use of Chugoku expressway; y = 0: use of Sanyo expressway		Driver choice model			Manager choice model		
All explanatory variables are introduced to utility function of y=1		Coef.	z-value	sig.	Coef.	z-value	sig.
SP attributes (1: yes, 0: no)							
Full compensation of tow truck fee when using Chugoku	only to trucks with insurance	-0.20	-0.27		3.10	3.52	***
	to all trucks	0.004	0.02		0.06	0.26	
Traffic congestion on Sanyo	once 10 times of drive	-0.20	1.26		-0.29	1.54	
	once 5 times of drive	-0.20	0.51		-1.33	-2.8	***
Refund to use of Chugoku	3000 yen	-0.04	-0.12		1.70	4.40	***
	2000 yen	0.36	0.53		-2.86	-3.49	***
Transporting fragile goods		-0.39	-1.23		1.02	2.57	**
Image of Chugoku expressway in comparison with Sanyo expressway (1: very good ~ 5: very bad)							
Safety on road		0.04	0.36		0.41	2.19	**
Security on road		-0.24	-1.78	*	-1.00	-4.35	***
Brightness of driving environment		-0.08	-1.42		0.33	1.95	*
Driving is not irritable		0.15	1.99	**	-0.06	-0.39	
Driving is calm		-0.13	-1.24		0.11	0.53	
Driving is not boring		-0.06	-0.83		0.23	1.67	*
Driver-specific attributes							
Experience of Sanyo use (1: yes, 0: no)		-0.95	-3.63	***			
Decision maker of Sanyo use reported: driver (1: yes, 0: no)		0.02	0.13				
Experience of Chugoku use (1: yes, 0: no)		0.47	2.72	***			
Decision maker of Chugoku use reported: driver (1: yes, 0: no)		0.08	0.44				
Age (years old)		-0.10	-1.29				
Professional driving age (years)		0.01	0.70				
Flexible workday (1: yes, 0: no)		-0.21	-1.63	*			
Working period: 9:00 am ~ 12:00 am (1: yes, 0: no)		-0.04	-0.26				
Working period: 12:00 am ~ 6:00 pm (1: yes, 0: no)		0.20	1.21				
Working period: 6:00 pm ~ 10:00 pm (1: yes, 0: no)		0.06	0.43				
Working period: 10:00 pm ~ 2:00 am (1: yes, 0: no)		-0.06	-0.37				
Working period: 2:00 am ~ 9:00 am (1: yes, 0: no)		0.31	1.68	*			
Ownership of vehicle type_1: wing		-0.22	-1.46				
Ownership of vehicle type_2: dry van		-0.11	-0.62				
Ownership of vehicle type_3: flat body		0.06	0.27				
Manager-specific factors							
Share of Sanyo/Chugoku in total transport (%)					-0.02	-5.98	***
Route decision maker reported: manager (1: yes, 0: no)					0.20	0.81	
Route decision maker reported: situational (1: yes, 0: no)					0.07	0.29	
Route choice reason: travel time (1: yes, 0: no)					-0.62	-2.99	***
Route choice reason: travel cost (1: yes, 0: no)					-0.24	-1.18	
Route choice reason: travel safety (1: yes, 0: no)					-1.23	-6.17	***
Experiential factors from drivers (ordered value)							
Frequency of traffic congestion experience		0.17	4.46	***	0.1523	3.65	***
Frequency of experiencing traffic accidents		0.21	4.04	***	0.1982	3.41	***
Frequency of experiencing vehicle malfunctions		0.005	0.08		-0.0081	-0.13	
Insurance purchasing by company (1: yes, 0: no)							
Insurance for damages of human and objects		0.77	3.72	***	0.85	3.03	***
Insurance for damages of vehicle itself		-0.57	-2.91	***	-0.54	-2.62	***
Insurance for tow-truck fee		0.78	3.84	***	0.62	2.67	***
Other insurances		-0.13	-0.58		0.06	0.23	
Company attributes							
Satisfaction with road information (1: dissatisfied ~ 4: satisfy)		0.15	1.33		0.16	1.05	
Contract of major frequent usage discount (1: yes, 0: no)		0.54	2.85	***	0.54	1.90	*
Number of vehicles owned		0.009	3.70	***	0.008	3.22	***
Number of employees		-0.06	-0.45		0.12	0.81	
Trading volume (tons/year)		-0.07	-1.31		0.14	1.97	**
Constant terms		-1.21	-1.26		-4.10	-3.11	***
ρ (correlation between error terms of two route choice models)		0.92	21.48	***			
Model accuracy: *Likelihood-ratio test of rho=0*		CHISQ(1) = 26.5724 (Prob. > 0.0000)					

Note: Significant level: *** 99%, ** 95%, * 90%; Sanyo: Sanyo expressway; Chugoku: Chugoku expressway.

Traffic congestion on Sanyo expressway leads to use of it, but not use of Chugoku expressway. This may be interpreted as, managers tend to choose use of Sanyo expressway because of popular use of it. Due to popular use of Sanyo expressways, traffic congestion often occur on it more than on Chugoku expressway. In this sense, there is a “chicken-egg” issue between route choice decisions and traffic congestion. One more influencing factor is whether fragile goods are transported or not. Estimation results suggest that transporting fragile goods leads to use of Chugoku expressway. In fact, there are more hilly road sections with undulations and curves on Chugoku expressway than on Sanyo expressway and it is expected that truck companies may attempt to avoid using Chugoku expressway. In this sense, this estimation result is unexpected. One positive explanation might be that damages due to use of hilly roads are more serious than due to congestion-induced speed changes.

Even though SP attributes under investigation are not influential at all to drivers’ decisions, model estimation results surely identified other influential factors, including security and “driving is not irritable” on Chugoku expressway. However, “driving is not irritable” on Chugoku expressway does not affect managers’ decisions. Instead, safety, brightness, and “driving is not boring” on Chugoku expressway are additionally identified influential to managers’ decisions. Both managers and drivers tend to choose Chugoku expressway if they think that Chugoku expressway is more secure. Even though parameters are statistically significant, it is difficult to justify the parameter signs with respect to safety, brightness, and “driving is not boring” because their meanings are not intuitive.

Focusing on driver-specific attributes, only four variables are identified influential, out of the 15 attributes introduced in the model. If drivers used Sanyo expressway in the past, they are less likely to use Chugoku expressway. In contrast, if drivers experienced use of Chugoku expressway, they tend to continue use of it. Use of Chugoku expressway is also confirmed with respect to working period: if the working period is between 2:00 am and 9:00 am, drvers are more likely to use Chugoku expressway. If flexible workday is available in companies, drivers prefer use of Sanyo expressway over use of Chugoku expressway. Unexpectedly, decision maker of expressway use reported by drivers does not affect drivers' route choice decisions, and other factors are not significant, either.

As for manager-specific attributes, half of them are significant and the other half are not. If the route choice reasons are travel time and safety, managers are more likely to choose use of Sanyo expressway because relevant parameter signs are negative. If companies have a higher share of transporting goods on Sanyo and Chugoku expressways, truck routes are more concentrated on Sanyo expressway. Travel cost is not a significant factor to use of the two expressways. Route choice decision makers reported by managers are not influential to managers' decisions. This result is consistent with drivers' decisions.

In this analysis, manager and driver are jointly built, where their interactions are captured by use of a correlation parameter. Correlation indicates unobserved interactions. In reality, observed interactions may also play a certain role in route choice decisions. In this regard, driver's experiential factors are introduced to both models. With this category of explanatory variables, drivers' influences on managers' decisions are reflected. In other words, it is assumed that drivers' involvements in traffic accidents and experiences of traffic congestion and vehicle malfunctions may force managers to take them into account in choices of truck routes. As a result of model estimation, drivers' involvements in traffic accidents and experiences of traffic congestion are found influential; however, experiences of vehicle malfunctions are not. These experiential factors encourage drivers to use of Chugoku expressway. Insurance purchasing variables are also introduced as common variables to explain decisions of managers and drivers. It is found that purchasing insurances for damages of human and objects and tow truck fee results in more use of Chugoku expressway, but insurance of vehicle itself leads to more use of Sanyo expressway. It is difficult to interpret the meaning of negative sign of insurance for damages of vehicle itself. For this, combinations of different types of insurances may matter to decision-making. In the future, combination effects of insurances should be examined.

The last set of common variables are company attributes. Model estimation results suggest that companies with a contract of major frequent usage discount with expressway authorities companies and more vehicles owned tend to choose Chugoku expressway, while in companies with more trading volume their managers are more likely to choose Chugoku expressway. Other attributes of companies are not influential to route choice decisions.

6.4 Summary

Recognizing the importance of human factors in traffic safety, research analysis in this chapter explored driver's avoidance driving behavior based on two different datasets, each of which represented one unique type of avoidance behaviors.

Firstly, focusing on general punishment avoidance driving behaviors from the perspective of driving safety performance, data collected from an app-based field experiment and a series of questionnaire surveys conducted over three months were utilized. Individual's avoidance behavior characteristics, specifically the deficiency of driver's avoidance behavior, have been investigated together with three types of objective driving risks (speed limit compliance, abrupt acceleration/deceleration, and driving stability), drivers' subjective well-being factors, and multitasking during driving. It is found that driving avoidance behaviors are statistically affected by speed limit compliance, driving stability, bad moods during driving, and multitasking behaviors in terms of mental distraction and radio operation. At the same time, it is observed that four types of driving avoidance behaviors significantly influence objective driving risks, especially speed limit compliance. Traffic avoidance behavior is significantly influential to driver's affective experience during driving. No significant impact of avoidance behavior has been identified influential to driver's multitasking experiences.

Secondly, emphasizing driver's situational avoidance behavior, a case study on truck route avoidance behaviors was carried out. Two substitutable expressways in the Chugoku area of Japan, i.e., Chugoku expressway and Sanyo expressway are targeted. Even though two expressway are substitutable to each other to some extent, Sanyo expressway has been facing up with a serious problem of traffic capacity saturation, while Chugoku expressway has been suffering from decreasing traffic demand in the sense that some SAs/PAs had to be closed down. Data analyses show that truck route choice decisions are diverse across companies. There types are revealed: decision by manager, decision by truck driver, and decision depending on circumstances. Analysis results further reveal that route choice decisions by company managers and drivers are not independent of each other. The resulting joint model estimation results confirm that use of Chugoku expressway is affected complicatedly by various factors. Compensation of tow truck fee, traffic congestion on Sanyo expressway, refund to use of Chugoku expressway, and transporting fragile goods, as SP attributes, are influential to managers' decisions; however, they are not influential at all to drivers' decisions. Both managers' and drivers' models capture some significant parameters of evaluation about images of Chugoku expressways, where only security has a consistent influence on both managers and drivers. Similar numbers of statistically significant driver-specific attributes and manager-specific attributes are identified. Drivers' experiential factors and insurance purchasing by companies consistently affect the two decision makers' route choices. Influential company attributes are not the same between managers' and drivers' models.

Chapter 7

Drivers' Adaptation Behavior under Traffic Accidents Related Dynamic Travel Information

In responding to the occurrence of traffic accident on expressways, real-time dynamic traffic information provision, especially accident related information, is quite important to help drivers adapt to any potential abnormal changes caused by accident as soon as possible, and therefore decrease the negative impacts of accidents. In line with this consideration, research in this chapter focus on drivers' adaptation behaviors based on a large scale RP based SP survey data to exploring influential factors on traffic accidents related dynamic travel information provision. To best reflect the real traffic situation and capture drivers decision changes to the provided information, data utilized in the SP survey all employed from information collected from the preference experiment. Three different decision context have been discussed with regarding to information provision to drivers under the scenes of "*before departure*", "*on the way to expressway*", and "*on expressway*", separately. Moreover, in addition to reflect the heterogeneity in human behavior, a new concept of travel information styles have been proposed to represent driver's heterogeneous information collection and responding properties.

Subsection 7.2 is written mainly based on Jiang and Zhang (2014) and Subsection 7.3 mainly based on Jiang and Zhang (2015a).

7.1 Aggregation analysis of driver's adaptation behaviors

In the SP questionnaire survey, totally 2,500 valid samples have been collected for data analysis. Respondents included in the SP survey were drivers with age ranging from 18 to 69 years old, with 78.4% of whom falling in the age band of 20~60 years old. Number of male drivers (1,249) was nearly equal to that of female drivers (1,251).

As shown in Figure 7-1, to help readers understand the scales of choice shares for different adaptation behaviors, we provided aggregate results, recognizing the fact that the choice shares usually differ across SP cards. It is found that 30% of respondents chose to change their trip plan (Before departure: 28.9%; on the way to expressway: 29.4%; on expressway: 26.2%), suggesting that these drivers might be captive users of expressways. It is also revealed that about 54% of respondents chose to give up using the expressway (46% changed to ordinary roads, 4% used other travel mode(s) and 4% cancelled the trip) for the scenes of "Before departure" and "On the way to expressway". For drivers who are already on expressways, about 28% of them chose to give up the expressway usage (23% changed to ordinary road, 1% used other travel mode(s) and 4% canceled the trip). In the scene of "On expressway", 21% of respondents prefer to "wait and see at nearby SA/PA". About 4% chose to cancel their trips for each of the three scenes, implying that they might be unshakable risk avoiders.

7.2 Context-sensitive information provision and individual adaptation behaviors

7.2.1 Context-sensitive adaptation choice alternatives

In order to quantify the effects of dynamic travel information on driver's adaptation behavior changes, a nested logit (NL) model is employed in the model estimation. Specific structures of the NL models for different decision scenes are shown in Figure 7-2, which was derived based on both behavioral considerations and repeated trial and error.

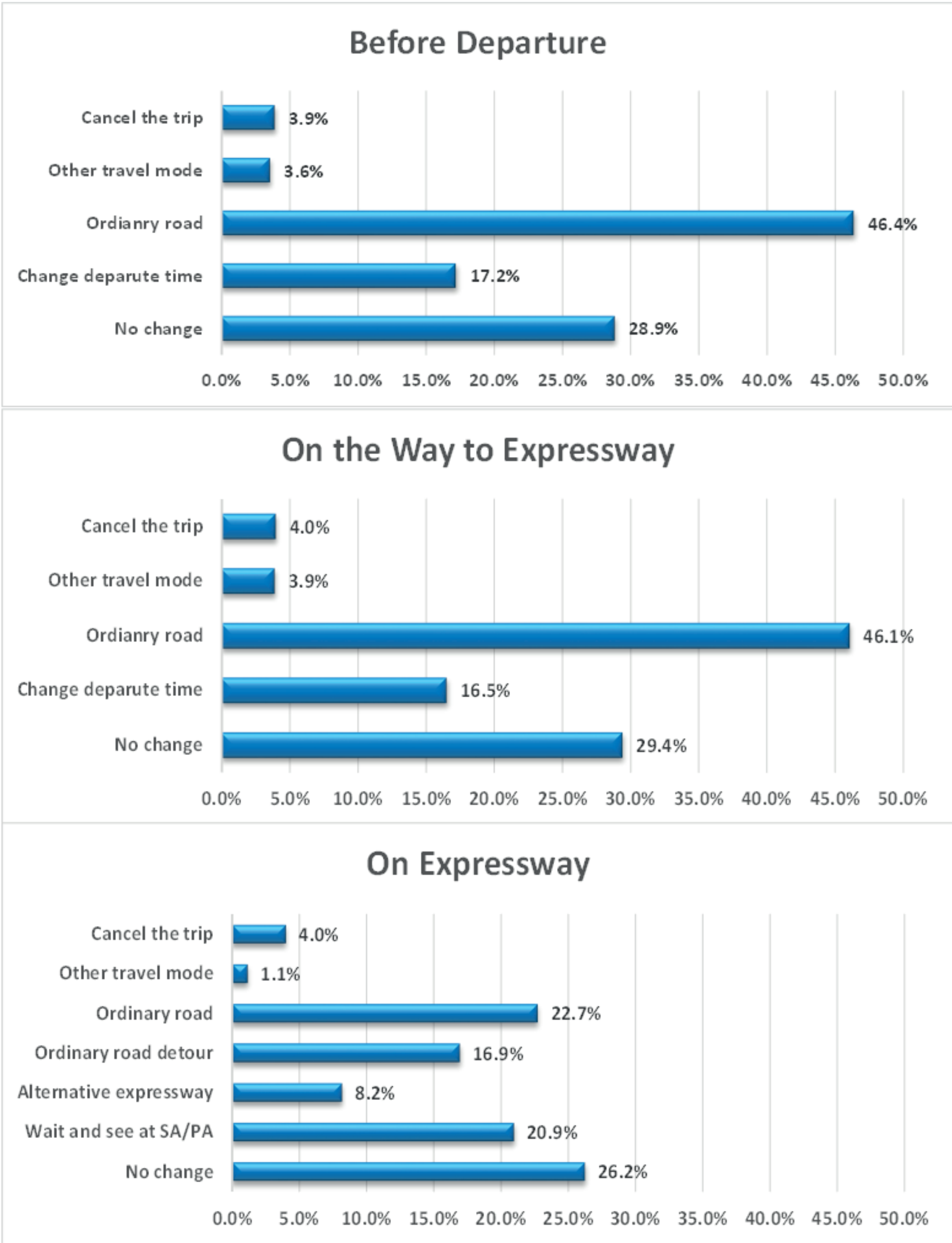


Figure 7-1 Aggregation results of route choices under three decision scenes

Since the shares of “other travel mode” and “cancel the trip” alternatives are considerably small, these two options are combined and named as “others” (share rates: 8% for “before departure” and “on the way to expressway”, 5.4% for “on expressway”).

For the scenes of "before departure" and "on the way to expressway", a same structure is applied. The first choice nest is a binary choice decision: whether or not make any changes responding to the provided information. The second nest includes two choice alternatives: change departure time and give up expressway. Finally, the lower nest accommodates the choices of "change to ordinary road" and "others".

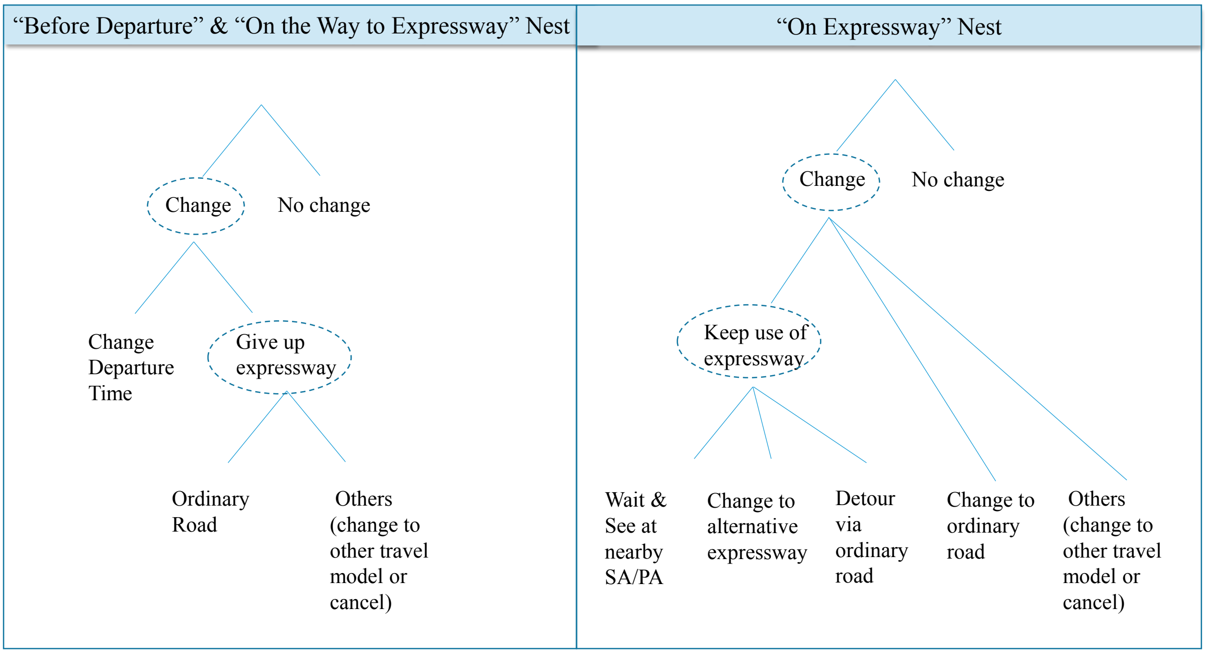


Figure 7-2 Nest choice structures in three decision scenes

As for the "on expressway" scene, more adaptation alternatives are included. The first nest deals with the "change" and "no change" options, followed by a choice nest that includes an additional nest of "keep use of expressway" and two options of "change to ordinary road" and "others".

7.2.2 Methodology: A nested logit (NL) model

Here, a general three-level nested logit model structure is provided. Joint probability that individual n selects choice j alternative can be described below.

$$\begin{aligned} P_{nj} &= P_n(i) \times P_n(k|i) \times P_n(j|k(i)) \\ &= \frac{\exp(V_{ni} + \theta_i \Gamma_{ni})}{\sum_{i'} \exp(V_{ni'} + \theta_i \Gamma_{ni'})} \times \frac{\exp((V_{nk} + \theta_k \Gamma_{nk})/\theta_i)}{\sum_{k'} \exp((V_{nk'} + \theta_k \Gamma_{nk'})/\theta_i)} \times \frac{\exp(V_{nj}/\theta_k)}{\sum_{j'} \exp(V_{nj'}/\theta_k)} \end{aligned} \qquad 7\text{-}1$$

$P_n(i)$ is the marginal probability of selecting alternative i at the first level, $P_n(k|i)$ is the conditional probability of selecting alternative k given sub-nest i at the second level, $P_n(j|k(i))$ is the conditional probability of selecting alternative j given sub-nest k at the third and lowest level. V represents the observed utility and θ is the parameters associated with the logsum variables (or inclusive values) of sub-nests of k and i, i.e., Γ_{nk} and Γ_{ni}, which are described below.

$$\Gamma_{nk} = \log\left(\sum_{j'} \exp(V_{nj'}/\theta_k)\right) \qquad 7\text{-}2$$

$$\Gamma_{ni} = \log\left(\sum_{k'} \exp(V_{nk'} + \theta_k \Gamma_{nk'}/\theta_i)\right) \qquad 7\text{-}3$$

To explore whether or not to provide the information and how the provided information influences drivers' adaptation behavior changes, the SP attributes with a level of "no information provided" are transformed into two dummy variables with value of 0 or 1. Take the attribute of "fatal accident" information as an example, "no information provided" is selected as a reference and two new variables "fatal accident" and "no fatal accident" with value of 0 or 1 are obtained. Other SP attributes are also included as a part of explanatory variables of the nested logit model. In addition, four individual attributes, age, gender, income, and housewife (1: housewife, 0: otherwise), were also included based on repeated trial and errors. The income variable indicates whether a respondent has a job with regular income sources. The resulting explanatory variables are shown in Table 7-3.

Table 7-1 Explanatory variables

Explanatory variables4	Detailed specifications
Trip purpose	1: with time constraint; 0: without time constraint
Distance to site	distance from the entry IC to the accident location (km)
Fatal accident	1: a fatal accident occurred; 0: no information is provided
No fatal accident	1: no fatal accidents occurred; 0: no information is provided
Queue length	queue length of traffic congestion caused by accidents (km)
Clearance time	clearance time of traffic congestion (minute)
Traffic regulation	1: with traffic regulation; 0: no information is provided
No traffic regulation	1: without traffic regulation; 0: no information is provided
Clearance time accuracy	Accuracy of clearance time prediction (high = 80%, low = 60%)
Value of clearance time interval	Value of clearance time interval provided (high or low: minute)
Time interval information	1: provide the interval value of clearance time; 0: provide exact time
Queue increasing trend	1: when the queue length is increasing; 0: no information is provided
Queue decreasing trend	1: when the queue length is decreasing; 0: no information is provided
Expressway	1: with alternative expressway route; 0: no information is provided
No expressway	1: without alternative expressway route; 0: no information is provided
Ordinary road	1: with alternative ordinary road; 0: no information is provided
No ordinary road	1: without alternative ordinary road; 0: no information is provided
Alternative mode	1: with alternative travel modes; 0: no information is provided
No alternative mode	1: without alternative travel modes; 0: no information is provided
Age	age（18-70 years old)
Gender	1: male; 0: female
Income	1: with fixed income; 0: others
Housewife	1: housewife; 0: others

7.2.3 Model estimation results

Estimated results of the three NL models are shown in Table 7-2. The adjusted McFadden's Rho-squares are 0.258 for the "before departure" model, 0.262 for the "on the way to expressway" model, and 0.162 for the "on expressway" model. Even though the Rho-squared of the "on expressway" model is a little smaller than the other two models, the accuracy value of 0.162 is acceptable. Statistical performance of two parameters of inclusive values (or logsum variables) in the "before departure" model (The nest of giving up expressway: 0.15; the nest of behavioral change: 0.10), the "on the way to expressway" model (The nest of giving up expressway: 0.16; the nest of behavioral change: 0.08), and the "on expressway" model (the nest of keeping expressway use: 0.43; the nest of behavioral change: 0.10) suggests that the assumed model structures are reasonable. Identified influential information on adaptation behavior are introduced from four parts.

1) The "before departure" scene

Positive and statistically significant parameter values are observed with respect to attributes of "*fatal accident*", "*queue length*", "*trip purpose*", and "*time interval value*". Concretely speaking, drivers more likely change their original trip plans when the accident information with fatality is provided, the queue length is longer, there is time pressure, and time interval values provided are larger. Interestingly, each of the above attributes has similar parameter value for each of three alternatives: i.e., change departure time, change to ordinary road, and other alternatives (change to other travel modes or cancel the trip). On the other hand, attributes of "*distance to site*", "*no fatal accident*", "*no traffic regulation*", "*clearance time accuracy*", and "*queue* *decreasing trend*" imposes a negative impact on drivers' adaptation behaviors. This implies that drivers are more likely to keep their original trip plans when a traffic accident occurs far away from the entry IC, no fatal accidents happen, there is no traffic regulation, the accuracy of clearance time prediction is higher, and the queue length is showing a decreasing trend. For the attributes of "*clearance time*", "*traffic regulation*", "*time interval information*", and "*queue increasing trend*" information, no significant parameter values are found.

All the attributes of available information of alternative routes and travel modes show an insignificant influence on adaptation behaviors. This may be because drivers at origins (e.g., homes or offices) can easily access various information sources via the Internet or other information searching media.

2) The "on the way to expressway" scene

Model estimation results are quite similar to those of the "before departure" scene model. Here, only the different points are described. First, there are more significant factors identified in this scene. Factors of "*clearance time*" and "*time interval information*" are statistically significant. Positive parameter value of "*clearance time*" implies that longer clearance time of congestion leads to a high propensity of drivers to change their original trip plans. Meanwhile, negative influence of "*time interval information*" method indicates that providing interval-based clearance time reduces the probability of drivers to change their original plans, compared to the conventional point-based clearance time information. As for the available information of alternative routes and travel modes, attributes of "*ordinary road*" and "*no alternative mode*" significantly affect drivers' adaptation behavior in a different way. Providing the information of available alternative ordinary roads leads to that more drivers may change their original plans, while drivers more likely keep their original trip plans when the information of "*no alternative mode"* is provided.

3) The "on expressway" scene

First, differences from the above two scenes are summarized. Attributes of "*trip purpose*" and "*fatal accident*" become insignificant, even though the parameter signs have no change. In contrast, information of alternative expressway shows a significant influence on adaptation behavior in a negative way, i.e., the existence of alternative expressway is more likely to help drivers keep their original trip plans. No alternative expressway more likely results in the decrease of choice probabilities of "change to alternative expressway" and "detour via ordinary road".

In the "on expressway" scene, there are more adaptation alternatives available for drivers, where "change to alternative expressway", "wait and see at nearby SA/PA" and "detour via ordinary road" are added. The common alternatives with the scenes of "before departure" and "on the way to expressway" share a similar pattern of responses to travel information. As for the "change to alternative expressway" alternative, its choice probability tends to increase if the distance to the accident site is close, no fatal accident information or no traffic regulation information is provided, the queue length and clearance time is longer, the value of clearance time interval is larger (its influence is especially larger than other attributes) or no time interval information is provided, the "*queue decreasing trend*" is not provided, there are no alternative expressways but ordinary roads, and the information of "*no alternative mode*" is not provided. Concerning the "wait and see at nearby SA/PA" alternative, only the differences from the "change to alternative expressway" alternative are briefly explained. Attributes of "*clearance time*", "*no expressway*", and "*ordinary road*" become insignificant. With regard to "detour via ordinary road", it receives similar influences from those attributes used to explain "change to alternative expressway", except for "*expressway*". The existence of "*expressway*" reduces the probability of drivers to make a detour via ordinary road.

4) Comparison among three scenes

Influencing factors common to the three scenes are "*distance to site*", "*no fatal accident*", "*queue length*", "*no traffic regulation*", "*clearance time accuracy*", "*value of clearance time interval*", and "*queue decreasing trend*". The influence of "*value of clearance time interval*" is remarkably larger considering its actual value and its parameter value, and especially, the influence becomes larger and larger moving from "before departure" to "on the way to expressway" and to "on expressway". This result suggests that the above information should be provided no matter where drivers are, especially the "*value of clearance time interval*" information. In other words, these sources of information show the context independence. On the other hand, providing the "*traffic regulation*" information does not affect any stated choices under any of the three scenes, but the "*no traffic regulation*" information commonly reduces drivers' choice probabilities of changing their original plans across the three scenes. The "*queue increasing trend*" information does not affect the behaviors under any scenes.

Table 7-2 Estimation results of drivers' adaptation behavior models

Choice alternatives / Explanatory variables	Before departure			On the way to expressway			On expressway				
	a	b	c	a	b	c	d	e	f	g	c
Constant term	1.573 **	1.681 **	1.407 **	1.601 **	1.667 **	1.428 **	1.355 **	0.791 /	1.420 **	1.551 **	1.431 **
Context variables											
Trip purpose	0.112 *	0.126 *	0.143 **	0.121 *	0.128 **	0.135 **	0.016 /	-0.019 /	0.041 /	0.017 /	0.015 /
Distance to site	-0.063 **	-0.066 **	-0.060 **	-0.073 **	-0.075 **	-0.070 **	-0.039 **	-0.052 **	-0.067 **	-0.046 **	-0.049 **
Traffic information related to accidents											
Fatal accident	0.317 **	0.338 **	0.353 **	0.245 **	0.251 **	0.253 **	0.051	0.132 /	0.099 /	0.078 /	0.092 /
No fatal accident	-0.190 **	-0.208 **	-0.194 **	-0.353 **	-0.363 **	-0.404 **	-0.254 **	-0.324 **	-0.357 **	-0.346 **	-0.338 **
Queue length	4.885 **	5.159 **	5.011 **	1.208 **	1.227 **	1.156 **	1.174 **	1.425 **	1.346 **	1.226 **	1.254 **
Clearance time	0.002 /	0.005 /	0.008 /	0.105 **	0.115 **	0.117 **	-0.016 /	0.035 **	0.042 **	0.039 **	0.041 **
Traffic regulation	0.063 /	0.059 /	0.065 /	-0.084 /	-0.088 /	-0.074 /	0.008 /	-0.015 /	-0.076 /	-0.027 /	-0.026 /
No traffic regulation	-0.117 *	-0.127 *	-0.140 *	-0.180 **	-0.185 **	-0.181 **	-0.150 *	-0.245 **	-0.278 **	-0.199 **	-0.198 **
Clearance time accuracy	-0.888 **	-0.938 **	-0.941 **	-0.673 **	-0.702 **	-0.742 **	-0.422 /	-0.390 /	-0.651 *	-0.491 *	-0.505 *
Value of clearance time interval	2.850 **	2.846 **	2.932 **	5.020 **	4.563 **	5.345 **	10.478 **	13.879 **	11.438 **	10.404 **	10.937 **
Time interval information	-0.090 /	-0.111 /	-0.095 /	-0.352 **	-0.337 **	-0.375 **	-0.496 **	-0.782 **	-0.603 **	-0.543 **	-0.551 **
Queue increasing trend	-0.002 /	-0.003 /	-0.010 /	-0.098 /	-0.089 /	-0.114 /	-0.029 /	-0.137 /	-0.114 /	-0.056 /	-0.071 /
Queue decreasing trend	-0.278 **	-0.302 **	-0.302 **	-0.331 **	-0.348 **	-0.374 **	-0.146 *	-0.280 **	-0.301 **	-0.230 **	-0.242 **
Information of alternative routes or travel modes											
Expressway	0.083 /	0.102 /	0.095 /	-0.081 /	-0.071 /	-0.100 /	-0.174 *	0.220 /	-0.165 *	-0.117 *	-0.106 /
No expressway	0.023 /	0.024 /	0.040 /	0.007 /	0.001 /	-0.005 /	-0.091 /	-0.166 *	-0.139 *	-0.101 /	-0.109 /
Ordinary road	0.052 /	0.083 /	0.022 /	0.153 **	0.175 **	0.115 *	0.095 /	0.247 **	0.211 **	0.167 **	0.125 *
No ordinary road	0.010 /	-0.010 /	0.002 /	-0.015 /	-0.033 /	0.002 /	0.100 /	0.114 /	0.025 /	0.056 /	0.075 /
Alternative mode	-0.024 /	-0.015 /	-0.028 /	0.006 /	0.005 /	0.025 /	0.003 /	0.013 /	-0.054 /	-0.006 /	-0.020
No alternative mode	-0.080 /	-0.087 /	-0.090 /	-0.191 **	-0.194 **	-0.177 **	-0.154 **	-0.220 **	-0.247 **	-0.187 **	-0.174 **
Individual attributes											
Age	0.088 **	0.093 **	0.093 **	0.066 **	0.068 **	0.073 **	0.062 **	0.074 **	0.119 **	0.092 **	0.095 **
Gender	-0.258 **	-0.249 **	-0.294 **	-0.242 **	-0.242 **	-0.271 **	-0.343 **	-0.302 **	-0.354 **	-0.339 **	-0.369 **
Income	-0.234 **	-0.222 **	-0.234 **	-0.140 *	-0.128 *	-0.157 **	-0.162 **	-0.167 *	-0.133 *	-0.136 *	-0.149 *
Housewife	-0.138 /	-0.135 /	-0.173 *	-0.220 **	-0.223 **	-0.250 **	-0.277 **	-0.249 **	-0.291 **	-0.271 **	-0.287 **
Inclusive value	Nest of giving up expressway: 0.15 (**)[**]			Nest of giving up expressway: 0.16 (**)[**]			Nest of keeping expressway: 0.43 (*)[**]				
(or logsum variable)	Nest of behavioral change: 0.10 ( )[**]			Nest of behavioral change: 0.08 (*)[**]			Nest of behavioral change: 0.10 (*)[**]				
Initial log-likelihood	-16092.77			-16092.77			-19457.16				
Converged log-likelihood	-11873.46			-11799.69			-16175.57				
McFadden's Rho-squared	0.262			0.267			0.169				
Adjusted McFadden's Rho-squared	0.258			0.262			0.162				

*(Note) Reference alternative in the model estimation: No change; **: significant at the 99% level, *: significant at the 95% level. /: insignificant.*

Choice alternatives: a: change departure time; b: change to ordinary road; c:others (other travel odes/trip cancel); d:wati and see at nearby SA/PA; e: change to alternative expressway;

f: detour via ordinary road; g: change to ordinary road

Differently, influences of "*fatal accident*", "*clearance time*", "*trip purpose*", "*time interval information*" are proved to be significantly different across scenes (i.e., context-dependent). Providing the information of "*clearance time*" and "*time interval information*" only significantly influences drivers who already departed. Attributes of "*fatal accident*" and "*trip purpose*" do not impose any significant influence on drivers' adaptation behaviors. This result may suggest that once drivers enter the expressway, information of fatal accidents and time pressure no longer influence on driver's decisions on adaptation behaviors.

In the "on expressway" scene, drivers prefer more information of alternative driving routes and other travel modes than in the other two scenes.

As for individual attributes, most of them are statistically influential to adaptation behavior in all the three scenes. Older and female drivers with low income tend to change the use of expressway. Housewives are more likely to keep the use of expressway (note that the same attribute does not significantly affect the "change departure time" and "change to ordinary road" alternatives. These results re-confirm the importance of incorporating individual heterogeneity into the design and management of travel information systems. (Table 7-3 shows the summary of factors significantly influencing drivers' adaptation behaviors)

Table 7-3 Factors significantly influencing drivers' adaptation behaviors

Factors	Before Departure	On the Way to Expressway	On Expressway
Context dependent factors			
Trip purpose	O	O	–
Fatal accident	O	O	–
Clearance time	–	O	O
time interval information	–	△	△
Context common factors			
Value of clearance time interval		O	
Distance to site		△	
No fatal accident		△	
Queue length		O	
No traffic regulation		△	
Clearance time accuracy		△	
Queue decreasing		△	

"O" positive influence, "△" negative inflence on behavior change significantly; "-" insignificnat

7.3 Additional influences of information preference on adaptation behavior

7.3.1 Introducing the concept of travel information styles

As verified by estimation result of last analysis section, driver's adaptation behavior will be strongly influenced by effective information provision with context sensitive property. On the other hand, heterogeneous responds across different drivers might also impose unneglectable influencing impact on individual's adaptation behaviors. In reality, responding to traffic accidents on expressways, drivers may be forced to alter their travel choices under the influence of their travel information styles, which have, however, been under-researched. To fill this research gap, this study first defines travel information styles based on driver preference for and experience of travel information usage and then examine drivers' heterogeneous adaptation behaviors. For this purpose, data collected from SP survey, which was implemented in Japan in 2011-2012, have been utilized. Finally, data collected from 1,923 drivers who participant in both the RP and SP survey have been employed, with totally 23,076 SP responses adaptation choices under different scenarios of dynamic travel information provision. A nested logit model is adopted to describe drivers' adaptation choices with respect to three travel information styles identified by a cluster analysis approach: high dependence on information for relatively inflexible trip-making, high dependence on experience for risky trips, and least information users. Influential information contents and their provision methods for drivers with different travel information styles are empirically explored.

7.3.2 Methodology: K-means Cluster Analysis

To clarify driver's travel information styles, a K-means cluster analysis was conducted. In total, 15 information search and usage variables were selected for the cluster analysis. They are variables related to, (1) situations under which information search on expressways had to be done (when weather is bad, when to travel with a partner, when information about emergent incidents is incomplete, when to visit several destinations in a single trip, when the time of an appointment is given, when to decide whether to make a trip or not and where to visit, when to decide departure time, always search travel information in case of using expressways, do not access any travel information), (2) time use and frequency of information search, (3) information preference (experience vs. information (dummy variable): "1" means that an individual is more likely to make a trip decision based on experience rather than travel information provided, 0 indicates an inverse case), purposes of usual expressway and car usage (2 items), and ownership of vehicle used for expressway driving.

Table 7-4 Decision on the optimal number of clusters

Number of clusters	Calinski/Harabasz pseudo-F index
2	2440.09
3	2639.92
4	2420.03
5	2121.29
6	1782.65
7	1658.36
8	1518.93
9	1304.18
10	1271.46

In order to decide the optimal number of clusters, a Calinski/Harabasz pseudo-F index is used as a stopping rule and the numbers of clusters ranging from 2 to 10 were tested (Table 7-4). Larger value of the pseudo-F index corresponds to a better distinguished cluster structure

(Calinski and Harabasz, 1974). As a result, when the number of cluster number is three, the maximum of Calinski/Harabasz pseudo-F index (2639.92) was reached. Therefore, in this study, drivers are grouped into three clusters.

Table 7-5 Summsty of cluster differences across three grouping variables

Variables for identifying information styles	Information Style 1 (n=1,045)	Information Style 2 (n=375)	Information Style 3 (n=504)
(1) do not access any travel information (1: yes, 0: no)	1%	1%	**19%**
(2) search information when weather is bad (1: yes, 0: no)	50%	**61%**	46%
(3) search information when to travel with a partner (1: yes, 0: no)	20%	20%	**13%**
(4) search information when information about emergent incidents is incomplete (1: yes, 0: no)	49%	**62%**	48%
(5) search information when to visit several destinations in a single trip (1: yes, 0: no)	14%	11%	**6%**
(6) search information when the time of an appointment is given (1: yes, 0: no)	**34%**	**44%**	**25%**
(7) search information when to decide whether to make a trip or not and where to visit (1: yes, 0: no)	**17%**	12%	**9%**
(8) search information when to decide departure time (1: yes, 0: no)	**20%**	13%	**9%**
(9) always search information in case of using expressways (1: yes, 0: no)	33%	33%	**11%**
(10) more likely to rely on experience rather than information provided (1: yes, 0: no)	25%	**38%**	25%
(11) trip with timing constraint (car use purpose) (1: yes, 0: no)	31%	**49%**	36%
(12) trip with timing constraint (expressway use purpose) (1: yes, 0: no)	5%	**26%**	9%
(13) frequency of information search on expressways (ordered values: 0 ~ 6)	**5.36**	3.11	3.38
(14) time use for information search (ordered values: 0 ~ 5)	**2.85**	2.00	**0.57**
(15) use drivers' own cars for expressways (1: yes, 0: no)	97%	96%	96%

Table 7-5 summarizes average values of the 15 variables selected for the cluster analysis, from which the following three distinctive travel information styles are identified.

— Information style 1: High dependence on information for relatively inflexible trip-making. Trip makers clustered into this style are highly dependent on information because of their higher frequency of information search on expressways (5.36: about twice per week) and time use for information search (2.85: about 10~20 minutes) than others. These trip makers are more likely to search information when the time of appointment is given (34%) and when they decide trip generation and destination (17%), and departure time (20%), compared to others.

— Information style 2: High dependence on experience for risky trips. Trip makers grouped into this style are more likely to rely on experience rather than information provided (38%) and their trips involve more risks in the sense that 61% of them search information when weather is bad, 62% when information about emergent incidents is incomplete, and 44% when the time of an appointment is given. Furthermore, these trip makers usually perform more trips with time constraints (49% for car use and 26% for expressway use).

— Information style 3: Least information users. Trip makers belonging to this style show the least interest in information search and usage: among the three styles, they show the highest share of not accessing any travel information (19%), the lowest shares of information search for decisions on trip (6% for visiting several destinations, 25% for the appointment with time given, 9% for trip generation and destination, and 9% for departure time. Especially, they have the lowest share of "always search information in case of using expressways".

To further quantify the effects of dynamic travel information on driver's adaptation behavior changes for drivers with different travel information styles, the NL model is employed in the model estimation for different decision scenes among three identified information styles. Specific structures of NL models for difference decision scenes are same as structure built in Figure 7-2. For the purpose of comparison, same structures are utilized for three identified travel information styles.

7.3.3 Model estimation results

Results of the NL models for three travel information styles are shown in Table 7-6, Table 7-7, and Table 7-8, respectively.

The adjusted McFadden's Rho-squared values are, 0.15, 0.11, and 0.12 for the "Before Departure" models of Style 1, Style 2, and Style 3; 0.15, 0.13, and 0.14 for the "On the Way to Expressway" models of Style 1, Style 2, and Style 3; and 0.10, 0.08, and 0.09 for the "On Expressway" models of Style 1, Style 2, and Style 3. Rho-squared values of the nine NL models range from 0.08 to 0.15, which are not higher enough, but still acceptable for this analysis. The assumed nested model structures are verified by the statistical performance of two parameters of inclusive values (or logsum variables), most of which are significantly different from 0 and 1. Influential information identified on each adaptation behaviors are summarized according to different scenes:

1) *The "Before Departure" Scene*

Positive and statistically significant parameter values are observed with respect to attributes of "*fatal accident*", "*clearance time*", and "*value of clearance time interval*". Concretely speaking, drivers more likely change their original trip plans when the accident information with fatality is provided, there is time pressure, and time interval values provided are larger. On the other hand, attributes of "*distance to site*", "*clearance time accuracy*", and "*queue decreasing trend*" impose a negative impact on drivers' decision choice behaviors. This implies information provision of far distance from accident site, high clearance time accuracy and decreasing trend provision of real time accident information would contribute to drivers' original trip plan

Table 7-6 Estimation results of drivers' adaptation behavior models for the "Before Departure" scene

Before Departure	Information Style 1: High dependence on information for relatively inflexible trip-making			Information Style 2: High dependence on experience for risky trips			Information Style 3: Least information users		
	Change Departure Time	Ordinary Road	Others (travel mode/ cancel the trip)	Change Departure Time	Ordinary Road	Others (travel mode/ cancel the trip)	Change Departure Time	Ordinary Road	Others (travel mode/ cancel the trip)
Constant	0.72 *	1.58 **	1.80 **	1.30 **	-3.30 **	2.29 **	1.76 ***	1.54 **	1.74 **
Trip purpose	0.13	0.15 *	0.22 **	0.01	0.04	-0.11	0.12	0.17	0.17
Distance_site	-0.07 **	-0.07 **	-0.07 **	-0.07 **	-0.08 **	-0.04	-0.05 **	-0.06 **	-0.05 **
Fatal accident	0.28 **	0.31 **	0.35 **	0.40 **	0.35 **	0.74 **	0.29 **	0.32 **	0.31 **
No fatal accident	-0.15	-0.19 **	-0.14	0.00	-0.02	0.07	-0.36 **	-0.39 **	-0.37 **
Queue length	-0.77	-0.57	0.33	2.67 **	2.18 **	-11.76 **	-0.75 **	5.58 **	5.74 **
Clearance time	0.28 **	0.28 **	0.28 **	0.27	0.38 *	0.62 **	-0.03	0.01	0.01
Traffic regulation	-0.02	-0.04	0.02	-0.08	-0.07	-0.35	0.28 **	0.31 **	0.29 **
No traffic regulation	-0.17 **	-0.19 **	-0.23 **	-0.19	-0.22	-0.16	-0.06	-0.05	-0.06
Clearance time accuracy	-1.06 **	-1.23 **	-1.18 **	-0.82	-0.92	-0.30	-1.26 **	-1.31 **	-1.41 **
Value of clearance tme interval	2.22	1.93	2.03	4.84 **	4.33 *	7.88 **	2.51 **	2.49 **	2.64 **
Time interval information	0.06	0.02	0.16	-0.03	-0.05	0.14	-0.15	-0.20	-0.19
Queue increasing trend	-0.05	-0.04	0.04	-0.16	-0.12	-0.50 **	0.11	0.08	0.06
Queue decreasing trend	-0.36 **	-0.40 **	-0.36 **	-0.19	-0.18	-0.61 **	-0.20	-0.25 *	-0.27 *
Expressway	0.22 **	0.25 **	0.23 **	0.07	0.03	0.26	-0.01	0.05	0.05
No expressway	0.14	0.13	0.15	0.01	-0.06	0.52 **	-0.09	-0.06	-0.03
Ordinary road	0.09	0.14 *	-0.05	-0.10	-0.03	-0.20	0.17	0.15	0.13
No ordinary road	0.06 *	0.00	0.07	-0.01	0.02	-0.06	-0.13	-0.18	-0.19
Alternative mode	-0.10	-0.08	-0.22 **	-0.06	-0.07	0.01	0.18	0.18	0.17
No alternative mode	0.02	0.02	0.06	-0.20	-0.26 *	-0.17	-0.15	-0.15	-0.15
Age	0.08 **	0.09 **	0.14 **	0.08 *	0.11 **	-0.06	0.13 **	0.13 **	0.13 **
Gender	-0.14 *	-0.14 *	-0.22 **	-0.35 **	-0.26 *	-0.78 **	-0.23 **	-0.20 *	-0.21 *
Fixed income	-0.15 *	-0.15 *	-0.12	0.04	0.05	0.24	-0.46 **	-0.45 **	-0.47 **
Housewife	-0.05	-0.06	-0.01	0.34	0.39 *	0.30	-0.42 **	-0.46 **	-0.49 **
Inclusive value (Logsum)									
Nonexpressway nest	0.34(**)[**]			0.96(**)[**]			0.05( )[**]		
Behavior change nest	0.13( )[**]			0.09( )[**]			0.15(**)[**]		
Sample size (SP responses)	4,180			1,500			2,012		
Initial log-likelihood	-5793.32			-2079.44			-2789.22		
Converged log-likelyhood	-4837.94			-1777.22			-2370.67		
McFadden's Rho-squared	0.16			0.15			0.15		
Adjusted Rho-squared	0.15			0.11			0.12		

Table 7-7 Estimation results of drivers' adaptation behavior models for the "On the Way to Expressway" scene

On the Way to Expressway	Information Style 1: High dependence on information for relatively inflexible trip-making			Information Style 2: High dependence on experience for risky trips			Information Style 3: Least information users		
	Change Departure Time	Ordinary Road	Others (travel mode/ cancel the trip)	Change Departure Time	Ordinary Road	Others (travel mode/ cancel the trip)	Change Departure Time	Ordinary Road	Others (travel mode/ cancel the trip)
Constant	1.60 **	1.79 **	1.65 **	0.57	0.82	0.78	2.52 **	2.44 **	2.25 **
Trip purpose	0.17 *	0.19 **	0.21 **	0.19	0.19	0.19	0.13	0.14	0.13
Distance_site	-0.08 **	-0.08 **	-0.08 **	-0.04	-0.05 *	-0.05 *	-0.12 **	-0.12 **	-0.12 **
Fatal accident	0.18 **	0.18 **	0.19 **	0.26 *	0.28 **	0.27 *	0.12	0.13	0.08
No fatal accident	-0.33 **	-0.36 **	-0.37 **	-0.40 **	-0.41 **	-0.43 **	-0.59 **	-0.58 **	-0.70 **
Queue length	0.24	0.28	0.29	-0.07	-0.03	-0.14	3.33 **	3.27 **	3.73 **
Clearance time	0.15 **	0.17 **	0.17 **	0.12 **	0.14 **	0.14 **	0.10 **	0.10 **	0.11 **
Traffic regulation	-0.10	-0.13	-0.11	-0.12	-0.13	-0.14	-0.19	-0.18	-0.20
No traffic regulation	-0.29 **	-0.28 **	-0.28 **	-0.08	-0.10	-0.09	-0.21	-0.21	-0.19
Clearance time accuracy	-0.87 **	-0.99 **	-0.99 **	0.82	0.71	0.70	-1.31 **	-1.30 **	-1.53 **
Value of clearance tme interval	5.38 **	4.35 **	4.77 **	5.97 **	4.97 **	4.88 **	5.98 **	5.77 **	6.64 **
Time interval information	-0.32 **	-0.30 **	-0.31 **	-0.47 **	-0.45 **	-0.45 **	-0.43 **	-0.41 **	-0.48 **
Queue increasing trend	-0.14	-0.10	-0.10	-0.06	-0.04	-0.05	-0.17	-0.14	-0.36 **
Queue decreasing trend	-0.35 **	-0.38 **	-0.38 **	-0.49 **	-0.55 **	-0.56 **	-0.47 **	-0.44 **	-0.69 **
Expressway	-0.03	-0.03	-0.04	-0.04	-0.04	-0.02	-0.15	-0.13	-0.22
No expressway	0.01	-0.04	-0.05	-0.07	-0.07	-0.06	0.05	0.05	0.05
Ordinary road	0.15	0.21 *	0.18	0.08	0.11	0.09	0.14	0.16	0.04
No ordinary road	0.10	0.05	0.06	0.00	0.00	0.00	-0.09	-0.09	-0.11
Alternative mode	0.03	0.04	0.03	0.05	0.07	0.08	0.18	0.15	0.35 **
No alternative mode	-0.12	-0.13	-0.13	-0.11	-0.11	-0.08	-0.29 **	-0.30 **	-0.22
Age	0.06 *	0.08 **	0.09 **	0.02	0.01	0.01	0.04	0.04	0.06
Gender	-0.09	-0.12	-0.11	-0.34 **	-0.38 **	-0.39 **	-0.30 **	-0.29 **	-0.37 **
Fixed income	-0.11	-0.09	-0.09	-0.14	-0.09	-0.08	-0.11	-0.07	-0.27 *
Housewife	-0.22 *	-0.25 **	-0.23 **	0.05	0.08	0.09	-0.27 *	-0.22	-0.52 **
Inclusive value (Logsum)									
Nonexpressway nest	0.05( )[**]			0.03( )[**]			0.35(*)[**]		
Behavior change nest	0.19( )[**]			0.13( )[**]			0.03( )[**]		
Sample size (SP responses)	4,180			1,500			2,012		
Initial log-likelihood	-5793.32			-2079.44			-2789.22		
Converged log-likelyhood	-4865.48			-1744.77			-2323.91		
McFadden's Rho-squared	0.16			0.16			0.17		
Adjusted Rho-squared	0.15			0.13			0.14		

Table 7-8 Estimation results of drivers' adaptation behavior models for the "On Expressway" scene

On Expressway	Information Style 1: High dependence on information for relatively inflexible trip-making					Information Style 2: High dependence on experience for risky trips					Information Style 3: Least information users				
	Wait & See at SA/PA	Alternative Expressway	Ordinary Road Detour	Ordianry Road	Others (travel mode/ cancel the trip)	Wait & See at SA/PA	Alternative Expressway	Ordinary Road Detour	Ordianry Road	Others (travel mode/ cancel the trip)	Wait & See at SA/PA	Alternative Expressway	Ordinary Road Detour	Ordianry Road	Others (travel mode/ cancel the trip)
Constant	1.64 **	1.16	1.63 **	1.86 **	1.64 **	0.41	-0.18	1.10 *	1.46 **	1.40 **	1.65 **	1.21	1.68 **	1.71 **	1.65 **
Trip purpose	0.01	-0.02	0.10	0.04	0.04	-0.02	-0.16	0.20	0.05	0.05	0.06	-0.03	0.07	0.04	0.06
Distance_site	-0.07 **	-0.08 **	-0.08 **	-0.07 **	-0.07 **	-0.03	-0.01	-0.07 **	-0.03	-0.03	-0.02	-0.02	-0.03	-0.02	-0.02
Fatal accident	0.03	0.09	0.03	0.05	0.03	-0.09	0.29	0.16	0.09	0.08	0.10	0.22	0.18	0.11	0.12
No fatal accident	-0.19	-0.28 **	-0.29 **	-0.29 **	-0.30 **	-0.15	0.10	-0.38 **	-0.21	-0.59 **	-0.40 **	-0.36 *	-0.43 **	-0.43 **	-0.46 **
Queue length	0.78	0.73	1.01 *	0.75	0.91	2.51 **	1.78 *	1.66 *	2.05 **	1.77 *	0.83	1.31	0.86	0.88	0.84
Clearance time	-0.01	0.05 **	0.05 **	0.05 **	0.05 **	-0.01	0.07 **	0.05	0.04	0.04	-0.02	0.01	0.03	0.03 *	0.04 *
Traffic regulation	-0.21 **	-0.25 **	-0.32 **	-0.26 **	-0.24 **	-0.09	0.11	-0.05	-0.01	0.37 **	0.26 *	0.25	0.23 *	0.26 *	0.22
No traffic regulation	-0.27 **	-0.40 **	-0.38 **	-0.29 **	-0.33 **	-0.04	0.15	-0.35 **	-0.11	0.32 **	-0.06	-0.13	-0.16	-0.12	-0.08
Clearance time accuracy	-0.47	-0.62	-0.91 **	-0.72 *	-0.71 *	-0.68	-2.55 **	-0.97	-1.05 *	-1.10 *	-1.02 *	-0.86	-1.26 **	-1.11 **	-1.15 **
Value of clearance tme interval	13.22 **	16.56 **	14.02 **	12.68 **	14.18 **	11.87 **	6.37 **	9.97 **	9.21 **	9.40 **	6.89 **	10.41 **	7.16 **	6.99 **	6.88 **
Time interval information	-0.71 **	-1.09 **	-0.79 **	-0.73 **	-0.80 **	-0.58 **	0.02	-0.25	-0.29 **	-0.28 *	-0.18	-0.51	-0.25	-0.23	-0.20
Queue increasing trend	-0.16	-0.21 *	-0.19 *	-0.15	-0.16	-0.26	0.24	-0.39 **	-0.18	-0.19	0.36 **	0.24	0.28	0.33 **	0.33 **
Queue decreasing trend	-0.27 **	-0.39 **	-0.37 **	-0.32 **	-0.32 **	-0.05	-0.34	-0.45 **	-0.27 *	-0.29 *	0.15	0.03	0.05	0.08	0.05
Expressway	-0.05	0.34	-0.06	-0.02	-0.01	-0.15	0.34	-0.30 *	-0.13	-0.10	-0.19	0.19	-0.08	-0.11	-0.03
No expressway	-0.05	-0.10	-0.08	-0.07	-0.07	-0.11	-0.21	-0.07	-0.09	-0.50 **	-0.20	-0.19	-0.21	-0.16	-0.13
Ordinary road	0.15	0.18	0.25 **	0.20 **	0.17	0.14	0.31	0.27	0.22	-0.21	-0.14	0.09	-0.03	-0.06	-0.13
No ordinary road	0.22 **	0.16	0.08	0.13	0.18 *	0.15	-0.07	0.09	0.05	0.04	-0.10	-0.04	-0.16	-0.12	-0.15
Alternative mode	0.10	0.19	0.12	0.13	0.10	0.14	-0.10	-0.32 **	-0.11	-0.10	0.00	-0.03	-0.13	-0.02	-0.07
No alternative mode	-0.17 *	-0.12	-0.13	-0.13	-0.13	0.31 **	0.11	-0.35 **	-0.02	0.03	-0.24 *	-0.39	-0.34 *	-0.25 *	-0.21
Age	0.05	0.08 **	0.13 **	0.09 **	0.10 **	0.08	0.22 **	0.07	0.11 **	0.10 **	0.09 **	0.06	0.13 **	0.11 **	0.10 **
Gender	-0.29 **	-0.21 *	-0.28 **	-0.27 **	-0.27 **	-0.60 **	-0.64 **	-0.48 **	-0.56 **	-0.61 **	-0.39 **	-0.41 **	-0.47 **	-0.40 **	-0.46 **
Fixed income	-0.09	-0.22 *	-0.15	-0.13	-0.12	0.11	0.01	0.34 **	0.19 *	0.23 **	-0.35 **	-0.29 **	-0.23	-0.27 **	-0.34 **
Housewife	-0.20	-0.20	-0.33 **	-0.25 **	-0.22 *	-0.09	-0.47 **	0.29 **	0.01	0.01	-0.61 **	-0.55 **	-0.65 **	-0.61 **	-0.69 **
Inclusive value (Logsum)															
Nonexpressway nest	0.42( )[**]					0.98(**)[**]					0.26( )[*]				
Behavior change nest	0.10( )[**]					0.05(**)[**]					0.12( )[**]				
Sample size (SP responses)	4,180					1,500					2,012				
Initial log-likelihood	-7487.76					-2687.64					-3605.02				
Converged log-likelyhood	-6630.95					-2348.34					-3148.23				
McFadden's Rho-squared	0.11					0.13					0.13				
Adjusted Rho-squared	0.10					0.08					0.09				

insistence decision. In general, factors of "*time interval information*", and "*queue increasing trend*" information impose no significant impact.

Comparison among three information styles in this decision scene, drivers with Information Style 1 are more sensitive to the provided information, especially for the alternative routes and travel modes information, significant influencing impacts of "*expressway*" and "*ordinary road*" could be identified in several route change alternatives. This implies that for drivers who are highly dependent on information for relatively inflexible trip-making, more incentive efforts could be made in the dynamic information provision. On the other hand, comparing drivers from Information Style 2 and Style 3, model estimation results reveal that less significant influencing factors are included in risky trips of drivers with high dependence on experience. This is understandable because drivers with Information Style 2 are more dependent on their experience, rather than information, which includes the dynamic information provided in the SP experiment.

2) *The "On the Way to Expressway" Scene*

In case of "On the Way to Expressway" scene, model estimation results of the parameter signs are similar to the "Before Departure" scene. However, different points were identified from obtained results between two scenes. First, accident related attributes in this scene impose more significant influencing impacts on driver's adaptation behavior. Factor of "*time interval provision*" shows a significant negative impact on driver's adaptation behavior, indicating that drivers are more likely to insist on their original trip plans with the estimated clearance time provision in form of time interval compared to the conventional point-based form under this scene. Moreover, no significant influencing impact of the "*traffic regulation*" information provision could be identified on driver's decisions. As for the available substitute information, only limited influencing impact could be identified in decisions of drivers belonging to Information Style 1 and Style 3.

3) *The "On Expressway" Scene*

In terms of "On Expressway" scene, more adaptation alternatives are available for drivers, where "*change to alternative expressway*", and "*detour via ordinary road*" are added, and option of "*change departure time*" is replace by "*wait and see at nearby SA/PA*".

Checking the detail influencing impact of provided information, attributes of "*trip purpose*" and "*fatal accident*" become insignificant while information provision under the situation that drivers already drive on expressways. Meanwhile, information of "*queue increasing trend*" imposes a significantly impact on driver's adaptation behavior. Interestingly, parameter signs in estimation results of Information Style 1 and Style 2 are negative; however, significant positive signs are obtained in results of drivers with Information Style 3. This difference implies that responding to the information provision of an "increasing queue trending", least information users (Style 3) are more likely to change to "wait & see at SA/PA", "ordinary road", and "other (travel mode/cancel the trip)", while other drivers might behave differently by insisting on their original trip plans. Similarly contrary influencing impacts could also be observed from attribute of "*traffic regulation*", where drivers with high information dependence tend to make "no change", while drivers with least information usage tend to decide to "change" accordingly.

Switching to the general impact comparison among three information styles, even though attribute parameters from the high information dependence group reveal the higher significant influencing impact in results of drivers with Information Style 1, sensitivity of the driver's decisions from other two groups are a little different from other two scenes. Attributes in Information Style 3 impose the least significant influencing impact on driver's adaptation behavior, which was showed in the Information Style 2 of previous "Before Departure" and "On the Way to Expressway" scenes. Potential explanation is that for drivers who are least information users and who already drive on expressways, they are quite reluctant to search information and also respond to the provided information. Concretely speaking, significant influencing impact of "*traffic regulation*", "*value of clearance time interval*" and "*queue increasing trend*" in Information Style 3 imply that the existence of traffic regulation, large clearance time interval value, and information provision of an increasing traffic queuing would contribute to drivers' original trip plan changes.

4) *Comparison among Three Scenes*

As discussed above, drivers' adaptation behaviors to the provided real time information from three scenes are quite different, especially when individual's heterogeneous information styles are considered. Inefficient information provision and even inverse effects of the provided information on different drivers' adaptation behaviors could be obtained. Therefore, studies focusing on the same adaptation behavior with different information styles and corresponding unique information provision solutions should be discussed.

— *Travel Information Style 1: High dependence on information for relatively inflexible trip-making*

  Influencing factors common to the three scenes are "*distance to site*", "*no fatal accident*", "*clearance time*", "*no traffic regulation*", "*clearance time accuracy*", and "*queue decreasing trend*". This suggest that regarding to information provision for drivers belonging to this group, the aforementioned important factors are quite context-independent and should be provided without the consideration of drivers specific driving location contexts. On the other hand, existence of "*fatal accident"* provision only contributes to behavior changes of drivers who are not driving on expressways yet (still "before departure" or "on the way to expressway") significantly. While similarly, impacts of attributes "*time interval provision*" and "*value of clearance time interval*" of the estimated clearance time only significantly influence drivers who already departed. Moreover, information provision of "*queue length*" and "*queue increasing trend*" does not impose any significant influencing effect on drivers belonging to this group. In terms of the availability of substitute routes and travel mode information, very limited influencing impact could be identified, except for the context-independent impact of the existence of "*ordinary road"* information on drivers "ordinary road" ("ordinary road detour" and "ordinary road" for "before departure" context) switching behavior. This result may suggest that for high information preference drivers (Information Style 1), information provision of available substitute ordinary roads could be used in driver's route change decision intervention strategies, which could further benefit to the relieving efforts of expressway disorder problems.

— *Travel Information Style 2: High dependence on experience for risky trips.*

For drivers in this group, influencing impacts of attributes are less significant than drivers with Information Style 1. Context-independent attributes showing a consistent and significant influencing impact are "*value of clearance time interval*" and "*queue decreasing trend*" information. Information provision of congestion queue decreasing trend would significant convince the drivers to insist on their original trip plans. On the other hand, increasing influencing power of the clearance time interval value could be identified by getting closer to the expressway (increasing parameter value from "before departure" to "on the way to expressway", and to "on expressway" scene). Attributes of "*trip purpose*" and "*fatal accident*" show no significant influence on driver's adaptation behavior changes.

Moreover, different from drivers with Information Style 1, the availability of substitute information imposes no significant influencing impact on drivers with Information Style 2.

— *Information Style 3: Least information users*

Similar to drivers with Information Style 2, significant increasing impact of "*value of clearance time interval*" could be identified across three different scenes. Moreover, significant negative context-independent impact of "*no fatal accident*" and "*clearance time accuracy*" could be recognized. Focusing on the context-dependent factors, similar influencing impacts could be identified from results of "Information Style 2" and "Information Style 3" in the context of "Before Departure" and "On the Way to Expressway". Focusing on the "On Expressway" scene, significant positive influencing impacts of "*traffic regulation*", and "*queue increasing*" information could be identified. Meanwhile, a significant positive impact of existence of "*alternative travel mode*" was observed with respect to driver's "others" adaptation behavior change in the context of "On the Way to Expressway".

As for individual attributes, same parameter signs could be identified from the significant estimation results across three decision contexts and driver clusters. Older and female drivers with low income are more likely to change their original expressway trip plans, while housewives are more likely to insist on their original plans.

7.4 Summary

Emphasizing the importance of real time dynamic information provision on driver's expressway route changing and even travel mode shifting behaviors, this study made an effort to figure out the important factors as well as proper information provision methods that will significantly influence on driver's adaptation behavior under the occurrence of traffic accident on expressways.

Based on a large-scale SP survey, 30,000 SP respondents collected from the 2,500 participants have been collected for data analysis. Among the 2,500 participant, 1,923 of them had also participated in a previous RP survey. Part of the information collected from the RP survey have been utilized in the design of SP attributes, specified by reflecting each individual's personal driving experience and travel information preferences. As a result, in the SP survey, context-dependent real time travel information have been introduced, including accident conditions and impact information, predicted clearance time, and available alternative travel mode for three decision scenes of before departure, on the way to expressway, and on expressway. Analyses based on nested logit models found that interval values (rather than point-based values) of clearance time of traffic congestion play a considerably larger role in influencing drivers' adaptation behavior than other information contents and especially, the influences become larger and larger moving from "before departure" to "on the way to expressway" and to "on expressway". Other common factors across the three scenes are "distance to site", "no fatal accident", "queue length", "no traffic regulation", "clearance time accuracy", and "queue decreasing trend". Influences of "fatal accident", "clearance time", "trip purpose", "time interval information" are proved to be significantly different across scenes (i.e., drivers' responses are context-dependent).

Moreover, to further improve the effectiveness of provided information, personal heterogeneous property, have been also considered with introducing of a new concept of information style. Totally, three types of information styles, including *high dependence on information for relatively inflexible trip-making, high dependence on experience for risky trips,* and *least information users*, have been summarized from 15 information search and usage related items, based on a K-means cluster analysis. Distinguishing three different information styles, estimation results of NL models of drivers' adaptation behaviors have been obtained, based on 23,076 SP responses of 1,923 drivers who participant in both the RP and SP survey. The model estimation result revealed that driver's behavioral responses among three information styles are quite different under different information provision contexts. Firstly, important and significant impacts of drivers' heterogeneous information adaptation properties in response to the dynamic information provision were illustrated by the opposite influencing impacts of the provided information on driver's adaptation behavior changes with different information styles. Context-sensitive travel information targeting at drivers with different travel information styles should be provided in the traffic management practice. Moreover, drivers who are highly dependent on information for relatively inflexible trip-making show a higher information search propensity and are influenced largely by the provided information than drivers with the other two information styles, suggest that more information should be provided to this type of drivers. On the other hand, an interesting finding is that drivers who are comfortable about their experiences are more stubborn and stick to their previous driving experience and therefore less significantly influenced by the information provided. Even though drivers show higher information search propensity than least information users, influencing impacts of the provided information are less influential and more concrete information such as the exactly "*value of clearance time interval*" and "*queue decreasing trend*" information should be provided to drivers who are highly dependent on their experience.

Chapter 8

Conclusions

Traffic accidents, especially those occurred on expressways, usually cause huge damages to properties, human injuries and fatalities, and sometimes even the occurrence of secondary accidents. Human behavior plays an incredible role in improving driving safety in the sense that a majority of traffic accidents are caused by human errors. Technological developments should be further promoted for driving safety on one hand, while voluntary behavioral changes toward safer driving should not be neglected on the other. Aiming to reduce driving risks and mitigate the impacts of traffic accidents via individual's voluntary behavioral changes with the assistance of traffic information, this study has investigated various driving risks, avoidance and adaptation behaviors on expressways by developing a simplified GPS-enabled smartphone app, *Safety Supporter* and implementing a three-month driving experiment and several unique questionnaire surveys with a comprehensive set of variables related to driving safety. Various modeling analyses have also been done for the above research purposes.

Concretely speaking, first, this study has investigated individual driving risks, including both internal risks and external risks. Internal driving risks are captured by objective driving risks and subjective awareness of driving risks. Objective driving risks are represented by driving speed control in terms of speed limit compliance, acceleration/deceleration and driving stability, multitasking behavior during driving, and avoidance driving behaviors in daily life. Awareness of driving risks is measured based on a series of subjective measurements, such as driving propensity, driving avoidance habits, and behavioral change stages of safe driving. Second, to further improve individual's driving safety, analyses have also been done from the perspective of driving avoidance behavior, which aims to mitigate and avoid driving risks via internal risk aversion. Third, factors affecting drivers' avoidance behaviors responding to both internal risks and external risks have also been investigated. Last but not least, the roles of traffic information provision in mitigating driving risks and the impacts of traffic accidents have been explored by focusing on drivers' heterogeneous responses under different decision contexts.

Here, the findings of this thesis are first summarized below, and then implications of these findings, research limitations, and directions for future research are discussed.

8.1 Findings

8.1.1 Smartphone app for traffic safety improvement

Motivated by the prevalence of individualized ITS devices in the context of driving safety, a simplified GPS-enabled smartphone app, *Safety Supporter*, is developed to help drivers develop a better understanding of their current driving performance, and to encourage drivers toward more voluntary behavior changes in safe driving. Effectiveness of the developed app have been evaluated from two perspectives: objective driving risks mitigation and subjective driving mood enhancement. Objective driving risks are diagnosed based on control behavior of speed limit compliance, acceleration/deceleration, and driving stability. The app captures driving safety level through a second-by-second diagnosis, and provides drivers with advices for safer driving based on diagnosis results. Moreover, a series of additional functions are also included, including blackspots warning information and SA/PA information provision, driving propensity diagnosis and advice feedback, online traffic education campaign, as well as social comparison functions of self-diagnosis and user ranking, which are unique even by comparing with existing apps. Nevertheless, it should be emphasized that developing the most advanced app for driving safety is not the research purpose of this study. In order to evaluate the effects of the app, a three-month driving experiment (February to May in 2014) was conducted, where a series of questionnaire surveys were also carried out in a sequential way. Based on data collected, effects of the app have been revealed from various aspects, as summarized below.

(1) Focusing on the short-term effects measured at a second-by-second level, it is concluded that the *Safety Supporter* could encourage most drivers, who are frequent expressway users, to be in compliance with speed limit, but its improvement of acceleration/deceleration control behavior is limited.

- Basic functions of the *Safety Supporter* are surely effective to improve the safety level of 60.0% of drivers (i.e., careless drivers) in terms of both speed limit compliance and acceleration/deceleration. Focusing on the speed limit compliance, use of the *Safety Supporter* with basic functions leads to the improvement of driving safety of 60.0% ~ 73.3% of drivers (i.e., irritable drivers and excessively confident drivers). As for aggressive drivers (60.0%), their control behavior of acceleration/deceleration could become better after use of the App.
- Additional functions of the *Safety Supporter* also significantly influence on individual's driving performance, however, heterogeneous effects identified from each function suggest the importance of careful combination of various information provision. In terms of the driving performance, driving propensity diagnosis and advices feedback to more speed limit compliance and better control of acceleration/deceleration. Traffic safety campaign via smartphones is influential to speed limit compliance, but the influencing power is almost ignorable. Unfortunately, SA/PA information provision, ranking of diagnosis results among drivers and self-diagnosis were not helpful to improve driving safety.

(2) Focusing on the long-term effects, measured at trip-based level, driving risks are measured based on violation rates of three driving performance indicators during one trip. The developed *Safety Supporter,* again, works and imposes an unneglectable influence on driver's risky driving behaviors significantly.

- Selected functions of SA/PA information provision, driving propensity diagnosis and advice feedback, traffic safety campaign, significantly contribute to the reduction of violations measured by drivers' abrupt acceleration/deceleration behavior.
- Ranking of diagnosis results among drivers and self-diagnosis function provision of the app could help drivers to control their driving stability better. However, unfortunately, app functions only impose limited effects on improving driver's violations of speed limit compliance at the trip level.

(3) Specific influencing impacts of various functions provided by the *Safety Supporter* (summarized in Table 8-1) highlighted that the importance of data measurement scales in traffic safety studies should be carefully considered before policy implication in deploying such individualized traffic safety measures. Careful combinations of various information provision could significantly improve the driving safety level.

8.1.2 Multi-faceted and correlated driving risks

Focusing on driving risks on expressways, this research has examined driving safety based on a series of risk indicators, which are usually interrelated. Firstly, individual's driving risks are diagnosed directly based on each driver's objective driving performance (in terms of speed limit compliance, acceleration/deceleration, and driving stability), multitasking behavior while driving, and driving avoidance behavior. Secondly, individual's driving risks are analyzed in association with individual's subjective well-being (SWB) (here, measured by affective experiences while driving) and driving propensities. In addition to internal driving risks that may result in driver's involvement in an accident, analyses were also done with respect to external driving risks (e.g., blackspots and risky driving environment). Based on data collected from the three-month field experiment with the developed app and questionnaire surveys, several findings have been derived with respect to multi-faceted risks of drivers who are frequent users of expressways:

Table 8-1 Effects of the app on driving risks across different analysis levels

	Analysis of driving risks at the second-by-second level			Analysis of driving risks at the trip level		
	Speed Limit Compliance	Abrupt Acc & Dec	Driving Stability	Speed Limit Compliance	Abrupt Acc & Dec	Driving Stability
Interaction between Basement Function (BF) &driving propensity						
BF*Irritable driver	–	+	+	–	/	+
BF*Careless driver	–	–	–	/	+	/
BF*Aggressive driver	+	–	–	(–)	–	+
BF*Self-confidence driver	–	+	+	(+)	/	–
Additional app function						
Function_1 (SA/PA info.)	+	+	+	/	–	+
Function_2 (Ranking and self-diagnose)	±	+	–	/	+	–
Function_3 (SAS & advice)	–	–	+	/	+	+
Function_4 (Drive &love campaign)	±	+	–	+	/	/

Note: "-" significant negative impact; "+" significant positive impact; "/" insignificant , "±" unstable sign; "()" unstable significance

(1) Correlations among three indicators of driving performance have been verified based on analyses of second-by-second data and trip-based data.

(2) Correlations between subjective and objectives risk factors are unneglectable at the trip level.

(3) At the trip level, individual's driving performance (especially, violation rates of speed limit compliance and abrupt acceleration/deceleration control) are significantly inter-correlated with driver's affective experience and multitasking behavior while driving. Moreover, affective experience and multitasking behavior while driving are also significantly inter-correlated with each other. This suggests that it is necessary to incorporate subjective well-being factors and multitasking behavior during driving in driving risk studies.

(4) The significance of self-recognition about driving risks is confirmed.

8.1.3 Drivers' avoidance behaviors and internal driving risks

This study made an initial attempt to capture the complicated relationships between driving performance, multitasking, affective experience during driving, and driving avoidance behavior (including punishment avoidance, weather-related avoidance, traffic-related avoidance, riding avoidance). Again, driving performance was measured using three driving risk indicators: speed limit compliance, abrupt acceleration and deceleration, and driving stability. A seemingly unrelated regression model is employed to jointly estimate six dependent variables. Findings of this study are summarized as follows:

(1) Introduction of the avoidance driving behavior will weaken the significant relationship between speed limit compliance and abrupt acceleration/deceleration behaviors at the trip-based level. This finding is understandable to some extent, because drivers may drive their cars very fast (to exceed speed limit) and smoothly by speeding up gradually (resulting in lower values of acceleration and deceleration control).

(2) Focusing on driving avoidance behaviors, their mutual influences with other dependent variables are confirmed. First, driving avoidance behaviors are statistically affected by

speed limit compliance, driving stability, bad moods during driving, and multitasking behaviors in terms of mental distraction and radio operation. Next, four types of driving avoidance behaviors significantly influence on driving performances, especially speed limit compliance behavior. Traffic avoidance behavior is significantly influential to affective experience during driving. No significant impact of avoidance behavior could be identified on driver's multitasking experiences reported.

8.1.4 External driving risk avoidance behavior

In order to explore external driving risks, a case study was done in the Chugoku Region of Japan. Two expressways, called Chugoku expressway and Sanyo expressway, have been facing up with an unbalanced traffic demand problem, even though two expressways are substitutional in many trips. Moreover, different levels of traffic accidents and the resulting congestion have also been observed from the two expressways. A RP/SP questionnaire survey was conducted in 2014 and 2015 to freight forwarder companies which are expected to use these two expressways. The purpose of the survey is to investigate factors affecting truck route avoidance behaviors. Potential factors that would significantly influence both company managers' and drivers' decisions on choosing expressway routes for avoiding risks caused by uncertain travel time have been explored. Analysis results of risk avoidance behavior of truck expressway route choices based on a bivariate probit model are summarized as follows:

(1) Three types of route choice decisions are revealed: decision by manager, decision by driver, and decision depending on circumstances and so on. And route choice decisions by company managers and drivers are interrelated. Route choice decisions of freight forwarders are diverse across company managers and truck drivers. These results

suggest that interventions to influence truck route choices should focus on both managers and drivers.

(2) Managers' decisions on route avoidance under the influence of uncertain travel time caused by traffic accidents are affected by compensation of tow truck fee, traffic congestion on Sanyo expressway, refund to use of Chugoku expressway, and transporting fragile goods. Unexpectedly, these attributes are influential at all to drivers' decisions.

(3) Some images of Chugoku expressways surely affect both managers' and drivers' decisions; however, only security on road shows a consistent influence on both managers and drivers.

(4) Similar numbers of statistically significant driver-specific attributes and manager-specific attributes are identified.

(5) Drivers' experiential factors and insurance purchasing by companies consistently affect the two decision makers' route choices.

(6) Influential company attributes are not the same between managers' and drivers' models.

(7) For truck drivers, who frequently use expressways, route avoidance behavior is significantly influenced by types of insurances purchased by their companies, and their experiences of encountering serious traffic congestion and traffic accidents. In contrast, the avoidance behavior of company managers is more likely to be influenced by the factors of road congestion information, characteristics of delivery goods (especially, fragile goods), and incentives of avoiding use of congested routes.

8.1.5 Drivers' adaptation behavior under traffic accidents related dynamic travel information

Recognizing that a variety of studies have been done with respect to the effects of dynamic travel information on travel behavior, this study made an additional effort. Concretely speaking, this study evaluated the effects of the information on driver adaptation behavior to the occurrence of traffic accidents on expressways under different decision contexts. This was done based on a large-scale SP survey, from which 30,000 SP responses were collected from 2,500 expressway users in the Western Japan. Even though the sample size is quite large, the SP attributes were specified by reflecting each respondent's personal driving experience and travel information preference. To the authors' knowledge, this is probably the first study in literature to deal with similar topics using such a large sample size. A series of context-dependent real-time travel information was introduced in the SP survey, including accident conditions and impact information, predicted clearance time (accuracy, point-based and interval-based prediction), and available alternative travel mode for three decision scenes of before departure, on the way to expressway, and on expressway. Findings obtained from based on nested logit models estimation result can be summarized as follows:

(1) More than 70% of respondent change their original trip plan influenced by the provided information.

(2) "Interval values" works better than "point-based values" for the information provision of clearance time of traffic congestion, and it plays a considerably larger role in influencing drivers' adaptation behavior than other information contents, especially, the influences become larger and larger moving from "before departure" to "on the way to expressway" and to "on expressway".

(3) Common factors across the three scenes are "distance to site", "no fatal accident",

"queue length", "no traffic regulation", "clearance time accuracy", and "queue decreasing trend".

(4) Influences of "fatal accident", "clearance time", "trip purpose", "time interval information" are proved to be significantly different across scenes (i.e., drivers' responses are context-dependent).

8.1.6 Travel information style in drivers' adaptation behavior

Same as concept of lifestyle in various human decision, it is proposed that travel information style may also play a significant role in the context of accident information influenced adaptation behavior. Therefore, to identify typical travel information styles and to clarify how drivers with different information styles adapt differently to uncertain situations caused by traffic accidents on expressways.

For this purpose, data collected from 1,923 drivers in the Chugoku Region (Yamaguchi, Hiroshima, Okayama, Shimane, and Tottori Prefectures) of Japan in 2011-2012, have been utilized for analysis, with both revealed preference (RP) and SP data. Three types of travel information styles are identified, including (1) *high dependence on information for relatively inflexible trip-making,* (2) *high dependence on experience for risky trips, and* (3) *least information users*, based on a cluster analysis. Nested Logit model is estimated for different travel information styles identified from the cluster analysis, and it is found that driver's behavioral responses among three information styles are quite different under different information provision contexts.

(1) Firstly, importance of drivers' heterogeneous information adaptation properties in response to the dynamic information provision have been verified. Context-sensitive travel

information targeting at drivers with different travel information styles should be provided in the traffic management practice.

(2) Drivers who are highly dependent on information for relatively inflexible trip-making show a higher information search propensity and are influenced largely by the provided information than drivers with the other two information styles, suggesting that more information should be provided to this type of drivers in further policy implication.

(3) Drivers who are comfortable about their experience are more stubborn and stick to their previous driving experience and therefore less significantly influenced by the information provided. More concrete information such as the exactly "*value of clearance time interval*" and "*queue decreasing trend*" information should be provided to drivers who are highly dependent on their experience.

8.2 Implications

Here, several important implications about the findings from this thesis study for practical applications are discussed.

(1) The simplified smartphone based driving diagnosis tool (*Safety Supporter*) can be utilized as a driving safety assistance tool, which can not only diagnose individual's driving risks, but also provide corresponding advices together with traffic warning information, to help drivers mitigate driving risks and prevent the occurrence of traffic accidents. In the meanwhile, the developed app can also work as a Big Data collection tool. Policy makers are interested in using this to collect information for traffic control and management as well as road maintenance, e.g., travel time measurement and prediction, measurement of road roughness for maintenance. The developed app could also be used as traffic safety campaign media with easy of information accessibility.

(2) From the perspective of dynamic accident information provision, information provision method of interval values of clearance time (rather than point-based values with prediction probability) of traffic congestion play a considerable larger role in influencing drivers' adaptation behaviors.

(3) Considering the significant influence of individual's heterogeneity, context-sensitive travel information targeting at drivers with different travel information styles should be provided in the real world traffic management practice.

(4) Recognizing the complicated "chicken and egg" relationships between multi-faceted and correlated driving risks factors, it is necessary to monitor the effects of various traffic safety measures at the individual driver level over time. In this study, we implemented a three-month driving experiment. For example, some avoidance behaviors due to the app intervention might occur after a much longer period. Intuitively, a moderate level of good moods during driving might be better than an extremely happy mood or an extremely bad mood, because these extreme moods might lead to unexpected driving actions involving unconscious risks. In this regard, drivers' personal efforts of mood management are surely important on one hand, while it might be worth exploring the roles of external interventions for better driving moods via vehicle design, road design and traffic management, and information provision on the other.

(5) It is not necessary to fully stop all multitasking behaviors during driving, because some tasks during driving (e.g., listening to music, talking with passengers) may be helpful for some drivers to mitigate the boringness of driving. However, operation of phone, radio, and/or navigation system without enough attention to surrounding traffic is clearly dangerous. In recent years, developments of autonomous vehicles have attracting an increasing attention of auto makers and ICT companies and so on. These new developments should be promoted; however, it is still far from actual deployment in the mass market.

What's more important, it is necessary to develop more advanced technologies that allow drivers to operate phone, radio, and/or navigation system more safely (e.g., via voice control). Finally, reducing dependence on car in people's daily life is more essential to dramatically reduce traffic accidents.

(6) Last but not least, it is needed to emphasize that under a series of driving risks analysis, importance of traditional enforcement of traffic rules is still unneglectable. It is re-confirmed that traditional enforcement of traffic rules (here, punishments of traffic rule violations) should be continuous emphasized despite the development of new types of driving safety countermeasures.

8.3 Limitations and future studies

Having summarized the findings of this study, we need to emphasize several research limitations.

(1) Analysis unit: Even though the influential traffic volume is measured every five minutes, our analysis was done every two seconds. Such inconsistent treatment of data may underestimate the influence of traffic volume and accordingly the analysis should be improved. In addition, from the decision-making viewpoint, it is necessary to clarify whether there is any optimal length of decision time or not, considering the influence of actual driving speed and the driving environment. Furthermore, it might be useful for traffic safety practices to carry out analyses focusing on road sections, rather than trips; however, such unit needs more data.

(2) Glance behavior: As revealed by Birrell and Fowkes (2014), drivers spent 4.3% of the real-world driving scenario looking at a smartphone based in-vehicle information systems and average glance duration was 0.43 seconds per glance. We cannot deny the influence of such

glance behaviors of drivers on our analysis results, and therefore, such influence should be properly captured in future.

(3) Data: Due to the complex experiment design and questionnaire implementation, only data under the free traffic flow situations were extracted. As a result, only data from 15 drivers were used in the analysis. Model estimation biases caused by such limited sample size may exist. Data from other drivers are excluded because of the difficulties to model their driving behaviors under complicated traffic conditions and obtain proper data from external sources for better the modeling representation. It is important to evaluate the long-term effects of the app on driving safety. For this purpose, it is necessary to invite more drivers to use the app over a longer period and re-conduct our analysis. In this study, the app was developed under the Android environment. In fact, the app can be easily expanded to work under the iOS environment. Drivers of iPhone users should be invited to use the app. In this thesis study, more than 50% of the 15 drivers experienced traffic accidents, 73.3% were fined by polices because of violation of traffic rules, and 86.7% experienced fatigue driving. In this sense, drivers in this case study are risky drivers. Other types of drivers should have been invited to participate in the driving experiment.

(4) App functions: Among the 15 drivers, 33.3% were satisfied with the performance of the app, 40.0% were dissatisfied and 26.7% showed neutral responses. And, 46.7% said that the app could contribute to the improvement of their driving safety and 40.0% reported neutral opinions. In contrast, 13.4% expressed negative opinions on safety improvement. To put the app into practice, it is necessary to identify the best combination of functions and enhance its public acceptance. Furthermore, function enrichment should be considered, autonomous emergency alarm and call for help function should also be provided for users under the emergency, such as vehicle malfunction, incident or accident involvement situations.

(5) Travel information style: In terms of limitation in the adaptation behavior analysis part, we have to admit that in this study, only 15 variables were selected for identify driver's travel information styles. In fact, there are more variables related to drivers' preference for and experience of information search and usage. We cannot deny this might be because of the use of cluster analysis. Therefore, it is worth exploring travel information styles by applying other promising segmentation methods in the next step future study.

(6) Dynamic analysis: This study has investigated risky driving behavior by incorporating some temporal elements in the analysis. However, it is unclear how long diagnosis results made in a previous trip may affect driving risks in future trips. More advanced dynamic analysis approaches should be applied/developed.

(7) Decision-making and behavioral change processes: Driving risks have been analyzed based on econometric approaches with correlated error terms and heterogeneities. To justify the results of model estimation, it may be important to look at the process to risky behavior, which has however been ignored in the analysis. Moreover, the three-month period may not be sufficient to capture behavioral changes toward safer driving. Observations should be made over a longer period.

(8) Traffic warning information: In the adaptation analysis, the significant influence of dynamic traffic warning information has been clarified. The development of information systems suitable to personal ICT devices (mobile phones, tablets, etc.) must be promoted, in which drivers' diverse information requirements and preferences can be flexible reflected. Recently, more and more people are enjoying the use of social media (e.g., Facebook, Twitter) and often acquire different types of information, even though the reliability of the information is questionable. It is worth exploring how to support inter-user communication with respect to the dynamic travel information under study. It is also important how to collect the real-time travel information directly from trip makers.

Needless to say, more efforts should be made to further improve the travel time prediction techniques.

(9) Analysis framework: Data analysis with consideration of more subjective factors included in the questionnaire into a unified analysis framework, as illustrated in Figure 8-1, should be further considered. However, those factors involve various complicated cause-effect relationships, making the modelling analysis very difficult. This leaves a future research task about how to integrate all those inter-correlated subjective factors into one modelling system.

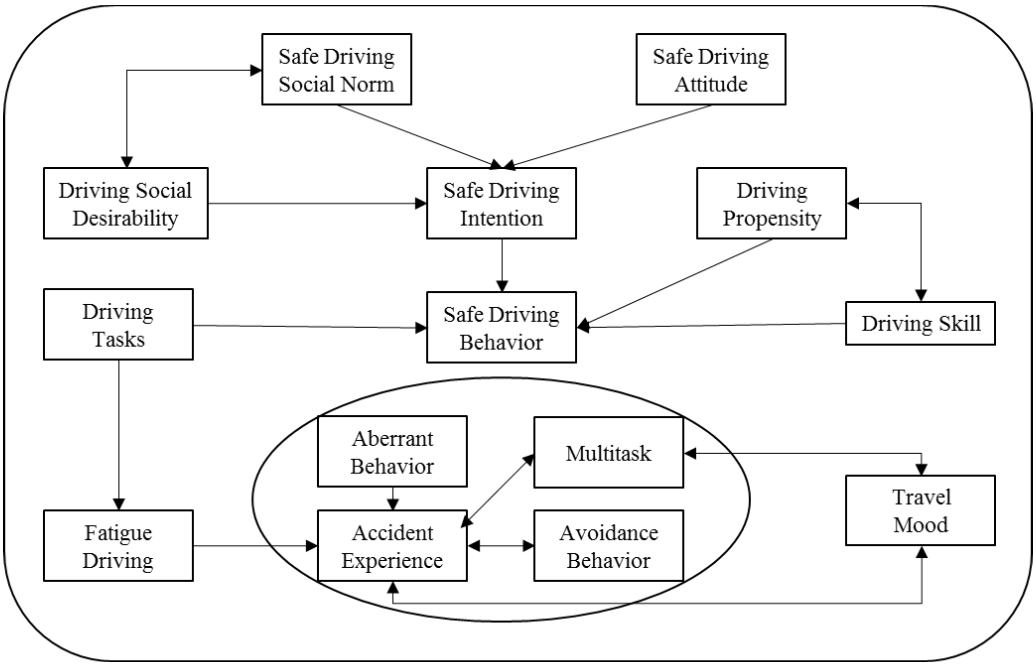


Figure 8-1 Analysis framework of subjective driving risk factors

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(2) Jiang, Y., Zhang, J. (2015) Drivers' travel information styles and adaptation behaviors to dynamic travel information about accidents on expressways. Asian Transport Studies, 4 (2) (in press).

(3) Jiang, Y., Zhang, J. (2017) Road traffic accidents studies in Asia. In: Zhang, J. and Feng, C.-M. (eds.), Routledge Handbook of Transport in Asia (forthcoming).

(4) Jiang, Y., Zhang, J. (2016) Risky behaviors in life: A focus on young people. In: Zhang, J. (ed.), Life-Oriented Behavioral Research for Urban Policy, Springer (in press)

(5) Zhang, J., Xiong, Y., Jiang, Y., Tanaka, N., Ohmori, N., Taniguchi, A. (2016) Behavioral changes in migration associated with jobs, residences, and family life. In: Zhang, J. (ed.), Life-Oriented Behavioral Research for Urban Policy, Springer (in press)

(6) Jiang, Y., Zhang, J. (2016) Developing a Smartphone APP to measure driving risks on expressways and capturing influential factors based on a three-month driving experiment. Compendium of Papers CD-ROM, the 95th Annual Meeting of Transportation Research Board (TRB), Washington, D.C., USA. January 10-14.

(7) Jiang, Y., Zhang, J. (2016) Effects of a GPS-enabled smart phone App with functions of driving safety diagnosis and warning information provision on over-speeding violation behavior on expressways. Selected Proceedings of the 14th World Conference on Transport Research (WCTR), Shanghai, China, July 12-16 (in press).

(8) Jiang, Y., Zhang, J. (2015) Effects of a smart phone App for driving safety diagnosis:

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(9) Jiang, Y., Zhang, J., Chikaraishi, M., Seya, H., Fujiwara, A. (2015) Driving speed control behavior and safety on expressways under smart phone app based traffic safety information provision. Proceedings of the 14th International Conference on Travel Behaviour Research, Widsor, UK, July 19-23.

(10) Zhang, J., Jiang, Y., Sasaki, K., Tsubouchi, M., Matsushita, T., Kawai, T., Fujiwara, T. (2014) A GPA-enabled smart phone app with simplified diagnosis functions of driving safety and warning information provision. Proceedings of the 21st ITS World Congress, Detriot, September 7-11 (CD-ROM) (***Best Scientific Paper Award***).

(11) Jiang, Y., Zhang, J., Fujiwara, A., Tomitaka, H., Matsushita, T. (2013) Analysis of the occurrence and clearance time of traffic congestion caused by accidents on expressways based on a copula modeling approach. Proceedings of the 18th International Conference of Hong Kong Society for Transportation Studies, 18, 409-418.

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(13) Jiang, Y., Zhang, J. (2012) Chinese drivers' multitasking behavior during driving and accident involvement: An analysis linked with aberrant driving behavior and unsafe driving propensity. Proceedings of the International Symposium on City Planning 2012, August 23-25 (CD-ROM)

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(1) Jiang, Y., Zhang, J. (2017) Effects of driving risk diagnosis and real-time information

provision via smartphones on driving speed control behavior: A case study of frequent expressway drivers in Japan. Transportation Research Record (SCI journal).

(2) Jiang, Y., Zhang, J. (2016) Effects of use of smartphone apps with driving safety diagnosis functions on traffic safety on expressways: A case study in Japan? Journal of Transportation Engineering (SCI journal).

(3) Jiang, Y., Zhang, J., Jin, X., Ando, R., Chen, L., Shen, Z., Ying, J. (2016) Rural migrant workers' residential, travel, and energy consumption behavior in a changing context of urban China. Transportation Research Part D: Transport and Environment (SCI journal).

(4) Zhang, L., Jiang, Y., Zhang, J. (2016) Rural migrant workers' intention to stay in cities under China's new urbanization policy. Journal of Urban Affairs (SSCI journal).

Invited Speeches

(1) Zhang, J., Jiang, Y. (2015) Can we promote safer driving based on smartphone apps? Keynote speech at the 3rd Conference of Transportation Research Group of India (CTRG), Kolkata, India, December 17-20.

(2) Zhang, J., Jiang, Y. (2014) Development of a GPS-enabled smart phone app for driving safety diagnosis. Invited Speech at 14th COTA International Conference of Transportation Professionals (CICTP2014), Changsha, China, July 4-7.

(3) Zhang, J., Jiang, Y. (2013) Post-accident adaptation behavior and dynamic travel information: A comparison between the elderly and non-elderly. Invited Speech at the International Workshop "Age-friendly Safety and Welfare in Transportation", Hanbat National University, Daejeon, South Korea, June 13.

Non-refereed Papers in Conference Proceedings

(1) Jiang, Y., Zhang, J. (2016) Factors affecting driving avoidance behavior and effects of a

smart phone based driving safety diagnosis tool. Proceedings of Civil Engineering Conference in the Asia Region (CECAR 7), Hawaii, USA, August 30 ~ September 2 (forthcoming).

(2) Jiang, Y., Zhang, J., Seya, H., Chikaraishi, M. (2016) Analysis of expressway route choice behavior incorporating the interaction between transport company manager and drivers, Proceedings of Infrastructure Planning, 53, Sapporo, Japan, May 28-29 (CD-ROM).

(3) Jiang, Y., Zhang, J. (2015) Driving risk, multitasking behavior, and affective experiences, Proceedings of Infrastructure Planning, 52, Akita, Japan, November 21-23 (CD-ROM)

(4) Zhang, J., Jiang, Y., Sasaki, K., Tsubouchi, M., Matsushita, T., Fujiwara, A. (2014) Development of a smart phone app "safety supporter" for assisting driver's safe driving. Proceedings of Infrastructure Planning, Japan Society of Civil Engineers, 49, Sendai, Japan, June 7-8 (CD-ROM).

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Thesis Studies
<u>Doctor Course Research</u>
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Calculating the Timing of Real-time Traffic Actuated Control Signal at Signalized Intersection (Department of Traffic and Transportation, Jilin University, China)

Awards
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(2) 2011.10 ~ 2016.09: MEXT Scholarship, Japan
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