DRIVING RISK, MULTITASKING BEHAVIOR, AND AFFECTIVE EXPERIENCES

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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.

Directly related to the above challenge, we developed a GPS-enabled smart phone App (called *Safety Supporter*) that not only automatically records second-by-second driving locations, but also diagnoses driving risks, provides feedbacks soon after driving to drivers with safe driving advices, and records multitasking and affective experience during driving. Furthermore, we implemented a three-month driving experiment, during which a series of questionnaire surveys were conducted. For this study, we extracted 320 trips from 29 individuals with 257,333 epochs. Expected outcomes of this study are to fill the research gap by providing empirical evidence in consideration of various cause-effect relationships and to derive useful insights into traffic safety countermeasures in practice.

Key Words : *affective experience, multitasking, driving risk, GPS-enabled smart phone App*

1. INTRODUCTION

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.

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' personal driving propensities and driving behaviors. 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. 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 smart phone 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).

In line with the above considerations, we developed a GPS-enabled smart phone App (called *Safety Supporter* :) that diagnoses driving safety by making full use of GPS information and provides feedback of diagnosis results, advices on safer driving, and traffic warning information to drivers for the prevention of traffic accidents (Zhang et al., 2014). The diagnosis is done every two seconds to measure three types of driving risks: compliance level of speed limit, abrupt acceleration and deceleration, and driving smoothness (unstable level of driving within a given time period). Using *Safety Supporter*, the driver can easily review the diagnosis results, which are provided in the forms of a summary of average driving performance with respect to each type of driving risk, a map showing the diagnosis results on the driving route, ranking of diagnosis results in the whole list of registered members. Each driver is also asked to self-report safe driving score based on their personal judgment, which can be used to measure the gap between actual driving behavior and self-perception.

Moreover, driver's affective experience, measured by percentages of different types of moods, and activities performed during driving (multitasking) (Jiang & Zhang, 2012), are collected in the forms of self-report by the driver at the end of each trip. looking around, turn-back talk (, which require drivers moving eyes away from the surrounding traffic), eating, smoking, radio operation, operation of navigation system (which still allow drivers to keep their eyes on the surrounding traffic, but require one hand from operating the vehicle), thinking without paying attention to driving, and dozing

Different from existing Apps, *Safety Supporter* makes use of the most common GPS information, which can be easily obtained from any type of smart phones, to measure driving risks and provide safer driving advices as well as traffic warning information, without any additional sensors. The development of *Safety Supporter* was motivated by the needs of easy and widespread deployment of such driving safety diagnosis devices.

Zhang et al. (2014) provided preliminary analysis results about the applicability of this App based on a pilot experiment conducted in December 2013. Based on the pilot experiment, we further implemented a three-month driving experiment in February ~ May, 2014. During the experiment, six driving scenarios, defined by a combination of different functions of the App, were tested for a certain length of time, respectively. In addition, a series of questionnaire surveys including various objective and subjective factors related to driving safety (both behavioral and psychological factors) were also conducted.

The purpose of this study is to fill the research gap, identified in the beginning of this section, by providing empirical evidence in consideration of various cause-effect relationships and to derive useful insights into traffic safety countermeasures in practice.

2. THE GPS-ENABLED SMART PHONE APP: *SAFETY SUPPORTER*

Currently, the App *Safety Supporter* can be only accessible in Japan and it was developed under the Android environment (in fact, our software design also allows it to be used under the iOS environment). It mainly has four types of functions as shown below (Figure 1).

(1) Diagnosis of driving risk: Even though 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 with respect to the following three indicators.

a) Compliance level of speed limit: The safest level is given 100 points when driving speed is equal to or slower than speed limit plus 5 km/h and the most dangerous level is given 0 point when driving speed exceeds speed limit by more than 50 km/h. Other driving speeds are scored depending on how much speed limit is violated. The scoring is given by reflecting the levels of fines determined by policy agencies.

b) Abrupt acceleration and deceleration: If the absolute value of acceleration or 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 set to 0 point. 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.

c) Driving smoothness: 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.

(2) Diagnosis of driving propensity: According to Japan Traffic Safety Association (2006), driving propensities can be classified into 6 types based on 27 question items: irritable, careless, aggressive, excessively-confident, indecisive, and safe driving. Different drivers might belong to two or more types driving propensities simultaneously. Therefore, we score the driving propensity based on how many types that a driver is classified into. If a driver is classified into the type of safe driving, 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.

Figure 1. System Design of the App *Safety Supporter*

(3) Information provision: i) black spots (i.e., dangerous road section, where traffic accidents occurred frequently), and ii) warning of fatigue for long-distance driving and automatic guidance of the closet service area (SA) or parking area (PA).

(4) Feedback of diagnosis results to drivers: i) average score of each driving safety indicator as a whole and that passing across black spots, ii) trajectory of driving route with driving safety level and average score in the previous time, iii) ranking over time among registered members, and iv) advices given based on diagnosis results.

3. SURVEY AND DATA

The three-month driving experiment was conducted with respect to 100 expressway drivers in the Chugoku region of Japan in February ~ May, 2014, who used expressways in the above region more than 4 times per month. In order to testify the impacts of different App functions, the three months were divided into six periods, in each of which a particular driving scenario was tested.

In the first month (1st ~ 4th weeks), drivers were asked to drive as usual and driving data were collected using *Safety Supporter*. Data in this period are used as a reference to identify changes in driving behaviors under other five scenarios. In the second period (5th ~ 6th weeks), drivers made use of *Safety Supporter* 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 *Safety Supporter* users and self-evaluation of driving safety for each trip before being shown with the score by *Safety Supporter*, 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), an online traffic safety education campaign "Drive & Love" was introduced to *Safety Supporter* (Function 4). After each drive under any driving scenario, the driver was asked to report multitasking and affective experience during driving.

For this study, trips lasting for less than 10 minutes were excluded. In order to investigate individual driver's behavioral changes influenced by *Safety Supporter*, only cases of free traffic flow (driving speed over 70km/h based on our analysis) and expressways with two or more lanes (where drivers can make a free choice of driving lane) were selected. As a result, 29 individuals who made 320 trips with totally 257,333 epochs (calculated every two seconds) were obtained for this study. The 29 individuals are all male drivers and aged from 30 ~ 59 years old (the average age is 42 years old).

During the three-month experiment, a series of questionnaire surveys were carried out for capturing driver's various personal factors, including self-evaluation of daily driving safety (scored ranging from 0~100 points), behavioral change stages of safe driving (precontemptation → contemplation → preparation → action → maintenance), driving tasks, items based on the theory of planed behavior, and aberrant driving behaviors and so on. Some of data collected from the experiment will be used in the following modeling analysis. In addition, data from external sources were also collected for this study, including traffic volume data (measured every five minutes), types of expressways, and land use types along expressways. The external data were matched with the second-by-second data from *Safety Supporter* along the whole driving route.

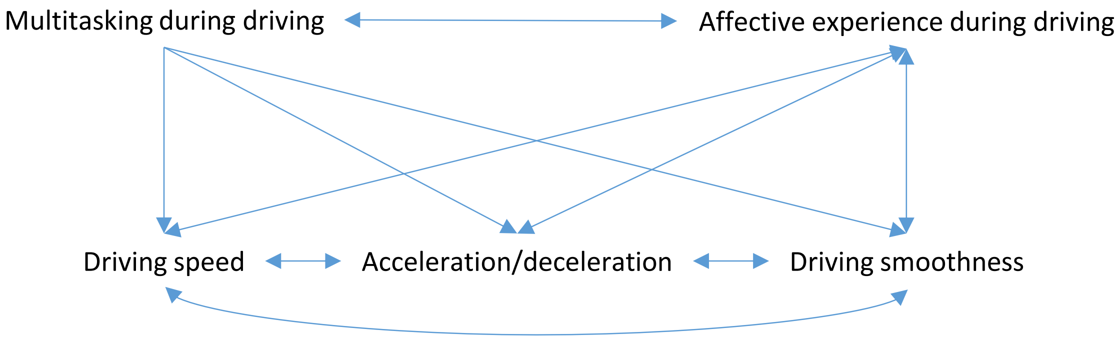

Figure 2. Potential cause-effect relationships among dependent variables in this study

4. METHOD, ANALYSIS, AND EXPECTED OUTCOMES

Here, drivers' multitasking and affective experience during driving and diagnosed scores of driving risks (three indicators with respect to compliance level of speed limit, abrupt acceleration and deceleration, and driving smoothness (unstable level of driving within a given time period)) are treated as mutually interrelated dependent variables (Figure 2).

Driver's affective experiences were measured by the percentages of bad mood, low mood, pleasant mood and very good mood during driving (the total percentage: 100%). Multitasking contents (15 types) include, looking around, turn-back talk (which require drivers moving eyes away from the surrounding traffic), eating, smoking, radio operation, operation of navigation system (which still allow drivers to keep their eyes on the surrounding traffic, but require one hand from operating the vehicle), thinking without paying attention to driving, and dozing.

Considering potential cause-effect relationships among dependent variables in this study and features of the variables (some with zero values depending on observations), we employ a seemingly unrelated regression model with Tobit structure (called SURE-Tobit model) to jointly estimate the dependent variables shown in Figure 2. And explanatory variables are shown below.

- App function dummy variables: basic functions (both diagnosis and traffic warning information provision) and additional functions tested during different periods of the experiments.
- Driving propensity: six types were identified from the survey, i.e., irritable, careless, aggressive, excessively-confident, indecisive, and safe driving, which are introduced as a dummy vari-

able, respectively.

- Driving contextual and environment factors: drive on holiday, drive at night, speed limit, driving direction, traffic factor (traffic volume and share of large vehicles in traffic), land use factors, and types of expressways
- Driving experience of traffic accidents and punishments of traffic rule violations
- Time-dependent factors: driving time elapsed corresponding to the measurement moment and trip duration
- Driver attributes: age, gender, occupation, driving frequency, driving age, and main trip purpose with expressway driving.

Analysis in this study is trip-based, i.e., 320 trips made by the 29 drivers during the three months. Multitasking and affective experience are collected with respect to each trip, which are directly used for this study. There are 15 types of multitasking, which will be further grouped before model estimation (discrete variable). Affective experience is measured as a continuous value. As for diagnosed scores of three types of driving risks (compliance level of speed limit, abrupt acceleration and deceleration, and driving smoothness), even though they are measured second-by-second, they are aggregated into violation rates during the trip, where the violation is defined differently for each type of driving risk based on the distributions of diagnosed scores.

Expected outcomes of this study are to fill the research gap by providing empirical evidence in consideration of various cause-effect relationships and to derive useful insights into traffic safety countermeasures in practice.

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