國 立 交 通 大 學

交通運輸研究所

博 士 論 文

No.53

不同交通資訊情境對高速公路駕駛人路線移轉行為之影響

Analysis of Freeway Drivers' Enroute Switching Behavior under Various Traffic Information Scenarios

研 究 生：郭奕妏

指導教授：馮正民　博士

中 華 民 國 九 十 六 年 七 月

不同交通資訊情境對高速公路駕駛人路線移轉行為之影響

Analysis of Freeway Drivers' Enroute Switching Behavior under Various Traffic Information Scenarios

研 究 生：郭奕妏　　　　Student：Yi-Wei Kuo

指導教授：馮正民　　　　Advisor：Cheng-Min Feng

國 立 交 通 大 學
交 通 運 輸 研 究 所
博 士 論 文

A Dissertation
Submitted to Institute of Traffic and Transportation
College of Management
National Chiao Tung University
in partial Fulfillment of the Requirements
for the Degree of
Doctor of Philosophy
in
Management

July 2007

Taipei, Taiwan, Republic of China

中 華 民 國 九 十 六 年 七 月

不同交通資訊情境對高速公路駕駛人路線移轉行為之影響

學生：郭奕妏 **指導教授：馮正民**

國立交通大學 交通運輸研究所

摘　　要

先進駕駛者資訊系統可藉由提供駕駛人即時交通資訊，以影響其路線移轉行為，進而改善路網績效和服務品質。然而，只有當駕駛人對交通資訊內容持正面態度時，先進駕駛者資訊系統才能真正發揮其應有的效益。因此，駕駛人對所接收即時交通資訊的觀點，將成為能否影響其改變路線移轉決策之關鍵因素。此外，提供何種交通資訊類型，才可有效影響駕駛人行駛中的路線移轉行為，亦為重要的考量因素。

惟過去探討即時交通資訊對駕駛人路線移轉行為的分析模式，較缺乏同時考量駕駛人對即時交通資訊與路線移轉之正負向潛在變數。駕駛人對即時交通資訊的認知、態度與偏好等潛在看法，也應作為改善資訊內容的重要參酌。因此，為深入釐清即時交通資訊對高速公路小汽車駕駛人路線移轉行為的影響，本研究以兩階段研究方式進行：首先採用結構方程模式衡量駕駛人內心潛在變數，確認影響路線移轉行為意向的正負向潛在變數；接著透過排序普羅比模式進一步確認影響駕駛人路線移轉行為的重要因素，分析不同交通資訊情境下之行為反應，並將正負向潛在變數納入路線移轉行為模式，以提升路線移轉行為模式的解釋能力。

本研究選擇高速公路北部區域進行案例研究，調查對象為行駛於高速公路基隆至新竹間的小汽車駕駛人，有效問卷回收 493 份。根據案例分析結果顯示，本研究所推論的因果關係假設皆確立。駕駛人對即時交通資訊之「認知價值」和「使用態度」可正向刺激其路線移轉行為，至於「塞車容受力」及「路線移轉障礙」等負向潛在變數為牽制駕駛人改道行為意向的關鍵因素，致使駕駛人在面臨塞車時仍多半選擇維持原行駛路線；基於改善駕駛人資訊需求的觀點，藉由提供更詳實的替代路線資訊，可協助駕駛人評估改道決策，提高路線移轉行為產生率，達到擁擠管理的效果。

關鍵字：即時交通資訊、路線移轉行為、潛在變數、結構方程模式、排序普羅比模式

Analysis of Freeway Drivers' Enroute Switching Behavior under Various Traffic Information Scenarios

Student：Yi-Wei Kuo **Advisors：Dr. Cheng-Min Feng**

Institute of Traffic and Transportation

National Chiao Tung University

ABSTRACT

Advanced Driver Information Systems (ADIS) have been considered to improve network performance and service quality by offering real-time traffic information to drivers for changing their enroute decisions. However, the benefits of ADIS are achieved only if the drivers respond to the real-time traffic information in a positive manner. Hence, the effectiveness of real-time traffic information greatly depends on the drivers' acceptance and compliance toward it. This is the critical factor for successful implementation of ADIS. Moreover, which types of real-time traffic information should be provided is also crucial to drivers' enroute switching behavior.

In the past, studies focusing on drivers' route switching behavior might not discuss the effects of drivers' viewpoints of real-time traffic information on positive and negative aspects simultaneously. Drivers' perceptions, attitudes, and preferences toward real-time traffic information should be taken into seriously consideration in the revision of information contents. To explore the effects of real-time traffic information on freeway drivers' enroute switching behavior, this study used two stage research methods. First, this paper applied "Structural Equation Modeling (SEM)" to verify the latent variables that would positively or negatively affect drivers' enroute switching intention and explore the causal effect between them. Then "Ordered Probit Model (OPM)" method was used to confirm whether latent variables and traffic information scenarios would affect drivers' stated enroute switching behavior in the congestion situation.

According to the case study, the research subjects were freeway drivers traveling between Keelung and Hsinchu City, and 493 valid questionnaires were collected. The results of SEM showed that all research hypotheses have been confirmed. Drivers' perceived value and usage attitude toward real-time traffic information had positive effects on their enroute switching intention. The drivers' enroute switching intentions were negatively impeded by the drivers' tolerance of congestion and perceived switching barriers. Therefore, it must be taken great consideration to provide more applicable route information contents in terms of drivers' opinions. The empirical results reveal that drivers' enroute switching behavior would be motivated by providing more detailed information on the alternative route. The improvement of the route information contents may help the traffic management agency to implement the strategies of congestion management.

Keywords: Real-time traffic information, Enroute switching behavior, Latent variables, Structural Equation Modeling (SEM), Ordered Probit Model (OPM)

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1 INTRODUCTION

1.1 Research Background

Since the traffic situation is worsening, methods for reducing traffic congestion have been issued recently. Advanced Driver Information Systems (ADIS) have been considered to improve network performance efficiency by offering real-time traffic information to drivers. The real-time traffic information can be communicated to drivers by several channels, such as radio traffic reports (RTRs), variable message signs (VMSs), or in-vehicle navigation system (IVNS), etc. The provision of real-time traffic information is a key determinant mechanism of ADIS. It may affect drivers' travel decisions, such as enroute diversion, route selection, and departure time decisions (Madanat et al., 1995). Thus, means of providing drivers with real-time traffic information to influence their driving behavior has gained much attention.

Many researchers have indicated that the provision of real-time traffic information can effectively improve network performance and service quality (Mahmassani and Liu, 1999; Abdel-Aty and Abdalla, 2004). The results from these studies show that the drivers' enroute switching intention can be stimulated by the provision of real-time traffic information. Thus, ADIS has recently been used as the means to alleviate traffic congestion by providing real-time traffic information to drivers for changing their enroute decisions.

However, the benefits of ADIS are achieved only if the drivers respond to the real-time traffic information in a positive manner. Hence, the effectiveness of real-time traffic information greatly depends on the drivers' acceptance and compliance toward it. This is the critical factor for successful implementation of ADIS. Moreover, which types of real-time traffic information should be provided is also crucial to drivers' enroute switching behavior.

Although real-time traffic information plays a vital role in the enroute decision of drivers, the development of technologies for traffic data collection is still in its infancy in Taiwan and consequently drivers merely obtain part or incomplete traffic information. Therefore, drivers cannot but take their experiences and preferences into account while receiving traffic information on the road. It may result in three negative impacts such as over-saturation, over-reaction and concentration (Ben-Akiva et al., 1991), which turn out unremarkable achievements of ADIS.

Contents of real-time traffic information are always provided based on the traffic manager's viewpoint, and they may not suitable for the real demand of drivers at present. A better understanding of drivers' enroute switching intention and behavior may help the traffic manager to improve the content of real-time traffic information. Drivers' perceptions, attitudes, and preferences toward real-time traffic information should be taken into seriously consideration in the revision of information contents. Less research has provided real-time traffic information content based on drivers' standpoints even though they are the key determinants of the behavioral response of drivers.

In the future, the application of several technologies such as probe vehicle, electronic toll collection (ETC), and vehicle position system (VPS) will be applied to broadcast traffic data collection along the freeway in Taiwan. More and more precise and useful real-time traffic information would be extracted from the process of data mining. Information quality may have a significant effect on drivers' enroute switching behavior. For the congestion management purpose, how to provide real-time traffic information from the drivers' point of view should be a great concern. According to the exploration of drivers' demand, the design of better traffic information contents would be beneficial for the development of ADIS.

1.2 Motivation and Objectives

Previous studies often incorporate quantitative factors rather than qualitative factors into route-choice models, so that the predictive ability might be queried. In order to enable the models to be more representative of drivers' behavior and improve the explanatory and predicting ability, latent variables have recently been taken consideration in the behavioral model. To date, the impacts of real-time traffic information on drivers' enroute switching behavior have received significant attention.

In addition to the socioeconomic characteristics, relevant studies found other significant latent variables which may affect the enroute switching behavior of drivers, such as their perceptions on the reliability of traffic information, their attitudes in complying with information suggestions, and various types of real-time traffic information (Madanat et al., 1995; Ng et al., 1995; Emmerink et al., 1996; Jou et al., 1997; Chen et al., 1999; Abdel-Aty and Abdalla, 2004; Jou et al., 2004; Jou et al., 2005).

However, studies focus on drivers' enroute switching behavior might not discuss the effects on positive and negative aspects simultaneously in the past. For the sake of realizing drivers' enroute behavior more explicit, this study will focus on both positive (such as perceived value and usage attitude) and negative variables (such as switching barrier and congestion tolerability). Moreover, this study will explore drivers' stated enroute switching behavior under various information scenarios. Therefore, this study proposes an analysis framework to incorporate latent variables, socioeconomic and travel characteristics in the model under various information scenarios to explain drivers' stated enroute switching behavior.

1.3 Problem Analysis and Research Issues

Even though drivers always receive real-time traffic information on the road, they may not comply with the enroute switching suggestion while encountering or anticipating a traffic jam. How does the driver react to the real-time traffic information? Based on the purpose of congestion management, it is necessary to explore drivers' real opinions (including perceptions, attitudes, and preferences) toward the real-time traffic information they received. To facilitate ADIS development, we should provide drivers more applicable information to make them more acceptable of and compliant with real-time traffic information. Thus, the research issues have been proposed as follows:

- Issue 1: To identify measurable variables in order to extract principle latent variables that will positively or negatively affect drivers' enroute switching intention.
- Issue 2: To explore the effects of latent variables (such as perceived value, usage attitude, switching barrier, and congestion tolerability, etc.) on drivers' enroute switching intention and their causal relationships while real-time traffic information given.
- Issue 3: To confirm whether latent variables and various traffic information scenarios will affect drivers' stated enroute switching behavior.

1.4 Research Scope

This study explores freeway drivers' enroute switching intention and switching behavior with an emphasis on receiving real-time traffic information. Some environmental conditions or decision situations would be controlled in the process of behavioral model formulation. Each driver would be regarded as a switching decision maker toward real-time traffic information. Besides, if all the vehicles switch their routes to the alternative for complying diversion suggestion, some negative impacts may occur. For keeping from some controversy, we also assume that the provision of traffic information would update real-time as soon as possible and consequently it may probably prevent too many vehicles from concentrating on the alternatives and resulting in worse situation.

Due to the past researches may lack of considering latent variables more completely into behavioral models, this study would focus on drivers' points of views, both positive and negative sides, toward received information. Several hypothetical traffic information scenarios would be proposed to discover drivers' stated switching behavior while driving on the road. It may be helpful to realize drivers' real demand toward traffic information and improve real-time traffic information contents.

To facilitate the formulation of behavioral models, this study discusses the case of Taipei metropolitan area in Taiwan and analyzes the effects of real-time traffic information broadcasted from radio traffic reports on drivers' enroute switching behavior. A structural equation model would present the causal relationship between positive/negative latent variables and switching intention, and then an ordered probit model would explain the significant variables on stated switching behavior under hypothetical traffic information scenarios.

1.5 Dissertation Framework

This dissertation is organized as follows. Chapter 1 is the introduction, which gives an overview of this research in terms of background, motivation and objective, problem analysis and research issues, research scope, and the framework of this dissertation. In Chapter 2, past researches for significant explanatory factors of route switching intention, applications of ordered probit model are reviewed. Chapter 3 profiles the analysis framework, research model and hypothesis; illustrates the methodology of Exploratory Factor Analysis (EFA), Structural Equation Model

(SEM), and Ordered Probit Model (OPM). Chapter 4 depicts the questionnaire design, survey, descriptive statistics, and the results of exploratory factor analysis. After that, the drivers' enroute switching intention model is developed and estimated by SEM in Chapter 5. Then, the hypothesized drivers' enroute switching behavior model is developed and elaborated by OPM in Chapter 6. The finial Chapter concludes the research and provides suggestions for future empirical studies. The flow chart of this dissertation is shown in Fig.1.1.

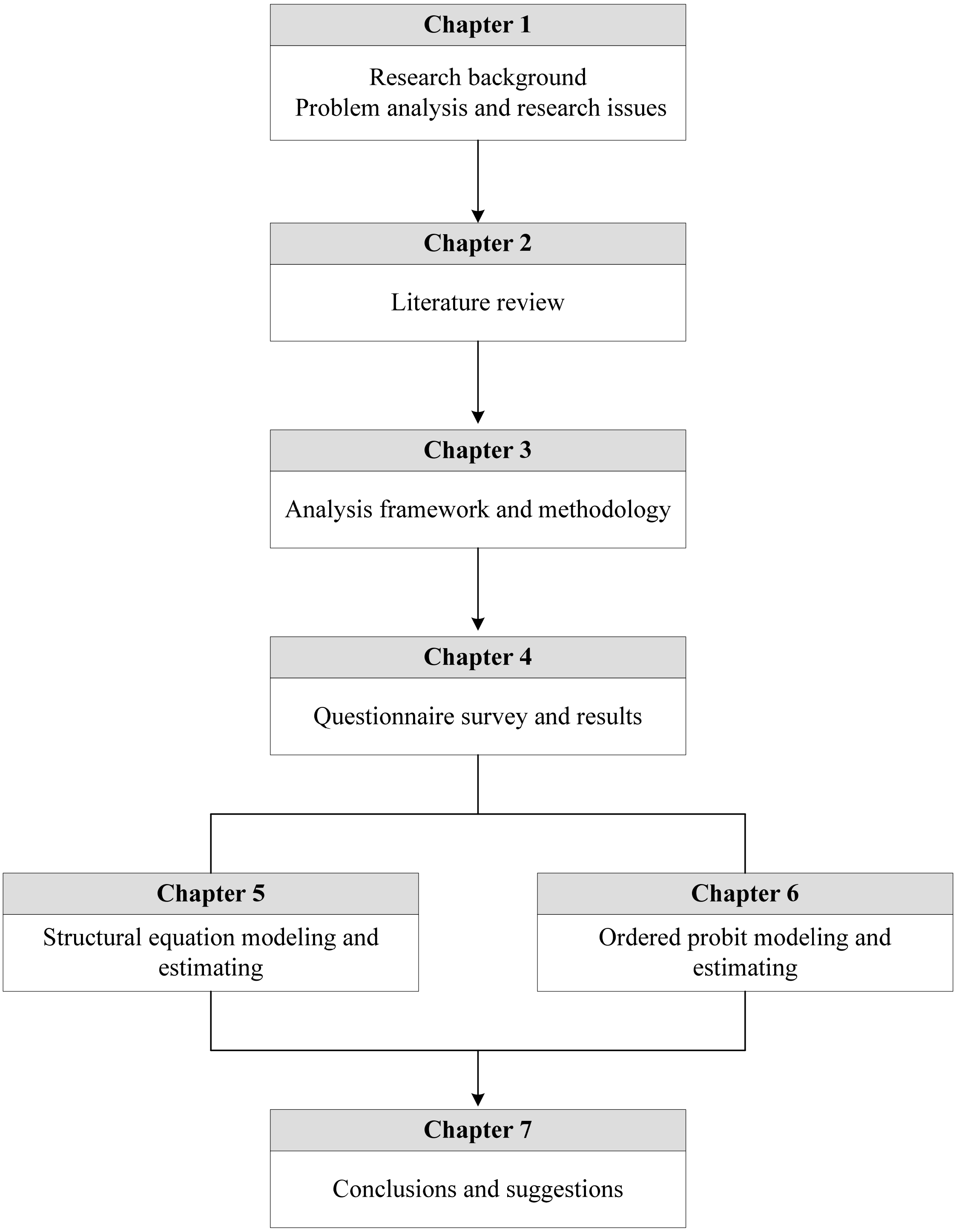


Fig.1.1 Flow-chart of dissertation

CHAPTER 2 LITERATURE REVIEW

2.1 Significant Explanatory Factors of Route Switching Intention

The factors that influenced drivers' intentions to divert from a regular route included length and cause of the delay, source of delay information, accuracy and reliability of delay information received, travel time and safety of regular and alternative routes, socioeconomic characteristics and personality of commuters, trip origin and destination, and situational factors such as time pressure, time of day or weather conditions (Khattak et al. 1993).

Several studies also indicated that drivers' expressed a higher propensity to switch routes when they were experiencing increasing delays and congestion, when congestion was caused by an unexpected incident rather than a recurring event, when travel times and travel distances on drivers' preferred routes were longer, and when their familiarity with the alternative routes increased (Heathington, 1971; Mahmassani, 1990; Khattak et al., 1993).

Besides, drivers' socioeconomic characteristics and personality would influence drivers' enroute switching intentions (Khattak et al., 1993; Madanat et al., 1995). It was reported that young, male, and unmarried drivers are more likely to switch to alternative routes (Heathington, 1971; Mahmassani, 1990; Khattak et al., 1993) due to the habitual and risk-aversive effects (Jou, 2005).

The factors that may influence drivers' route switching intentions are summarized in Table 2.1. The factors identified by review of the literatures could be grouped into several categories, such as information types, latent variables, travel characteristics, socioeconomic characteristics, and environmental situations, etc. With an emphasis on the research purpose of this study, we review the following literatures about the categories of information types and latent variables.

Table 2.1 Explanatory factors of route switching intention

Category	Explanatory factors
Information types	quantitative information, qualitative information, prescriptive information, descriptive information, alternative routes guidance, source of delay information (RTRs, VMSs, personal observation of congestion)
Latent variables	attitudes toward route diversion, perceptions of the accuracy and reliability of delay information, familiarity with the alternative routes
Travel characteristics	trip origin and destination, time pressure, time of day, commuting characteristics commuting distance and traffic safety on the route
Socioeconomic characteristics	age, gender, marital status, personality, driving experience
Environmental situations	delay situation (length and cause of the delay), attributes of regular and alternative routes (travel times, travel distances, travel cost, safety, types of roads), weather conditions

A. Information types

Many previous studies have investigated the effects of traffic information on drivers' route switching behavior. Several studies found that prescriptive and descriptive traffic information encourage route diversion (Heathington, 1971; Mahmassani, 1990; Khattak et al., 1993). Researchers also indicated that drivers had higher intentions in switching routes when they received real-time information with more detailed descriptions such as delay situation and alternative routes guidance (Khattak, 1993; Jou et al., 1997; Jou et al., 2005).

Madanat et al. (1995) determined the factors that affected drivers' stated intentions to divert from their usual routes when faced with traffic congestion and the type of information were identified to be the significant explanatory variables of route diversion intentions. Abdel-Aty et al. (1997) explored the factors that influence drivers' route choice, including advanced traffic information with travel time estimates. Traffic information can help to reduce drivers' uncertainty of travel time and to enable them to choose routes adaptively. Jou et al. (2005) investigated the drivers' route switching behavior on freeways in reaction to the provision of different types of real-time traffic information, and the route guidance and quantitative information were more preferable to drivers. The study applied indifference band approach to the model in consideration of saving travel time and travel cost. The effect of travel time on freeway switching behavior was larger than travel cost.

Abdel-Aty et al. (1997) used the stated preference techniques and a binary logit model to explore the factors that influence drivers' route choices, including advanced traffic information with travel time estimates. The study revealed that drivers' attitudes toward commuting characteristics (e.g. commuting distance and traffic safety on the route), expected travel time and variation in travel time, freeway usage and gender influence route choice. Receiving traffic information is found to be a significant variable in the route choice model. Information might be used by drivers' to reduce degrees of travel time uncertainty and also enable them to choose routes adaptively.

Lan, Wen, and Hsu (2001) used the revealed preference survey and several logit models to explore the effect of different traffic information on intercity commuter route choice behavior. The results indicated that trip characteristics (distance, travel cost, and types of roads), drivers' perception (familiar with multiple routes, traffic congestion, and pre-trip diversion), personal characteristics (driving experience, age, and sex), and the frequency of different traffic information usage (radio, television, internet, and telephone) are important factors affecting route choice models; trip characteristics (distance, travel time, travel cost, types of roads, and times of substitute routes usage), drivers' perception (familiar with multiple routes, traffic congestion, pre-trip and enroute diversion, and time pressure), and personal characteristics (driving experience, age, sex, and the degree of education) are important factors affecting different traffic information usage models.

B. Latent variables

In order to enhance the explanatory and predictive ability of the travel behavior model, researchers recently considered the latent variables concerning drivers' perceptions and attitudes into the model (Adler et al., 1994; Madanat et al., 1995; Abdel-Aty et al., 1997; Jou et al., 2003; Tong et al., 2004). Madanat et al. (1995) applied two latent variables (drivers' attitudes toward route diversion and their perceptions of the reliability of information) to the models to determine the factors that affected drivers' stated intentions to divert from their usual routes while encountering traffic congestion.

Jou et al. (2003) proposed a methodological framework to incorporate latent variables, such as attitudes and perception in structural equations model. With the estimated latent variables in the discrete choice model, both explanatory and predicting abilities are expected to satisfy up to a certain level. Tong et al. (2004) explored the personal variation in response to various information strategies supplied by in-vehicle information devices and extract each driver's individual characteristics into two latent variables identified as "attitude" and "cognition" towards in-vehicle information.

Koppelman and Pas (1980) analyzed the relationships among perceptions, feelings, preference, and choice as illustrated in Fig.2.1. Feelings about modes are investigated to determine whether psychological or perceptual factors other than evaluations of mode performance influence transportation preference and choice. Preference logit models are used to estimate the important weights that relate perceptions and feelings to preferences. The estimated important weights are used to compute a preference index of each individual for each mode. Multinomial logit choice models are used to estimate the influence of the preference index and a particular situational constraint (automobile availability) in determining choice behavior.

A central hypothesis shown in Fig.2.1 is that individuals choose among alternatives based on their perceptions of these alternatives rather than on objectively measured characteristics. That is, perceptions of modal attributes (system characteristics) serve as mediating variables between objective measures and preference. Because formulation of perceptions is influenced by both measured (age, income) and unmeasured (experience, psychological make-up) individual characteristics, as well as by modal attributes, perceptions of alternatives differ among individuals.

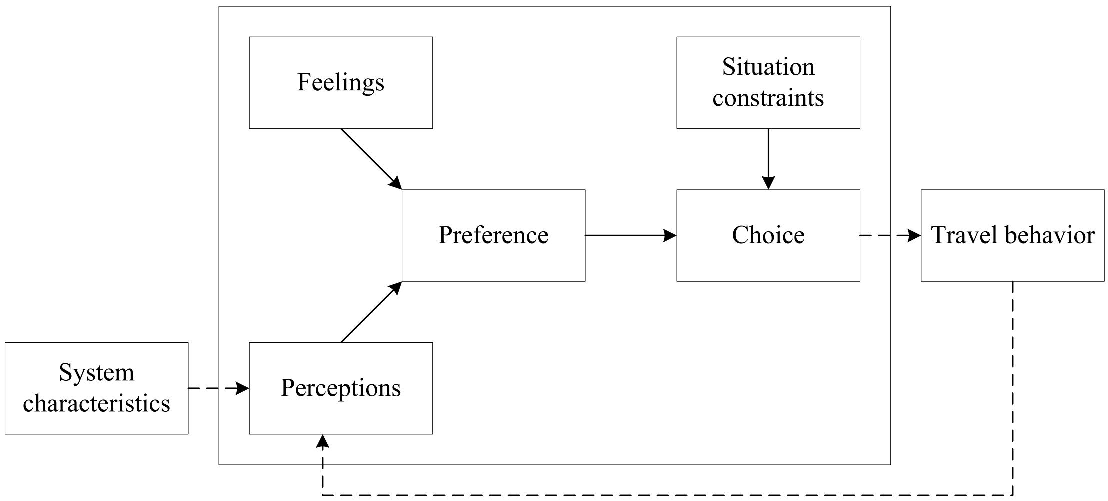


Fig.2.1 Model of modal choice behavior

According to the technology acceptable model (TAM) proposed by Davis (1993), a prospective user's overall attitude toward using a given system is hypothesized to be a major determinant of whether or not the user actually uses it. The proposed TAM is shown in Fig.2.2. Attitude toward using is a function of two beliefs, i.e. perceived usefulness and perceived ease of use. Perceived ease of use has a causal effect on perceived usefulness. System design features directly influence perceived usefulness and perceived ease of use while indirectly influence attitude toward using and actual usage behavior through their direct effect on perceived usefulness and perceived ease of use.

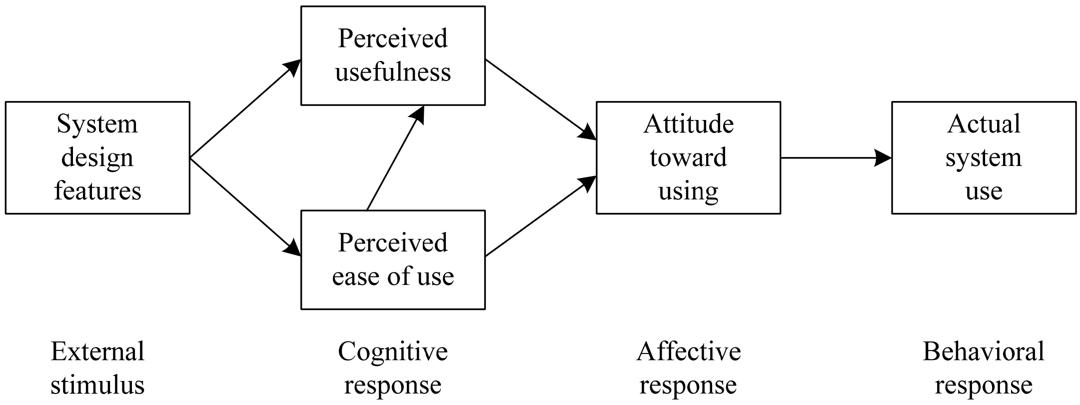


Fig.2.2 Technology acceptance model

Since drivers would not necessarily switch routes while receiving real-time traffic information, we suppose that it might be some negative restrictions impede drivers' enroute switching propensity. In the consumer behavioral research, switching barriers represent any factor, which makes it more difficult or costly for consumers in changing providers (Jones et al., 2000). Such three barriers in the context of consumer services, namely interpersonal relationships, perceived switching costs, and the attractiveness of competing alternatives. The switching barrier refers to the difficulty of switching to another provider that is encountered by a customer who is dissatisfied with the existing service, or to the financial, social and psychological burden felt by a customer when switching to a new carrier (Fornell, 1992). Therefore, the higher the switching barrier is, the more customers are forced to remain with their existing carriers (Kim et al., 2004).

2.2 Applications of Ordered Probit Model

Since some multinomial variables are inherently ordered, the ordered probit model (McKelvey and Zavoina, 1975) is used for analyzing such responses, which the ordinal nature of the dependent variable. The ordered probit model has been applied broadcast in the social behavioral researches recently. Many researches in transportation category also used the ordered probit model to explore travel behavior or evaluate managerial strategies.

Emmerink et al. (1996) analyzed the impact of both radio traffic information and variable message sign information on route choice behavior; the factors that influence route choice behavior are estimated by several types of discrete choice models (ordered probit, multiple logit, and bivariate ordered probit). The analysis showed that commuters tend to be less influenced by information than motorway users with other trip purposes Moreover, the level of satisfaction with alternative routes is strongly related to the type and distance of the alternative road. It also revealed that the impacts of radio traffic information and variable message sign information on route choice behavior are very similar, and that route choice adaptations based on radio traffic information are positively related to route choice adaptations based on variable message sign information.

Bhattacharjee et al. (1997) developed ordered probit models to evaluate commuters' attitudes toward different Transportation Demand Management (TDM) strategies in Bangkok, Thailand. Among four broad categories of suggested measures, public transportation improvement was found to be the most popular whereas fiscal restraint to be the least desirable approach. Of all the ten possible ways to reduce travel demand, introduction of rapid rail transit was voted as the most desirable approach whereas increasing parking fees in government offices was found to be the least welcome solution to the respondents. Ordered probit models revealed that commuters working in private companies and those who used cars to commute were less supportive of TDM measures.

Khattak (1999) applied the ordered probit model to examine the effect of information (accuracy of information conveyed by brake and turning lights) as well as other factors on rear-end crash propagation and the propensity of driver injury in such crashes. Results on injury severity showed that in a two-vehicle crash, the leading driver is more likely to be injured On the other hand, in a three-vehicle crash, the driver in the middle is likely to be more severely injured. Furthermore, as rear-end crashes propagate from two-vehicles to three-vehicles the last driver is relatively less severely injured.

Abdel-Aty (2001) studied the effect of advanced transit information systems on transit ridership by using ordered probit model. The study investigated whether advanced transit information would increase the acceptance of transit and determined which types and levels of information that are desired by commuters. The respondents had to determine their likelihood of choosing transit on a 10-point ordered scale; thus, the ordered probit model was used to estimate the likelihood of using transit given the availability of information. The results indicated a promising of potential of advanced trasit information in increasing the acceptance of transit as a commute mode. It also showed that the commuters seek several types of transit information, such as operating hours, frequency of service, fare, transfers, seat availability, and walking time to the transit stop.

Lan, Wen, and Chao (2001) used the ordered probit models to estimate the customers' acceptance of lower-deck seats for intercity bus evaluated by Likert five points. The results indicate that socio-economic characters, trip characters and previous experience with lower-deck seats are important factors affecting the lower deck seats acceptance. Lan, Wen, and Hsu (2001) analyzed the effect of different traffic information on intercity commuter route choice behavior. They developed the ordered probit model of the drivers' usage in the effectiveness of different traffic information (radio, television, internet, and telephone). The results indicate that trip characteristics, drivers' perception, personal characteristics, and the frequency of different traffic information usage are important factors affecting route choice models.

Kockelman and Kweon (2002) examined the risk of different driver injury levels sustained under all crash types (i.e. two-vehicle crashes and single-vehicle crashes) by using ordered probit models. The results suggested that pickups and sport utility vehicles were less safe than passenger cars under single-vehicle crash conditions. In two-vehicle crashes, these vehicle types are associated with less severe injuries for their drivers and more severe injuries for occupants of their collision partners. It also indicated that males and younger drivers in newer vehicles at lower speeds sustain less severe injuries.

Abdel-Aty (2003) analyzed driver injury severity levels by using the ordered probit modeling methodology. Models were developed for roadway sections, signalized intersections, and toll plazas in Central Florida. All models showed the significance of drivers' age, gender, seat belt use, point of impact, speed, and vehicle type on the injury severity level. Drivers' violation was significant in the case of signalized intersections. Alcohol, lighting conditions, and the existence of a horizontal curve affected the likelihood of injuries in the roadway sections' model. A variable specific to toll plazas, vehicles equipped with Electronic Toll Collection (ETC), had a positive effect on the probability of higher injury severity at toll plazas. This study illustrates the similarities and the differences in those factors which that affect injury severity among different locations.

De Palma and Picard (2005) applied the ordered probit model to explore the users' route choice behavior when travel time is uncertain. They analyzed which factors influence users' attitudes toward risk adversity in the Paris area. The results highlighted the impact of key socio-economics factors (gender, employment status, purpose of the trip, etc.) which explain the level of risk aversion. Jou, Liu, and Lien

(2006) applied ordered probit models to investigate users' propensities of acceptance on HOV lanes along the Sun Yat-Sen Freeway in Taiwan. Three incentive alternatives were examined their effects on users' propensities of acceptance on HOV lanes.

2.3 Conclusion Remarks

In order to understand the effects of real-time traffic information more deeply, this study further explores the significant determinants that may affect the enroute switching intention of drivers. Like other researchers, this study incorporates the latent variable into behavioral models presenting drivers' points of view to information they receive. For the complete consideration of the explanatory latent variables which affect on enroute switching intention of drivers, this study puts both positive (such as drivers' perceptions and attitude toward traffic information and diversion) and negative variables (such as switching barriers and congestion tolerability) in the models.

Referring to the consumer behavioral research, this study considers the switching barrier (Jones, 2000) variable in the switching intention model to explain its negative impact. For example, drivers may feel troublesome for searching alternative routes information or concern for uncertainty situation of alternative routes. Besides, drivers often tolerate the low speed and long queue while encountering traffic congestion on freeway due to their inherent patience and unadventurous. These negative concerns lead drivers always remain with their existing driving routes. Thus, the negative latent variables switching barrier (Jones, 2000; Feng and Kuo, 2007) and congestion tolerability will be incorporated into the behavioral model. Various hypothetic information scenarios will also approve their effects on drivers' switching decisions using ordered probit model.

CHAPTER 3 ANALYSIS FRAMEWORK AND METHODOLOGY

3.1 Analysis Framework

In order to explore the effects of real-time traffic information on drivers' enroute switching behavior, this study proposes a two-stage analysis framework (Fig.3.1). Since discrete choice model is unable to measure the latent variables, structural equation model would be applied to offer a feasible solution for extracting latent variables in this behavioral research. However, the effects of explanatory variables on drivers' enroute switching behavior should be discussed further by using discrete choice model.

Firstly, we shall extract which significant latent variables may influence drivers' enroute switching intentions by using the structural equation modeling process. This process contributes to realize drivers' real perceptions and attitudes toward the revealed traffic information and enroute switching behavior. The latent variables are supposed to comprise drivers' perceived value, usage attitude, switching barrier, and congestion tolerability, which may have positively or negatively influence their enroute switching intention, respectively. We shall then explore the causal effects between these latent variables. For realizing the causal relationship with considering drivers' background (i.e. drivers' socioeconomic and travel characteristics), we will proceed with several multi-group path analysis in this process.

Then, we should confirm whether or not latent variables and various scenarios of real-time traffic information would affect drivers' stated enroute switching behavior. These latent variables are transferred into explanatory variables for drivers' enroute switching behavior model. Latent variables will be taken as input data into the following ordered probit model. When drivers encounter different congestion conditions, their enroute switching decisions may be influenced by latent variables, socioeconomic and travel characteristics under various information scenarios.

It should be taken notices that stage I discusses drivers' experimental enroute switching intention toward the provided traffic information at present, yet stage II anticipates drivers' enroute switching behavior while receiving stated traffic information. The two-stage research models and hypotheses are described in the following sections respectively.

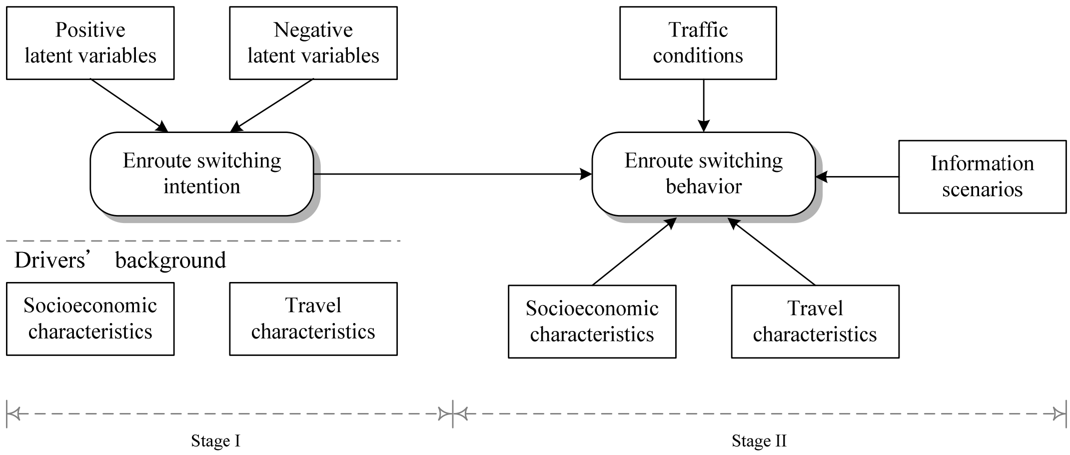


Fig.3.1 Two-stage analysis framework

3.2 Research Model and Hypothesis

A. Switching Intention Model

Based on all findings of previous studies, this study summarizes significant variables which may affect enroute switching intention of drivers. It mainly focuses on exploring the causal relationship between positive/negative latent variables and the enroute switching intention. Several causal relationships could be confirmed by literature reviews as listed in Table 2.1, such as "perceived value → usage attitude → behavioral intention", "perceived value → behavioral intention", "switching barrier → behavioral intention", and "congestion tolerability → behavioral intention".

Thus, five hypotheses associated with the research questions are proposed. The hypothesized relationships between these latent variables and the enroute switching intention are shown in Fig.3.2. The latent variables are supposed to comprise drivers' perceived value, usage attitude, switching barrier, and congestion tolerability have positively or negative influence on enroute switching intention, respectively. The five hypotheses of causal relationship are particularly described as follows:

H₁: Drivers' perceived value of received information has a positive impact on their usage attitude.

H₂: Drivers' perceived value of received information has a positive impact on their enroute switching intention.

H₃: Drivers' usage attitude toward real-time traffic information has a positive impact on their enroute switching intention.

H₄: Drivers' enroute switching barrier has a negative impact on their enroute switching intention.

H₅: Drivers' congestion tolerability has a negative impact on their enroute switching intention.

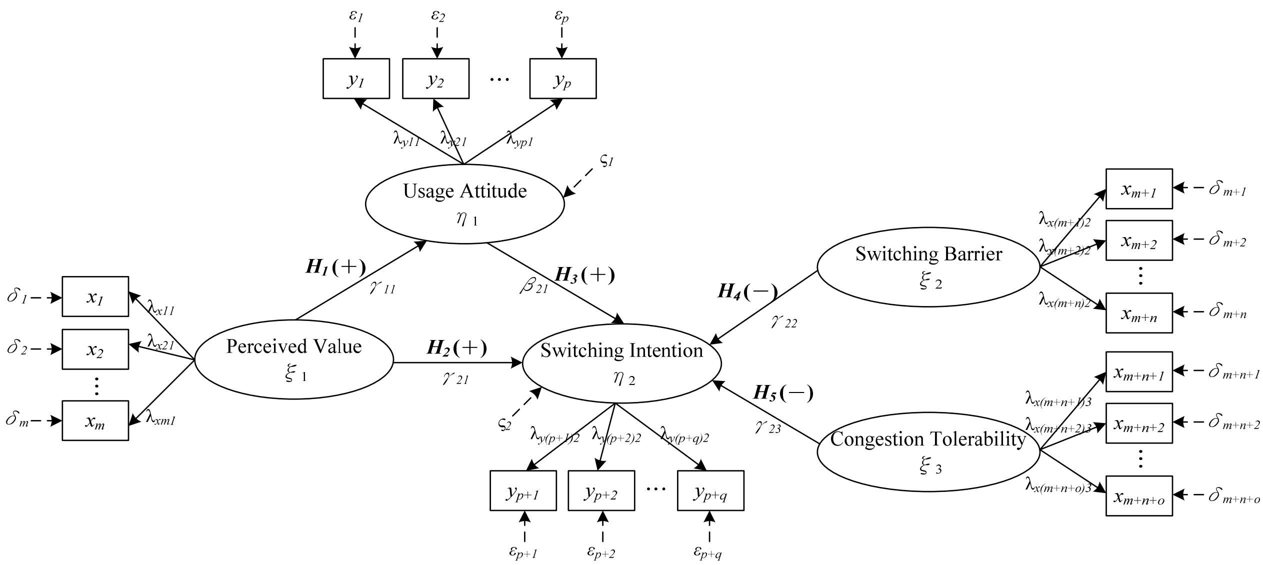


Fig.3.2 Causal relationships and hypotheses of switching intention model

The definitions of parameters in this model are listed in Table 3.1. Three exogenous and two endogenous latent variables are included in this model.

Table 3.1 Definitions of parameters in switching intention model

Parameter	Definition
ξ	Exogenous latent variables
η	Endogenous latent variables
x	Observed variables of ξ
y	Observed variables of η
γ	Coefficient between exogenous and endogenous variables
λ	Coefficient between latent variables and observed variables
δ	Measurement error of x
ε	Measurement error of y
ζ	Disturbance

B. Switching Behavior Model

While these latent variables are proved to have significant effects in switching intention model, they would be considered into the following switching behavior model in favor of enhancing the explanatory ability of behavior model. In addition, socioeconomic and travel characteristics may also influence drivers' enroute switching behavior through findings of literatures review. Therefore, the research model of switching behavior is shown in Fig.3.3.

In the switching behavior model, the explanatory variables are proposed to include positive/negative latent variables (such as perceived value, usage attitude, switching barrier, and congestion tolerability), socioeconomic characteristics (such as gender, age, level of education, personal income, driving experience, and familiarity with alternative routes), travel characteristics (like trip purpose), traffic condition (depending on driving speed in traffic-jam, includes non-accident congestion and accident congestion), and types of real-time traffic information.

Respecting the benefit of real-time traffic information on drivers' enroute switching behavior, the improvement of traffic information contents is focusing on accuracy and details. On the other hand, the traffic information is assumed to be updated immediately. Thus, this study would try to explore the drivers' reaction toward the several types of traffic information. Moreover, the driving speed represents the different severity scenario of traffic congestion in the switching behavior model. In this research stage, whether or not these explanatory variables have significant effects on drivers' enroute switching behavior and their causal relationships would be confirmed.

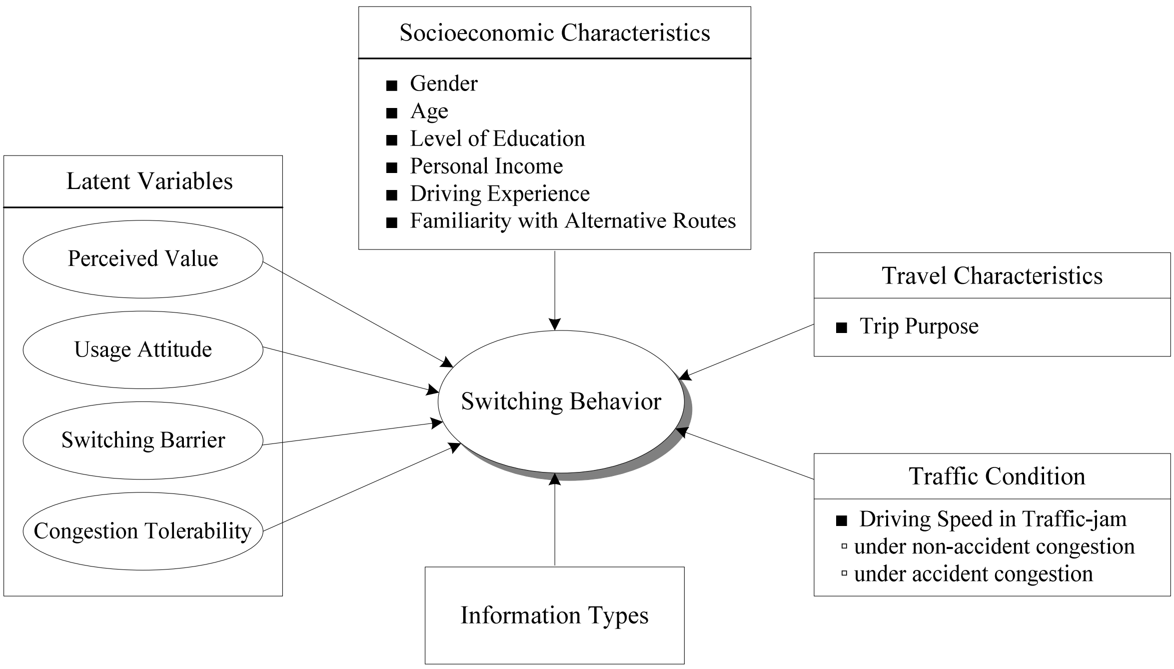


Fig.3.3 Research framework of switching behavior model

3.3 Research Methodology

The data used in this study were collected through a questionnaire survey of drivers and the information scenarios were designed using the stated preference method. The structure of the research methodology and data flow is illustrated in Fig.3.4. Three categories of data included drivers' perceptions and attitudes toward revealed traffic information, socioeconomic and travel characteristics, and stated switching behavior under various information scenarios. Then the data applied in three principal methodologies: the exploratory factor analysis, structural equation model and ordered probit model.

Through the methods of the exploratory factor analysis and structural equation model, the manifest variables of drivers' perceptions and attitudes can be transferred into latent variables as the input variables into ordered probit model. In addition to the latent variables, stated switching behavior, socioeconomic and travel characteristics are also entered into the ordered probit model as explanatory variables. Finally, drivers' enroute switching behavior model on the freeway would be estimated.

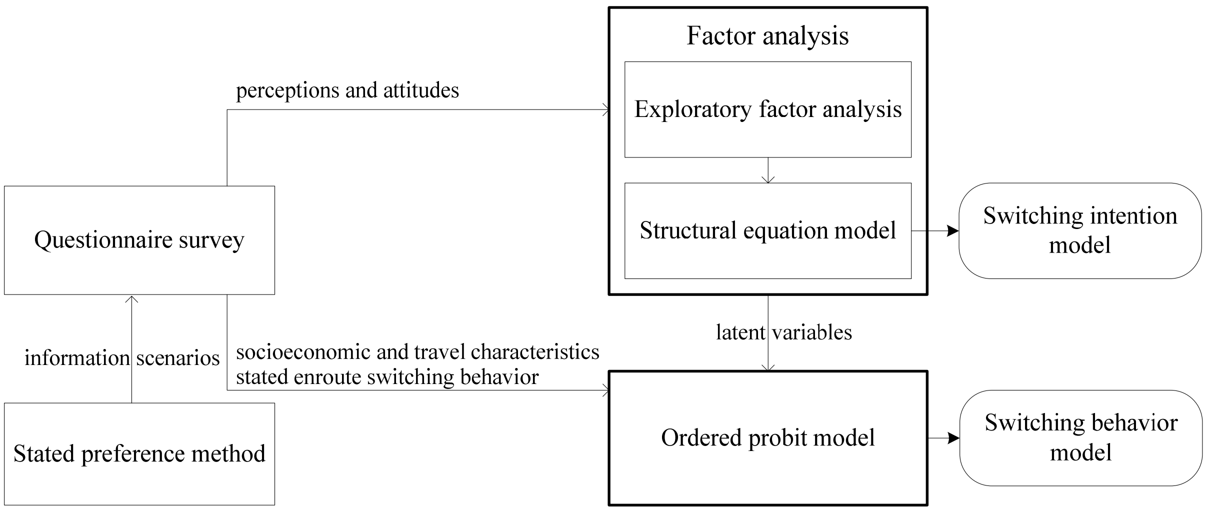


Fig.3.4 Research methodology and data flow

A. Exploratory factor analysis

In order to explore the main factors about drivers' perception or attitude toward real-time traffic information that influence drivers' enroute switching intention, factor analysis approach is used first. Factor analysis is conducted to better realize latent variables underlying the reason that real-time information might affect the drivers' enroute switching intention. These principal factors are extracted and transfer into explanatory variables for drivers' enroute switching intention model. Latent variables will be taken as the input data to the following ordered probit model.

When the factors are inter-correlated and an underlying factor structure is hypothesized, it is preferred to use the principal components analysis. Principal components analysis can reduce a relatively large multivariate data set and to interpret data (Johnson and Wichern, 1992). The method is suitable for variables measured on the interval and ratio scales (Washington et al., 2003). The results of analysis are obtained from the pattern matrix via using a factor rotation method.

Some criteria are used to select the principal factors and which are: (1) eigenvalues greater than 1 and accounting for 3% or more of the explained variance, (2) the item loadings greater than 0.32, (3) the magnitude and number of the item loadings with other factors, and (4) the meaningful concept of the factors (Steven, 1992; Tabachnik and Fidell, 1996). This analysis can be completed using SPSS software.

B. Structure equation model

The latent variables are analyzed by using the SEM method and LISERAL 8.2 software in this study. The structure equation model consists of the measurement model and the structural model. The measurement model defines the relationship between the observed (manifest variables) and unobserved variables (latent variables) that influence the enroute switching intention. The structural model specifies the relationship between these latent variables. The general SEM equations can be expressed as follows:

The measurement model for the x-variables: $$x = \Lambda_x \xi + \delta \tag{1}$$

The measurement model for the y-variables: $$y = \Lambda_y \eta + \varepsilon \tag{2}$$

The structural model: $$\eta = B\eta + \Gamma\xi + \zeta \tag{3}$$

where

x = the vector of observed exogenous variables;

y = the vector of observed endogenous variables;

ξ = the vector of exogenous latent variables;

η = the vector of endogenous latent variables;

Λ_x = the regression matrix that relates exogenous variables ξ to each of the observed exogenous variables;

Λ_y = the regression matrix that relates endogenous variables η to each of the observed endogenous variables;

δ = the vector of error terms corresponding to x;

ε = the vector of error terms corresponding to y;

ζ = the vector of residuals representing errors and random disturbance terms;

B = the matrix of coefficients that relates η variables to another one;

Γ = the matrix of coefficients that relates ξ variables to η variables.

The x variables are regarded as the indicators for the explanatory latent variables ξ and the y variables are regarded as the indicators for the dependent latent variables η. The elements of B represent the direct causal effects of η variables on another one; the elements of Γ represent the direct causal effects of ξ variables on η variables. ε is assumed to be uncorrelated with η. δ and ζ are assumed to be uncorrelated with ξ.

C. Ordered Probit Model

Regarding drivers' enroute switching behavior under different information scenarios, we should construct the models to interpret their behavioral reactions. The drivers' stated response on enroute switching is of degrees rather than just "yes" or "no". Hence, while the dependent variable is discrete and with order, it would be more appropriate to use the ordered probit model than multinomial logit model or other regression models.

It would be inappropriate to use the multinomial logit because this model does not account for the ordering of the dependent variable. Further, a regression model would not be appropriate because it assumes difference between categories of the dependent variable to be equal, whereas, the data are only ordinal. The ordered probit model provides the thresholds which would indicate the levels of inclination toward switching routes, so there are no arbitrary assumptions about the magnitudes of differences between categories of the dependent variable. Thus, we choose the ordered probit to construct drivers enroute switching behavior model in this study. This model can be performed by using LIMDEP 7.0 software.

The ordered probit model was developed by McKelvey and Zavoina (1975), which is always used for the discrete-valued dependent variable taking more than two values and natural ordering. Researchers often treat ordinal dependent variables as if they were interval. In principle, the decision of respondents in the ordered probit model does not follow the rule of utility maximization. Likert scales on surveys ask respondents whether they strongly agree, agree, have no opinion, disagree, or strongly disagree with a statement (Long, 1997).

In modeling, we assume the willingness to switch route -- y_i^* is the unobserved variable (latent variable) and y_i^* is expressed as:

$$y_i^* = \beta x_i + \varepsilon ,$$

where y^* is the dependent variable coded as 0, 1, 2,…, J, β is the vector of coefficients, x_i is the vector of independent variables, and ε is the error term, normally distributed with mean 0 and variance 1.

The dependent variable is observed as the likelihood to route switching as follows:

$$y = 0 \ \text{ if } \ y^* \le 0,$$

$$y = 1 \ \text{ if } \ 0 \le y^* \le \mu_1,$$

$$y = 2 \ \text{ if } \ \mu_1 \le y^* \le \mu_2,$$

$$\vdots$$

$$y = J \ \text{ if } \ \mu_{J-1} \le y^*.$$

where the threshold values μ are the unknown parameters to be estimated with β, assuming that ε is normal.

The following probabilities result from the normal distribution:

$$\Pr\text{ob}[y = 0] = \Phi(-\beta x)$$

$$\Pr\text{ob}[y = 1] = \Phi(\mu_1 - \beta x) - \Phi(-\beta x)$$

$$\Pr\text{ob}[y = 2] = \Phi(\mu_2 - \beta x) - \Phi(\mu_1 - \beta x)$$

$$\vdots$$

$$\Pr\text{ob}[y = J] = 1 - \Phi(\mu_{J-1} - \beta x)$$

Hence, the Probability function is written as

$$\Pr\text{ob}[y_i = j] = \Phi(\mu_j - \beta x_i) - \Phi(\mu_{j-1} - \beta x_i), j = 0,1,\ldots J,$$

where Φ is the cumulative standard normal distribution function.

The log likelihood function is the sum of individual log probabilities specifically as

$$L = \sum_{j=1}^{J} \sum_{y=j} \log(\Phi(\mu_j - \beta x_i) - \Phi(\mu_1 - \beta x_i)).$$

The ordered probit model includes two sets of parameters. The constant and other threshold parameters indicate the range of normal distribution associated with specific values of explanatory variables. The remaining parameters represent the effect of changes in each explanatory variable on the underlying scale. These parameters indicate the relative importance of each variable in determining the likelihood to switch routes.

CHAPTER 4 QUESTIONNAIRE SURVEY AND RESULTS

4.1 Questionnaire Design and Survey

A. Information Medium

To develop a better understanding of drivers' enroute switching behavior in considering positive/negative latent variables and traffic information scenarios in the models, a questionnaire survey was conducted. The survey was based on those data collected from an on-line questionnaire and interview survey in Taipei metropolitan area in Taiwan with the objectives to analyze the behavioral impacts of real-time traffic information. Since more than 82% drivers choose the radio traffic reports (RTRs) as the channel to access real-time traffic information in Taiwan (Jou, 2005), we suppose respondents received real-time information content via RTRs in this survey.

B. Questionnaire Structure

The questionnaire consists of three parts: the socioeconomic and travel characteristics of drivers, perceptions and attitudes toward received real-time traffic information, and stated enroute switching behavior under various scenarios of real-time traffic information. The latent variables and observed variables in structural equation model of this study are summarized in Table 4.1. These observed variables that are derived from the literatures review in Chapter 2 and exploratory factor analysis (EFA) process in Section 4.3. Five constructs (latent variables) and 13 items (observed variables) are hypothesized in the proposed structural equation model.

Table 4.1 Latent variables and observed variables

Latent variable	Observed variable	Representation
Perceived value ξ_1	x_1	The traffic information content describes in detail.
	x_2	The traffic information content can update real-time.
	x_3	The traffic information content is helpful to predict travel time.
	x_4	The traffic information content can express the guidance of alternative routes definitely.
Switching barrier ξ_2	x_5	I feel troublesome to search for alternative routes information.
	x_6	Switching to alternative routes will waste time instead.
Congestion tolerability ξ_3	x_7	I can tolerate the low speed while encountering traffic jam.
	x_8	I can tolerate the long queue while encountering traffic jam.
Usage attitude η_1	y_1	To receive real-time information is very important while driving on freeway.
	y_2	As long as driving on freeway, I must receive real-time information.
	y_3	While encountering in traffic jam, I want to receive real-time information.
Switching intention η_2	y_4	I often switch routes while receiving congestion information ahead.
	y_5	I often switch routes while receiving route-switching suggestion.

The latent variable perceived value of real-time traffic information is measured through four indicators ($x_1 \sim x_4$): detailed description, real-time update, helpful to predict travel time, and express the guidance of alternative routes definitely. And the variable switching barrier is described by two indicators: feel troublesome to search for alternative routes information and switching to alternative routes is time-wasting. Another two indicators show drivers' tolerance toward low speed and long queue while encountering traffic jam.

The latent variable usage attitude comprises three indicators that representing the importance of receiving real-time traffic information to the driver: receiving real-time information is very important, must receive real-time information, and want to receive real-time information while driving on freeway. In the case of the latent variable switching intention, it can be measured through two indicators that represent the driver who often switches routes while receiving congestion information ahead or receiving route-switching suggestion.

C. Scenario Design

To identify commuting characteristics, a stated trip purpose of working and the commuting network were assumed under the given information scenarios. The hypothetical commuting network provided for stated enroute switching behavior is shown in Fig.4.1. The respondents were assumed to ride a car on the regular route from the origin location to the destination location and receive real-time information contents via radio traffic reports (RTRs).

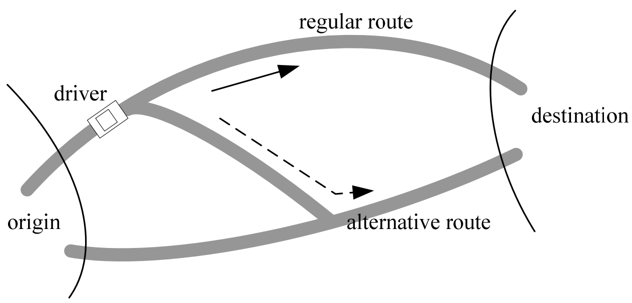


Fig.4.1 Hypothetical commuting network for switching

Since the respondent would prefer to switch seemingly based on the congestion severity, we hypothesize some worse situations for switching in this questionnaire. To prevent too many hypothetical congestion situations would lead respondents confused and undistinguishable, we assumed that respondents would encounter two hypothetical traffic conditions (compared in Table 4.2) when they are driving on the regular route. The congestion severity could be distinguished by travel speed and corresponding travel time.

The *Congestion I* of the regular route is recurrent congestion, without accident, 30~40 km/hr travel speed and spend 40 minutes travel time. The *Congestion II* is worse than *Congestion I*, and it is non-recurrent congestion, with accident, 10~20 km/hr travel speed, 60 minutes travel time. Both of the two hypothetical traffic conditions about the alternative route is no congestion, without accident, 70~80 km/hr travel speed and 20 min travel time.

Table 4.2 Comparison with two hypothetical congestion situations

Route	Characteristics	*Congestion I*	*Congestion II*
Regular route	Congestion type	Recurrent congestion	Non-recurrent congestion
	Accident	Without accident	With accident
	Travel speed	30~40 km/hr	10~20 km/hr
	Travel time	40 min	60 min
Alternative route		No congestion, without accident, 70~80 km/hr travel speed, 20 min travel time	

While receiving five hypothetical information scenarios as listed in Table 4.3, drivers should make decisions to switch to the alternative route or not. The content of information *Scenario0* is relatively rough and which only broadcasts the information of travel speed concerning the regular route. Then, more information richness on the regular and alternative route is gradually provided from *Scenario0* to *Scenario4*. Thus, the content of information *Scenario4* is the most detailed, providing travel speed and travel time both on the regular and suggested alternative route.

Table 4.3 Five hypothetical information scenarios

Information scenario	Information contents on the regular route	Information contents on the alternative route
Scenario 0	Travel speed	—
Scenario 1	Travel speed and travel time	—
Scenario 2	Travel speed	Switching suggestion
Scenario 3	Travel speed	Switching suggestion and travel speed
Scenario 4	Travel speed and travel time	Switching suggestion, travel speed and travel time

Respondents had to determine their likelihood of perceptions and attitudes toward the traffic information they had received on a five-point ordered scale. The responses relate to perceptions and attitudes were rated on a five-point Likert scale with a positive statement and classified to five degrees as "strongly disagree", "disagree", "neutral", "agree", and "strongly agree". Using 1-5 scale with 1 being strongly disagree and 5 being strongly agree, they were asked about their experiences of revealed traffic information.

According to the drivers' enroute switching behavior under five hypothetical information scenarios, a stated preference (SP) choice set was presented to respondents who should decide whether they would switch to the alternative route or not on ordered choice. The responses of switching tendency were also rated on a five-point Likert scale with a positive statement and classified to five degrees as "strongly unlikely", "unlikely", "undecided", "likely", and "strongly likely". Using 1-5 scale with 1 being strongly unlikely and 5 being strongly likely, they were asked about their likelihood of switching to the alternative route.

A pilot survey was implemented to revise the ambiguous and abstruse items in the questionnaire as well as delete the improper and similar items to prevent too many items. The whole completed questionnaire is attached in the appendix.

D. Sampling Methods

Since the population of drivers on freeway is unknown, we may use nonprobability sampling procedures in this study. While probability sampling may be superior in theory, there are breakdowns in its application. The ideal probability sampling may be only partially achieved because of the human element. Therefore, it is also possible that nonprobability sampling may be the only feasible alternative. The total population may not be available for study in certain cases. At the scene of major event, it may be infeasible to even attempt to construct a probability sample (Cooper et al., 2003).

We use nonprobability sampling procedures because they satisfactorily meet the sampling objectives. While a random sample will give us a true cross section of the population, this may not be the objective of the research. If there is no desire or need to generalize to a population parameter, then there is much less concern about whether the sample fully reflects the population. Additional reasons for choosing nonprobability over probability sampling are cost and time. Probability sampling clearly calls for more planning and repeated callbacks to ensure that each selected sample member is contacted. These activities are expensive. Carefully controlled nonprobability sampling often seems to give acceptable results, so the investigator may not even consider probability sampling.

Two methods, convenience and purposive sampling, of nonprobability sampling are used in this study. Nonprobability samples that are unrestricted are called convenience samples, which researchers have the freedom to choose whomever they find such as friends and neighborhoods. While a convenience sample has no controls to ensure precision, it may still be a useful procedure.

A nonprobability sample that conforms to certain criteria is called purposive sampling, which includes two major types--judgment sampling and quota sampling. In order to improve representativeness of samples, we use quota sampling to collect data. The logic behind quota sampling is that certain relevant characteristics describe the dimensions of the population. If a sample has the same distribution on these characteristics, then it is likely to be representative of the population regarding other variables on which we have no control. In most quota sampling, researchers specify more than on control dimension. Some controls would be used in this survey, such as gender, level of education, and age.

4.2 Descriptive Statistics

A. Statistical summary

A total of 493 valid questionnaires were returned during August, 2005. The survey characteristics are given in Table 4.4. More than sixty percent of the respondents are males (64.3%), between the ages of 18 and 44 (58.6%), half of the respondents are college and graduate school (47.3%) educational level, and most, personal incomes are between 20~60 thousands per month (70.2%). Nearly half of the respondents are having at least 10 years driving experience. The percentage of trip purposes are working (31.0%), business (21.9%), social (24.9%), and recreational (22.1%) respectively.

Table 4.4 Characteristics distributions of respondents

Characteristics	Samples	Distribution (%)
Gender		
male	317	64.3
female	176	35.7
Age		
18 ~ 24 years old	28	5.7
25 ~ 34 years old	128	26.0
35 ~ 44 years old	133	27.0
45 ~ 54 years old	114	23.1
55 ~ 64 years old	56	11.4
> 65 years old	34	6.9
Level of education		
high-school	260	52.7
college	159	32.3
graduate school	74	15.0
Monthly income		
< NT$ 20 thousands	50	10.1
NT$ 20 ~ 40 thousands	165	33.5
NT$ 40 ~ 60 thousands	181	36.7
NT$ 60 ~ 80 thousands	59	12.0
> NT$ 80 thousands	38	7.7
Years of driving		
< 1 year	22	4.5
1 ~ 3 years	43	8.7
4 ~ 6 years	51	10.3
7 ~ 9 years	89	18.1
> 10 years	288	58.4
Trip purpose		
working	153	31.0
business	108	21.9
social	123	24.9
recreational	109	22.1

B. Switching Response

The percentage of the responses toward respondents' stated enroute switching behavior with five information scenarios under two congestion situations are shown in Table 4.5. It revealed that providing more detailed information to drivers would induce more diversion probabilities. While providing more information richness both on regular and alternative routes (i.e. *Scenario2~Scenario4*), the respondents would more likely to switch to the alternative route. Besides, comparing with two congestion situations, the more traffic congestion is, the more probabilities they would switch to alternative routes. Therefore the percentage of the respondents that would likely to switch route in *Congestion II* is consequently larger than *Congestion I*.

Table 4.5 Percentage of switching response

Congestion situation	Information scenario	strongly unlikely	unlikely	undecided	likely	strongly likely
Congestion I	*Scenario 0*	7.30%	35.90%	16.84%	28.60%	11.36%
	Scenario 1	5.68%	28.40%	19.27%	31.24%	15.42%
	Scenario 2	6.49%	17.04%	17.04%	39.15%	20.28%
	Scenario 3	5.07%	12.98%	14.60%	34.69%	32.66%
	Scenario 4	5.07%	10.75%	12.37%	23.94%	47.87%
Congestion II	*Scenario 0*	4.06%	15.42%	16.63%	35.09%	28.80%
	Scenario 1	3.65 %	15.62%	18.86%	33.87%	27.99%
	Scenario 2	3.25 %	10.75%	22.31%	29.61%	34.08%
	Scenario 3	4.06 %	8.92%	10.75%	35.29%	40.97%
	Scenario 4	4.26 %	10.75%	7.10%	31.03%	46.86%

In *Congestion I* (see Fig. 4.2), more than half of the respondents expressed their willingness to switch routes when they received information *Scenario2~Scenario4*. Even more than 70 percent of the respondents indicated their propensities of diversion while receiving information *Scenario4*. Due to the traffic situation in *Congestion II* is worse than *Congestion I*, more than 60 percent of the respondents would likely switch to the alternative route during all information scenarios (see Fig. 4.3). Only if the respondents receiving information *Scenario2~Scenario4*, more than 70 percent of the respondents represented the diversion propensity. For information *Scenario4*, nearly 80 percent of the respondents would likely switching to the alternative route.

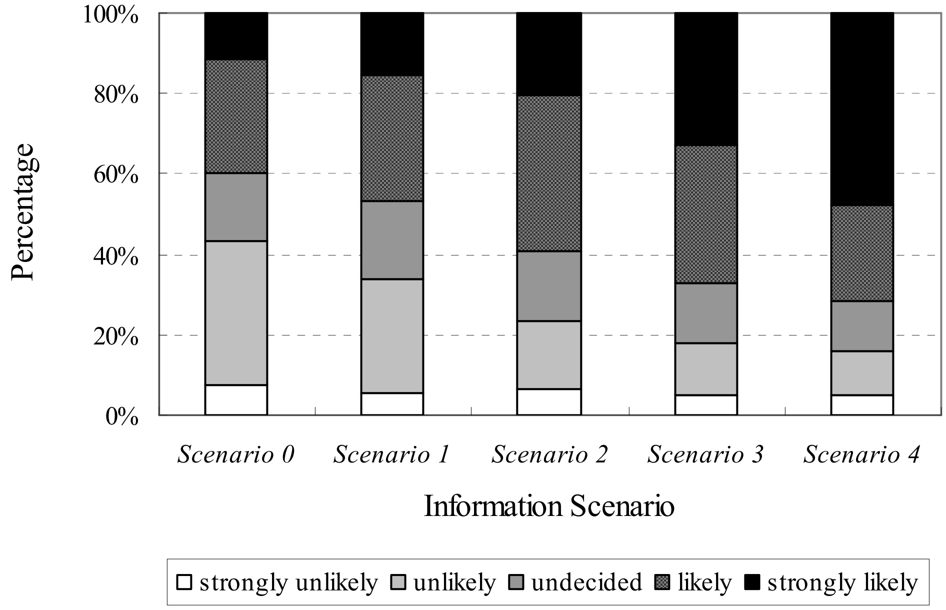


Fig.4.2 Percentage of switching with five scenarios under *Congestion I*

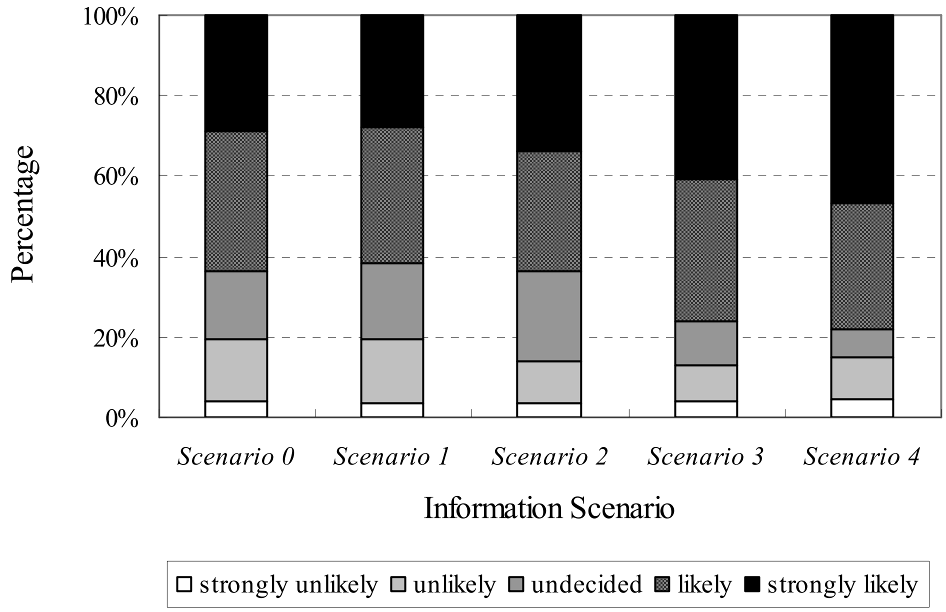


Fig.4.3 Percentage of switching with five scenarios under *Congestion II*

C. Multi-group Analysis

In order to realize the difference in mean of respondents' switching response among diverse samples, we proceed with multi-group analysis by gender, age, educational background, monthly income, driving-experience, and trip-purpose of respondents. The results of multi-group analysis are summarized in Table 4.6, which show the statistical comparison with five information scenarios under two congestion situations at 0.05 significant levels.

In accordance with testing results, there is no significant different between female and male group on their switching response while receiving various information scenarios. Among different age groups, behavioral responses apparently reveal divergence especially in a worse congestion situation. While receiving more detailed information contents, it shows significant difference in switching response among multi-educational groups.

Table 4.6 Multi-group analysis

Scenario / Multi-group	*Congestion I*					*Congestion II*				
	Scenario0	*Scenario1*	*Scenario2*	*Scenario3*	*Scenario4*	*Scenario0*	*Scenario1*	*Scenario2*	*Scenario3*	*Scenario4*
Gender [a]	-0.34	-0.84	-0.72	-0.41	-0.01	0.30	0.61	0.35	0.26	0.49
age [b]	1.34	1.95*	1.67	2.48*	4.42*	5.77*	4.73*	5.35*	5.57*	5.93*
educational background [b]	1.81	1.71	3.70*	6.02*	11.06*	1.98	11.98*	13.22*	13.12*	21.44*
monthly income [b]	1.36	1.01	1.84	1.91	3.91*	3.44*	4.40*	4.38*	6.21*	6.89*
driving-experience [b]	2.62*	2.57*	3.93*	1.49	7.07*	1.38	1.52	1.14	0.86	2.00
trip purpose [b]	1.29	4.86*	3.44*	4.99*	6.69*	3.41*	5.09*	3.67	4.01*	3.09*

[a] indicates *t* test
[b] indicates *F* test
* denotes a significant value ($p<0.05$)

The switching willingness of multi-income groups has greatly distinction only in *CongestionII*. In the case of different driving experiences, there is definite evidence in respondents' switching behavior under *CongestionI* situation. However, various trip purposes showing their variations in providing mostly of information contents. We can conclude that the divergence of switching response among multi-group roughly occur in a worse congestion situation or receiving more detailed information contents.

4.3 Exploratory Factor Analysis

Four latent variables concerning drivers' switching intention were extracted by the processing of principal factor analysis and the results were summarized in Table 4.7. Each rotated factor was composed of measurement variables to be considered with factor loadings ≥0.45. Based on the minimum factor loading criterion and order of extraction, four factors were extracted. Factor I represented the construct of perceived value and was composed of four measurement variables $x_1 \sim x_4$. Factor II was appeared to measure the construct of switching barrier and was made up of x_5 and x_6. Factor III was measured the construct of congestion tolerability and was including x_7 and x_8. Factor IV, which was labeled as the usage attitude, consisted of three measurement variables $y_1 \sim y_3$. Finally, Factor V emerged two measurement variables y_4 and y_5 as the construct of switching intention.

The value of Cronbach's alpha was calculated for the scale items to ensure the internal consistency. The reliability of each construct was assessed by using Cronbach's alpha lager than 0.6 (Hatcher, 1998; Chen, 1998) or 0.7 (Nunnally, 1978), which is the recommended level in exploratory research. In this survey, the values of Cronbach's alpha ranged from 0.613 to 0.799 that indicating the scales are internally consistent and reasonably free of measurement error. The factor (i.e. latent variables) would be consequently taken as explanatory variables, and then incorporated into the switching intention model.

Table 4.7 Exploratory factor analysis results

Factor	Measurement variable	Factor loadings	Cronbach's alpha if item deleted	Cronbach's alpha
Factor I Perceived value	x_1	0.815	0.724	0.775
	x_2	0.841	0.732	
	x_3	0.758	0.745	
	x_4	0.694	0.781	
Factor II Switching barrier	x_5	0.875	0.640	0.779
	x_6	0.828	0.636	
Factor III Congestion tolerability	x_7	0.796	0.627	0.738
	x_8	0.864	0.619	
Factor IV Usage attitude	y_1	0.796	0.653	0.613
	y_2	0.805	0.653	
	y_3	0.826	0.762	
Factor V Switching intention	y_4	0.794	0.726	0.799
	y_5	0.881	0.714	

CHAPTER 5 STRUCTURAL EQUATION MODELING AND ESTIMATING

5.1 SEM Analysis and Results

The conceptual model of SEM shown in Fig.3.2 is used for exploring the relationships between perceived value, usage attitude, switching barrier, congestion tolerability, and switching intention. SEM is a multivariate technique which combines confirmatory factor analysis modeling and path analysis modeling. The primary objective of SEM is to explain the pattern of inter-related dependence relationships simultaneously between a set of latent constructs (unobserved variables), each measured by one or more manifest variables (observed variables). Thus, the simultaneous estimation of: (1) a measurement model can be obtained that items in each scale to the construct represented, giving factor loadings for each item; (2) a structural model that related constructs to one another, providing parameter value. The SEM model represents a series of hypotheses, and how the variables are related.

A confirmatory factor analysis and path analysis for the causal relationships which defined by hypotheses H_1~H_5 are performed by using the LISREL 8.2 software. To estimate the model, the "Generalized Least Squares (GLS)" method is selected because it typically provides valid parameter estimates (Joreskog and Sorbom, 1993). Two exogenous constructs dealing with usage attitude and switching intention and three endogenous constructs including the variables of perceived value, switching barrier and congestion tolerability are analyzed with structural equation modeling procedures. The means, standard deviations and covariance matrix of the manifest variables are listed in Table 5.1.

Table 5.1 Covariance matrix for the SEM

	Mean	Std.	y_1	y_2	y_3	y_4	y_5	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8
y_1	3.90	0.85	0.728												
y_2	3.56	1.00	0.568	1.003											
y_3	4.20	0.87	0.361	0.398	0.762										
y_4	3.23	1.00	0.305	0.341	0.127	1.000									
y_5	3.15	0.96	0.273	0.325	0.148	0.720	0.930								
x_1	3.19	0.80	0.204	0.198	0.133	0.108	0.061	0.636							
x_2	3.16	0.81	0.169	0.169	0.118	0.096	0.063	0.466	0.657						
x_3	3.53	0.90	0.330	0.392	0.238	0.304	0.270	0.270	0.312	0.814					
x_4	3.00	0.94	0.162	0.159	0.003	0.155	0.194	0.391	0.360	0.295	0.878				
x_5	3.27	1.07	-0.028	-0.078	0.053	-0.208	-0.176	0.109	0.090	-0.081	0.017	1.150			
x_6	3.09	1.05	-0.091	-0.127	0.066	-0.296	-0.210	0.051	0.098	-0.121	-0.065	0.753	1.111		
x_7	2.82	1.21	-0.012	0.030	-0.002	-0.268	-0.267	-0.137	-0.099	-0.005	-0.151	-0.056	0.034	1.473	
x_8	2.56	1.23	-0.096	-0.034	-0.067	-0.418	-0.344	-0.057	-0.039	-0.058	-0.079	0.069	0.121	0.616	1.511

A. Confirmatory Factor Analysis

Confirmatory factor analysis should first be processed to validate the measurement model with manifest variables before proceeding to the path analysis for latent variables. The evaluation of the goodness-of-fit of the measurement model should examine several indices, and these indices can be classified into three types. The results of goodness-of-fit test are shown in Table 5.2 with suggested values listed.

The first type is absolute fit measures, which assesses the fit of the overall model without adjustment of the over-fitting degree. These measures are used to indicate the absolute fit, such as the ratio of chi-square to degrees of freedom (χ^2/df), goodness-of-fit index (GFI), root mean square residual (RMR), and root mean square error of approximation (RMSEA).

The second type is the incremental fit measures, which compares the proposed model to a null model and indicates the improvement degrees. The null model is a single-factor model with no measurement errors. These measures are used to indicate the incremental fit, such as the adjusted goodness-of-fit (AGFI), non-normed-fit index (NNFI), normed fit index (NFI), comparative fit index (CFI) and critical N (CN).

The third type is the parsimonious fit measures, which indicate the over-fitting degrees in the model. It selects the simplest model that achieves similar goodness of fit among others. The parsimonious goodness of fit index (PGFI) is used to indicate the parsimonious fit.

Researchers have recommended using the ratio of chi-square to the degrees of freedom (χ^2/df) lower than 5.0 to indicate a reasonable fit (Marsh and Hocevar, 1985; Joreskog and Sorbom, 1993). The GFI, AGFI, NFI, and NNFI values of 0.90 or higher are considered evidence of good fit (Bentler and Bonett, 1980; Bentler, 1982). It would be ideal that the values of RMR and RMSEA are smaller than 0.05 (Browne and Cudeck, 1993), or otherwise it could be acceptable that the RMSEA is smaller than 0.08 (McDonald and Ho, 2002). The CFI would be larger than 0.95 (Bentler, 1988), and the CN would be greater than 200. The value of PGFI is suggested to be exceeded or to approach 0.50 (Mulaik, 1989).

As the standard of fit measures mentioned above, it shows that most of the three types of fit measures, the absolute fit measures, incremental fit measures, and parsimonious fit measurement, are acceptable in the case. The χ^2/df ratio for the measurement model in this study is 4.194 (=239.08/57), which indicates an acceptable fit in this sample. Furthermore, the results in Table 5.1 indicate a good fit to the data. As the values of GFI, AGFI, NNFI, and NFI all exceeded or equal to 0.9, RMSEA is below 0.08, CPI exceeded 0.95, CN is higher than 200, and RMR estimate is approximately 0.05. Consequently, we can conclude that the model fits the sample data fairly well.

Table 5.2 Evaluation of goodness-of-fit measures

Type	Fit statistics	Value	Suggested value
Absolute Fit Measures	Chi-square to the degrees of freedom (χ^2/df)	239.08/57 (=4.194)	< 5
	Goodness-of-fit index (GFI)	0.93	> 0.9
	Root mean square residual (RMR)	0.055	< 0.05
	Root mean square error of approximation (RMSEA)	0.071	< 0.05 or < 0.08
Incremental Fit Measures	Goodness of fit (AGFI)	0.90	> 0.9
	Non-normed fit index (NNFI)	0.90	> 0.9
	Normed fit index (NFI)	0.90	> 0.9
	Comparative fit index (CFI)	0.95	> 0.95
	Critical N（CN）	214.51	> 200
Parsimonious Fit Measures	Parsimonious goodness of fit index (PGFI)	0.58	> 0.5

The validity of the measures is assessed using standardized factor loadings, as listed in Table 5.3. According to the *t*-value shown in Table 5.3, all of standardized factor loadings of measurement variables are statistically significant ($p<0.001$). And all of them exceeded 0.5, which indicates an acceptable explanation in this model. On the other hand, the reliability of each construct exceeded 0.6 satisfying the minimally acceptable level (Hatcher, 1998; Chen, 1998).

Table 5.3 Confirmatory factor analysis results

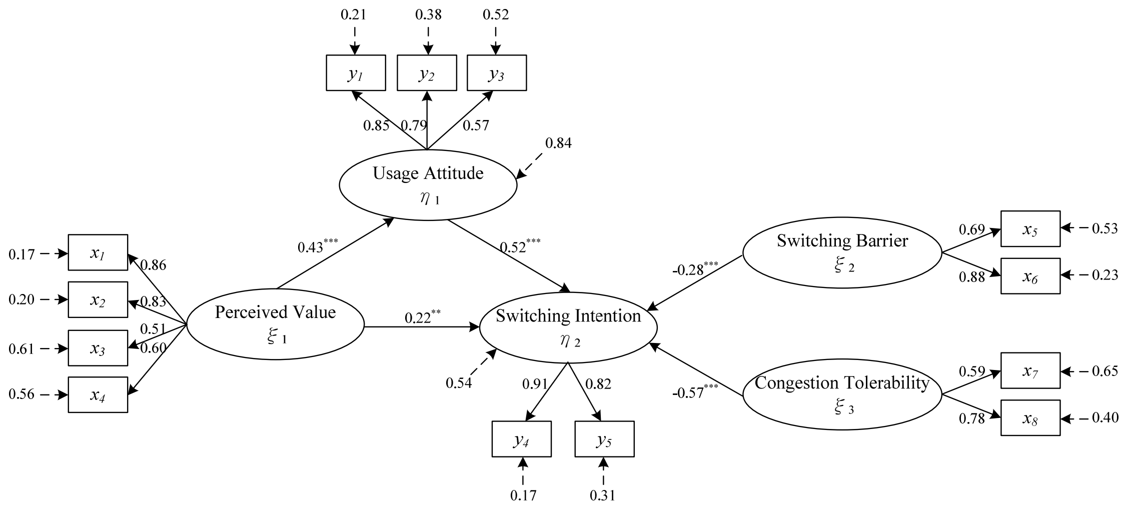
Variable	Standardized factor loadings	t-value	Reliability
Perceived value			0.778[a]
x_1	0.850	7.90***	0.72[b]
x_2	0.848	8.80***	0.69
x_3	0.506	14.71***	0.47
x_4	0.778	14.17***	0.56
Switching barrier			0.800
x_5	0.906	16.04***	0.66
x_6	0.900	4.15***	0.79
Congestion tolerability			0.685
x_7	0.829	10.91***	0.69
x_8	0.801	4.75***	0.65
Usage attitude			0.773
y_1	0.785	5.82***	0.73
y_2	0.772	8.99***	0.61
y_3	0.837	14.09***	0.62
Switching intention			0.854
y_4	0.849	3.99***	0.88
y_5	0.882	7.82***	0.63

*** denotes a significant value ($p<0.001$)
[a] indicates the reliability of construct
[b] indicates the square of factor loading

B. Path Analysis

The causal relationship between these constructs would be confirmed in the structural model. Fig.5.1 presents the results of path analysis, and most of path coefficients in the structural model are statistically significant at $p<0.001$ level. Drivers' perceived value positively and directly affects their usage attitude toward real-time traffic information, and both perceived value and usage attitude positively relates to drivers' switching intention for enroute diversion suggestion. Besides, drivers' switching barrier and their congestion tolerability negatively and directly influence drivers' switching intention. The results of path analysis verify five hypotheses (i.e. H_1~H_5) that are assumed in structural equation model (shown in Fig.3.2).

It deserves to be mentioned that switching barrier and congestion tolerability have greater negative effects on drivers' switching intention than positive effects from perceived value and usage attitude. Thus, we can conclude that the effects of revealed traffic information provided to drivers can not play a dominant role on drivers' enroute switching intentions (i.e. their compliance rate). Therefore, we should make more efforts to provide suitable and acceptable real-time information for drivers. Consequently, in the next chapter we will explore the enroute switching reaction of drivers under various hypothetical information scenarios.



*** denoted a significant path at p-value<0.001
** denoted a significant path at p-value<0.05

Fig.5.1 Results of the structural equation model

Table 5.4 Path analysis results

Construct	Hypothesis	Standardized path coefficient	t-value
Usage Attitude (*UA*)			
Perceived Value (*PV*)	$\boldsymbol{H_1}$	0.43	7.57^{***}
Switching Intention (*SI*)			
Perceived Value (*PV*)	$\boldsymbol{H_2}$	0.22	3.28^{**}
Usage Attitude (*UA*)	$\boldsymbol{H_3}$	0.52	7.69^{***}
Switching Barrier (*SB*)	$\boldsymbol{H_4}$	-0.28	-5.08^{***}
Congestion Tolerability (*CT*)	$\boldsymbol{H_5}$	-0.57	-6.51^{***}

*** denoted a significant path at p-value<0.001;
** denoted a significant path at p-value<0.05

After using structural equation modeling to test the causal relationship between switching intention and the antecedent factors, some summaries can be in accordance with the research hypotheses and detail below.

1. Direct effects

The normalized regression weights of the structural model are shown in Table 5.5. It is proved that perceived value, usage attitude, switching barrier, and congestion tolerability have direct effects on switching intention.

Table 5.5 Standardized regression weights

Path	Standardized regression weight
Perceived value → Switching intention	0.22
Usage attitude → Switching intention	0.52
Switching barrier → Switching intention	-0.28
Congestion tolerability → Switching intention	-0.57

2. Indirect effects

As illustrated in Fig.5.1, perceived value not only direct affects switching intention but also indirect affects switching intention by usage attitude. The calculated result of the standard indirect effect is listed in Table 5.6. Therefore, the total effect of perceived value on switching intention is 0.4436 (= 0.22+0.2236).

Table 5.6 Standardized indirect effects

Path	Standardized indirect effect
Perceived value → Usage attitude → Switching intention	0.43*0.52=0.2236

5.2 Multi-group Path Analysis

Following the outcomes of confirmatory factor analysis and path analysis for the entire model discussed previously, this section proceeds with several multi-group path analyses by gender, driving-experience, and trip-purpose of respondents in order to explore the diversities of switching intention among different socioeconomic and travel characteristics of respondents. The path analysis results of each group model are shown in Table 5.7~5.9 and Fig.5.2~5.4, and compared to the entire model separately.

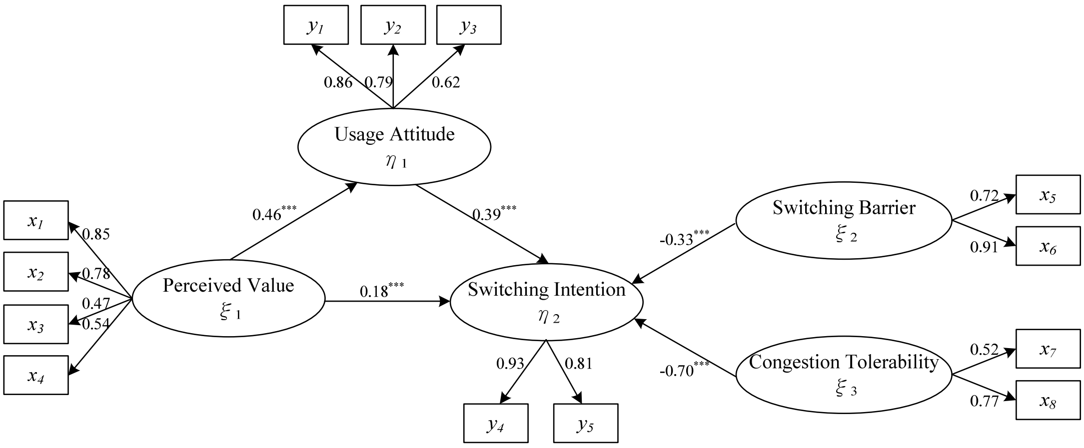
All path coefficients of each group model are statistically significant on their causal relationship. Drivers' perceived value of received information has a positive impact on their usage attitude toward real-time traffic information and enroute switching intention. Similarly, drivers' usage attitude toward real-time traffic information has a positive impact on their enroute switching intention. But Drivers' enroute switching barrier and congestion tolerability have negative impacts on their enroute switching intention.

Based on the comparison of the path coefficients of the entire model and gender group model listed in Table 5.7, females could tolerate more serious congestion situation than males while encountering traffic delay on the freeway. Congestion tolerability is the dominate factor to restrict enroute switching intention of females and males as well. According to the effects of positive latent variables on switching intention, females perceive more poorly information quality and have indefinite usage attitude than males. It reveals that females may easily maintain their driving route due to their inherent patience and much less influence from traffic information when they make diversion decision. Thus, we can conclude that males would be probably influenced by providing real-time traffic information to switch routes.

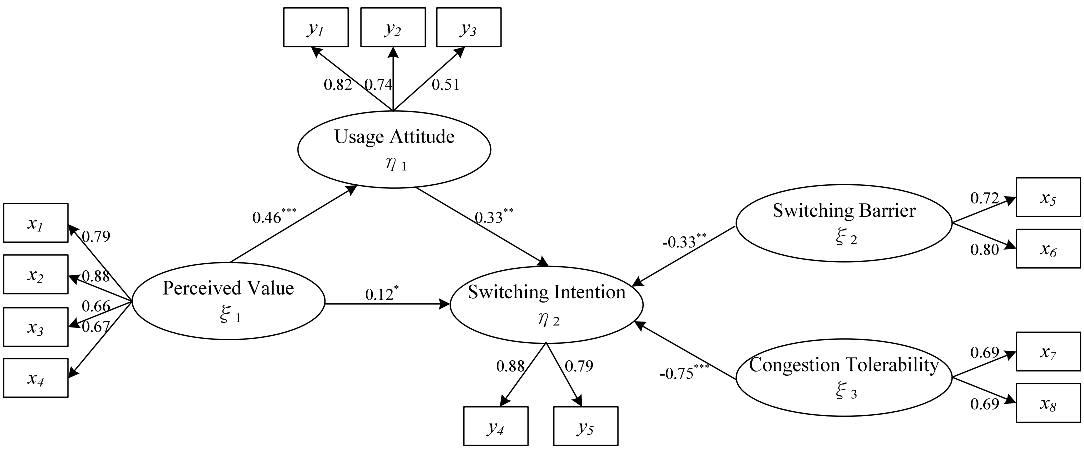
Table 5.7 Path analysis results for gender group model

Construct	Entire model	Gender group model	
		Male	Female
Usage Attitude (*UA*)			
Perceived Value (*PV*)	0.43^{***}	0.46^{***}	0.46^{***}
Switching Intention (*SI*)			
Perceived Value (*PV*)	0.22^{**}	0.18^{***}	0.12^{*}
Usage Attitude (*UA*)	0.52^{***}	0.39^{***}	0.33^{**}
Switching Barrier (*SB*)	-0.28^{***}	-0.33^{***}	-0.33^{**}
Congestion Tolerability (*CT*)	-0.57^{***}	-0.70^{***}	-0.75^{***}

*** denoted a significant path at p-value<0.001;
** denoted a significant path at p-value<0.01;
* denoted a significant path at p-value<0.1



Male



Female

Fig.5.2 Path analysis for gender group model

Respondents having richer driving-experiences (≥10 years) would perceive more serious switching barrier and congestion tolerability than others. As shown in Table 5.8 and Fig.5.3, congestion tolerability is also the significant factor to limit drivers' enroute switching intention. The more driving-experience respondents have, the more negative effects would be on their enroute switching behavior. It seems like that respondents having rich driving-experiences would concern about information incompletion and diversion uncertainty, so they would prefer to keep their initial route decision. But the usage attitude toward received information could enhance more switching intention for the respondents who have 10 years of driving experience than others. Therefore, providing more precise traffic information contents to rich driving-experience drivers might eliminate their concerns then increase diversion probabilities.

The results of path analysis for trip-purpose group models, including working-trip, business-trip, social-trip and recreational-trip groups, are displayed in Table 5.9 and Fig.5.4. In terms of positive latent variables, the working-trip group would perceive more information value on usage attitude than other trip-purpose groups. Thus, their usage attitude toward traffic information could be effectively enhanced by improving the information quality perceived by them. For the working-trip group, congestion tolerability plays a vital role on switching intention. It makes sense that commuters could get used to traffic congestion situation on the freeway. And the working-trip group has lower switching barrier due to their familiarity to the driving route and received information.

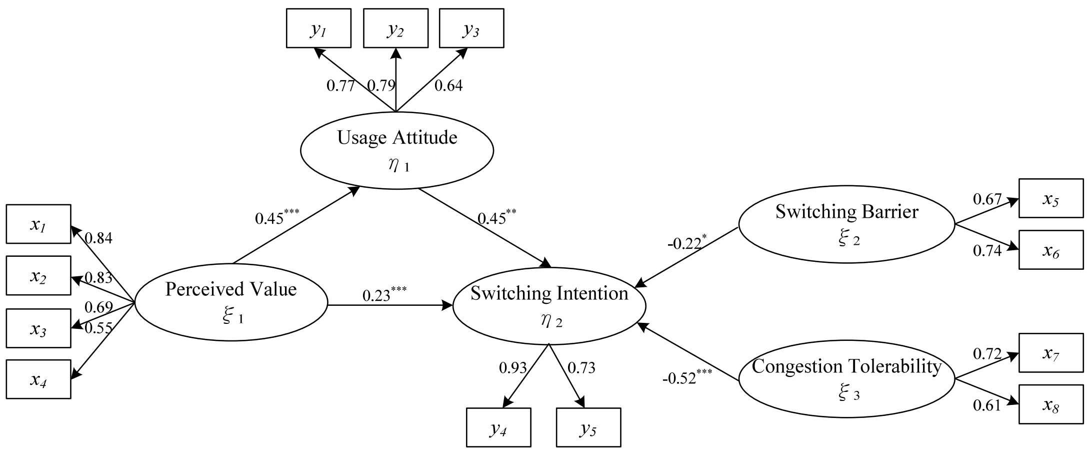
On the contrary, the business-trip group has higher switching barrier and lower congestion tolerability on switching intention than others. This group always drives on the freeway during off-peak hours and has definite business date, so they might not probably tolerate traffic delay and switch routes. The value of traffic information they perceive would obviously influence their switching intention than others, and their usage attitude toward traffic information would be larger than the entire model. So we could explain that they have larger switching barrier due to the travel restriction than the information acquisition. Thus, providing better quality of information contents could explicitly benefit to heighten their switching intentions.

The social-trip group also has a manifest usage attitude toward traffic information than other trip-purpose groups. The effects of negative latent variables have considerable influences on the switching intention and are slightly larger than the entire model. Besides, since the recreational-trip group has the flexibility of departure time and often drives on the freeway during off-peak hours, they have a weak usage attitude toward traffic information. And their switching barriers are lower than other groups owing to their trip identity.

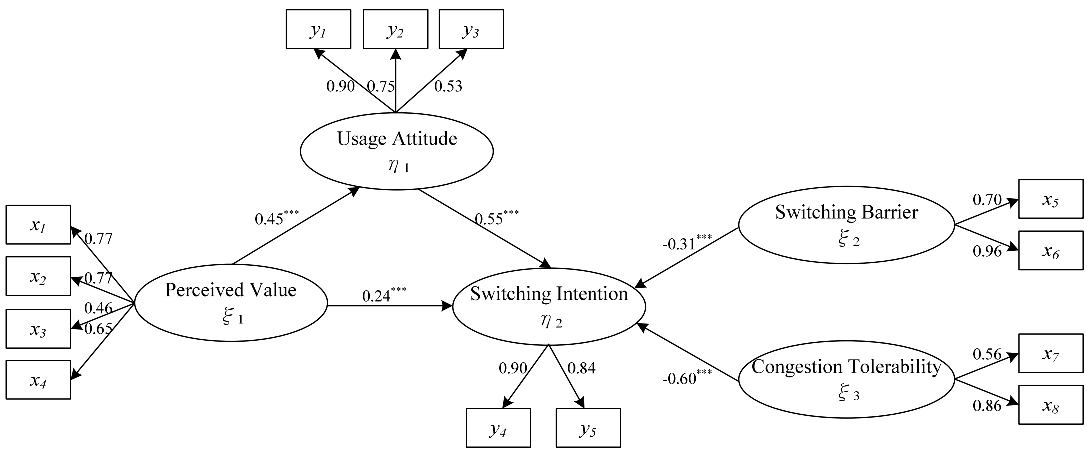
Table 5.8 Path analysis results for driving-experience group model

Construct	Entire model	Driving-experience group model	
		<10 years	≥10 years
Usage Attitude (*UA*)			
Perceived Value (*PV*)	0.43***	0.45***	0.45***
Switching Intention (*SI*)			
Perceived Value (*PV*)	0.22**	0.23***	0.24***
Usage Attitude (*UA*)	0.52***	0.45**	0.55***
Switching Barrier (*SB*)	-0.28***	-0.22*	-0.31***
Congestion Tolerability (*CT*)	-0.57***	-0.52***	-0.60***

*** denoted a significant path at p-value<0.001;
** denoted a significant path at p-value<0.01;
* denoted a significant path at p-value<0.1



Years of driving (<10 years)



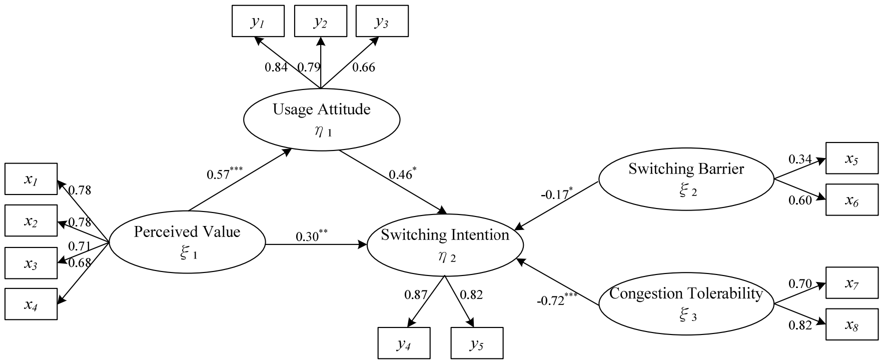
Years of driving (≥10 years)

Fig.5.3 Path analysis for driving-experience group model

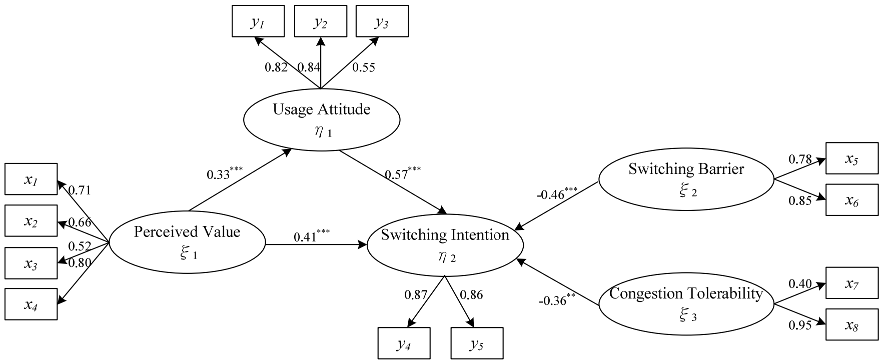
Table 5.9 Path analysis results for trip-purpose group model

Construct	Entire model	Trip-purpose group model			
		Working	Business	Social	Recreational
Usage Attitude (*UA*)					
Perceived Value (*PV*)	0.43***	0.57***	0.33*	0.39**	0.39**
Switching Intention (*SI*)					
Perceived Value (*PV*)	0.22**	0.30**	0.41***	0.23**	0.24*
Usage Attitude (*UA*)	0.52***	0.46*	0.57***	0.59***	0.41*
Switching Barrier (*SB*)	-0.28***	-0.17*	-0.46***	-0.29***	-0.15*
Congestion Tolerability (*CT*)	-0.57***	-0.72***	-0.36**	-0.59***	-0.68***

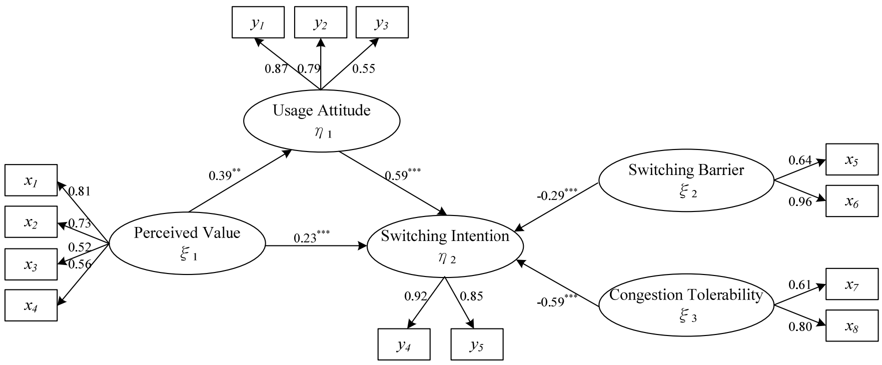
*** denoted a significant path at p-value<0.001;
** denoted a significant path at p-value<0.01;
* denoted a significant path at p-value<0.1



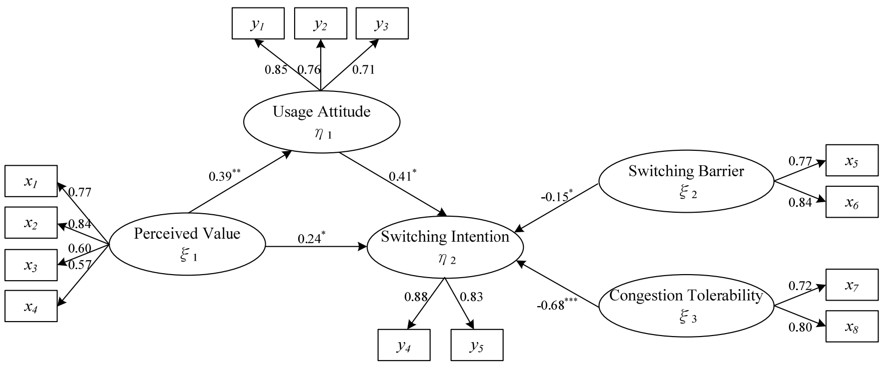
Working



Business



Social



Recreational

Fig.5.4 Path analysis for trip-purpose group model

5.3 Testing the Hypotheses

The models indicate several significant explanatory variables that affect drivers' propensity to switch routes. It is important to take these variables into consideration while interpreting whether their effects on drivers' enroute switching intention is positive or negative to exam a number of hypothesized relationships. These variables and the outcomes of hypotheses tested are summarized in Table 5.10. The hypotheses tested by the relationships in the entire model and multi-group models are all supported (see Table 5.11).

The analysis reveals that positive and negative latent variables are important to drivers' enroute switching intentions. While the perceived value on the information received by drivers increases, their usage attitude toward real-time traffic information would increase ($\boldsymbol{H_1}$). As the values of perceived value ($\boldsymbol{H_2}$) and usage attitude ($\boldsymbol{H_3}$) increase, it is expected that drivers would enhance their willingness to switch routes. Otherwise, the switching barrier ($\boldsymbol{H_4}$) and congestion tolerability ($\boldsymbol{H_5}$) would limit drivers' enroute switching intentions.

$\boldsymbol{H_1}$: Drivers' perceived value of received information has a positive impact on their usage attitude.

$\boldsymbol{H_2}$: Drivers' perceived value of received information has a positive impact on their enroute switching intention.

$\boldsymbol{H_3}$: Drivers' usage attitude toward real-time traffic information has a positive impact on their enroute switching intention.

$\boldsymbol{H_4}$: Drivers' enroute switching barrier has a negative impact on their enroute switching intention.

$\boldsymbol{H_5}$: Drivers' congestion tolerability has a negative impact on their enroute switching intention.

Table 5.10 Outcomes of hypotheses tested

Hypotheses	Causal relationship	Effects	Hypotheses tested
$\boldsymbol{H_1}$	Perceived value → Usage attitude	positive	support
$\boldsymbol{H_2}$	Perceived value → Switching intention	positive	support
$\boldsymbol{H_3}$	Usage attitude → Switching intention	positive	support
$\boldsymbol{H_4}$	Switching barrier → Switching intention	negative	support
$\boldsymbol{H_5}$	Congestion tolerability → Switching intention	negative	support

Table 5.11 Hypotheses supported in the model

model / Hypotheses	Entire model	Multi-group model							
		gender		driving-experience		trip-purpose			
		male	female	<10yrs	≥10yrs	working	business	social	recreational
$\boldsymbol{H_1}$	○	○	○	○	○	○	○	○	○
$\boldsymbol{H_2}$	○	○	○	○	○	○	○	○	○
$\boldsymbol{H_3}$	○	○	○	○	○	○	○	○	○
$\boldsymbol{H_4}$	○	○	○	○	○	○	○	○	○
$\boldsymbol{H_5}$	○	○	○	○	○	○	○	○	○

○ denoted the hypothesis is supported in the model

CHAPTER 6 ORDERED PROBIT MODELING AND ESTIMATING

6.1 Operation of Explanatory Variables

Since the stated preference behavioral responses have a natural ordering, the ordered probit formulation would be appropriate to model the likelihood that a respondent would switch routes while encountering traffic congestion. The main objective of this modeling process is to investigate whether the latent variables about perceptions or attitudes of drivers would have influence on their enroute switching behavior, and to determine which scenarios of traffic information are significant. The model is also important in investigating the explanatory variables and their levels on the propensity to switch routes.

Two congestion situations with five information scenarios are modeled separately. In these models, four sets of explanatory variables are considered. The first is the latent variables that extracted from principal components analysis previously, the second is the dummy variables that describe various scenarios of traffic information, the third is the dummy variables that represent trip purpose of respondents, and the fourth is the socioeconomic and travel characteristics of respondents.

A. Latent Variables

The latent variables perceived value, usage attitude, switching barrier, and congestion tolerability are extracted and identified using the structural equation model. The latent variables which positively or negatively affect drivers' enroute switching intention are also regarded as significant explanatory variables in the switching behavior model. The latent variables are entered into the models via the factor analysis process in which the factors are transferred into variables.

B. Information Scenario Dummy Variables

Various scenarios of traffic information entered into the models as dummy variables (see Table 6.1). This effort would enable the identification of what are the significant information contents that are considered important by the respondents. Since the information *Scenario0* is taken as the base information in the models, the dummy variables I_1~I_4 are equal to zero representing *Scenario0*. The information on *Scenario1~ Scenario4* are represented by the dummy variables I_1~I_4 equaling to 1 separately. The hypothetical information scenarios are assumed to be provided by the radio traffic reports.

Table 6.1 Dummy variables for traffic information scenarios

Information scenario \ Dummy variable	I_1	I_2	I_3	I_4
Scenario 0	0	0	0	0
Scenario 1	1	0	0	0
Scenario 2	0	1	0	0
Scenario 3	0	0	1	0
Scenario 4	0	0	0	1

C. Trip Purpose Dummy Variables

The trip purpose of a respondent who has often taken the freeway also entered into the models as dummy variables, listed in Table 6.2. A trip to work is considered as the basis of trip purposes in the models, so the dummy variables T_1~T_4 are equal to zero representing trips to work. The trip purposes involving business trips, social trips, and recreational trips are represented by the dummy variables T_1~T_3 equaling to 1 separately.

Table 6.2 Dummy variables for trip purposes

Trip purpose \ Dummy variable	T_1	T_2	T_3
Working-trip	0	0	0
Business-trip	1	0	0
Social-trip	0	1	0
Recreational-trip	0	0	1

D. Socioeconomic and Travel Characteristics

The socioeconomic and travel characteristics of respondents are taken into consideration in the models. It includes gender, age, educational background, monthly income, years of driving, experience of encountering congestion, and familiarity with the alternative route. Most of these characteristics are transferred into dummy variables then entered into the behavioral models, and the familiarity with the alternative route is expressed by using five scales of degrees.

6.2 Estimation Results

In the estimation process of the behavioral models, four sets of variables are input. Before reaching the final models, there are several modeling attempts that have been performed. The final models relating to respondents' enroute switching behavior with *CongestionI* and *CongestionII* are presented in Table 6.3. Most explanatory variables are statistically significant in these ordered probit models, hence these explanatory variables play an important role in respondents' enroute switching behavior. It is important to note that the signs of coefficients are shown in the models, because they may have different effects on the probabilities of respondents' enroute switching behavior.

A. Latent Variables

As expected, the latent variables would have positive or negative effects on respondents' enroute switching behavior. The results show that while the perceived value and usage attitude toward received information increase, respondents would be likely to switch routes on the road. However, as the switching barrier or congestion tolerability increases, respondents would reduce their propensity to switch routes. In the worse congestion situation (i.e. *CongestionII*), respondents who have higher level of congestion tolerability would obviously maintain their regular routes. It means that the higher the information quality to be considered, the higher the enroute switching probabilities would be. Nevertheless, if respondents need make extra efforts before switching routes, it would negatively impede their enroute switching behavior.

It is important to note here that the magnitudes of the estimated coefficients of the negative variables (i.e. switching barrier and congestion tolerability) are greater than the positive variables (i.e. perceived value and usage attitude). Hence, we should provide better information quality (such as information *Scenario3* or *Scenario4*) to drivers in order to overcome the negative impacts from the latent variables switching barrier and congestion tolerability.

B. Information Scenarios

The models illustrate the significant contents of traffic information. The respondents value the contents of the information scenarios and make their switching decision based on the information contents. Most information scenario dummy variables appeared to be significant in the models. Under the *CongestionI* situation, the more detailed the information is provided, the more likely the respondents are willing to switch routes. The enroute switching rates will increase while providing respondents more detailed information (i.e. information *Scenario3* and *Scenario4* are shown in Table 4.3), especially relating to the alternative route. The estimated coefficients of the variables dummy I_1, dummy I_2, dummy I_3, and dummy I_4 correspond to information *Scenario1*, *Scenario2*, *Scenario3*, and *Scenario4*, respectively. Therefore, respondents would likely switch routes on the freeway while they receive more information regarding the alternative routes provided.

The values of the estimated coefficients of the four information scenario dummy variables increase from dummy I_1 through dummy I_4, so the variable dummy I_4 has the highest value of all information scenario dummy variables. In accordance with the magnitude of coefficients, the probability relationship between information scenarios under the *CongestionI* situation can be expressed as *Scenario0* > *Scenario1* > *Scenario2* > *Scenario3* > *Scenario4*. Thus, the more richness of traffic information on the alternative route will enhance the enroute switching rates. Respondents would comply with enroute switching suggestion while providing more detailed information concerning the alternative or comparing the traffic situation of the regular route with the alternative route.

Another situation *CongestionII* is almost similar to the *CongestionI* mentioned above. But the dummy variable I_1 that indicates information *Scenario1* does not have significant difference between information *Scenario0*. Exploring the possible reason, respondents may measure the queuing time they can still bear since the information *Scenario1* is with more information about travel time and length of the delay on the regular route. When respondents face the worse congestion situation (i.e. *CongestionII*), the influence of these information scenarios on switching behavior is much slighter than *CongestionI* in accordance with magnitude of estimated coefficients. And the difference of positive effects on switching willingness between these information scenarios is lessened in *CongestionII*. Consequently, the probability relationship under the *CongestionII* situation can be expressed as *Scenario0* = *Scenario1* > *Scenario2* > *Scenario3* > *Scenario4* according to the sorting of their coefficients.

In terms of the magnitude of coefficients, more information richness on the alternative route provided to drivers would effectively overcome the degree of negative latent variables. Respondents would get more information about the network traffic by providing more rich information that might reduce their concerns for confusion and uncertainty. Thus, the provision of more information richness on the alternative route or both on the regular and alternative routes would be confirmed to have remarkable effects. The magnitudes of thresholds under accident congestion are roughly smaller than non-accident congestion since the respondents would be likely to switch routes while they encounter the worse traffic congestion.

C. Trip Purposes

Respondents on business trips would be more likely to switch routes than those on trips to work when they face traffic congestion on freeway. But respondents on social trips or recreational trips would be less likely to switch routes. The identity of business trips is more flexible than that of trips to work, hence it appears that respondents on business trips would have higher likelihood of switching routes while receiving diversion suggestion. Since the social trips or recreational trips often occur in off-peak hours, respondents on social trips or recreational trips are less influenced by receiving traffic information. The probability relationship between these trip purpose in *CongestionI* can be expressed as *Business* > *Working* > *Social* > *Recreational* according to the magnitude and signs of their coefficients. But in *CongestionII* situation, there is no significant difference between these trip purposes.

D. Socioeconomic and Travel Characteristics

Finally, the results show that among the socioeconomic and travel characteristics, several variables also appeared to be significant in the models. Respondents are male, elder (> 55 years old), lower level of education, or less monthly income (< NT$ 80 thousands) might be less likely to switch routes under the provision of traffic information. But in the worse congestion situation (i.e. *CongestionII*), there is no significant difference between males and females. Moreover, respondents who are familiar with alternative routes and have shorter periods of driving experience (<10 years), or often encounter congestion on freeway are likely to switch routes. The causes might be attributed to their inherent personal characteristics. According to the magnitude of estimated coefficients of these characteristics, respondents who experience more congestion incidents would apparently show their willingness to switch routes.

E. Thresholds

The estimated coefficient for the constant term is positive but smaller than the value 2, refers to the five-point Likert scale is the "undecided" degree for switching, and it indicates that respondents would be unlikely to switch to the alternative route while only receiving travel speed information for the regular route (i.e. information *Scenario 0* shown in Table 4.3). Since all the values of threshold μ on the *CongestionII* situation are smaller than the ones on the *CongestionI* situation, respondents would easily switch to the alternative route while encountering the worst congestion. However, comparing with the two congestion situations, the estimated coefficient for information scenario dummy variables on *CongestionI* is smaller than the one on *CongestionII*. Therefore, it is revealed that respondents would be more likely to switch routes under worsening travel condition mainly due to the suffering of the more intolerable congestion.

Table 6.3 Ordered probit models estimation

Variables	Coefficients (t-statistics)			
	Congestion I		*Congestion II*	
Latent variables				
Perceived value (PV)	0.105	(2.23)*	0.112	(2.50)*
Usage attitude (UA)	0.171	(7.86)***	0.224	(9.64)***
Switching barrier (SB)	-0.374	(-16.23)***	-0.308	(-12.65)***
Congestion tolerability (CT)	-0.268	(-11.66)***	-0.271	(-10.83)***
Information scenario dummy variables				
dummy I_1 (=1, if information *Scenario 1*; =0, otherwise)	0.211	(2.95)**	0.019	(0.27)
dummy I_2 (=1, if information *Scenario 2*; =0, otherwise)	0.463	(6.40)***	0.137	(1.94)*
dummy I_3 (=1, if information *Scenario 3*; =0, otherwise)	0.763	(10.87)***	0.362	(5.13)***
dummy I_4 (=1, if information *Scenario 4*; =0, otherwise)	1.047	(15.40)***	0.454	(6.54)***
Trip purpose dummy variables				
dummy T_1 (=1, if business; =0, otherwise)	0.182	(2.85)**	0.140	(1.99)*
dummy T_2 (=1, if social; =0, otherwise)	-0.090	(-1.69)*	-0.093	(-1.71)*
dummy T_3 (=1, if recreational; =0, otherwise)	-0.089	(-1.65)*	-0.086	(-1.69)*
Socioeconomic and travel characteristics				
gender (=0, if female; =1, if male)	-0.167	(-3.08)**	-0.128	(-2.50)*
age (=0, if 18 ~ 54 yrs old; =1,if > 55 yrs old)	-0.142	(-2.55)*	-0.242	(-2.92)**
educational background (=1, if college or graduate school; =0, otherwise)	0.261	(4.67)***	0.461	(7.73)***
monthly income (=0, if < NT$ 80 thousands; =1, if > NT$ 80 thousands)	0.184	(2.09)*	0.526	(5.04)***
years of driving (=0, if < 10 yrs; =1, if > 10 yrs)	-0.273	(-5.23)***	-0.173	(-3.26)**
experience of encountering congestion (=0, if driving speed always > 60 km/hr; =1, if driving speed always < 60 km/hr)	0.120	(2.57)*	0.104	(2.05)*
familiarity with the alternative route (=0, if unfamiliar; =1, if familiar)	0.098	(3.84)***	0.058	(2.43)*
Thresholds				
Constant	1.481	(16.59)***	1.776	(17.25)***
μ_1	1.170	(24.81)***	1.018	(18.15)***
μ_2	1.702	(34.16)***	1.627	(27.12)***
μ_3	2.721	(49.93)***	2.641	(41.97)***
Summary statistics				
Log likelihood at zero $L(0)$	-3700.13		-3457.09	
Log likelihood at convergence $L(\hat{\beta})$	-3247.73		-3045.09	
Adjusted likelihood ratio index $\bar{\rho}^2$	0.117		0.113	
No. of observations	493		493	

*** denoted a significant path at p-value<0.001; ** denoted a significant path at p-value<0.01;
* denoted a significant path at p-value<0.1

6.3 Managerial Implications

Drivers' enroute switching behavior is typically influenced by their perceived value, usage attitude, switching barrier, and congestion tolerability toward the received information or switching decision. Specifically, the negative latent variables, switching barrier and congestion tolerability, exert great impacts than the benefits from the traffic information received. It indicates that drivers would be unlikely to switch routes since their switching intentions are constantly impeded by the incomplete information and concerned about the unpredictable traffic condition. Consequently, drivers always tolerate the traffic congestion instead of switching when they drive on the freeway.

Thus, the traffic manager should focus on creating valuable traffic information in order to diminish drivers' concerns toward traffic condition especially the alternative route. Switching behavior can be increased through valuable and satisfactory information contents that can be perceived by drivers. Increasing drivers' perceived value would increase the enroute switching behavior. If the drivers' usage attitude toward real-time traffic information could also be enhanced by providing qualified information contents, meanwhile, it could be contributive to simulate drivers' enroute switching behavior.

When the development of data collection achieves at the level of state-of-the-art technique, the traffic information could be delivered faster and more accurately via the process of data mining. The more detailed description of real-time traffic information would be helpful for drivers to make diversion decision due to the acquisition of rich information. Besides, the traffic manager should offer accurate real-time information with the update frequency by minutes even seconds. And the guidance information of the alternative route should be expressed definitely in accurate and specific statements. The contents of real-time traffic information should similarly help drivers to predict their travel time on the road.

According to the research results, drivers would switch to alternative route when they receive the quantitative elaboration of real-time traffic information regarding the regular route and alternative route simultaneously. In addition to provide the qualitative information such as cause of delays, the quantitative information contents including queuing length, occurring site in definite mileage, travel speed, travel time, route guidance in definite mileage, and the estimated time for incident excluded are also preferred. Furthermore, drivers can compare the traffic situation while receiving the traffic information about the regular and alternative route simultaneously. It may be helpful for drivers to judge their enroute switching decision due to thorough understanding of their travel situation.

When respondents encounter traffic delay on the freeway, the priority of information contents they desired to receive is investigated additionally in this study, which is listed in Table 6.4. Respondents are asked to rank the information contents that may need to acquire on the road. The information contents comprise five statements, information *C1~C5*, namely travel speed and travel time related to the delay segment, cause of the delay and queuing length, forecast the incident excluded time, how to switch to the alternative route, travel speed and travel time related to the alternative route respectively.

As the statistical results summarized in Table 6.4, the most desirable information that respondents would acquire is the delay situation, including the travel speed and travel time related to the delay segment, causes of the delay and queuing length, and forecast the incident excluded time, etc. Then they would try to obtain the following information contents about travel speed and travel time related to the alternative route and how to switch to the alternative route.

Table 6.4 Priority of information contents for respondents desired

information content \ priority		1st		2nd		3rd		4th		5th	
		samples	%	samples	%	samples	%	samples	%	samples	%
C1:	Travel speed and travel time related to the delay segment	**225**	**42.1**	124	23.2	87	16.3	52	9.7	47	8.8
C2:	Cause of the delay and queuing length	**195**	**36.4**	171	32.0	66	12.3	50	9.3	53	9.9
C3:	Forecast the incident excluded time	63	11.8	130	24.3	**203**	**37.9**	52	9.7	87	16.3
C4:	How to switch to the alternative route	34	6.4	61	11.4	109	20.4	**181**	**33.8**	150	28.0
C5:	Travel speed and travel time related to the alternative route	18	3.4	49	9.2	70	13.1	**200**	**37.4**	198	37.0

Furthermore, the traffic manager should provide diversion suggestion for peak period travel depending on diverse demand for different trip purposes since their differential usage of freeway is in temporal or spatial distinction. For the freeway commuters, the availability of detailed real-time information is important for them to judge their travel decision accurately in time. Since the commuters have definite usage attitude toward real-time information on the road, the improvement of information quality they perceive would raise their recognition of traffic environment and then make diversion decision. With regarding to the more flexible trips, the manager should describe explicit instructions on how to switch to the alternative route. In addition to the revise of information contents, the broadcast frequency and display interface of traffic information should also be taken into account.

CHAPTER 7 CONCLUSIONS AND SUGGESTIONS

7.1 Conclusions

An on-line questionnaire survey and interview survey are conducted in the Taipei metropolitan area of Taiwan to explore the effects of latent variables and various information scenarios on drivers' enroute switching behavior. A two-stage approach is used to construct the appropriate switching behavior model. The positive/negative latent variables are extracted and identified using the structural equation modeling process. This study adopts the switching barrier and congestion tolerability as negative factors for drivers' enroute switching intention, and finds these factors have significant effects. The ordered probit models have explained the relationship between the provision of information scenarios and drivers' latent variables, relating to the perceived value, usage attitude, switching barrier, congestion tolerability and information scenarios.

The study reveals several conclusions regarding the enroute switching behavior on freeway drivers as follows. First, the latent variables toward received information have significant influences on drivers' enroute switching intention no matter whether the aspects are positive or negative. The perceived value and usage attitude toward information could positively reinforce drivers' switching intention while the switching barrier and congestion tolerability could negatively restrict them. Five proposed hypotheses of causal relationships are also confirmed in the structural equation model. Among latent variables extracted, the negative latent variables, switching barrier and congestion tolerability, dominate drivers' opinions toward enroute switching. Consequently, drivers would always tolerate congestion situation instead of complying with diversion suggestions.

Second, according to the findings of multi-group path analysis, similar to the entire model, all path coefficients of each group model are also statistically significant to their causal relationship. While encountering traffic delay on the freeway, females could tolerate more serious congestion situation than males. Females perceive information quality more poorly and have indefinite usage attitude toward received information. Thus, males would be probably easily influenced switching to the alternative route by providing real-time traffic information. Moreover, drivers having richer driving-experiences would perceive more serious switching barrier and congestion tolerability than others, so they would prefer to keep their initial route decision. In regard to trip-purpose group models, the working-trip group would perceive more information value on usage attitude and has lower switching barrier than other trip-purpose groups. Contrarily, the business-trip group has higher switching barrier and lower congestion tolerability on switching intention than others. Besides, the social-trip group has manifest usage attitude toward traffic information while the recreational-trip group has weak usage attitude than other trip-purpose group.

Third, drivers' enroute switching behavior would be enhanced distinctly with providing more information richness both on the regular and alternative routes (i.e. information *Scenario 3* and *4*). Providing more information richness on the alternative route would be favorable to the drivers than just on the regular route in order to enhance the drivers' understanding of network situation. More information richness on the alternative route such as detailed route guidance, travel speed, and travel time could enhance the switching willingness to the alternative route. Perhaps drivers could evaluate the time savings from switching to the alternative route with more detailed information received. Thus, drivers would comply with diversion suggestion while providing more detailed information about the alternative or comparing the traffic situation of the regular route with the alternative route. It may benefit to help drivers for changing their travel decisions. This insight can help the traffic manager to offer some suggestions for the management strategy of freeway information systems in

Taiwan.

Last but not least, although the switching barrier and congestion tolerability obviously have negative impact on drivers' switching propensity, fortunately, the negative restriction on drivers' diversion intentions may be partially offset by providing richer information about the alternative route or better information quality while they encounter traffic congestion on the road. The more information richness provided both on the regular and the alternative route could effectively overcome drivers' switching barrier and congestion tolerability while eliminating the uncertainty in alternative route situation. So drivers would be likely to accept more information richness while they encounter traffic congestion on the road. If the improvement on the advanced driver information system could be implemented, drivers would have more confidence in the information contents they receive.

7.2 Suggestions

This study discusses the primary latent variables affecting drivers' enroute switching behavior from positive and negative viewpoints, and constructs the enroute switching behavioral models incorporating perceived value, usage attitude, switching barrier, and congestion tolerability latent variables. Consequently, according to the empirical results in this survey, the explanatory abilities of the drivers' enroute switching behavioral models are absolutely enhanced by considering these latent variables.

However, drivers' decision making process should be more complicated in the real situation, and there would be many unmeasurable variables referring to inherent concerns in drivers' mind without incorporating in these behavioral models. Some limitations relating to travel situation or traffic condition may not be considered in these proposed models as well. So the behavioral models established in the study could not completely explain drivers' actual behavior about enroute switching decision. Thus, future research could collect more relevant explanatory variables and latent variables, such as personality, belief, and preference, etc., relating to behavioral decision in order to explicitly explain drivers' real enroute switching behavior and effectively enhance the explanatory abilities of the behavioral models.

Relating to hypothesized information scenarios, there are only two congestion situations and five information scenarios simulated by the SP design in this study. To analyze the effects of real-time traffic information under different traffic condition for traffic management purpose, other scenarios of traffic information or travel condition could be simulated and considered into the proposed model. Thus, the traffic manager can predictably evaluate drivers' behavioral responses in advance using stated preference method. Besides, this study chooses the radio traffic reports as a receiving channel of real-time information, thus further study could explore the latent variables and information scenarios by other advanced driver information systems.

With the limitation of the efforts of labor, time and expense, the selected subjects of this survey are only conducted in the Taipei metropolitan area of Taiwan. Thus, the estimation results of these behavioral models are merely suitable to explain the drivers' enroute switching behavior in the northern area of Taiwan. Through expanding the samples of survey, future survey could apply the proposed models to explore drivers' enroute switching behavior in other areas of Taiwan. It would enable to improve the applicable and explanatory abilities of the behavioral model to realize all drivers enroute switching behavior in Taiwan.

BIBLIOGRAPHY

a) Books

Bentler, P. M., *Theory and implementation of EQS: A Structural Equations Program*, Newbury Park, CA: Sage, 1988.

Chang, C. C., *The Analysis of User's Demand in Advanced Traveler Information System*, Master's Thesis, Taiwan: Institute of Traffic and Transportation, National Chiao Tung University, 2001. (in Chinese)

Chen, Y. L., *The Acceptance(Satisfaction) Tendency of TDM Strategies and Their Effects on Travelers' Behavior*, Master's Thesis, Taiwan: Institute of Civil Engineering, National Chi Nan University, 2005. (in Chinese)

Chiou, H. J., *Principles and Practice of Structural Equation Modeling with LISREL*, Taiwan: Yeh Yeh Book Gallery, 2003. (in Chinese)

Cooper, D. R. and Schindler, P. S., *Business Research Method*, 8th ed., McGraw-Hill, 2003.

Hatcher, L., *A Step-by-Step Approach to Using the SAS System for Factor Analysis and Structural Equation Modeling*, SAS Institute Inc., 1998.

Hayduk, L. A., *Structural Equation Modeling with LISREL: Essentials and Advances*, Baltimore: Johns Hopkins University Press, 1987.

Huang, F. M., *Structural Equation Modeling--Theory and application*, Taiwan: Wunan, 2003. (in Chinese)

Joreskog, K. G. and Sorbom, D., *LISREL8: User's Reference Guide*, Chicago, IL: Scientific Software International, 1993.

Long, J. S., *Regression Models for Categorical and Limited Dependent Variables*, Thousand Oaks: SAGE, 1997.

Nunnally, J. C., *Psychometric Theory*, 2nd ed., New York: McGraw-Hill, 1978.

Chen, S.Y., *Multivariate Analysis*, 3rd ed, Taiwan: Hwatai, 2004. (in Chinese)

b) Journal Papers

Abdel-Aty, M. A., "Using Ordered Probit Modeling to Study the Effect of ATIS on Transit Ridership", Transportation Research, Vol.9C, No.4, pp.265-277, 2001.

Abdel-Aty, M. A. and Abdalla P. E. F., "Modeling Drivers' Diversion from Normal Routes under ATIS Using Generalized Estimating Equations and Binomial Probit Link Function, Transportation , Vol.31, No,3, pp.27-348, 2004.

Abdel-Aty, M. A., Kitamura, R., and Jovanis P. P., "Using Stated Preference Data for Studying the Effect of Advanced Traffic Information on Drivers' Route Choice", Transportation Research , Vol.5C, No.1, pp.39-50, 1997.

Adler, J. L., "Investigating the Learning Effects of Route Guidance and Traffic Advisories on Route Choice Behavior", Transportation Research, Vol.9C, pp.1-14, 2001.

Bagozzi, R. P. and Yi, Y., "On the Evaluation of Structural Equation Models", Journal of the Academy of Marketing Science, Vol.16, No. 1, pp.74-94, 1988.

Balabanis, G., Reynolds, N., and Simintiras, A., "Bases of E-Store Loyalty: Perceived Switching Barriers and Satisfaction", Journal of Business Research, Vol.59, pp.214 – 224, 2006.

Ben-Akiva, M., de Palma, A., and Kaysi, I., "Dynamic Network Models and Driver Information System", Transportation Science, Vol.25A, No.5, pp.309-318, 1991.

Bentler, P. M., "Confirmatory Factor Analysis via Noniterative Estimation: A Fast, Inexpensive method", *Journal of Marketing Research*, Vol.19, pp.417-424, 1982.

Bentler, P. M. and Bonett, D. G., "Significance Tests and Goodness of Fit in the Analysis of Covariance Structures", Psychological Bulletin, Vol.88, pp.588-606, 1980.

Bhattacharjee, D., Haider S. W., Tanaboriboon, Y., and Sinha, K. C., "Commuters' Attitudes towards Travel Demand Management in Bangkok", Transport Policy, Vol.4, No.3, pp.161-170, 1997.

Chang, M. S., Chou, C. Y., and Hsu, C. Y., "A Study on Route/Departure Time Choices Behavior for the Urban Commuters in Hsin-Chu Area", WEB Journal of Chinese Management Review, Vol. 6, No, 6, pp.83-97, 2003. (in Chinese)

Chen, P. S. T., Srinivasan, K. K., and Mahamassani, H. S., "Effect of Information Quality on Compliance Behavior of Commuters under Real-time Traffic Information", Transportation Research Record, Vol.1676, pp.53-60, 1999.

Davis, F. D., "Perceived Usefulness, Perceived Ease of Use, and Behavioral Impacts of Information Technology", MIS Quarterly, Vol.15, No.3, pp.319-340, 1989.

Davis, F. D., "User Acceptance of Information Technology: System Characteristics, User Perceptions and Behavioral Impacts", International Journal of Man-Machine Studies, Vol.38, pp.475-487, 1993.

Davis, F. D., Bagozzi, R. P., and Warshaw, P. R., "User Acceptance of Computer Technology: A Comparison of Two Theoretical Model", Management Science, Vol.35, No.8, pp.982-1003, 1989.

De Palma, A. and Picard, N., "Route Choice Decision under Travel Time Uncertainty", Transportation Research, Vol.39A, pp.295-324, 2005.

Dick, A. S. and Basu, K., "Customer Loyalty: Toward an Integrated Conceptual Framework", Journal of the Academy of Marketing Science, Vol.22, pp. 99-113, 1994.

Emmerink, R. H. M., Nijkamp, P., Rietveld, P., and Van Ommeren, J. N., "Variable Message Signs and Radio Traffic Information: An Integrated Empirical Analysis of Drivers' Route Choice Behavior, Transportation Research, Vol.30A, No.2, pp.135-153, 1996.

Feng, C. M. and Huang, Y. K., "The Effects of Switching Cost and Service Quality on Choice Behavior of the Pick-up Point for the Online Shopping", Transportation Planning Journal, Vol.35, No.6, pp.391-426, 2006. (in Chinese)

Floyd, M. F., Jang, H., and Noe, F. P., " The Relationship Between Environmental Concern and Acceptability of Environmental Impacts among Visitors to Two U.S. National Park Settings", Journal of Environmental Management, Vol. 51, pp.391–412, 1997.

Fujii, S., Gärling, T., Jakobsson, C., and Jou, R. C., "A Cross-Country Study of Fairness and Infringement on Freedom as Determinants of Car Owners' Acceptance of Road Pricing", Transportation, Vol.31, pp.285–295, 2004.

Heathington, K., Worrall R., and Hoff, G., "Attitudes and Behavior of Drivers regarding Route Diversion", Highway Research Record, Vol.363, pp.18-23, 1971.

Hu, S. R. and Chen, C. M, "A Study on the Effects of Pre-trip Traffic Information on Intercity Traveler's Mode Choice Behaviors", Journal of the Chinese Institute of Transportation, Vol. 18, No.1, pp.75-108, 2006. (in Chinese)

Jakobsson, C., Fujii, S., and Garling, T., "Determinants of Private Car Users' Acceptance of Road Pricing", *Transport Policy*, Vol.7, pp.135-158, 2000.

Jen, W. and Hu, K. C, "Application of Perceived Value Model to Identify Factors Affecting Passengers' Repurchase Intentions on City Bus: A Case of the Taipei Metropolitan Area", Transportation, Vol. 30, No. 3, pp.307-327, 2002.

Jen, W. and Lu, T. J, “Effects of Perceived Service Quality, Customer Satisfaction and Switching Barriers on Passengers’ Behavioral Intentions on Scheduled Coach Service on National Freeway”, Transportation Planning Journal, Vol.33, No.2, pp.421-448, 2004. (in Chinese)

Jen, W., Tung S. W., and Lu, T. J, “Effects of Servicescape and Waiting Experience on Passengers’ Behavioral Intentions and Choice Behavior in Scheduled Coach Service”, Transportation Planning Journal, Vol.34, No.3, pp.413-442, 2005. (in Chinese)

Jones, M. A., Mothersbaugh, D. L., and Beatty, S. E., “Switching Barriers and Repurchase Intentions in Services”, Journal of Retailing, Vol.76, No.2, pp.256-274, 2000.

Jones, M. A., Mothersbaugh, D. L., and Beatty, S. E., “Why Customers Stay: Measuring the Underlying Dimension of Services Switching Costs and Managing Their Differential Strategic Outcomes”, Journal of Business Research, Vol. 55, pp. 441-450, 2002.

Jou, R. C., Chen, C. C, and Weng, M. C., “The Effects of Real Time Traffic Information on Freeway Travelers’ Route Switching Behavior”, *Journal of the Chinese Institute of Transportation*, Vol. 15, No.1, pp.25-47, 2003. (in Chinese)

Jou, R. C., Hu, T. Y., and Lin, C. W., “Empirical Results from Taiwan and Their Implications for Advanced Traveler Pre-trip Information Systems”, Transportation Research Record, Vol.1607, pp.126-133, 1997.

Jou, R. C., Lam, S. H., Liu, Y. H., and Chen, K. H., “Route Switching Behavior on Freeways with the Provision of Different Types of Real-Time Traffic Information”, Transportation Research, Vol.39A, No.5, pp.445-461, 2005.

Jou, R. C., Lam, S. H., Weng, M. C., and Chen, C. C., “Real Time Traffic Information and ITS Impacts on Route Switching Behavior of Expressway Drivers”, Journal of Advanced Transportation, Vol.38, No.2, pp.187- 223, 2004.

Jou, R. C., Liu, Y. H, and Lien, S. Y., “Acceptance Analysis of High Occupancy Vehicle Lanes on Sun Yat-Sen Freeway”, Journal of the Chinese Institute of Transportation, Vol. 18, No.4, pp.331-364, 2006. (in Chinese)

Jou, R. C., Weng, M. C., and Chen, C. C., “The Evaluation of High Occupancy Vehicle Lanes on Sun Yat-Sen Freeway in Taiwan”, Journal of Advanced Transportation, Vol.39, No.2, pp.169-192, 2005.

Khattak, A. J., Koppelman, F. S., and Schofer, J. L. "Stated Preferences for Investigating Commuters' Diversion Propensity", Transportation, Vol.20, No.2, pp.101-111, 1993.

Khattak, A. J., Schofer, J. L., and Koppelman, F. S., "Commuters' Enroute Diversion and Return Decisions: Analysis and Implications for Advanced Traveler Information Systems", Transportation Research, Vol.27A, No.2, pp.101-111, 1993.

Kim, M. K., Park, M. C., and Jeong, D. H., "The Effects of Customer Satisfaction and Switching Barrier on Customer Loyalty in Korean Mobile Telecommunication Services", Telecommunications Policy, Vol. 28, pp.145-159, 2004.

Koppelman, F. S. and Pas, E. I., "Travel-choice Behavior: Models of Perceptions, Feelings, Preference, and Choice," Transportation Research Record, No.765, pp.26-33, 1980.

Kroes, E. P. and Sheldon, R. J., "The Use of Attitude Models and Stated Preference Models in Practical Transport Analysis", Behavioural Research for Transport Policy, pp.307-326, 1986.

Madanat, S. M., Yang, C. Y., and Yen, Y. M., "Analysis of Stated Route Diversion Intentions under Advanced Traveler Information Systems Using Latent Variables Modeling", Transportation Research Record, No.1485, pp.10-17, 1995.

Mahmassani, H. S., and Liu, Y. S., "Dynamics of Commuting Decision Behaviour under Advanced Traveler Information Systems", Transportation Research, Vol. 7C, pp.91-107, 1999.

Maute, M. F. and Forrester, W. R., "The Structure and Determinants of Consumer Complaint Intentions and Behavior", Journal of Economics Psychology, Vol.14, pp. 219-247, 1993.

McKelvey, R. D. and Zavoina, W, "A Statistical Model for the Analysis of Ordinal Level Dependent Variables", Journal of Mathematical Sociology, Vol.4, No.2, pp.103-120, 1975.

Ng, L., Barfield, W., and Mannering, F., "A Survey-Based Methodology to Determine Information Requirements for Advanced Traveler Information Systems, Transportation Research, Vol.3C, No.2, pp.113-127, 1995.

Patterson, P. G. and Smith, T., "A Cross-Cultural Study of Switching Barriers and Propensity to Stay with Service Providers", Journal of Retailing, Vol. 79, pp. 107–120, 2003.

Quddus, M. A., Noland, R. B., and Chin, H. C., "An Analysis of Motorcycle Injury and Vehicle Damage Severity Using Ordered Probit Models", Journal of Safety Research, Vol.33, pp.445-462, 2002.

Schade, J. and Schlag, B., "Acceptability of Urban Transport Pricing Strategies", Transportation Research, Vol.6F, No.5, pp.45-61, 2003.

Tong, C. C. and Chen, Y. H., "Route Switching Behavior under the Influence of In-Vehicle Information with Latent Variable Modeling", Journal of the Chinese Institute of Transportation, Vol. 18, No.4, pp.365-390, 2006. (in Chinese)

Yin, Y. and Yang, H., "Simultaneous Determination of the Equilibrium Market Penetration and Compliance Rate of Advanced Traveler Information Systems", Transportation Research, Vol.37A, No.2, pp.165-181, 2003.

c) Papers Presented to Conferences

Abdel-Aty, M. A., Vaughn, K. M., Kitamura, R, Jovanis, P. P., and Mannering, F. L, "Models of Commuters' Information Use and Route Choice: Initial Results Based on a Southern California Commuter Route Choice Survey", Presented at 73rd Annual Meeting of the Transportation Research Board, Washington, D. C., 1994.

Adler, J.L., Golob, T.F., and McNally, M.G., "A structural model with discrete-choice variables for predicting enroute behavior under ATIS", Presented at 73rd Annual Meeting of the Transportation Research Board, Washington, D. C., 1994.

Feng, C. M. and Huang, Y. K., "The Choice Behavior Analysis of the Pick-up Point for the E-commerce Retailing Delivery", Journal of the Eastern Asia Society for Transportation Studies, Vol. 6, pp. 2778 - 2793, 2005.

Khattak, A. J., "Effect of Information and Other Factors on Multivehicle Rear-end Crashes: Crash Propagation and Injury Severity", Presented at the 78th Annual Meeting of the Transportation Research Board, Washington, D.C., 1999.

Khattak, A. J., Kanafani, A., and Colletter E. L., "Stated and Reported Route Diversion Behavior: Implications on the Benefits of ATIS", Presented at 73rd Annual Meeting of the Transportation Research Board, Washington, D. C., 1994.

Tong, C. C. and Chen, S. P., "A Survey of Route Choice Behavior under the Influence of Traffic Information", TAIWAN's International Conference & Exhibition on ITS 2000, Taipei, 2000. (in Chinese)

Tong, C.C. and Chen, Y. H. "Modeling route switching behavior under the influence of in-vehicle information with latent variables", Proceeding of the 19th Annual Conference for the Chinese Institute of Transportation, Vol.8, pp.1459-1482, 2004. (in Chinese)

Wen, C. H., Lan, L. W., and Chao, K. T., "A Study of Customer Acceptance on Lower Deck Space with Seats or Sleepers for Intercity Bus", Proceeding of the 16th Annual Conference for the Chinese Institute of Transportation, pp.221-230, 2001. (in Chinese)

Wen, C. H., Lan, L. W., and Hsu, F. S., "Effect of Different Traffic Information on Intercity Commuter Route Choice Behavior", Proceeding of the 6th Annual Conference on Transportation Networks, pp.1-9, 2001. (in Chinese)

Wu, P. H., Jou, R. C, and Liu Y. H, "A Study on the Relationship Between Road Pricing Acceptance and Usage Expectations of Car Users", Proceeding of the 19th Annual Conference for the Chinese Institute of Transportation, Vol.1, pp.51-67, 2004. (in Chinese)

d) Others

http://www.ris.gov.tw/ch4/static/st10-0.html

APPENDIX : QUESTIONNAIRE

高速公路即時資訊內容對小汽車駕駛人路線移轉行為的影響

您好:

感謝您撥冗填答此份問卷，請依您對廣播所報導高速公路路況內容及路線移轉的實際經驗或看法回答相關問題，填答內容僅供學術研究使用。敬祝　行車平安、旅途愉快。

國立交通大學交通運輸研究所　　指導教授:馮正民

研 究 生:郭奕妏

※本問卷是以居住在**新竹以北的小汽車駕駛人**為調查對象※

第一部份：高速公路使用狀況

1.請問您**最常**行駛高速公路的頻率？(單選)

□每天 1 次　□兩、三天 1 次　□一星期 1 次

□兩星期 1 次　□一個月 1 次　□很少

2.請問您**最常**因何種目的行駛高速公路？(單選)

□上班　□商務洽公　□探親訪友　□旅遊　□其他 ________

3.請問您**最常**行駛高速公路的路線？(單選)

□只有中山高　□只有二高

□經常使用兩條以上高速公路　□偶爾使用兩條以上高速公路

4.請問您行駛上述路線時，**通常**車速是多少？(單選)

□20 公里/時以下　□20~40 公里/時　□40~60 公里/時

□60~90 公里/時　□90 公里/時以上

5.原路線塞車時，您是否會改走**其他替代路線**(如快速道路或另一條高速公路)？

□完全不會(續答 *A.*)　□不太會(續答 *A.*)　□普通

□偶爾會(續答 *B.*)　□經常會(續答 *B.*)

*A.*請問塞車時您**不會**改走其他替代路線的原因？(可複選)

(“完全不會”及”不太會”者才答)

□習慣原來的路線　□改走替代路線反而會花費更多時間　□不趕時間

□對如何行駛替代路線不熟悉　□有關替代路線的路況報導不夠詳細

□其他 ________

*B.*請問塞車時您**會**改走其他替代路線的原因？(可複選)

(“偶爾會”及”經常會”者才答)

□無法忍受塞車走走停停　□改走替代路線能節省更多時間　□趕時間

□對如何行駛替代路線熟悉 □有關替代路線的路況報導詳細

□其他 ____________

6.請問您對**其他替代路線**的熟悉度？

□非常不熟悉 □不熟悉 □普通 □熟悉 □非常熟悉

7.請問高速公路塞車時，通常車速低於多少時，您**就會**想改道？(單選)

□60 公里/時以下 □50 公里/時以下 □40 公里/時以下 □30 公里/時以下

□20 公里/時以下 □無論車速多慢都不會想改道

8.請問您在高速公路上聽到前方塞車資訊，通常車陣回堵長度多少時，您**就會**想改道？(單選)

□10 公里以上 □5~10 公里 □3~5 公里 □1~3 公里 □無論回堵多嚴重都不會想改道

第二部份：即時資訊內容

1.開車在高速公路上塞車時，請問您**最希望**獲知什麼路況內容？

(請在 _____ 中填入偏好順序 1~5)

_______ 塞車路段的車速和行車時間

_______ 塞車原因和回堵長度

_______ 預測塞車排除時間

_______ 如何行駛至替代路線

_______ 替代路線的車速和行車時間

2.請依您開車在高速公路上**收聽廣播路況報導的經驗**回答下列問題：

題項	非常不同意	不同意	普通	同意	非常同意
(1)開車在高速公路上，您認為收聽廣播路況報導對您開車非常重要？	□	□	□	□	□
(2)**只要是一上高速公路**，您就會收聽廣播了解路況？	□	□	□	□	□
(3)當您在高速公路上**遇到塞車時**，您會想要收聽廣播了解路況？	□	□	□	□	□
(4)您認為廣播所報導的高速公路路況，內容描述夠詳細？	□	□	□	□	□
(5)您認為廣播所報導的高速公路路況，內容更新速度夠快？	□	□	□	□	□
(6)您認為廣播所報導的高速公路路況，能幫助您預估所需的行車時間？	□	□	□	□	□
(7)您認為高速公路塞車時，廣播能明確指示替代路線？	□	□	□	□	□

第三部份：路線移轉意向

1.依過去您開車在高速公路上的經驗，您認為塞車時要去了解如何改走替代路線

很麻煩？

□非常不同意 □不同意 □普通 □同意 □非常同意

2.依過去您開車在高速公路上的經驗，您認為塞車時改走替代路線反而會花費更多時間？

□非常不同意 □不同意 □普通 □同意 □非常同意

3.依過去您開車在高速公路上的經驗，您認為廣播所提供的替代路線資訊並不詳細，因此降低塞車時您改走替代路線的意願？

□非常不同意 □不同意 □普通 □同意 □非常同意

4.若您開車在高速公路上遇到塞車，即使獲知如何改走替代路線的完整資訊，您仍然會維持原來的行駛路線？

□非常不同意 □不同意 □普通 □同意 □非常同意

5.依過去您開車在高速公路上的經驗，您常因收聽廣播得知"前方塞車資訊"而改走替代路線？

□非常不同意 □不同意 □普通 □同意 □非常同意

6.依過去您開車在高速公路上的經驗，您常因聽從廣播"替代路線建議"而改道？

□非常不同意 □不同意 □普通 □同意 □非常同意

7.**假設**您開車上國道一號自楊梅往台北**上班**，若收聽**廣播**獲知前方路段塞車，**在還有機會改道時**，您是否會因聽到以下幾種"不同詳細度"的路況後**改走替代路線**？

題　　項	非常不可能	不太可能	普通	有點可能	非常可能
(1)『國道一號北上中壢至林口車多擁擠，時速 30~40』 **請問聽到以上路況後，您是否會改走替代路線？**	□	□	□	□	□
(2)『國道一號北上中壢至林口車多擁擠，時速 30~40，行車時間 40 分鐘』 **請問聽到以上路況後，您是否會改走替代路線？**	□	□	□	□	□
(3)『國道一號北上中壢至林口車多擁擠，時速 30-40，可由 65 公里處接台 66 快速道路改走國道三號』 **請問聽到以上路況後，您是否會改走替代路線？**	□	□	□	□	□
(4)『國道一號北上中壢至林口車多擁擠，時速 30-40，可由 65 公里處接台 66 快速道路改走國道三號(相同區間行車時速 70~80)』 **請問聽到以上路況後，您是否會改走替代路線？**	□	□	□	□	□
(5)『國道一號北上中壢至林口車多擁擠，時速 30-40，行車時間 40 分鐘，可由 65 公里處接台 66 快速道路改走國道三號(相同區間時速 70~80、行車時間 20 分鐘)』 **請問聽到以上路況後，您是否會改走替代路線？**	□	□	□	□	□

8.**假設**您開車上國道一號自楊梅往台北**上班**，若自**廣播**獲知前方路段發生事故而塞車，**在還有機會改道時**，您是否會因聽到以下幾種"不同詳細度"的路況後**改走替代路線**？

題　　項	非常不可能	不太可能	普通	有點可能	非常可能
(1)『國道一號北上 42 公里發生小貨車翻覆事故，回堵五公里，時速 10~20』 **請問聽到以上路況後，您是否會改走替代路線？**	□	□	□	□	□
(2)『國道一號北上 42 公里發生小貨車翻覆事故，回堵五公里，時速 10~20，中壢至林口行車時間 60 分鐘，預計 30 分鐘後排除事故』 **請問聽到以上路況後，您是否會改走替代路線？**	□	□	□	□	□
(3)『國道一號北上 42 公里發生小貨車翻覆事故，回堵五公里，時速 10~20，可由 65 公里處接台 66 快速道路改走國道三號』 **請問聽到以上路況後，您是否會改走替代路線？**	□	□	□	□	□
(4)『國道一號北上 42 公里發生小貨車翻覆事故，回堵五公里，時速 10~20，可由 65 公里處接台 66 快速道路改走國道三號(相同區間行車時速 70~80)』 **請問聽到以上路況後，您是否會改走替代路線？**	□	□	□	□	□
(5)『國道一號北上 42 公里發生小貨車翻覆事故，回堵五公里，時速 10~20，中壢至林口行車時間 60 分鐘，預計 30 分鐘後排除事故，可由 65 公里處接台 66 快速道路改走國道三號(相同區間時速 70~80、行車時間 20 分鐘)』 **請問聽到以上路況後，您是否會改走替代路線？**	□	□	□	□	□

第四部份：個人資本資料

1.性別：□男 □女

2.年齡：□24 歲以下 □25~34 歲□35~44 歲 □45~54 歲 □55~64 歲 □65 歲以上

3.教育程度：□國中(含)以下 □高中職 □大學專科 □研究所(含)以上

4.個人每月所得：□2 萬元以下 □2~4 萬元 □4~6 萬元 □6~8 萬元 □8 萬元以上

5.實際開車經驗：□1 年以下 □1~3 年 □4~6 年 □7~9 年 □10 年以上

～ 本問卷到此結束，感謝您的協助!! ～