FACTORS AFFECTING COST OF ACCIDENT FOR PERSONAL CAR USERS IN THAILAND

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การศึกษาปัจจัยที่ส่งผลต่อมูลค่าอุบัติเหตุสำหรับผู้ใช้รถยนต์ส่วนบุคคลในประเทศไทย

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Suranaree University of Technology has approved this thesis submitted in partial fulfillment of the requirements for a Degree of Doctor of Philosophy.

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คำสำคัญ: ความเต็มใจที่จะจ่าย/มูลค่าของชีวิตทางสถิติ/มูลค่าของการบาดเจ็บทางสถิติ

ประเทศไทยยังคงประสบปัญหาความรุนแรงและความเสียหายจากอุบัติเหตุทางถนนอย่างต่อเนื่อง (ผู้เสียชีวิตจากอุบัติเหตุทางถนน 32.7 คน ต่อประชากรหนึ่งแสนคน) ผลกระทบต่อสังคมและเศรษฐกิจของประเทศสามารถประเมินได้จากมูลค่าของอุบัติเหตุ หากอุบัติเหตุมีมูลค่าสูงหมายความว่าอุบัติเหตุมีความรุนแรงสูงเช่นกัน ดังนั้นการศึกษานี้จึงมีวัตถุประสงค์เพื่อประเมินความเสียหายของอุบัติเหตุทางถนนที่ได้จากการประเมินของผู้ขับขี่รถยนต์ส่วนบุคคลในประเทศไทยจำนวน 1,650 คน รวมถึงค้นหาปัจจัยที่มีอิทธิพลต่อการรับรู้ความเสี่ยงและการประเมินค่าความเต็มใจที่จะจ่าย (willingness to pay: WTP) เพื่อลดโอกาสเกิดอุบัติเหตุของผู้ใช้รถยนต์ทั้งในระดับผู้ขับขี่และระดับพื้นที่

การศึกษานี้ใช้แบบสอบถามโดยการสัมภาษณ์แบบตัวต่อตัว การประเมินค่าความเต็มใจที่จะจ่ายของการศึกษานี้ประกอบด้วย 2 วิธี คือ การสอบถามมูลค่าแบบปลายเปิด (contingent valuation) และการประเมินค่าแบบให้ตัวเลือก (choice experiment) การศึกษานี้ได้ประมาณค่าความเสียหายของอุบัติเหตุทางถนนโดยคำนวณเป็นมูลค่าของชีวิตและบาดเจ็บสามารถทางสถิติ (value of statistical life and injury) นอกจากนั้น การศึกษานี้ยังคงวิเคราะห์ปัจจัยที่ส่งผลต่อความเต็มใจที่จะจ่ายของผู้ขับขี่ด้วยแบบจำลองทางสถิติประกอบด้วย แบบจำลองสมการเชิงโครงสร้าง การวิเคราะห์องค์ประกอบเชิงยืนยัน แบบจำลองถดถอยโลจิสติกส์แบบผสม และการวิเคราะห์ความแตกต่างที่ไม่สามารถสังเกตเห็นได้

ผลลัพธ์จากการศึกษานี้สามารถใช้เป็นแนวทางสำหรับหน่วยงานที่เกี่ยวข้องในการจัดสรรงบประมาณที่เหมาะสมสำหรับพัฒนาความปลอดภัยทางถนน ในระดับของผู้ขับขี่ ผลการวิเคราะห์ยังแสดงให้เห็นลักษณะทางสังคมและเศรษฐกิจของผู้ขับขี่ ประสบการณ์ขับขี่ ประสบการณ์เกี่ยวกับอุบัติเหตุ มุมมองทางจิตวิทยาที่มีผลต่อการรับรู้ความเสี่ยง และประเมินมูลค่าอุบัติเหตุ แนวทางนี้ช่วยให้หน่วยงานที่เกี่ยวข้องเห็นปัจจัยที่มีความสำคัญและช่วยในการออกแบบนโยบายการจัดการความเสี่ยงและความรุนแรงของอุบัติเหตุทางถนนได้อย่างเหมาะสม

นอกจากนี้ ในระดับพื้นที่ ผลจากการศึกษานี้ยังแสดงให้เห็นว่า การบังคับใช้กฎหมาย การสนับสนุนของรัฐบาล และสภาพแวดล้อมของการขับขี่ มีผลต่อการรับรู้ความเสี่ยงของผู้ขับขี่และส่งผล

ต่อมูลค่าความเต็มใจที่จะจ่ายเพื่อลดโอกาสเกิดอุบัติเหตุ หน่วยงานที่เกี่ยวข้องสามารถนำผลการศึกษาไปประยุกต์ใช้เพื่อจัดการความปลอดภัยที่ทางให้สอดคล้องกับบริบทของพื้นที่ได้

สาขาวิชา วิศวกรรมขนส่ง

ปีการศึกษา 2565

ลายมือชื่อนักศึกษา____________________.

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PANUWAT WISUTWATTANASAK : FACTORS AFFECTING COST OF ACCIDENT FOR PERSONAL CAR USERS IN THAILAND. THESIS ADVISOR: ASST. PROF. SAJJAKAJ JOMNONKWAO, Ph.D., 147 PP.

Keyword: Willingness-to-pay/Value of statistical life/Value of statistical injury

Thailand continues to suffer from violence and damage from road accidents. (32.7 deaths from road accidents per 100,000 people). The impact on the country's society and economy can be estimated from the value of the accident. If the accident has a high value, it means the accident is of high severity as well. Therefore, the purpose of this study was to assess the damage of road accidents as assessed by 1,650 personal car drivers in Thailand, as well as to find factors influencing risk perception and willingness to pay (WTP) to reduce the risk of accidents for Thai car drivers both at the driver and local level.

The study used a questionnaire and a face-to-face interview. There are two approaches to evaluating the willingness to pay for this study, the contingent valuation and the choice experiment. The study estimated the damage of road accidents by calculating the statistical value of lives and injuries. In addition, the study continues to analyze factors affecting driver willingness to pay with statistical models including: structural equation modeling, confirmatory factor analysis, mixed logistics regression model and analysis of unobserved heterogeneity

The results of this study can serve as a guide for relevant agencies to allocate appropriate budgets for improving road safety. At the driver level, the analysis also reveals the socioeconomic characteristics of drivers, their driving experience, accident-related experiences, psychological perspectives on risk perception, and accident valuation. This approach enables relevant agencies to see the factors that are important and to assist in the design of appropriate policies for managing the risk and severity of road accidents.

In addition, on a local level, the results of this study show that law enforcement, government support, and the driving environment affect drivers' perceptions of risk and affect the value of their willingness to pay to reduce the chance

of an accident. Relevant agencies can apply the results of the study to manage safety in accordance with the context of the area.

School of Transportation Engineering Student's Signature__________.
Academic Year 2022 Advisor's Signature__________.

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Panuwat Wisutwattanasak

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LIST OF ABBREVIATIONS

α	=	Statistically significant level
β	=	Structural coefficient
χ^2	=	Chi-square
df	=	Degree of freedom
RMSEA	=	Root mean square of approximation
SRMR	=	Standardized root mean residual
CFI	=	Comparative fit index
TLI	=	Tucker Lewis Index
EFA	=	Exploratory factor analysis
CFA	=	Confirmatory factor analysis
SEM	=	Structural equation modeling
MSEM	=	Multilevel structural equation modeling
CR	=	Composite reliability
AVE	=	Average variance extracted
LL	=	Log-Likelihood
AIC	=	Akaike information criterion
SD	=	Standard deviation
SK	=	Skewness
KU	=	Kurtosis

CHAPTER 1

INTRODUCTION

1.1 Rationale of the research

1.1.1 Background

Recently, road accidents remain a major problem that affects many sectors in many countries worldwide, especially in developing countries. These countries contain registered car exceed 60% that of the world (World Health Organization, 2018), due to inefficient public transport system that is unable to meet the needs of the country's population (Marshall et al., 2005). Therefore, the majority of the population still needs to travel by private cars, which results in high traffic volume and increases the proportion of road accidents in these countries. In addition, statistics demonstrate developing countries have more than 9 out of 10 road accident deaths in the world, which leads to social and economic losses (Elvik, 2000). Thailand is a developing country and ranks eighth worldwide in terms of road accidents at 32.7 fatalities per 100,000 population (World Health Organization, 2018). Moreover, the number of private cars registered is increasing on a yearly basis (Department of Land Transport, 2020). Road accidents are related to and directly affect drivers. Therefore, examining driver attitudes is an important aspect to reflect on the causes of violence and perspectives on road accidents. In turn, doing so may also reduce the severity of road accidents. Assisting drivers and improving road safety are key element in the sustainability development of the country (Road Safety Center, 2019).

1.1.2 Willingness-to-pay approach and value of road accident

Many methods can be used to analyze the severity of and damage due to road accidents. One of the methods that consider accident severity is evaluating the value of an accident (Litman & Fitzroy, 2017; Meyer & Elrahman, 2019). In other words, the more serious the accident, the more the damage will be. Each case of accident will affect drivers, and others involved in many ways, whereas damage may be direct, as in injury, death, and property (Ram & Chand, 2016). The indirect effects include productivity, income, and mental health for drivers and their families (Jomnonkwao et al., 2021; Wijnen, 2021). Damage due to deaths and injuries can be assessed using the value of statistical life (VSL) and the value of statistical injury (VSI), respectively (Flügel et al., 2015). Moreover, the results of analysis using the VSL and VSI together with the number of fatalities and injuries per year can be used to illustrate the cost of road accidents at the national level. This study used the willingness-to-pay (WTP) method to estimate VSL and VSI, because WTP is a concept of economic valuation used to evaluate the value of product. In part of road safety, WTP can refer to risk valuation from accident of road users (increasing of drivers' risk perception, increase in their WTP). Therefore, WTP is appropriate for adapting to the assessment of road accident risk (Varian, 1992). Moreover, WTP is used in various applications and is proven to provide results that remain effective and popular today.

1.1.3 Factors affecting the willingness-to-pay

The factors influencing accident value and drivers' assessments of the severity of the accident can be categorized into three parts:

1) Sociodemographics of drivers: According to many past studies, more than 90% of road accidents are caused by drivers (people). This means that studying the sociodemographic of each driver can show how they are different and how that affects WTP.

2) Psychological factors: The driver's accident valuation is consistent with their attitudes and ideas about the severity of the accident. The study underscores the importance of psychological influences that may affect drivers' perceptions of risk and the valuation of accidents. The health concept was applied to the study of factors influencing WTP, including theory of planned behavior (TPB), health belief model (HBM), and health access process approach (HAPA). Previous research evinced that these concepts were correlated with the driver's perception of risk and beliefs about the health of the driver, but this correlation has not been found in applying the WTP to the road accident reduction study.

3) District (area) factors: factors related to the environment or driving area, whether law enforcement, government support, and the driving environment or

traffic, affect the perception of risk and the valuation of accidents. Because if a driver perceives an unsafe danger on the road because of traffic factors or ineffective law enforcement, including a lack of good staff support, this will cause drivers to be aware of the dangers on the road and affect their road accident valuation.

1.1.4 Context of urban and rural road accident

Most researchers reported considerable differences in the results between area contexts (urban and rural) in their analysis of road accidents and factors influencing the severity in multiple countries, which may lead to certain interesting observations (Antoniou, 2014; Champahom et al., 2020; Nasrollahtabar Ahangar et al., 2020; Wu et al., 2021). Factors that influence different outcomes include respondent characteristics, road and environmental conditions, policies and law enforcement, and traffic volume. In Thailand, the nature of drivers or residents differs significantly between urban and rural areas, e.g., the results of Se et al. (2021a) and Champahom et al. (2020) demonstrated that the accident severity and influencing factors are related to area contexts; such an evidence is common in developing countries. In most developing countries, investments in road safety, transportation systems, and access to a good quality of life for urban or rural residents are unequal (Ariyaarpakamol, 2019) and that prosperity and sustainability are frequently concentrated in large cities, without change in rural areas. Consequently, different drivers have different attitudes toward road safety, driver nature, and social status. Recognizing the importance of this issue; we intend to investigate the differences in risk valuation classified by urban and rural areas in Thailand.

1.2 Purpose of the research

- To study the psychological factors influencing the drivers' willingness to pay
- To analyze the complexity of factors affecting the drivers' willingness to pay using multilevel structural equation modeling
- To study the difference between urban and rural area contexts affecting the valuation of drivers' road accident risk

- To apply confirmatory factor analysis and an advanced heterogeneity model for analyzing the factors affecting drivers' willingness to pay for road accident reduction

1.3 Scopes of the research

- Study the demographics and psychological factors obtained from personal car drivers
- Study only the willingness to pay of car drivers using contingent valuation (CV) and choice experiment (CE) survey
- Study on the difference between urban and rural drivers' valuation of road accidents
- Study only the data obtained from face-to-face interviewing questionnaires of Thai personal car drivers (four regions)

1.4 Research questions

- What factors affecting the willingness to pay for road accident of drivers?
- What is the influence of district factors resulting in drivers' valuation of road accidents?
- Urban and rural area context are affecting the value of road accident?
- How are the unobserved heterogeneity that influence the drivers' risk valuation and willingness to pay?

1.5 Research contribution

- The research finding can be used as an updated value of appropriate budget allocation for road safety improvement
- The results presented for district factors (policy, support, and environment) can influence the perceived road accident risk of each driver.
- The finding illustrated the difference characteristics of area contexts affecting the willingness to pay of drivers

- The results of unobserved heterogeneity model can reveal the insight effect on drivers' risk valuation

1.6 Organization of the research

This research is consisting of 6 main chapters as follows:

Chapter I: Introduction section includes the rationale and the importance of the research, purpose of the research, scope of the research, research questions and expected contribution of the research.

Chapter II: Factors influencing willingness to pay for accident risk reduction among personal car drivers in Thailand.

Chapter III: Multilevel structural equation modeling of willingness to pay for road accident reduction: Perspectives of driver and district levels.

Chapter IV: Correlated random parameter model with heterogeneity in means for analysis of factor affecting the value of road accident and travel time.

Chapter V: Influence of psychological perspectives and demographics on drivers' valuation of road accident: A combination of confirmatory factors analysis and preference heterogeneity model.

Chapter VI: Conclusion and recommendations. This section concludes the results from sections 2 – 5, and practical application of the research.

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CHAPTER 2

FACTORS INFLUENCING WILLINGNESS TO PAY FOR ACCIDENT RISK REDUCTION AMONG PERSONAL CAR DRIVERS IN THAILAND

2.1 Abstract

Thailand ranks near the top for the road accident fatality rate worldwide, and more and more vehicles are being registered in Thailand every year. Obtaining the opinions of road commuters may help us reduce road accidents in Thailand. This study seeks to understand damage value in road accidents for personal car drivers in Thailand, using the willingness to pay approach and establishing factors affecting willingness to pay with the theory of planned behavior (TPB). This study obtained data using questionnaires in face-to-face interviews with 1,650 personal cars drivers in Thailand. The average willingness to pay (WTP) for 50% fatality or injury reduction was 23.00 baht/person/50 km trip (US $0.74/person/50 km trip). We obtained the value of statistical life (VSL), assessing this to fall between US $815,385 and US $872,942, and the value of statistical injury (VSI), between US $150,059 and US $160,652. Overall, national damage was assessed at US $4,701,981,170 annually. According to the analysis of factors affecting WTP, TPB comprises four factors, namely, driver attitude, subjective norm, perceived behavioral control, and behavioral intention. Analysis using structural equation modeling (SEM) found all mentioned factors were relevant and positively influenced personal car drivers' WTP in Thailand, with a statistical significance at a 99% confidence interval ($p < 0.01$). This study can develop recommendations for relevant organizations to analyze the results as part of considerations regarding budget allocation and developments on road safety policy due to driver attitude as important as environmental factors or any other factors.

2.2 Introduction

2.2.1 Background

Road accidents are drawing significant research attention. Currently, 93% of world traffic fatalities occur in low- and middle-income countries, and 60% of registered vehicles worldwide are found in these countries (World Health Organization, 2018). Recreational Vehicle-vehicle, vehicle-pedestrian, or vehicle-animal accidents (Abra et al., 2019) have significant effects, both direct ones, including injuries, medical bills, property damage, and indirect effects, including productivity loss, income loss, and mental effects on the person in the accident and others. Increasing numbers of accidents will affect the overall image of the country's economy and society. The problem of road accidents urgently requires resolution (Rizzi and Ortúzar, 2006; Trawén et al., 2002).

Thailand is a middle-income country (World Bank, 2019), and it ranks near the top for dangerous road accidents. Thailand has an average road accident fatality at 32.7 persons per 100,000 population, ranking first among Southeast Asian countries and eighth worldwide (World Health Organization, 2018). The problem of road accident fatality is important and requires to be improved. In addition, personal vehicles are the most commonly represented type in accidents worldwide, suggesting regular drivers cause accidents. As many as 2,785 deaths from car accidents occur yearly in Thailand and 15,133 severe injuries (Bureau of Highway Safety, 2020a). The increasing fatality rate is accompanied with an increasing number of car registrations. The increasing car registrations result from the continuous growth of Thailand's population, a symptom of increased transport demand (Marshall et al., 2005). Where transport demand is growing, but public transit cannot meet the demand, people depend on personal cars. In 2020, there were 10,880,759 car registrations, an annual average of 599,158 units, a 2.7-time increase from the annual rate 10 years ago (Department of Land Transport, 2020). This match accident reports finding that the road accident situation in Thailand in the last 10 years was 7.13% higher than average, with 10.26% more fatalities than average. These numbers are quite worrisome (Ministry of Transport, 2019), and they are only exacerbated by the increasing availability of transportation and road commuting. Moreover, Thailand is a center of tourism, society, and economy of Southeast Asia in general, representing road accident problems, attitudes, and driving behaviors for vehicle and road commuters in this region.

2.2.2 Willingness to pay approach and factor affecting the willingness to pay

The willingness to pay (WTP) approach indicates the maximum value that a person would consider paying to get a unit of one thing or agrees to pay for not losing that thing (Varian, 1992). This study uses WTP on transport safety to evaluate the value of a statistical life (VSL) and statistical injury (VSI) in a road accident. Using the WTP approach, we can establish how human beings evaluate their road accident risk and determine how much they would agree to pay to reduce risks (Rizzi and Ortúzar, 2006; Trawén et al., 2002). This can be combined with the concept value of human life, which is not restricted to seeking one’s benefit but other values, such as helping others in society (Landefeld and Seskin, 1982). WTP has recently become a more commonly used approach, as determined by analyses that have produced suitable results in safety tasks.

"Accident" and "crash" term are widely used in road safety research, this distinction was presented by Stewart and Lord (2002) who stated that accidents are the event could not have reasonably been prevented, such as a sudden change in the weather or road conditions, or rock avalanche takes you off the road as you are driving (Knechel, 2015). In contrast, road crashes are caused by misconduct of drivers, speeding, distracted, or careless drivers and, therefore, are not accidents (Stewart and Lord, 2002). In WTP studies, the "accident" term are suitable and largely used (Ainy et al., 2016; Ainy et al., 2014; Niroomand and Jenkins, 2016) as WTP is the intention to reduce the risk. These are not only caused by driver’s faults, but also raised from unpredictable events as defective car equipment or sudden environmental change.

In general, the cause of accidents has three parts, namely, human, vehicle, and environmental (Dewar and Olson, 2007; Evans, 2012; Ratanavaraha and Amprayn, 2003; Shinar, 2007). Several studies indicate that the human factor is key and should emphasize safety investigations regarding accidents (Dewar and Olson, 2007). Human causes are responsible for over 90% of all road accidents, not only pre-driving behavior but also during driving, such as drinking alcoholic beverages, going over the speed limit, and driving while sleepy. Physical factors in general play a role, being differentiated by the individual, such as gender (Delavary Foroutaghe et al., 2019), age, attitude, and accident experience (Hong et al., 2020). These factors produce different driving behaviors in drivers, each of which has its risks of causing road accidents, which affect the estimation of the value of individual safety being differentiated by various basic factors of each person (Ainy et al., 2014; Chakrabarty et al., 2013; Dewar and Olson, 2007). This study does not focus on obtaining a list of factors causing accidents. Instead, it focuses on factors affecting WTP for accident risk reduction based on personal factors, attitudes toward safety, perceived behavioral control, and subjective norms. All of these factors are considered within the Theory of Planned Behavior (TPB) (Ajzen, 1991) to establish the extent to which attitudes, perceptions, and intentions influence how drivers see the importance of safety. Using WTP, we consider that if drivers are willing to pay more to reduce their chance of accident risk, they are more aware of effects of a road accident.

2.2.3 Theory of planned behavior and relevant literatures

WTP for reducing accidents is judged according to the behavioral intention factor, which can be understood in terms of TPB, which comprises three factors that affect behavioral intention, as presented in Figure 2.1. 1) Attitude is the overall evaluation of any particular thing. The results of behavioral beliefs can cause one's attitude toward behavior. If one's evaluation of the following effect is positive, the person will have a good attitude toward the behavior. By contrast, if the evaluation is negative, the person has a negative attitude toward the behavior. 2) Perceived behavioral control is the difficult or simple responsive feeling toward behaviors caused by individual control beliefs that may support or block such behaviors, including perceived forces toward trust, which leads one to behave in a certain way or not to (Ajzen, 1991). 3) A subjective norm represents the perception of a social trend concerning a person that leads to a certain behavior or its omission. A behavioral, subjective norm is caused by individual beliefs toward the social trend, particularly in terms of intimate friends. Normative beliefs will make a person express either one or another behavior.

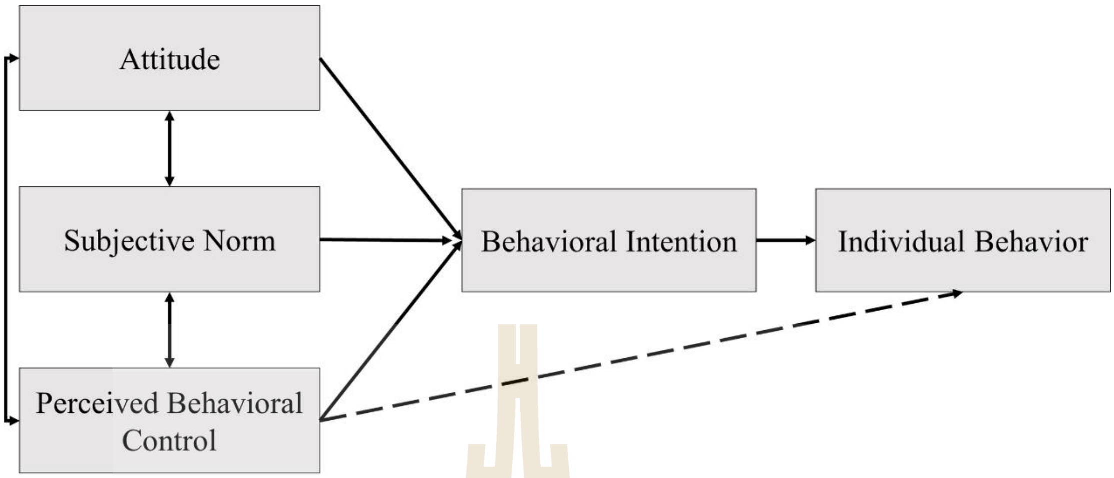

Figure 2.1 Theory of planned behavior model. (Ajzen, 1985)

Nowadays, several studies take TPB to apply its analysis along with WTP in various fields, such as the sustainability field. Obeng et al. (2019) applied TPB to factors influencing WTP for rainwater source restoration in a degenerated tropical zone. Pouta and Rekola (2001) took TPB to seek for factors affecting WTP to restore forest conditions in Southern Finland sustainably. In transportation and logistics, Asri and Ngah (2018) analyzed factors influencing WTP for halal transportation cost with the TPB. Due to the large and growing Muslim populations in many countries, knowledge of halal transportation has come into demand.

For valuation of WTP in road accident research, one of the most widely used methods is the contingent valuation method (CVM). Several studies used CVM to collect the WTP for risk reduction, such as Ainy et al. (2014), who studied the cost of road traffic injuries in Iran. Mon et al. (2019) estimated the WTP and the value of fatality risk reduction for car drivers. Yang et al. (2016) used WTP to estimate the VSL in China, Bhattacharya et al. (2007) studied the value of mortality risk reductions in India, and Andersson (2007) used WTP method to study road safety and estimate of the risk of death in Sweden. Many studies used CVM to obtain the WTP (see Table 2.1). This CVM involved direct questions; respondents were asked how much they were willing to pay per year for accident risk reduction or how much they were willing to pay for safety equipment per year to reduce the risk of accidents. The results of the related studies indicated many limitations in the research on the value of the accident. For example, the valuation of life or road accident is difficult for driver or road users especially when considering the value for a year as there is no criterion to measure the value clearly, driving behavior factors and road accident experiences also were overlooked, these will create gaps and driver inequality to estimate their WTP. To study WTP for road accidents based on drivers, the valuation of risk should be a concept that all drivers can valuate as clearly as possible.

Table 2.1 Previous studies on willingness to pay with contingent valuation method.

Author	Country	Method	Willingness-to-pay	Analysis	Factor
Yang et al. (2016)	China	CVM	risk reduction per year.	Logit model	Demographics
Mon et al. (2019)	Myanmar	CVM	risk reduction per year.	SEM	Demographics
Ainy et al. (2014)	Iran	CVM	risk reduction per year.	Regression	Demographics
Bhattacharya et al. (2007)	India	CVM	risk reduction per year.	Probit model	Demographics
Andersson (2007)	Sweden	CVM	risk reduction per year.	Probit model	Demographics
Robles-Zurita (2015)	Spain	CVM	risk reduction per year.	Probit model	Demographics
Svensson and Johansson (2010)	Sweden	CVM	risk reduction per year.	Regression	Demographics
Haddak (2016)	France	CVM	risk reduction per year.	Tobit model	Demographics
Corso et al. (2001)	USA	CVM	risk reduction per year.	Regression	Demographics
Widyastuti and Utanaka (2020)	Indonesia	CVM	risk reduction per year.	Logit model	Demographics
Hoffmann et al. (2017)	China	CVM	risk reduction per year.	Regression	Demographics
Alberini et al. (2006)	Canada	CVM	risk reduction per year.	Regression	Demographics
Giergiczny (2008)	Poland	CVM	risk reduction per year.	Regression	Demographics
Gibson et al. (2007)	Thailand	CVM	risk reduction per year.	Regression	Demographics
Andersson and Lindberg (2009)	Sweden	CVM	risk reduction per year.	Logit model	Demographics
This study	Thailand	CVM	risk reduction per trip kilometers.	SEM	Theory of planned behavior

Note: CVM = contingent valuation method; SEM = structural equation modeling.

As mentioned above, the accident rate relates to increasing traffic volumes, and previous research did not consider such concerns. This study will obtain WTP for accident risk reduction of personal car drivers in Thailand based on driving distance to reduce gaps and bias. Moreover, factors affecting WTP in most previous studies are demographics. However, from a psychological perspective, intention is the best factor for predicting behavior. In this context, WTP can be predicted by intention, which is part of TPB. This study will investigate the correlation between WTP and TPB, which has never been studied in road safety research, to develop a new alternative. We will use these results as representative data of the national level. The results of this analysis can be used as a guideline for budget allocation for road accident mitigation to increase safety for road commuters and to use it as a method of study for other kinds of vehicles later.

2.3 Materials and methods

This section will explain the calculations on VSL and VSI acquired from the WTP approach. Structural equation modeling (SEM), model fit criteria, questionnaire design, and data collection.

2.3.1 Value of statistical injury and value of statistical life

This study gathered the WTP per trip for a 50% injury or fatality reduction. According to VSL and VSI, they can be measured by WTP for accident reduction, divided by decreasing numbers of injuries or fatalities (Chaturabong et al., 2011). In this study, we calculate the value of WTP per kilometer by using the average WTP per trip, divided by the number of kilometers per trip, as presented in Equation (2.1), for accident ratio per kilometer (Niroomand and Jenkins, 2016). The ratio can be calculated in terms of decreasing number of annual fatalities or injuries, divided by annual vehicle kilometers traveled as presented in Equations (2.2) and (2.3).

$$\text{WTP per km.} = \frac{\text{WTP per trip}}{\text{Trip km.}} \tag{2.1}$$

$$\text{Fatality chance per km.} = \frac{\Delta \text{ fatalities}}{\text{Annual VKT}} \tag{2.2}$$

$$\text{Injury chance per km.} = \frac{\Delta \text{ injuries}}{\text{Annual VKT}} \tag{2.3}$$

Thus, according to Equations (2.1)–(2.3), we can calculate the VSL and VSI using WTP for 50% accident reduction per kilometer, divided by 50% of annual fatalities per kilometer, as presented (Equations (2.4) and (2.5)) below.

$$\text{VSL}=\frac{\text{WTP per km.}}{\text{Fatality chance per km.}}=\frac{\text{WTP per Trip}}{\text{Trip km.}}\times\frac{\text{Annual VKT}}{\Delta\text{ fatalities}} \tag{2.4}$$

$$\text{VSI}=\frac{\text{WTP per km.}}{\text{Injury chance per km.}}=\frac{\text{WTP per Trip}}{\text{Trip km.}}\times\frac{\text{Annual VKT}}{\Delta\text{ injuries}} \tag{2.5}$$

2.3.2 Structural equation modeling

SEM can be created from a theory to express the relationship between variables. Variables can be divided into two groups: exogenous or independent variables and endogenous or dependent variables (Wiratchai, 1999). This model results from a synthesis of three analytical methods including factor analysis, path analysis, and parameter estimation toward regression analysis. SEM consists of two sub-models (Hox and Bechger, 1998), as below.

1) Measurement model: A measurement model presents a relationship between the latent variable and observed variables used as indicators for each latent variable. The measurement model can be both exogenous measurement models and endogenous measurement models (Jöreskog, 1969).

2) Structural model: A structural model expresses the relation between exogenous latent variables and endogenous latent variables. However, the relation format is not a measurement model, but it is a path analysis from one variable to the next (Fassinger, 1987; Kahn, 2006; Weston and Gore Jr, 2006).

3) Model fit criteria: The analysis must consider statistical values to establish whether the model can explain the following relationships to test the accuracy and model fit: the value of chi-square per degree of freedom (χ^2/df), where initially, it should not be over 5 (Sun et al., 2013; Washington and Karlaftis, 2003); then, the good value of root mean square error of approximation (RMSEA), which should not be specified over 0.07 (Steiger, 2007). Good value or Tucker–Lewis index (TLI) or non-normal fit index should be equal to or over 0.80 (Hooper et al., 2008). A suitable value of the comparative fit index (CFI) for the model is specified at/or over 0.90, and a proper value of standardized root mean square residual (SRMR) should be equal to or

less than 0.08 (Hu and Bentler, 1999; Marsh et al., 2004). The statistical testing values can be calculated by Equations (2.6)–(2.9), as follows.

$$SRMR=\sqrt{\sum_i \sum_k \frac{r_{jk}}{p^*}}, \tag{2.6}$$

when r_{jk} is standardized residuals from a covariance matrix with j rows and k columns, and p^* is the number of non-duplicated elements in the covariance matrix.

$$RMSEA=\sqrt{\frac{\chi_T^2\text{-}df_T}{df_T(N\text{-}1)}}, \tag{2.7}$$

$$TLI=1-\frac{[\left(\chi_T^2\text{-}df_T\right),0]}{max[\left(\chi_T^2\text{-}df_T\right),\left(\chi_B^2\text{-}df_B\right),0]}, \tag{2.8}$$

$$CFI=\frac{\left(\frac{\chi_B^2}{df_B}\right)\text{-}\left(\frac{\chi_T^2}{df_T}\right)}{\left(\frac{\chi_B^2}{df_B}\right)\text{-}1} \tag{2.9}$$

where $\chi_T^2-\chi^2$ values of the target model, df_T=df the target model, $\chi_B^2-\chi^2$ values of the baseline model, and df_B=df of the baseline model.

2.3.3 Questionnaire design

The study questionnaire consists of three main sections, namely, Section 1: WTP for 50% fatality or injury risk reduction by using CVM. This part is an open-ended question; respondents were asked “How much are you willing to pay to use improved roads that have 50% fatality or injury risk reduction for 50 kilometer-trip” (WTP per trip), to use this value of WTP to calculate for the VSL and VSI later. Next, Section 2 concerns general information on economic and social characteristics, such as gender, age, income, education, number of people in the family, etc. This information can explain the family structure, maturity characteristics, and economic status that are the norm and differences in the sample. The final relates to the TPB obtaining the necessary information to perform SEM, while questions concerning the TPB will measure the opinion of car drivers, this section consists of four groups, including attitude, subjective norm, perceived behavioral control, and behavioral intention. The answers in this section are given on a 5-point Likert scale (Wuensch, 2005) to determine opinions on various factors phrased as statements, where 5 meant strongly agree and 1 meant strongly disagree. All questions of this questionnaire have already been passed the Index of Item-Objective Congruence test by three road safety field experts.

2.3.4 Data collection and preliminary analysis

Regarding the desirable numbers of respondents used in the analysis of SEM, in previous studies, there was a suggestion regarding suitable numbers of samples for Maximum Likelihood estimation, namely that it should be at least 15 times for the numbers of observed variables (Bentler and Chou, 1987; Golob, 2003). In this study, we find 15 relevant variables, so there should be data from at least 225 samples before we can analyze the model properly. This study conducted its data survey using face-to-face interviews for questionnaire collection from car drivers in Thailand. Four regions of Thailand were represented (North, South, Central, and Northeast). We used random sampling from eight provinces that have the highest proportion of road accident fatalities for each region. We obtained 1,650 samples suitable for the analysis by using SEM and Table 2.2 presents the preliminary analysis.

Ethical approval: The ethics committee of the Suranaree University of Technology approved this study on November 13, 2020. Human research ethics application documents were submitted; then, the ethics evaluation result was that the study was low risk, it does not affect daily life, and oral informed consent is allowed.

Table 2.2 Preliminary analysis

Category	Frequency	Percentage (%)
Gender		
Male	1,020	61.8
Female	630	38.2
Education		
Primary school	130	7.9
Lower secondary school	298	18.1
Higher secondary school/Vocational certificate	210	12.7
Diploma/high vocational certificate	126	7.6
Bachelor’s degree	802	48.6
Master’s degree	71	4.3
Doctor of philosophy	13	0.8
Occupation		
Student	79	4.8
Government/State enterprise officer	175	10.6

Table 2.3 Preliminary analysis (Continued)

Category	Frequency	Percentage (%)
Private company	627	38.0
Self-employed	313	19.0
Farmer	139	8.4
Laborer	274	16.6
Others	43	2.6
Accident experience		
Never	1,405	85.2
Ever	245	14.8
Personal income (Baht per month)		
Less than 10,000	26	1.6
10,000 – 14,999	205	12.4
15,000 – 19,999	343	20.8
20,000 – 24,999	447	27.1
25,000 – 29,999	221	13.4
30,000 or higher	408	24.7
Mean of age	36.33 year-old	

2.4 Results

2.4.1 Descriptive statistics

Table 2.3 presents the descriptive statistics, including the mean, standard deviation, skewness, kurtosis, and the reliability test, obtained from the questionnaire responses to items in four groups, namely, attitude, subjective norm, perceived behavioral control, and behavioral intention (Section 3 of the questionnaire). We have tested the descriptive statistic to achieve a normal distribution, following Kline (2015), who indicated that a good skewness should be between −2 and 2, and kurtosis should be between −7 and 7. According to Tavakol and Dennick (2011), suitable reliability should show a Cronbach's alpha value of 0.7 or higher. The statistical values of four groups of factors were within acceptable ranges for analysis.

In a questionnaire response where a pair of variables is very closely related, respondents likely understood them to mean the same thing. It might impede the analysis of the model and impact the correlation of observed variables that should not be over ±0.750 (Mukaka, 2012). The correlation analysis in Table 2.4 indicated that no pair of variables had a higher correlation than the acceptable value, so we could take all variables to analyze the model.

Table 2.4 Descriptive statistics

Item	Description	Mean	SD	SK	KU	Alpha
	Attitude					0.782
A1	It is useful to pay for safety on road usage because it helps to reduce the risk of accidents.	4.57	0.57	−0.96	1.14	
A2	To pay for safety on road usage for accident reduction makes me feel safer.	4.56	0.57	−0.87	−0.13	
A3	Most of my family members probably agree if I pay more for safer road usage.	4.52	0.60	−0.96	0.33	
A4	Most of my friends probably agree if I pay more for safer road usage.	4.51	0.62	−0.92	−0.03	
	Subjective norm					0.793
S1	Most of my family members pay for safety on road usage for accident reduction.	4.15	0.75	−0.28	−1.11	
S2	Most of my friends pay for safety on road usage for accident reduction.	4.18	0.75	−0.33	−1.12	
S3	Most people in my community pay for safety on road usage for accident reduction.	4.12	0.78	−0.22	−1.28	
	Perceived behavioral control					0.793
P1	It is my own decision to pay for safety on road usage, not by others.	4.04	0.77	−0.12	−1.17	
P2	Risk of accident depends on self. If I pay for safety, there will be no accident.	4.03	0.77	−0.07	−1.28	
P3	I can reduce accident myself by paying for safety on road usage.	4.04	0.78	−0.08	−1.33	
	Behavioral intention					0.732
I1	I will pay more for safer road usage.	4.35	0.68	−0.58	−0.71	
I2	I will pay for safety on road usage because I believe that it can safe my life.	4.30	0.72	−0.57	−0.69	
I3	I will recommend my intimates to pay for safety on road usage for accident risk reduction.	4.47	0.63	−0.85	0.15	
I4	I have planned to pay for safety on road usage for accident reduction.	4.51	0.61	−0.90	−0.05	

Note: SD = standard deviation, SK = skewness, KU = kurtosis, Alpha = Cronbach's alpha.

Table 2.5 Correlation coefficients

	A1	A2	A3	A4	S1	S2	S3	P1	P2	P3	I1	I2	I3	I4
A1	1	.292**	.210**	.130**	.074**	.080**	.063*	-.019	.054*	.044	.077**	.403**	.096**	.100**
A2		1	.295**	.277**	.075**	.095**	.026	.033	.108**	.059*	.162**	.137**	.261**	.311**
A3			1	.333**	.039	.102**	.058*	.074**	.118**	.094**	.087**	.075**	.108**	.146**
A4				1	.030	.106**	.048*	.076**	.088**	.115**	.030	.010	.079**	.130**
S1					1	.295**	.314**	-.345**	-.335**	-.347**	.001	-.114**	.070**	.080**
S2						1	.369**	-.313**	-.253**	-.276**	-.109**	-.107**	.004	.083**
S3							1	-.318**	-.336**	-.356**	-.158**	-.174**	.002	.006
P1								1	.571**	.581**	.321**	.184**	.207**	.049*
P2									1	.649**	.288**	.219**	.113**	.107**
P3										1	.245**	.227**	.106**	.064**
I1											1	.489**	.356**	.314**
I2												1	.287**	.244**
I3													1	.325**
I4														1

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

2.4.2 Estimating the VSL and VSI

We have obtained the average WTP at 23.00 baht per person per 50 km trip (US $0.74 per person per 50 km trip; exchange rate: US $1 = 31.28 baht (2020)) and a standard deviation of 16.250 baht. The estimated amount of personal car transport on the highways in Thailand in 2020 was about 7.993 x 10^{10} kilometers (Bureau of Highway Safety, 2020b), and there were 2,785 fatalities and 15,133 injuries from car accidents in Thailand (Bureau of Highway Safety, 2020a). If we apply our values of WTP, annual vehicle kilometers traveled, fatalities, and injuries to Equations (1)-(5), we find a VSL and VSI of car accidents, as follows.

VSL was calculated to 26,405,425 baht (US $844,163), with a 95% confidence interval of between 25,505,238 and 27,305,612 baht (US $815,385 to US $872,942).

VSI was calculated to 4,859,520 baht (US $155,355), with a 95% confidence interval of between 4,693,854 and 5,025,185 baht (US $150,059 to US $160,652).

2.4.3 Analysis of factors influencing WTP using SEM

1) Structural model: Figure 2.2 shows the SEM for our study on WTP for accident risk reduction using Mplus 6.12 software by Muthén & Muthén, Los Angeles, CA, USA. The analysis found that attitude, subjective norm, and perceived behavioral control influenced behavioral intention. Further, behavioral intention influenced WTP to the degree that it was significant at a 0.01 level. To test the model fit of the SEM, the analysis found that the model had values of chi-square (χ^2) = 162.841, degree of freedom (df) = 65, $p < .001$, (χ^2/df) = 2.505, CFI = 0.982, TLI = 0.971, SRMR = 0.031, and RMSEA = 0.030. Comparing these statistics with acceptable values, we find that the SEM is in accordance with empirical data.

2) Measurement model: The four parts of the measurement model were attitude, subjective norm, perceived behavioral control, behavioral intention, and model parameter, as shown in Table 2.5 and explained below.

Attitude was measured by observed variables A1-A4. The analysis found that all four observed variables were components of attitude at $p < 0.01$ significance.

A2 had the highest factor loading, “To pay for safety on road usage for accident reduction makes me feel safer” (Est. = 0.605, t = 18.510).

Subjective norm was measured by observed variables S1-S3. The variable analysis showed that all three variables could be used as components of the subjective norm at $p < 0.01$ significance. S1 had the highest factor loading, “Most of my family members pay for safety on road usage for accident reduction” (Est. = 0.570, t = 23.756).

Perceived behavioral control was measured by observed variables P1-P3. All three variables were components of perceived behavioral control at $p < 0.01$ significance. Perceived behavioral control had P3 observed variable as the highest factor loading, “I can reduce accident myself by paying for safety on road usage” (Est. = 0808, t = 63.324).

Behavioral Intention was measured by observed variables I1-I4. The analysis found that all four observed variables could be used as components of behavioral intention at $p < 0.01$ significance. I1 had the highest factor loading, “I will pay more for safer road usage” (Est. = 0.813, t = 15.424).

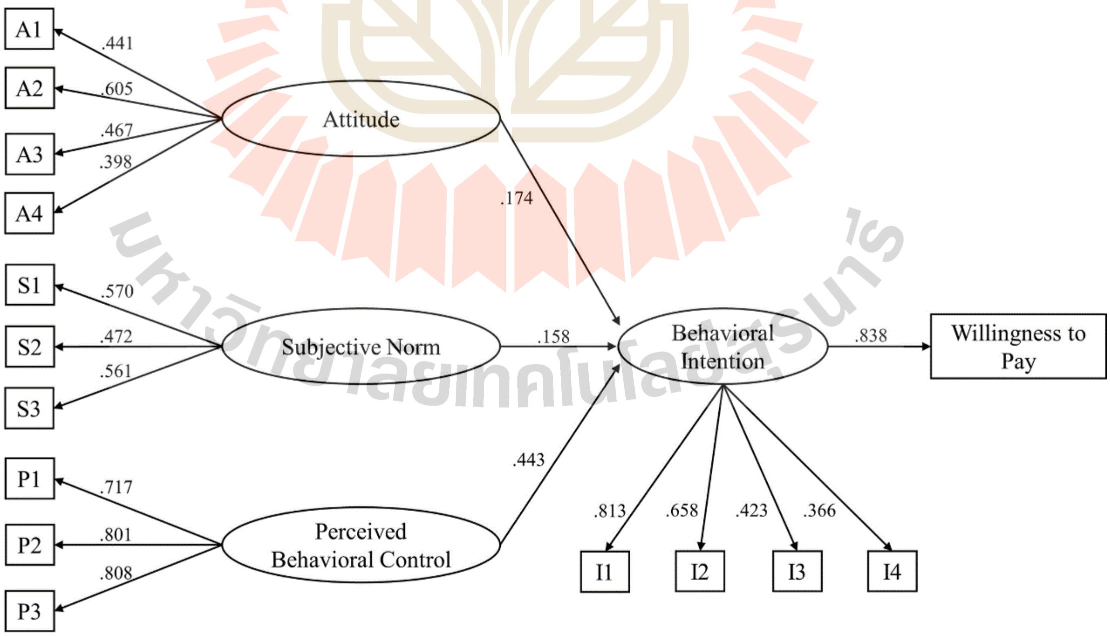

Figure 2.2 Factors influencing willingness to pay according to the structural equation modeling

Table 2.6 Standardized model results

Item	Description	Est.	*t*-value	*p*-value
Measurement model				
	Attitude			
A1	It is useful to pay for safety on road usage because it helps to reduce the risk of accidents.	0.441	16.062	<0.01
A2	To pay for safety on road usage for accident reduction makes me feel safer.	0.605	18.510	<0.01
A3	Most of my family members probably agree if I pay more for safer road usage.	0.467	14.865	<0.01
A4	Most of my friends probably agree if I pay more for safer road usage.	0.398	12.500	<0.01
	Subjective norm			
S1	Most of my family members pay for safety on road usage for accident reduction.	0.570	23.756	<0.01
S2	Most of my friends pay for safety on road usage for accident reduction.	0.472	17.437	<0.01
S3	Most people in my community pay for safety on road usage for accident reduction.	0.561	22.355	<0.01
	Perceived behavioral control			
P1	It is my own decision to pay for safety on road usage, not by others.	0.717	48.154	<0.01
P2	Risk of accident depends on self. If I pay for safety, there will be no accident.	0.801	61.975	<0.01
P3	I can reduce accident myself by paying for safety on road usage.	0.808	63.324	<0.01
	Behavioral intention			
I1	I will pay more for safer road usage.	0.813	15.424	<0.01
I2	I will pay for safety on road usage because I believe that it can safe my life.	0.658	14.323	<0.01
I3	I will recommend my intimates to pay for safety on road usage for accident risk reduction.	0.423	12.207	<0.001
I4	I have planned to pay for safety on road usage for accident reduction.	0.366	10.711	<0.001
Structural model				
	Attitude $\rightarrow$ Behavioral intention	0.174	4.197	<0.001
	Subjective norm $\rightarrow$ Behavioral intention	0.158	11.943	<0.001
	Perceived behavioral control $\rightarrow$ Behavioral intention	0.443	13.474	<0.001
	Behavioral intention $\rightarrow$ Willingness to pay	0.838	14.859	<0.001

Note: Est. = Standardized estimates.

2.5 Discussion

This study obtained a VSL from road accidents of personal car drivers at approximately US $844,163, or between US $815,385 and US $872,942 in Thailand in 2020. For the VSI, it was US $155,355, or between US $150,059 and US $160,652. Comparing our results to those obtained in previous research indicated that high-income countries, calculated by gross national income (GNI) per capita, often have a higher VSL. Low- and middle-income countries have a lower VSL (World Bank, 2019).

In a previous study, the accident value in North Cyprus, incorporating five country regions, found that the VSL was between US $380,579 and US $1,349,453. This was a high value and fluctuated due to the different physical characteristics of the regions, such that some are valleys with curves, where it is dangerous and difficult to drive, so drivers in such areas assign a higher priority to accidents than drivers living in other areas (Niroomand and Jenkins, 2016). Veisten et al. (2013) studied road accidents in Norway, one of the top 10 countries by per capita income, and found a VSL between US $8.81 million and US $23.05 million. This shows developed countries place a high level of importance on violent road accidents. With a significant budget allocated to road safety and enforcement of effective road laws, there are fewer accidents in developed countries than in developing ones (Delavary Foroutaghe et al., 2020; Ning et al., 2016). However, when each accident occurs, it causes significant damage to property (Keller et al., 2021).

On the other hand, VSL was studied in road accidents and pollution in Santiago, Chile, using the CVM and the stated preferences method, and a VSL from road accidents was around US $285,113 (de Dios Ortúzar et al., 2000). A study of WTP for road accident reduction in Myanmar found that the VSL was US $163,000 per person (Mon et al., 2019). Ainy et al. (2016) studied accident value in Iran, a middle-income country, found a road accident VSL of about US $22,342 per person and a VSI of US $3,138 per person, where the total value of damage from road accidents reaching US $335,003,163 per year.

Thus, higher-income countries such as Norway and Cyprus show a high value of damage from accidents. However, comparing Thailand to other low- and middle-income countries, such as Chile, Myanmar, and Iran, the value for damage from accidents in Thailand is clearly higher than its peers. It may be that drivers in Thailand consider road accidents important and agree to pay more to reduce the risk because Thailand’s rate of accident fatalities is high relative to other countries, including those of peer countries (De Blaeij et al., 2003). Therefore, WTP for road accident reduction in each country may depend on several factors, such as socioeconomics, experience, physical characteristics of the driving area, and GNI per capita as well (Niroomand and Jenkins, 2016). In summary, low- and middle-income countries tend to estimate a low value for accidents, so they cannot control and improve effective road safety. This affects the high accident ratio at over 90% for all road accidents worldwide (Staton et al., 2016). However, in developed countries, many factors are different from those in developing countries. For example, suppose drivers have high incomes and high awareness of accident severity. In that case, they will have greater ability and intention to pay, which makes the valuation of the accident higher as well. Therefore, they can allocate a budget for proper safety management, which decreases the number of accidents. Paying for accident reduction is cheaper than having an accident, which causes income and productivity loss, as well as mental and physical damage to themselves and those close to them (Rizzi and Ortúzar, 2006; Trawén et al., 2002).

The analysis of factors affecting WTP indicated that behavioral intention influences WTP, with a statistical significance at a 0.01 level, which positively influences WTP. This means that if the driver has greater behavioral intention, the value of WTP will also be higher (Hendratmoko and Tjahjono, 2016).

TPB, showed the factor most affecting behavioral intention was perceived behavioral control. This factor is relevant to perceived behavioral self-capacity and the feeling regarding any behavior that reflects how well one considers oneself able to practice or control it (Li et al., 2016).

The second factor that affects behavioral intention is attitude. It is well known that any behavioral expression is caused by an attitude toward behavior. That is, if one has bad or negative attitudes toward a behavior, this will decrease behavioral intention. In conclusion, if a driver is not interested in road accidents, this affects WTP accordingly (Liu and Liu, 2008). The obtained result showed that attitude positively influenced behavioral intention, which is consistent with previous research (Hendratmoko and

Tjahjono, 2016). This means that where attitudes toward safety improve among drivers, they will agree to pay more for it.

The third factor was the subjective norm, or the influence of society or intimates that affects one's behavior. The subjective norm develops from personal belief concerning social trends, particularly in relation to one's intimates. In other words, if family members, for instance, show a certain behavior, others may follow the same behavior, in a phenomenon called conformance. If one's intimates have a preferred behavior regarding safety on the road for accident reduction, it will influence others in the same society or environment to have the same behavior. According to the results obtained, subjective norms have positive influences on behavioral intention, which means that drivers tend to behave in the same way as their intimates behavior. However, this part has the lowest factor of all three factors. That is, drivers still prioritize attitudes and perceived behavioral control toward road safety themselves rather than conforming to those of others (Cristea and Gheorghiu, 2016).

2.6 Conclusions

This study collected VSL and VSI concerning road accidents among personal car drivers in Thailand using the WTP approach, including the study of factors affecting the value of an accident. The analysis was divided into two parts, consisting of the following. 1) WTP for accident risk reduction, implying a VSL between US $815,385 and US $872,942 and a VSI between US $150,059 and US $160,652, for a total national value of property damage at US $4,701,981,170 per year. 2) For factors affecting WTP, this study developed a model with the TPB using SEM. The analysis result indicated that the three factors of attitude, subjective norm, and perceived behavioral control positively influence behavioral intention. Further, behavioral intention positively influences WTP for accident risk reduction with statistical significance at a 0.01 level. Thus, TPB was associated with attitude to pay for accident risk reduction, while subjective norm related to the influence of one's intimates, which lead to drivers' behavior. Drivers themselves cause the relation to attitude and perceived behavioral control. That is, producing a good attitude toward drivers' road safety allows them to develop knowledge and understanding, as they place more importance on road accidents. Following this, these drivers will pass on such behavior to others as well.

As it moves toward becoming a fully developed country, road accidents are a main issue that Thailand must address (Veisten et al., 2013) to allow different purposes of traveling and transport to operate safely and efficiently. The uniqueness of this study is that we do not study the value of accidents based on basic factors or the components of accident occurrence, as in other research. However, we focus on the importance of attitudes and perspectives of drivers toward road accidents, which are human factors. The analysis results indicated that good attitudes on accident reduction, perceived behavioral control of drivers, and subjective norm of one's intimates increased behavioral intention relevant to road safety and increased the value of an accident. Therefore, we recommend that organizations who work on road safety management take this result as a guideline for budget allocation regarding accidents, including the development of the policy of road accident reduction. Organizing training on attitudes toward road safety or adding such lessons into training programs for people who apply for car driving licenses raises awareness that drivers' attitudes are as important to road safety as any other factor.

Among the limitations of this study is that we did not allow sociodemographics influencing the WTP of drivers, this could help relevant authorities to promote specific Road Safety Education programs (Alonso et al., 2021). Moreover, we did not include drivers under 18 years old in the analysis due to licensing laws in Thailand. Because adults are often more intellectually independent, certain factors such as attitude or subjective norm might be different among the young. A similar study on a younger age group may produce different results and capture a more representative share of the population.

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CHAPTER 3
MULTILEVEL STRUCTURAL EQUATION MODELING OF WILLINGNESS-TO-PAY FOR ROAD ACCIDENT REDUCTION: PERSPECTIVES OF DRIVER AND DISTRICT LEVELS

3.1 Abstract

Road accidents in Thailand remain a serious problem and lack attention regarding the effectiveness of corresponding measures. As road accidents are related and directly affect the car drivers. Therefore, the perspectives and opinions of drivers are important in improving road safety and reducing accident severity. The objectives of this study are to empirically examine damage due to road accidents, injuries, and fatalities among private car drivers using the willingness-to-pay (WTP) approach and to analyze the factors that influence WTP at the driver and district levels. This study obtained data on WTP derived from private car drivers across Thailand, which covers four major regions, 96 districts, and a total of 1,600 respondents. The average WTP was 0.718 USD/person/50 km per trip, which is equal to 824,344 USD of value of statistical life (VSL) and 151,708 USD of value of statistical injury (VSI) or an annual loss of 4,591,594,555 USD. The results of multilevel structural equation modeling (MSEM) revealed that the health belief model (HBM), sociodemographic, and district factors influence WTP in terms of reducing road accident risk with a statistical significance of $p < 0.01$. At the driver level, HBM and sociodemographic exert a positive influence on the intention to pay. Alternatively, district-level factors exert a negative influence on this intention. In other words, if the district provides effective road safety arrangements, then it will result in the decreased WTP of drivers, because they tend to perceive safety during driving. This finding can be used as a guideline for budget allocation and policy recommendation for relevant agencies in improving road safety according to the context of driving areas.

3.2 Introduction

3.2.1 Background

Recently, road accidents remain a major problem that affects many sectors in many countries worldwide, especially in developing countries. These countries contain registered car exceed 60% that of the world (World Health Organization, 2018), due to inefficient public transport system that is unable to meet the needs of the country's population (Marshall et al., 2005). Therefore, the majority of the population still needs to travel by private cars, which results in high traffic volume and increases the proportion of road accidents in these countries. In addition, statistics demonstrate developing countries have more than 9 out of 10 road accident deaths in the world, which leads to social and economic losses (Elvik, 2000). Thailand is a developing country and ranks eighth worldwide in terms of road accidents at 32.7 fatalities per 100,000 population (World Health Organization, 2018). Moreover, the number of private cars registered is increasing on a yearly basis (Department of Land Transport, 2020). Road accidents are related to and directly affect drivers. Therefore, examining driver attitudes is an important aspect to reflect on the causes of violence and perspectives on road accidents. In turn, doing so may also reduce the severity of road accidents. Assisting drivers and improving road safety are key element in the sustainability development of the country (Road Safety Center, 2019).

3.2.2 Value of road accident

Many methods can be used to analyze the severity of and damage due to road accidents. One of the methods that consider accident severity is evaluating the value of an accident (Litman and Fitzroy, 2017; Meyer and Elrahman, 2019). In other words, the more serious the accident, the more the damage will be. Each case of accident will affect victims, drivers, and other people involved in many ways, whereas damage may be direct, as in injury, death, and property. The indirect effects include productivity, income, and mental health for drivers and their families (Jomnonkwao et al., 2021; Wijnen, 2021). Damage due to deaths and injuries can be assessed using the value of statistical life (VSL) and the value of statistical injury (VSI), respectively. Moreover, the results of analysis using the VSL and VSI together with the number of fatalities and injuries per year can be used to illustrate the cost of road accidents at the national level. This study used the willingness-to-pay (WTP) method to estimate VSL and VSI, because WTP is a concept of economic valuation used to evaluate the value of product. In part of road safety, WTP can refer to risk valuation from accident of road users (increasing of drivers' risk perception, increase in their WTP). Therefore, WTP is appropriate for adapting to the assessment of road accident risk (Varian, 1992). Moreover, WTP is used in various applications and is proven to provide results that remain effective and popular today (Mohan, 2002).

3.2.3 Importance of multilevel analysis

Examining the factors or variables that influence VSL and VSI using traditional statistical methods, such as regression, logit model, or structural equation modeling (SEM) can help in the analysis of the relationship between observed variables or their influence, which influences dependent variables. However, the model can only describe relationships at the individual or the driver level (level one). In the context of the study on factors that influence VSL and VSI among drivers, other factors apart from driver factors undeniably influence accident risk, such as traffic volume, condition of areas (Albalate and Fageda, 2021; Wang et al., 2013), government policies and support (Mittal, 2008), and law enforcement (Delavary Foroutaghe et al., 2020). However, these factors frequently differ across regions. Therefore, examining the factors that influence VSL and VSI using multilevel analysis can better explain the complex relationship of models and enable the results to reflect the importance of spatial factors.

3.2.4 Summary and objective

As previously discussed, the objectives of this study are to examine the VSL and VSI of private car drivers; determine the socio-demographics and attitudes toward health that affect the VSL and VSI of road accidents; and to identify factors based on area context, which influences the attitude of drivers toward accidents and results in different forms of WTP. The findings of the present study can be used as reference for appropriate budget allocation to improve road safety. Moreover, it can serve as a recommendation for relevant agencies to understand the attitude of drivers toward road safety, health, and various related factors to propose policies that address such problems in accordance with the context of a region and affectivity.

3.3 Theoretical and literature reviews

This section provides a review of the relevant literature and theories related to the health belief model (HBM), which will be applied to the analysis of factors influencing WTP. Moreover, it can be used for multilevel structural equation modeling (MSEM) to analyze the influence of and relationship among relevant factors.

3.3.1 Theory of health belief model

HBM is one of the psychological theories related to health management. It is a suitable theory to be applied to the study on the costs of road accidents. Moreover, accidents are classified as a health problem or disease (Gordon, 1949). Therefore, they are directly related to health issues. HBM is a psychosocial model of health behavior change, which describes and predicts health-related behaviors (Janz and Becker, 1984; Siddiqui et al., 2016). It posits that a person will seek guidance to follow recommendations for prevention and rehabilitation given that the preventive action is relatively easy. In summary, HBM refer to beliefs, feelings, thoughts, and the understanding to accept or recognize health conditions. A concept of HBM consists of six factors (Figure 3.1), namely, perceived susceptibility, perceived severity, perceived barriers, perceived benefits, cues to action, and health motivation. These components are related to the health perspective, which influences behavior. A hypothesis posits that if drivers have belief and awareness about health, then they will exhibit the intention to behave or respond to various factors to achieve good health.

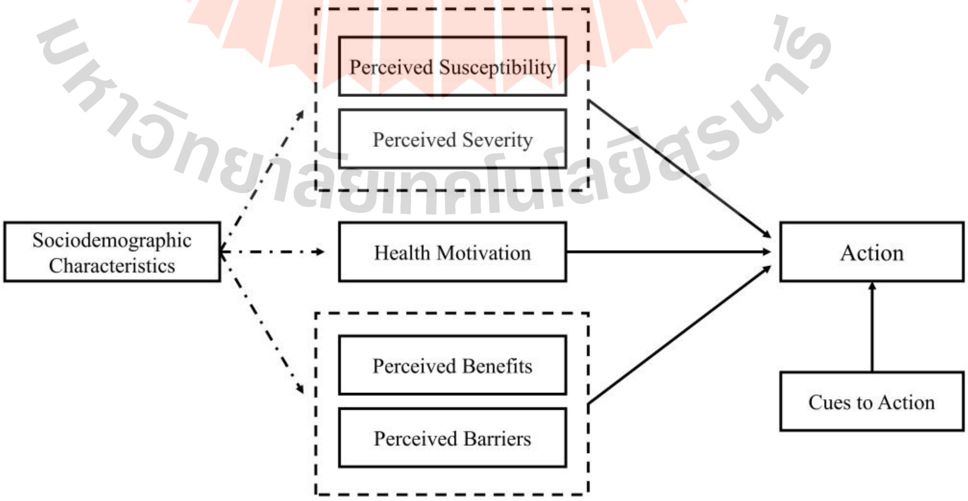

Figure 3.1 The health belief model

3.3.2 Previous studies on WTP and road safety

Previous studies on the cost, VSL, and VSI of road traffic accidents used the WTP approach. For example, Antoniou (2014) examined WTP to reduce traffic accident risk in urban and rural roads, Ainy et al. (2014) valuated road traffic injury and fatality cost in Iran. Moreover, Haddak et al. (2016) analyzed the WTP for road accident in France using the Tobi model, Lastly, Widyastuti and Utanaka (2020) estimated the subjective cost of motorcyclists and used WTP using the logit model. Table 3.1 summarizes the findings of 17 studies in 12 countries that aimed to study the factors affecting WTP. According to the table, the majority studies analyzed the sociodemographic information of the respondents.

Further, we also found a few studies of HBM on road traffic safety, Razmara et al. (2018) and Morowatisharifabad (2009) found that HBM were shown to be the strongest indicators of a safe drivers' behavior. Rezapur-Shahkolai et al. (2017) studied the HBM on preventive behaviors related to road traffic injuries and found that HBM could promote health knowledge and performance of injuries prevention. And findings of Zhang et al. (2013) stated that HBM could explain injury related behavior, especially for traffic injury-related behavior. As mentioned, the majority of such studies focus on factors that are related with risky driving behavior. In contrast, studies on WTP that applied the HBM are lacking. Thus, the current study applies this psychological theory for the analysis of sociodemographic information and WTP-related factors. Analysis using the HBM can reveal the perspective or attitude of drivers toward road safety risk. Moreover, the present study examined the complexity of the model using multilevel analysis, which has never been used in previous studies on WTP and road safety. To understand the in-depth correlation of factors, therefore, the study uses HBM and multilevel analysis to present alternative and different results on the research on the value of road accidents.

Table 3.1 Summary of previous studies on WTP for risk reduction and findings

Author (year)	Location	Method	Factors	Key finding
Persson, Norinder, Hjalte, and Gralén (2001)	Sweden	Regression	Demographics	The findings found that the number of cars and subjective risk are more likely to increase the WTP of drivers. On the other hand, age has significantly decreased the WTP.
Fauzi, Ghani, Umar, and Hariza (2004)	Malaysia	Regression	Demographics	The study found that gender and accident have a negative influence on WTP, but income and experiences found to be positive influenced the WTP.
Alberini, Cropper, Krupnick, and Simon (2006)	Canada	Regression	Demographics	The statistical results revealed that age, gender, and education significantly affected the WTP.
Andersson (2007)	Sweden	Probit model/ and OLS regression	Demographics	The results found the significant factors that influence the WTP, including age, gender, income, marital status, and mileage.
Bhattacharya, Alberini, and Cropper (2007)	India	Probit model	Demographics	This result implied that age, income, education, accident experiences, and job correlated with WTP.
Gibson et al. (2007)	Thailand	Regression	Demographics	The result showed that the factors related with WTP, including gender, age, and education.
Andersson and Lindberg (2009)	Sweden	Regression	Demographics	The findings illustrated that age, gender, household size, and child affecting the WTP.
Svensson and Johansson (2010)	Sweden	Regression	Demographics	This result illustrated that age significantly affected the WTP for within-sample models. For the between-sample model, it was found that age, gender, and safety tax significantly influenced the WTP.
Hoffmann et al. (2012)	Mongolia	Regression	Demographics	The study demonstrated that education, birth city, risk averse, and income were influencing the WTP.
Ainy, Soori, Ganjali, Le, and Baghfalaki (2014)	Iran	Regression	Demographics	The study revealed that WTP was significantly associated with age, gender, daily payment, and trip mileage from road users.

Table 3.1 Summary of previous studies on WTP for risk reduction and findings (Continued)

Author (year)	Location	Method	Factors	Key finding
Haddak, Lefèvre, and Havet (2016)	France	Tobit model	Demographics	The results of the Tobit model found that income, trip purpose, and children have correlated with WTP significantly.
Yang, Liu, and Xu (2016)	China	Logit model	Demographics	The study demonstrated that WTP was affected by motorists' WTP for risk reduction, including income, education, gender, and drive age.
Hoffmann, Krupnick, and Qin (2017)	China	Regression	Demographics	The regression results on WTP stated that income and college have positive effects on WTP, but age has negative effects on WTP.
Mon, Jomnonkwao, Khampirat, Satiennam, and Ratanavaraha (2019)	Myanmar	SEM	Demographics	The results of SEM found indicated that the driver's gender, age, driving behavior, and risk perception influence WTP.
Balakrishnan and Karuppanagounder (2020)	India	Binary logit	Demographics	The results disclosed that WTP significantly positively correlated with gender, age, accident, and household size, but negatively correlated with income.
Widyastuti and Utanaka (2020)	Indonesia	Logit model	Demographics	The findings showed that age, income, and number of children significantly correlated with WTP.

Note: WTP = Willingness-to-pay, SEM = Structural equation modeling, OSL = Ordinary least squares.

3.4 Material and method

3.4.1 Estimating the values of statistical life and injury

Chaturabong et al. (2011) calculated VSL and VSI using the ratio of WTP to change in risk. The current study uses WTP per trip to reduce fatalities or injuries by 50%, which were obtained from private car drivers to estimate the VSL and VSI. WTP per kilometer can be derived as WTP per trip divided by trip length (kilometer) (Jomnonkwao et al., 2021; Niroomand and Jenkins, 2016) (Equation (3.1)). The chance of fatalities and injuries per kilometer can be calculated in terms of the change in annual fatalities and injuries divided by annual vehicle kilometers traveled (AVKT) (Equations (3.2) and (3.3)).

$$\text{WTP per km.} = \frac{\text{WTP per trip}}{\text{Trip length (km)}} \tag{3.1}$$

$$\text{Fatality chance per km.} = \frac{\Delta\ \text{fatalities}}{\text{Annual VKT (km)}} \tag{3.2}$$

$$\text{Injury chance per km.} = \frac{\Delta\ \text{injuries}}{\text{Annual VKT (km)}} \tag{3.3}$$

According to these equations, VSL and VSI for road accident risk reduction can be derived as WTP to reduce risk by 50% per kilometer, divided by fatalities and injury chance per kilometer, as Equations (3.4) and (3.5) (Hensher et al., 2009).

$$\text{VSL} = \frac{\text{WTP per km.}}{\text{Fatality chance per km.}} = \frac{\text{WTP per Trip}}{\text{Trip length (km)}} \times \frac{\text{Annual VKT (km)}}{\Delta\ \text{fatalities}} \tag{3.4}$$

$$\text{VSI} = \frac{\text{WTP per km.}}{\text{Injury chance per km.}} = \frac{\text{WTP per Trip}}{\text{Trip length (km)}} \times \frac{\text{Annual VKT (km)}}{\Delta\ \text{injuries}} \tag{3.5}$$

3.4.2 SEM and multilevel analysis

1) Structural equation modeling: SEM can be generated using the relationship between the variables in the model, which can be divided into two groups, namely, exogenous (independent) and endogenous (dependent) variables (Wiratchai, 1999). The model is a result of three analysis models, including factor analysis, path analysis, and parameter estimation toward regression analysis. The SEM structure consists of two sub-models, namely, measurement and structural models (Hox and Bechger, 1998).

2) Multilevel structural equation modeling: Multilevel modeling (MLM) refers to methods of research questions and data structures that involve more than one unit type (Snijders and Bosker, 2011). It can be applied to studies involving multilevel integration, such as individual-district, teacher-school, and staff-company (Mohammad and Hadikusumo, 2017; Ratanavaraha et al., 2016).

MSEM is the combination of the SEM concept and MLM, which was first conducted by Muthén (1989), to examine the variation and relationship among variables in the model that contain two or more levels. The MSEM consists of two sub-models, namely, within-group model (represents the relationships among individual-level variables) and between-group model (reflects the relationships among the group-level variables).

3) Model fit criteria: According to model fit indices, such an analysis needs to consider the statistical basis to determine whether the model can accurately describe the relationship among variables. For example, Washington et al. (2020) and Sun et al. (2013) stated that the value of the chi-square per degree of freedom (χ^2/df) should not exceed 5. Moreover, the positive value of the root mean square error of approximation (RMSEA) should not exceed 0.06 (Steiger, 2007). Hooper et al. (2008) illustrated that the positive value of the Tucker–Lewis index (TLI) or the non-normal fit index should be approximately 0.80. Moreover, the suitable value of the comparative fit index (CFI) for the model is specified at or more than 0.90, whereas the part of the value of the standardized root mean square residual (SRMR) should be less than 0.08 (Hu and Bentler, 1999; Marsh et al., 2004). The values for statistical testing can be calculated using Equations (3.6)–(3.9) as follows:

$$\mathrm{SRMR}=\sqrt{\sum_{i}\sum_{k}\frac{r_{jk}}{p^{*}}}, \tag{3.6}$$

$$\mathrm{RMSEA}=\sqrt{\frac{\chi_T^2\text{-}df_T}{df_T(N-1)}}, \tag{3.7}$$

$$\mathrm{TLI}=1-\frac{\max[\left(\chi_T^2\text{-}df_T\right),0]}{\max[\left(\chi_T^2-df_T\right),\left(\chi_B^2-df_B\right),0]}, \tag{3.8}$$

$$\mathrm{CFI}=\frac{\left(\frac{\chi_B^2}{df_B}\right)-\left(\frac{\chi_T^2}{df_T}\right)}{\left(\frac{\chi_B^2}{df_B}\right)-1} \tag{3.9}$$

where r_{jk} denotes the standardized residuals from the covariance matrix with *j* rows and *k* columns; p^* stands for the number of non-duplicated elements in the covariance matrix; $\chi_T^2-\chi^2$ pertain to the values of the target model; df_T=df represents the target model; $\chi_B^2-\chi^2$ denote the values of the baseline model; and df_B=df is the baseline model.

3.4.3 Questionnaire design

The questionnaire for the study was divided into four sections. The first part pertains to WTP to reduce road accident risk, which is composed of an open-ended question and uses the contingent valuation method. The drivers were asked, “What is the maximum payment that you willing to pay to use improved roads to reduce the risk of fatality or injury due to road accidents by 50% for a 50-kilometer trip?" (WTP per 50 km trip). This value will be used for the VSL and VSI calculation. The second part intends to obtain the demographic information of drivers, such as age, gender, marital status, personal income, and education to describe the norm and differences among respondents. Moreover, questions were asked about trips, such as the objective of the trip, driving experience, and driving behavior, which represent the different attitudes of drivers. The third part asks questions related to the HBM and measures the perspective of drivers about the HBM to assess intention and WTP. It consists of six factors, namely, perceived susceptibility, perceived severity, perceived barriers, perceived benefits, cues to action, and health motivation. The final part is related to data, which will be used to analyze relationships at the district level. This section is related to the attitudes of drives toward various factors in the area where the drivers live or drive regularly. These factors include traffic conditions, roads, government support, and law enforcement and intend to reflect the influence of such factors influence on attitudes toward WTP for accident risk reduction. The items in parts 3 and 4, which indicate opinions on various factors, are rated using a five-point Likert-type scale (Wuensch, 2005) (5 = strongly agree; 1 = strongly disagree). This survey questions have undergone tool testing using the Index of the Item–Objective Congruence test.

3.4.4 Data collection and sample statistics

Several studies reported the appropriate sample size for SEM analysis. Kline (2015) stated that the minimum sample size for SEM analysis should be more than 200, whereas Bentler and Chou (1987) and Golob (2003) suggested that the sample size for the maximum likelihood estimation should exceed 15 times of the observed variables. The current study found 27 observed variables. Therefore, the minimum sample size should not be less than 405. However, the appropriate sample size for multilevel analyses should also be considered. In this regard, Muthén (1989) suggested that the number of groups should more than 50 with at least two respondents per group. Using the criterion of Kreft (1996), this number could be 30 groups with 30 respondents per group.

This study obtained survey data using face-to-face interviews for questionnaire collection from private car drivers from four main regions across Thailand

(North, South, Central, and Northeast). We used simple random sampling from eight provinces with the highest proportions of road accident fatalities per region and per three districts in each province. Finally, we identified 96 districts and obtained a total of 1,600 respondents, which is a suitable size for MSEM analysis. Table 3.2 presents the preliminary analysis. This study has been approved by the ethics committee of the Suranaree University of Technology (November 13, 2020). A human research ethics document was submitted. The result was that the research presents a low risk; thus, oral informed consent is permissible.

Table 3.2 Sample statistics of respondents

Category		Frequency	Percentage (%)
Gender	Male	988	61.75
	Female	612	38.25
Age (year)	Under 26	259	16.19
	26–35	635	39.69
	36-45	377	23.56
	Over 45	329	20.56
Status	Married	636	39.75
	Otherwise	964	60.25
Education	Primary school	124	7.75
	Lower secondary school	294	18.38
	Higher secondary school/Vocational certificate	206	12.88
	Diploma/high vocational certificate	124	7.75
	Bachelor’s degree and higher	852	53.24
Own accident	Never	1,393	87.06
	At least 1 time	207	12.94
Personal income	Less than 15,000	228	14.25
	15,000 – 29,999	982	61.38
	30,000 or higher	390	24.37

Note: Sample size = 1,600

3.5 Results

3.5.1 Descriptive statistics

The study examined the normal distribution of data obtained from the questionnaire on driver attitudes to questions about HBM and district factors from 1,600 drivers. Table 3.3 presents the results (mean = 2.23–4.56, SD = 0.57–1.00, skewness: −1.12–0.44, kurtosis: −1.36–1.29). Comparing the results of the preliminary statistical analysis with the study of Kline (2015), who reported that data with normal distribution and suitable for statistical analysis must obtain skewness values between −2 and 2 and kurtosis values between −7 and 7. The study found that these statistical values are within the acceptable range, whereas data were normally distributed. Additionally, the questionnaire reliability test indicated that Cronbach's alpha greater than 0.6 is within the acceptable range and is suitable for subsequent analysis (Hinton et al., 2014).

Table 3.3 Descriptive statistics

Code	Description (Cronbach's alpha)	Mean	SD	SK	KU
INT	**Intention (0.670)**				
INT1	I will pay more for safer road usage.	4.34	0.68	−0.56	−0.77
INT2	I will pay for safety on road usage because I believe that it can safe my life.	4.30	0.72	−0.52	−0.90
INT3	I will recommend my intimates to pay for safety on road usage for accident risk reduction.	4.47	0.62	−0.75	−0.43
INT4	I have planned to pay for safety on road usage for accident reduction.	4.52	0.62	−1.12	1.29
PSU	**Perceived Susceptibility (0.649)**				
PSU1	I know that every time I drive, there have risk of accidents.	4.17	0.75	−0.31	−1.12
PSU2	I know that road or routing factors are one of the causes of accidents.	4.16	0.78	−0.29	−1.29
PSU3	I know that road accidents do not depend on me alone.	4.16	0.75	−0.28	−1.11
PSU4	I know the risk of road accidents is inevitable.	4.17	0.75	−0.29	−1.19
PSE	**Perceived Severity (0.723)**				
PSE1	I know that if I take an unsafe road, when an accident happens, it can kill me.	4.20	0.78	−0.36	−1.29
PSE2	I know that road accidents may cause me injuries or disability.	4.19	0.77	−0.34	−1.26
PSE3	The accident will have a huge impact on my studies/works.	4.17	0.80	−0.31	−1.36
PSE4	Each accident will affect the lives of related people, such as family.	4.23	0.76	−0.42	−1.17
PBE	**Perceived Benefits (0.734)**				
PBE1	I think driving on the safe road can reduce risk accidents.	4.30	0.70	−0.49	−0.89
PBE2	I think driving on the safe road, when an accident occurs, I will be injured less.	4.30	0.71	−0.50	−0.90
PBE3	I feel that paying for safe roads will make me benefit more.	4.32	0.72	−0.56	−0.87
PBA	**Perceived Barriers (0.681)**				
PBA1	I feel that paying for safer roads makes me uncomfortable.	2.62	1.00	−0.06	−0.98
PBA2	I feel there is no need for safe roads, if others still use the current road.	2.31	0.83	0.27	−0.28
PBA3	I feel that using the current road or alternative road, the benefits are no different.	2.48	0.75	0.44	0.35

Table 3.3 Descriptive statistics (Continued)

Code	Description (Cronbach's alpha)	Mean	SD	SK	KU
PBA4	I think paying for safe roads is expensive and no need to pay.	2.51	0.74	0.35	0.18
CUE	**Cues to Action (0.645)**				
CUE1	I follow the accident news, making me afraid that it will happen to me or related people.	4.56	0.57	−0.93	0.08
CUE2	I saw the campaign of "Road safety" on a regular basis.	4.51	0.61	−0.86	−0.09
CUE3	Most of my close people always encouraged me to choose safe roads.	4.52	0.60	−0.84	−0.28
CUE4	Most of the people around me are always talking about the benefits of safe roads.	4.50	0.62	−0.88	−0.11
MOT	**Health Motivation (0.711)**				
MOT1	I think getting into a road accident is the most dangerous.	4.36	0.68	−0.58	−0.73
MOT2	I think driving in good environment will have a positive effect on health and mind.	4.13	0.73	−0.22	−1.13
MOT3	I attach great importance to safety when driving.	4.13	0.72	−0.20	−1.06
MOT4	I think if I get into accidents, it will make my physical and mental health never be the same again.	4.10	0.74	−0.16	−1.15
DV	**District Variables**				
DV1	In my district, law enforcement on the road traffic is efficient and make me feels safe.	2.38	0.83	0.04	−0.46
DV2	In my district, police checkpoints are set up and there are enough staff to do the task.	2.42	0.84	−0.00	−0.50
DV3	In my district, there is no gaps in traffic laws for drivers to disobey, and may cause the dangerous.	2.74	0.71	0.13	0.24
DV4	In my district, there is a safe driving campaign and maintain regular traffic discipline.	2.24	0.85	−0.22	−0.99
DV5	In my district, useful information and advice are provided to commuters.	2.49	0.62	−0.26	0.20
DV6	In my district, the government has allocated a budget to manage road safety appropriately.	2.46	0.67	−0.47	−0.11
DV7	In my district, road conditions are safe and regularly improved.	2.56	0.58	−0.10	−0.11
DV8	In my district, there is enough road safety equipment, makes me feel confident when driving.	2.31	0.81	−0.39	−0.92
DV9	In my district, other road users are proficient in driving, makes me feel safe when driving.	2.23	0.87	−0.08	−0.74

Note: Sample size = 1,600, SD = standard deviation, SK = skewness, KU = kurtosis.

3.5.2 Obtaining the VSL and VSI

This study empirically obtained the average WTP at 22.46 baht (0.718 USD) per person per 50-km trip with a median of 20.00 baht (0.639 USD), and a standard deviation of 15.944 baht (0.510 USD). The estimated total AVKT of private car transport on highways in Thailand for 2020 reached approximately 7.993×10^{10} km (Bureau of Highway Safety, 2020b) with 2,785 fatalities and 15,133 injuries due to car accidents (Bureau of Highway Safety, 2020a). Table 3.4 presents the VSL and VSI of car accidents after the application of the mean and median of WTP, AVKT, fatalities, and injuries to Equations (1)–(5).

Table 3.4 Estimating the VSL and VSI

Type	Value[a]	WTP/km[a]	VSL[b]	VSI[c]	Total damage
Mean	0.718	0.014	824,343.73 (853,110 to 795,761)[d]	151,708.01 (157,002 to 146,448)[d]	4,591,594,555
Median	0.639	0.013	734,054.97 (762,729 to 705,381)[d]	135,091.73 (140,369 to 129,815)[d]	4,088,686,157

Note: [a] USD per person per 50 km trip; exchange rate: 1 USD = 31.28 baht (2020), [b] value of statistical life, [c] value of statistical injury, [d] 95% confidence interval.

3.5.3 Exploratory factor analysis of district variables

This study employed exploratory factor analysis (EFA) study to reduce the number of subfactors that reflect different area contexts and other factors (district-level variables: DV), and included as the main factors. Table 3.5 presents the EFA results, which indicate the district component factors of all nine items (DV1-DV9). These factors can be classified into three groups, namely, government support (SUP), law enforcement (LAW), and environment (ENV). The item distribution for SUP, LAW, and ENV are DV4-DV7, DV1-DV3, and DV8 and DV9, respectively. The three factors produced Cronbach's alpha values that ranged from 0.831 to 0.865; construct reliability from 0.958 to 0.973, and average variance extracted from 0.662 to 0.874. All statistical values are within acceptable the acceptable ranges (Fornell and Larcker, 1981; Hair, 2009; Kaiser, 1974). Thus, the three factors can be appropriately analyzed using the MSEM.

Prior to MSEM, the study analyzed the relationship between relevant factors used in the model to verify that no pair of factors was overly correlated. Mukaka (2012) indicated that the correlation between variables should be less ±0.750. The correlation results of the current study were within this acceptable range (Table 3.6).

Table 3.5 The exploratory factor analysis

Code	Component			CR	AVE	Cronbach's alpha
	Government Support	Law Enforcement	Environment			
DV1		0.644		0.764	0.522	0.835
DV2		0.672				
DV3		0.837				
DV4	0.681			0.808	0.513	0.831
DV5	0.753					
DV6	0.733					
DV7	0.696					
DV8			0.820	0.788	0.650	0.865
DV9			0.792			

Note: Extraction method = Principal component analysis, Rotation method = Varimax with Kaiser normalization, CR = Composite reliability, AVE = Average variance extracted, KMO = 0.730, total variance explained = 60.135%.

Table 3.6 Correlation among relevant factors

	INT	PSU	PSE	PBE	PBA	CUE	MOT	LAW	SUP	ENV
INT	1	−.081**	−0.018	.536**	−.071**	.170**	.371**	−.131**	−.121**	.330**
PSU		1	−.321**	−.265**	.383**	0.039	.111**	.161**	.285**	−.190**
PSE			1	−0.039	−.484**	.138**	−.241**	.083**	−.153**	−.139**
PBE				1	−.161**	.113**	.435**	−.081**	−.054*	.519**
PBA					1	−.059*	.138**	.163**	.284**	−.160**
CUE						1	.180**	−.082**	−.110**	−.061*
MOT							1	.190**	.269**	.326**
LAW								1	.537**	−0.042
SUP									1	.053*
ENV										1

**Correlation is significant at the 0.01 level (2-tailed); *Correlation is significant at the 0.05 level (2-tailed).

3.5.4 Factors influencing WTP using MSEM

1) Intra-class correlation and goodness-of-fit statistics: Intra-class correlation (ICC) is a preliminary statistical analysis that describes the relationship between the observed variables at within (drivers) and between (districts) levels (Bartko, 1966). If the ICC is low, then any variations at the district level do not explain the driver variables. Snijders and Bosker (2011) suggested that ICC values should be higher than 0.05. Therefore, the current data set is suitable for multilevel analysis. Toward this end, five variables were analyzed, namely INT1, INT2, INT3, INT4, and WTP, where the study found ICC values of 0.329, 0.347, 0.196, 0.186, and 0.121, respectively. These values are acceptable and appropriate for multilevel analysis.

Figure 3.2 depicts the MSEM of the study on WTP for accident risk reduction using Mplus 6.12. To test the model fit of the MSEM, analysis indicated that the model obtained the following values: chi-square (χ^2) = 201.711, degree of freedom (df) = 101, p < .001, (χ^2/df) = 1.997, CFI = 0.980, TLI = 0.951, $SRMR_{within}$ = 0.048, $SRMR_{between}$ = 0.069, and RMSEA = 0.025. Comparing these statistics with the acceptable ranges, we found that the MSEM is in accordance with empirical data.

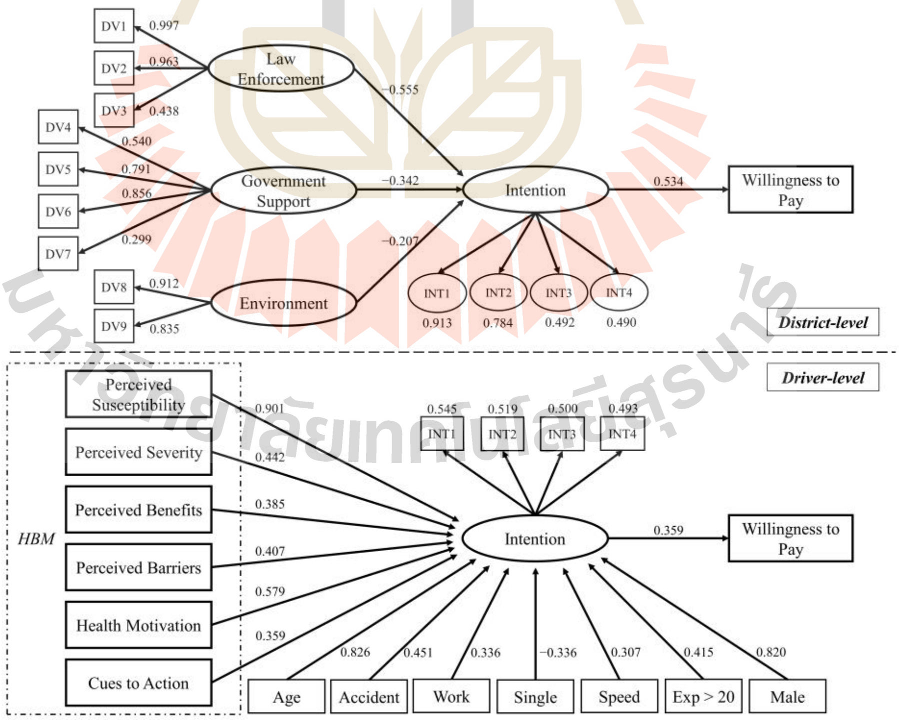

Figure 3.2 Factors influencing the WTP for accident risk reduction according to the MSEM

2) Measurement model: Considering the significant factors obtained from the model results. It was divided into two sub-levels, namely, driver and district levels, where intention is a factor that can be measured at both levels. Three factors of the measurement model influenced intention at the district level, namely, law enforcement, government support, and the environment. Table 3.7 presents the model parameters.

Law enforcement was measured using DV1-DV3. The analysis indicated that the three variables were components of law enforcement at $p < 0.01$. DV1 displayed the highest factor loading, “In my district, law enforcement on the road traffic is efficient and make me feels safe” (Est. = 0.997, t = 12.087).

Government support was estimated using DV4 to DV7, which could be used as components of government support at $p < 0.01$. DV6 is the best factor for measuring government support: “In my district, the government has allocated a budget to manage road safety appropriately” (Est. = 0.856, t = 24.836).

Environment was measured using DV8 and DV9, which were components of environment at $p < 0.01$. DV8 obtained the highest factor loading, “In my district, there is enough road safety equipment to feel confident when driving” (Est. = 0.912, t = 23.314).

For intention, the study found that such factors were presented at the driver and district levels of the model, which was measured using INT1-INT4. All variables were components of intention at $p < 0.01$. At the driver level, INT1 obtained the highest factor loading, “I will pay more for safer road usage” (Est. = 0.545, t = 4.683). At the same time INT1 obtained the highest loading factor for intention at the district level (Est. = 0.913, t = 3.356).

3) Structural model: The results of the structural model indicated the factors that influence intention, which leads to WTP. The study found that two components explain intention at the driver level, namely, sociodemographic factors of driver, which consists of seven observed variables ($p < 0.01$). These factors are age (Est. = 0.826, t = 4.618), gender (Est. = 0.820, t = 4.634), accident experience (Est. = 0.451, t = 3.822), driving experience (Est. = 0.415, t = 4.632), work involved during driving (Est. = 0.336, t = 4.583), marital status (Est. = −0.336, t = −4.573), and driving over speed

limits (Est. = 0.307, t = 4.933). The second is related to the HBM, where the results also illustrated that all six factors of HBM significantly and positively influence intention (p < 0.01). The most influential factor was perceived susceptibility (Est. = 0.901, t = 4.526) followed by health motivation (Est. = 0.579, t = 4.576), perceived severity (Est. = 0.442, t = 4.862), perceived barriers (Est. = 0.407, t = 4.594), perceived benefits (Est. = 0.385, t = 4.632), and cues to action (Est. = 0.359, t = 4.591). Furthermore, intention also positively and significantly influenced WTP.

Considering the degree of influence of the predicted variables at the district level on WTP for accident risk reduction, the results indicated that three factors, namely, law enforcement (Est. = −0.555, t = −2.916), government support (Est. = −0.342, t = −3.245), and environment (Est. = −0.207, t = −3.192) negatively influenced intention. In turn, intention significantly and positively influenced WTP at the 0.01 level (Est. = 0.534, t =3.539), which is similar to that at the driver level (Est. = 0.359, t = 4.440).

Table 3.7 Standardized model results (MSEM)

Variable	Within group (driver-level)			Between group (district-level)		
	Est.	*t*–value	*p*–value	Est.	*t*–value	*p*–value
Measurement model:						
Intention was measured by;						
INT1	0.545	4.683	<0.001	0.913	3.356	<0.001
INT2	0.519	5.650	<0.001	0.784	3.441	<0.001
INT3	0.500	7.348	<0.001	0.492	3.193	<0.001
INT4	0.493	10.949	<0.001	0.490	3.151	<0.001
Law enforcement was measured by;						
DV1				0.997	12.087	<0.001
DV2				0.963	11.650	<0.001
DV3				0.438	4.926	<0.001
Government support was measured by;						
DV4				0.540	18.007	<0.001
DV5				0.791	15.897	<0.001
DV6				0.856	24.836	<0.001
DV7				0.299	5.060	<0.001
Environment was measured by;						
DV8				0.912	23.314	<0.001
DV9				0.835	18.537	<0.001

Table 3.7 Standardized model results (MSEM) (Continued)

Variable	Within group (driver-level)			Between group (district-level)		
	Est.	*t*–value	*p*–value	Est.	*t*–value	*p*–value
Structural model:						
Health belief model;						
Perceived susceptibility ⟶ Intention	0.901	4.526	<0.001			
Perceived severity ⟶ Intention	0.442	4.862	<0.001			
Perceived benefits ⟶ Intention	0.385	4.632	<0.001			
Perceived barriers ⟶ Intention	0.407	4.594	<0.001			
Health motivation ⟶ Intention	0.579	4.576	<0.001			
Cues to Action ⟶ Intention	0.359	4.591	<0.001			
Demographic;						
Gender (male)	0.820	4.634	<0.001			
Marital status (single) ⟶ Intention	−0.336	−4.573	<0.001			
Age (26-35-year-old)	0.826	4.618	<0.001			
Accident experiences⟶ Intention	0.451	3.822	<0.001			
Involved work driving⟶ Intention	0.336	4.583	<0.001			
Driving over speed limits⟶ Intention	0.307	4.933	<0.001			
Driving experiences⟶ Intention	0.415	4.632	<0.001			
Law enforcement⟶ Intention				−0.555	−2.916	<0.001
Government support⟶ Intention				−0.342	−3.245	<0.001
Environment⟶ Intention				−0.207	−3.192	<0.001
Intention ⟶ Willingness to pay	0.359	4.440	<0.001	0.534	3.539	<0.001

Note: Est. = Standardized estimates.

3.6 Discussion

3.6.1 Value of road accidents

The study obtained the results for VSL and VSI for road accidents of private car drivers, which were calculated using the mean of WTP at approximately 824,344 USD and 151,708 USD, respectively. Comparing such values to the results of VSL and VSI calculated using the median of WTP at 734,055 USD and 135,091.73 USD, respectively, we found that mean values are higher than median. This result is consistent with those of previous studies in Asia and Europe (Ainy et al., 2014; Fauzi et al., 2004; Mon et al., 2019; Sánchez-Martínez et al., 2021). The average WTP is above the median, which indicates that there is a gap in accident risk assessment or the ability to pay between drivers. However, we calculated the VSL and VSI for road accidents together with the number of fatalities and injuries in Thailand and found that the impact was 4,591,594,555 USD. This result is relatively worrying, whereas this issue persists in developing countries. Notably, the majority of developed countries have higher VSL and VSI values than those of developing countries (de Blaeij et al., 2003; Milligan et al., 2014; Wijnen et al., 2019). When assessing the overall damage in developed countries, however, the damage is minimal, because they can allocate a budget for safety management, which decreases the number of accidents. If developing countries can increase awareness about accident severity and eliminate such problems, then it will decrease the socioeconomic burden of road accident severity (Wijnen and Stipdonk, 2016).

3.6.2 Factors influencing VSL and VSI at the driver and district levels

1) Driver level: Several factors influence intention, which lead to WTP to reduce the risk of road accidents. The analysis of such factors at the driver level indicated that two main factors could explain the intention to pay, namely, sociodemographic factor and HBM. These results are consistent with those of previous studies in terms of the background of drivers, social status, and other related behaviors that can influence the assessment of drivers about road accident risk (Ainy et al., 2014; Dewar and Olson, 2007) and results in the change in WTP. The most influential factor was age (26–35 years). Drivers within this age range are those who spend the majority of their lives working to generate income. Thus, they are greatly affected by accidents (Ainy et al., 2014). Therefore, this group is willing to pay as much as possible to reduce the chances of road accidents. The next factors is gender, where being male influenced the intention to pay (Balakrishnan and Karuppanagounder, 2020). This result can be explained by driving behavior. Yang et al. (2016) and Mon et al. (2019) stated that male drivers are more likely to engage in risky driving behaviors than females do, which render male drivers more willing to pay. Accident experience is a relatively reasonable factor, because drivers will be able to perceive the severity and impact of accidents due to previous injuries or road accidents (Andersson, 2007), which could result in high levels of intention and WTP. Driving experiences are similar to accident experiences, because driving experiences also indicate driving expertise and perception of road

hazards. This finding is in line with that of Brown and Groeger (1988), who indicated that drivers with more experience can better assess their risk of road accident than those with less experience (Benda and Hoyos, 1983). The study also found that if the majority of driving objectives are work-related in terms of driving as work or as part of work, the driver will pay more for safety (Haddak, 2016). The respondents reported that each accident leads to more damage than the amount of money they were willing to pay (Rizzi and Ortúzar, 2006; Trawén et al., 2002). Marital status also exerted a negative influence on intention. In addition, non-married drivers were less likely to pay less to reduce the risk of road accidents than married drivers. This result is similar to that of Antoniou (2014), who argued that married drivers are more responsive to accident risks and more willing to pay for road safety than do non-married drivers due to the burden of the family. Thus, drivers are more aware of the impact and loss of accidents (Balakrishnan and Karuppanagounder, 2020). Moreover, driving behavior influenced intention and WTP for safety. The results demonstrated that drivers who regularly use high speeds (>90 km/h) can assess the risks of their driving (Hong et al., 2020; Mon et al., 2019). Thus, such behaviors lead to their intention to increase safety and increased WTP.

Apart from socio-demographics, the present study also examined the relationship between psychological theory related to health using the HBM and intention and found the factors of HBM positively influenced intention, which leads to WTP. The results illustrated that HBM is more appropriate for addressing safety behaviors (Glanz et al., 2008) as well as intention to pay for road safety (Lakhan et al., 2020).

The most influential factor on intention is perceived susceptibility, which is the perception of risk and is consistent with the study of Morowatisharifabad (2009). The reason for this notion is that any form of sensitivity, vulnerability, or concern about road accidents can occur at any time. For drivers who spend long hours on roads, perceived susceptibility is a factor that strongly influences WTP to reduce the risk of accidents. This factor was followed by health motivation. In other words, health is one of the motivations for drivers for seeking safety on the road (Jomnonkwao et al., 2020). Perceived severity was also associated with behavioral intention in the same manner as perceived susceptibility. Drivers who are concerned about road accidents tend to be aware of accident severity (Dadipoor et al., 2020) and are ready to behave according to their intention to minimize risks and violence. Concerns for change or perceived barriers are factors that mostly deters the intention to behave. Humans tend to develop a routine for repetitive actions and may be biased toward changes in the surrounding (Janz and Becker, 1984), Thus, this factor may exert a negative influence on intention (Razmara et al., 2018). In the current study, however, perceived barriers continue to exert a positive influence on intention and WTP, whereas the causes of road accidents remain a concern for all drivers, who do not feel that paying to reduce the risk of accidents is a hindrance. Perceived benefits and cues to action exerted a positive influence on intention (Razmara et al., 2018). Given the relationship between the two factors, if drivers perceive the benefits of reducing accidents, then cues to action will occur as well. Consistent with past research, the attitudes of drivers about these factors tend to go in the same direction (Razmara et al., 2018).

2) District level: The findings presented the factors that influence behavioral intention and WTP to reduce road accident risk at the district level. The significant factors in the between-group (district-level) model of MSEM indicate that the impact of these factors differs significantly among each district. Latent factor analysis at the district level demonstrated the influence of the environmental factors of district areas that influence attitudes, perceptions, and awareness of drivers on the severity of road accidents. These factors exert an indirect influence. Thus, drivers living in different areas will experience different levels of these influences. The result of district factors illustrated that government support, law enforcement, and environment negatively influence intention, which affects WTP. The results imply that district-level factors pertain to the expectations of drivers on environment or safety in the area in which they are driving regularly.

Given the three factors, law enforcement was found to be the greatest influence on intention (Delavary Foroutaghe et al., 2020), which indicates that drivers hold their expectations of law enforcement. Strict law enforcement will reduce risky driving behavior or traffic violations (Ali et al., 2019), which will render roads safer. This finding is consistent with those of Yannis et al. (2007) and Stanojević et al. (2013), who reported that good and efficient law enforcement can significantly reduce the number of road accidents. In the present study, the drivers realize that the effectiveness of the law is insufficient for ensuring road safety. This will cause them to have a high concern about accident risk, and therefore, they are more likely to pay more to reduce the chances of road accidents. if they perceive that the law enforcement for road safety management is effective, it will increase the safety perception of drivers and result in no intention to pay.

Roads fall under the supervision of the government. Therefore, government support is crucial to road safety. Analysis pointed out that the concerns of Thai drivers lie on the budget allocation of government. As such, good expenditure allocation and management will improve road safety in an effective and comprehensive manner (World Health Organization, 2020). Support can be realized through road safety campaigns, route information, or traffic congestion management by staff (Bump et al., 2019). Nevertheless, such factors were found to be inadequate from the view of road users, which led them to perceive that risks on the road lack thorough attention. As such drivers are more intentional in paying to reduce their risk of road accidents.

The environment also exerted a negative influence on intention to pay for safety. The result illustrated that safety equipment on roads are important for driver awareness. In other words, they prefer to drive on roads with sufficient safety equipment and positive traffic conditions to increase their confidence. Thus, if drivers perceived safe driving conditions, then they will also perceive that their risk of road accidents is reduced (Shah et al., 2018). Therefore, the need to pay to reduce the chance of accidents no longer exists. However, the perspective of drivers about such factors did not meet their expectations regarding road safety equipment, traffic conditions, or driving behavior of other drivers (Farooq et al., 2019). As a result, the risk of accidents remains, which raises drivers' risk concerns and presents such a concern in terms of their WTP.

3) Practical implications: On a macroeconomic scale, the value of fatalities and injuries that explored in this study can be used as updated estimates for

authorities, in terms of road safety budget allocation. Further, the present study reveals empirical evidence that can benefit policymakers in road safety improvement projects. For example, we found risk valuation of drivers is influenced by their sociodemographic, this could help relevant agencies to promote the Road Safety Education programs specifically (F. Alonso et al., 2021). HBM showed the role of psychology and health awareness on the valuation of road accidents as well. This result can serve as a guideline to increase awareness and attitude toward road safety (e.g., adding such issues into programs for people who apply for driving licenses or communication campaigns) (Francisco Alonso et al., 2021). In addition, we also disclosed three factors (law enforcement by staff, support from local government, and environment in driving areas) at district-level that can help local governmental institutions understand their local road accident risk by assessment of drivers and would give the alternatives to improve their local road safety.

3.7 Conclusion

The results presented the total accident damage in Thailand at more than 4,591,594,555 USD when calculated using the mean and 4,088,686,157 USD when calculating using the median. Such values are result of the VSL and VSI assessments combined with the number of road fatalities and injuries in Thailand, which are among the top in the world. Accidents lead to damage to the overall economic and social system of the country. Therefore, road accident issues should be improved; appropriate budget should be allocated to solve such problems to reduce the damage value at the national level.

The factors that influence behavioral intention and WTP at the driver level were socioeconomic characteristics, such as age, gender, accident experience, driving behavior, marital status, and purpose of the trip. These factors enable drivers to assess risks and severity in a different manner, which leads to b difference in WTP. Driver perspective was also evaluated according to the HBM. The results indicated that the belief of drivers in health renders them more willing to pay for safety to maintain their health.

The district-level analysis found that the different contexts of each region influenced behavioral intention and WTP of drivers in that area. Law enforcement, government support, and environment exert a significant impact on the intention to pay. Scholars pointed out that if drivers feel that their driving area exhibit more risk of accidents and less of safety, then they will present it in term of WTP. The WTP value received from the driver indicates the risk or unsafe concern of a road accident in monetary terms. Alternatively, if the authorities have taken care of a driving area and presented the environment as safe and suitable for driving, then drivers are unwilling to act to ensure safety.

Finally, this study demonstrated that analysis of the factors influencing the value of road accident at more than one level is possible. In this manner, the results can be more relevant in explaining the complexity of the topic, whereas the implementation will be consistent across the contexts of each area. The findings can be used as reference for relevant agencies in addressing road accidents that may be caused by drivers or factors that result from the different contexts of districts.

One of the limitations of the study is that drivers less than 18 years old were excluded from the analysis due to licensing laws in Thailand. Adults are typically more intellectually independent and experienced than younger drivers. Thus, certain factors, such as attitudes, perceptions, and decisions may differ among respondents. Studies on younger groups may be able to pinpoint differences and may be more representative of the population.

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CHAPTER 4

CORRELATED RANDOM PARAMETER MODEL WITH HETEROGENEITY IN MEANS FOR ANALYSIS OF FACTOR AFFECTING THE VALUE OF ROAD ACCIDENT AND TRAVEL TIME

4.1 Abstract

Road safety funding and management have become important for improving the quality of life of residents; there is evidence that there is a difference in the driving behavior or the role of road use between urban and rural areas, which is reflected in different road safety valuations. The purpose of this study is to empirically assess financial losses caused by road accidents on Thailand's highways. Data were obtained from 640 urban car drivers and 960 rural drivers by stated choice (SC) questionnaire using face-to-face interviews. According to the results, the value of statistical life and injury for urban drivers was 1.63 times higher than that for rural drivers, and the value of travel time reduction per hour for urban drivers is ~1.14 times higher than for rural drivers. Furthermore, the results of correlated random parameter binary logit model with heterogeneity in means (CRPBLHM) reported that although certain factors are significant in both models. However, there are significant differences in drivers' safety intentions and willingness-to-pay (WTP) between urban and rural drivers. In the urban model, driving behavior (ticket, seatbelt, and speed) and weekday trips significantly increase WTP, and household size and gender are unobserved characteristics among drivers. The rural model reported that driver's education (bachelor's and master's degree), and a compelling trip made drivers possibly pay for safety; moreover, it was discovered that household size, sole earner, own accident, doctoral, and young were significant as unobserved characteristics. The results demonstrated differences in the value of road safety and unobserved heterogeneity among drivers, which influence risk perception and valuation by the area context. Furthermore, relevant agencies can use the results as a guideline for budget allocation and road safety management.

4.2 Introduction

4.2.1 Background

For a long time, solving road traffic-related accidents has been an on-going challenge, and all countries around the world are attrempting to resolve this issue, particularly developing countries (Heydari et al., 2019). These effects affect drivers, passengers, vulnerable groups, and private and public property (Champahom et al., 2022; Mayou and Bryant, 2003). Many researchers attempted to explain the influencing factors and develop guidance to mitigate this violence as much as possible. However, the number of fatalities and serious injuries was significantly higher than that in developed countries (Jadaan et al., 2018). According to statistics, such countries account for >91% of all road fatalities worldwide (World Health Organization, 2018).

Thailand is a developing country undergoing rapid social, economic, and industrial development. Furthermore, Thailand is the center of transportation and tourism in Southeast Asia (Thailand Board of Investment, 2020); however, the severity of road accidents has not decreased along with this growth. Statistically, Thailand ranks eighth in the world as the country with the highest accident death on road (32.7 fatalities per 100,000 population), which is unacceptable (World Health Organization, 2018). This issue is becoming considerably serious because the number of registered cars and traffic volume increases every year (Department of Land Transport, 2020), increasing the accident rate (Champahom et al., 2021). Road traffic accidents affect the economic burden of >6% of Thailand's GDP (Office of the National Economic and Social Development Council, 2020; Thailand Development Research Institute, 2017); World Bank (2017) reported that the reduction in accidental deaths and injuries by 50% could potentially add 22% to GDP per capita in Thailand. Furthermore, the higher traffic volume causes significant traffic congestion on the roads; INRIX (2017) reported that Thailand leads with the highest average hours spent in peak congestion (average of 56 h per driver per year). This issue resulted in both direct (those borne directly by the driver through wasted time and fuel) and indirect costs (those caused indirectly through the increased costs to businesses; lost working time or productivity). Consequently, redirecting the damage caused by fatalities, injuries, and lost travel time in the road safety investments in the transportation sector will help improve the quality of life of the population and the country's overall economy (Wijnen and Stipdonk, 2016).

4.2.2 Differences between urban and rural areas in Thailand

Most researchers reported considerable differences in the results between area contexts (urban and rural) in their analysis of road accidents and factors influencing the severity in multiple countries, which may lead to certain interesting observations (Antoniou, 2014; Champahom et al., 2020; Nasrollahtabar Ahangar et al., 2020; Wu et al., 2021). Factors that influence different outcomes include respondent characteristics, road and environmental conditions, policies and law enforcement, and traffic volume. In Thailand, the nature of drivers or residents differs significantly between urban and rural areas, e.g., the results of Se et al. (2021a) and Champahom et al. (2020) demonstrated that the accident severity and influencing factors are related to area contexts; such evidence is common in developing countries. In most developing countries, investments in road safety, transportation systems, and access to a good quality of life for urban or rural residents are unequal (Ariyaarpakamol, 2019) and that prosperity and sustainability are frequently concentrated in large cities, without change in rural areas. Consequently, different drivers have different attitudes toward road safety, driver nature, and social status. Recognizing the importance of this issue; we intend to investigate the differences in risk valuation classified by urban and rural areas in Thailand.

4.2.3 Studies on the stated choice survey and unobserved heterogeneity

The severity of accidents and fatalities is difficult to assess because road violence is not a marketing product that can be directly valued (Ale et al., 2021). Many studies attempted to assess the damage of road accidents in monetary terms (Hills and Jones-Lee, 1981; Jacobs, 1995) and discovered that road safety monetary is closely related to the economic concept; microeconomic theory suggests that goods or services valuation was derived from individual choices (Hensher et al., 2011; Nicholson and Snyder, 2012) and that the individual will decide to pay for products if they believe the product is worthwhile; this is the concept of willingness-to-pay (WTP) approach (Entorf and Jensen, 2020; Wijnen et al., 2019). Consequently, the valuation of road safety should be based on the experiences of drivers or other road users who are directly affected. As reported previously, stated choice (SC) experiments are increasingly being used in road safety research for WTP valuation (Iragüen and de Dios Ortúzar, 2004; Niroomand and Jenkins, 2016); this is a stated preference method that values goods or choices based on the utility that respondents believe is extremely valuable. Such an approach provides respondents with situations (alternatives) to compare cost and risk (Johnson et al., 2007), and road safety costs can be calculated using the value of statistical life (VSL) and value of statistical injuries (VSI) of road accidents. Thus, the benefits of a good investment in road safety management and transportation efficiency can be assessed by an increase in the quality of life of road users, as confirmed by the decrease in fatalities, injuries, and travel time.

Previous studies on WTP to reduce road accidents and value of time (VOT) using SC survey reported that many researchers presented empirical results using the fixed-effect model (e.g., see de Dios Ortúzar et al. (2000), Liu and Zhao (2013), Antoniou (2014), and Balakrishnan and Karuppanagounder (2020)); however, such studies were weak in terms of describing the influence of random parameters that can explain the variance of the model and lead to WTP valuation. Subsequently, because of the lack of variance explanation of the fixed parameter model, the concept of the random parameter (or mixed) model became more extensively used in recent studies (González et al., 2018; Hensher et al., 2009; Niroomand and Jenkins, 2016; Yang et al., 2016) because this method can more accurately capture the complexity and factors related to WTP. However, modeling with random parameters, particularly when there are two or more random parameters, can generate a correlation (Washington et al., 2020) that can demonstrate the direction of impact on dependent variables. A majority of previous studies on WTP have not focused on the correlation between random parameters, which may have resulted in certain important insights being missed. Furthermore, the concept of unobserved heterogeneity was introduced first in the study of traffic safety by Mannering et al. (2016); it was reported to be interesting to apply in monetary studies on road safety. Unobserved heterogeneity refers to the characteristics that have no direct influence on dependent variables but may indirectly influence, i.e., it affects random parameters of the model, resulting in increased model complexity, which is consistent with the results of (Se et al., 2021a) and Fountas et al.

(2018a) who reported that the random parameter model with unobserved heterogeneity has higher predicting accuracy and explanatory power compared to the traditional model.

4.2.4 Study aims and scopes

In previous studies, there are still multiple factors that require to be captured. Correlation between random parameters and unobserved heterogeneity across the drivers require to be addressed, and these factors often differ depending on the driver's context. To address these gaps and weaknesses, this study conducts an in-depth analysis using a logit model with correlated random parameters and unobserved heterogeneity to empirically examine the WTP of car drivers on Thailand's highways. The contributions of this study are as follows: (1) determine the socio-demographics, experiences, and driving behavior as more as the trip purpose that affects the VSL, VSI, and VOT of drivers classified by urban and rural areas; and (2) provide novel insights into unobserved heterogeneity factors among drivers influencing road risk valuation using a correlated random parameter logit model with heterogeneity that has never been examined on WTP. The study's findings could help determine the appropriate budget allocation for road safety investments. Furthermore, it can serve as management guidelines for relevant agencies to improve road safety in the context of the driving area.

The remainder of this study is organized as follows. Section 2 describes the methodological approach, and Section 3 guides survey design and data collection. Section 4 then presents the results of the statistical analysis and discussion, and the final section provides a study summary and conclusion.

4.3 Methodological approach

4.3.1 Model development (correlated random parameter with heterogeneity)

We now developed the model in this study in a discrete choice framework, where the utility function, V_{ij}, is a function of the attributes of alternative routes *i* that were obtained from respondent *j*, as shown in Equation (4.1):

$$V_{ij} = \beta_1 A_{ij} + \beta_2 T_{ij} + \beta_3 C_{ij} \tag{4.1}$$

where A is the accident rate (refers to fatality and injury), T is the travel time, and C is the total travel cost of the trip. We can calculate the WTP to reduce accidents per trip by β_1/β_3 (Bliemer and Rose, 2013; Hojman et al., 2005) and derive the WTP for travel time reduction from β_2/β_3 (Bliemer and Rose, 2013; Hensher et al., 2009). In this study, we assume U_{ijk} to be a random utility model of alternative *i* in choice set *k* for individual *j*, where V refers to the deterministic component and ε was an error component reflecting the unobserved utility component, as shown in Equation (4.2) (Hensher, 2010; Niroomand and Jenkins, 2016),

$$U_{ijk} = V_{ijk} + \varepsilon_{ijk} \tag{4.2}$$

Individual-specific unobserved heterogeneity is permitted, and the β_j vector is assumed to have a continuous density function $Prop(\beta_j = \beta) = f(\beta|\varphi)$, where φ is a vector of parameters denoting this function. Consequently, the resulting random parameters logit probabilities are shown in Equation (4.3) (Mannering et al., 2016; Train, 2009),

$$P_{jk}(i) = \int \frac{EXP(V_{ijk})}{\sum_{\forall I} EXP(V_{ijk})} f(\beta|\varphi) d\beta \tag{4.3}$$

where $P_{jk}(i)$ is the probability of alternative route *i* associated with respondent *j* and choice set *k*, and all other variables are as previously defined. Maximum likelihood estimation with logit probabilities is used to estimate the model.

The correlation between random parameters in a random parameter (mixed) logit model with two or more random parameters can be empirically tested as follows (Equation (4.4)) (Ahmed et al., 2021; Fountas et al., 2018a; Washington et al., 2020),

$$\beta_j = b + \eta Z_j + \Gamma \omega_j \tag{4.4}$$

where *b* is the mean value of the random parameter vector, η is the coefficient parameters, Z_j is the vector of explanatory variables influencing the mean of β_j, Γ is the symmetric Cholesky matrix that is used to estimate the standard deviation of the random parameters, and ω_j is the error term with a mean value of zero and variance equal to σ^2.

The standard deviation of the correlated random parameters is based on the diagonal and off-diagonal elements of the Cholesky matrix, which can be defined as Equation (4.5) (Se et al., 2021b; Washington et al., 2020),

$$\sigma_r = \sqrt{\sigma_{k,k}^2 + \sigma_{k,k-1}^2 + \sigma_{k,k-2}^2 + \ldots + \sigma_{k,1}^2} \quad (4.5)$$

where σ_r is the standard deviation of the random parameter r, $\sigma_{k,k}$ is the Cholesky matrix's respective diagonal element, and $\sigma_{k,k}$, $\sigma_{k,k-1}$, $\sigma_{k,k-2}$, ..., $\sigma_{k,1}$ are lower triangular matrix's off-diagonal elements.

For each correlated random parameter, the standard error and t-statistic of the standard deviation (σ_{rn}) are defined as Equations (4.6) and (4.7) (Washington et al., 2020), where $S_{\sigma_{rn}}$ is the standard deviation of the observation-specific σ_{rn}, and N is the number of observations in the model.

$$SE_{\sigma_r} = \frac{S_{\sigma_{rn}}}{\sqrt{N}} \quad (4.6)$$

$$t_{\sigma_r} = \frac{\sigma_{\sigma_r}}{SE_{\sigma_r}} \quad (4.7)$$

The correlation coefficient between random parameters $Cor(x_{r,n}, x_{r',n})$ are calculated by Equation (4.8), $cov(x_{r,n}, x_{r',n})$ is the covariance between the two variables with random parameters r and r', and $\sigma_{r,n}$ and $\sigma_{r',n}$ are their standard deviation, respectively (Fountas et al., 2018a; Fountas et al., 2018b).

$$Cor(x_{r,n}, x_{r',n}) = \frac{cov(x_{r,n}, x_{r',n})}{\sigma_{r,n}, \sigma_{r',n}} \quad (4.8)$$

4.3.2 Statistical fit and model comparison

The evaluation of the goodness-of-fit statistics of the models, the Akaike Information Criterion (AIC), Akaike Information Criterion corrected (AIC_c), McFadden ρ^2, adjusted ρ^2, and Chi-square (χ^2) statistics (this is a statistical test of model superiority (e.g., fixed model and model with random parameter; calculated by the difference in log-likelihood, and degree of freedom between two models); note that these statistics were calculated using Equations (4.9)–(4.13) (Washington et al., 2020),

$$AIC = 2K - 2LL(\beta) \quad (4.9)$$

$$AIC_c = AIC + \frac{2K(K+1)}{N-K-1} \quad (4.10)$$

$$\rho^2 = 1 - \frac{LL(\beta)}{LL(0)} \quad (4.11)$$

$$Adjusted\ \rho^2 = 1 - \frac{LL(\beta)-K}{LL(0)} \quad (4.12)$$

$$\chi^2 = -2[LL(\beta_A) - LL(\beta_B)] \quad (4.13)$$

where K is the number of estimated parameters, $LL(\beta)$ is the log-loglikelihood at convergence, and N is the number of observations. $LL(0)$ is the log-likelihood for only constants and $LL(\beta_A)$ and $LL(\beta_B)$ are the log-likelihood at convergence, which stands for models A and B.

4.4 Data collection

4.4.1 Questionnaire structure

Section 1 of the questionnaires in this study collects sociodemographic information about drivers such as gender, age, marital status, income, and education. This data can be used to describe norm and differences among respondents. Section 2 presents information about the trip, including the purpose of the trip, which can be used to justify alternative decisions and payment intentions. Furthermore, driving behavior and accident experience are collected, this information may show different attitudes of drivers, concerns, and awareness about road accident risks. The final section is the SC experiment, which creates a scenario as route choice (compare between existing and alternatives), with three attributes, namely, travel cost, travel time, and accident rates of alternatives. Drivers must consider and select the option that they believe is the most cost-effective for them by comparing the total utility of all attributes, each person has to respond to six scenarios.

4.4.2 Establishing the attributes

The attribute to be evaluated in the model comprises two major parts: 1) monetary (travel cost) attribute and 2) non-monetary (travel time, fatality, and injury) attributes, the following details can then be achieved for each attribute.

The situation created for this survey is based on an average distance of 50 km on Thailand's highway in an area where drivers regularly drive. The total cost of one trip is defined using operating costs, fuel, and breakage, and the average fuel consumption of a personal car is ~15–20 km per liter (we set the average fuel price equal to 30 baht (Energy Policy and Planning Office, 2020)), and therefore the initial value of travel cost is set to 80 baht.

We used data from the Bureau of Highway Safety (2019c) for the accident attribute, which demonstrated that there were ~2,700 car accident fatalities and 16,129 serious injuries in 2019. Many studies presented risks in the form of probability, which was reported to be difficult for respondents to understand (Kahneman and Tversky, 2013), whereas Antoniou (2014) and Iragüen and de Dios Ortúzar (2004) reported that the actual value appears to be clearly defined for respondents. Consequently, this study focused on presenting road risks to respondents using probabilities, in addition to actual values (we presented the actual value of 8 fatalities and 48 injuries daily).

The actual travel time of the 50 km trip is calculated based on the speed limit on the Thailand highway (Royal Thai Police, 1979), and driving at a speed of 90 km/h over a distance of 50 km on the highway with a slight delay takes about 40 min. Furthermore, based on the average traffic volume on Thai highways, we added the annual average daily traffic (AADT) of the private car in surveyed provinces is equal to 5,691 vehicles per day for an urban area, and 3,938 vehicles per day for a rural area (Bureau of Highway Safety, 2019a, 2019b) in the experiment (respondents were informed that they would have to drive in such traffic along the trip) to use in VSL and VSI calculation.

4.4.3 Experimental design

As previously stated, we developed the SC model for alternatives based on three attributes: travel cost, travel time, and accident rate (fatality and injury). Each attribute has a total of three levels (Table 4.1), which are based on a travel situation in which all drivers are in their area. Consequently, the full factorial design (Rizzi and Ortúzar, 2003) demonstrated that there would be a total of 27 possible choice sets (3^3); with an initial base value of 80 baht, travel time of 40 min, and accident rate of 100% (8 fatalities and 48 injuries per day). However, when all 26 choice sets (excluding base value) were considered, there were a lot of profiles, making it difficult for respondents to provide their information. Consequently, 14 choice sets were removed from the questionnaire using a D-optimal design to make it more efficient and reasonable, (Bliemer et al., 2017; Huber and Zwerina, 1996; Niroomand and Jenkins, 2016). Finally, we arrived at 12 choice sets and base values. To reduce the overburden of respondents, the 12 profiles were split in two blocks (6-profile per block) and each respondent was asked to randomly answer only one block (Hensher et al., 2009; Rizzi and Ortúzar, 2003); Figure 4.1 shows a sample choice set.

Table 4.1 Attributes and levels

Attributes	Base value	Level 1	Level 2
Travel cost (baht)	80	90	100
Travel time (minute)	40	30	50
Accident (times)	100%	Reduced by 50%	Reduced by 25%
	8 fatalities/day	4 fatalities/day	6 fatalities/day
	48 injuries/day	24 injuries/day	36 injuries/day

Attributes	**Presently**	**Alternative**
Travel cost (baht)	80	100
Travel time (minute)	40	30
Accident rate (per day)	100% (8 fatalities and 48 injuries)	Reduced by 50% (4 fatalities and 24 injuries)
Please prefer your preference	○	○

Figure 4.1 Choice set (example)

4.4.4 Data collection and sample statistics

The survey data in this study were collected from personal car drivers in four major regions in Thailand, the sample target was drivers aged 18 years or older (with a driving license) living in urban and rural areas (classified from the residential district; municipality district represented urban area and other districts for rural area). We used random sampling from eight provinces with the highest proportions of road fatalities in each region, this study wants respondents to be as representatives of the population as possible in terms of age, gender, education, income, and driving experience. We gathered 1,600 samples (640 urban and 960 rural). Face-to-face interviews were used to ensure that respondents understood the risk reduction valuations and concept of WTP, and they were asked about their knowledge of road accidents, choice experiments, and certain important survey information before answering the questions. The Suranaree University of Technology ethics committee has approved this survey (November 13, 2020). We had already submitted a human research ethics document, and the results indicated that the study was a low risk; thus, oral informed consent of participants is permissible, and the demography of respondents is shown in Table 4.2.

Table 4.2 Characteristic of respondents

Code	Definition	Urban (640 drivers)		Rural (960 drivers)	
		Frequency	%	Frequency	%
Gender	Male	404	63.1	584	60.8
	Female	236	36.9	376	39.2
Age	≤ 25 years	113	17.6	146	15.2
	26–35 years	248	38.8	387	40.3
	36–45 years	143	22.3	234	24.4
	≥ 46 years	136	21.3	193	20.1
Marital status	Married	242	37.8	394	41.0
	Otherwise	398	62.2	566	59.0
Education	Uneducated/Below bachelor	288	45.0	460	48.0
	Bachelor	316	49.4	454	47.2
	Master	31	4.8	38	4.0
	Doctoral	5	0.8	8	0.8
Occupation	Government/State enterprise officer	69	10.8	101	10.5
	Private company	237	37.0	370	38.5
	Self-employed	99	15.5	194	20.2
	Farmer	61	9.5	74	7.7
	Laborer	109	17.0	160	16.7
	Others	65	10.2	61	6.4
Personal income*	Less than 15,000	98	15.3	130	13.5
	15,000 – 29,999	388	60.6	594	61.9
	30,000 or higher	154	24.1	236	24.6
Accident experience	Never	557	87.0	816	85.0
	Ever	83	13.0	144	15.0

Note: *Baht per month

4.4.5 Model specification and descriptive statistics

In this study, we used the NLOGIT6 program to create a correlated random parameter model with heterogeneity. We defined the SC experiment as a dependent variable (binary; 1 if respondent stated alternative route, 0 if current route), and 28 parameters were defined as independent variables that were classified into four groups: Driver's demographic, experiences, driving behavior, and trip information. Table 4.3 shows the type of variable, variable details, and descriptive statistics. The total observations were 9,600 (3,840 urban and 5,760 rural) as each respondent provided six options.

Table 4.3 Definitions of variables coded and descriptive statistic

Variables	Type	Urban (3,840 observations)		Rural (5,760 observations)	
		Mean	S.D.	Mean	S.D.
Dependent variables					
Route choice (1 if Alternative, 0 current)	Dummy	0.67	0.469	0.66	0.475
Independent variables					
Driver's demographic;					
Gender (1 if male driver, 0 otherwise)	Dummy	0.63	0.483	0.61	0.488
Marital status (1 if married, 0 otherwise)	Dummy	0.38	0.485	0.41	0.492
Age 26-35 years (1 if yes, 0 otherwise)	Dummy	0.39	0.487	0.40	0.491
Age 36-45 years (1 if yes, 0 otherwise)	Dummy	0.22	0.417	0.24	0.430
Age above 45 years (1 if yes, 0 otherwise)	Dummy	0.21	0.410	0.20	0.401
Bachelor (1 if Bachelor, 0 otherwise)	Dummy	0.49	0.500	0.47	0.500
Master (1 if Master, 0 otherwise)	Dummy	0.05	0.215	0.04	0.195
Doctoral (1 if Doctoral, 0 otherwise)	Dummy	0.01	0.088	0.01	0.091
INC1 (1 if 15,000 baht ≤ income < 30,000 baht, 0 otherwise)	Dummy	0.61	0.489	0.62	0.486
INC2 (1 if income ≥ 30,000 baht, 0 otherwise)	Dummy	0.24	0.428	0.25	0.431
Older (1 if there have elder (Age ≥ 60) in the household excluding participant, 0 otherwise)	Dummy	0.20	0.399	0.20	0.399
Young (1 if there have children (Age ≤ 18) in the household, 0 otherwise)	Dummy	0.22	0.415	0.23	0.420
Sole earner (1 if yes, 0 otherwise)	Dummy	0.60	0.490	0.51	0.500
Household size	Continuous	3.05	1.398	2.90	1.377
Number of cars	Continuous	1.18	0.450	1.19	0.468
Experiences;					
Annual mileage (1000 km)	Continuous	22.43	11.010	23.05	11.696

Table 4.3 Definitions of variables coded and descriptive statistic (Continued)

Variables	Type	Urban (3,840 observations)		Rural (5,760 observations)	
		Mean	S.D.	Mean	S.D.
Driving experience (year)	Continuous	13.94	9.968	14.18	9.366
Own accident (1 if driver has been involved in a road accident, 0 otherwise)	Dummy	0.13	0.336	0.15	0.357
Family injured (1 if family/close friends have been injured in a road accident, 0 otherwise)	Dummy	0.27	0.445	0.28	0.449
Family died (1 if family/close friends have been died in a road accident, 0 otherwise, 0 otherwise)	Dummy	0.10	0.296	0.09	0.286
Risk perception (1 if driver stated that his/her risk is higher than the average in Thailand, 0 otherwise)	Dummy	0.57	0.495	0.39	0.488
Driving behavior;					
Ticket (orders for traffic violations) (1 if driver has ever been received a ticket, 0 never)	Dummy	0.53	0.499	0.53	0.499
Safety belt usage (1 if often, 0 never)	Dummy	0.34	0.473	0.33	0.469
Alcohol (1 if driver has ever been drunk while driving, 0 never)	Dummy	0.06	0.245	0.05	0.224
Driving exceeds speed limit (1 if often, 0 never)	Dummy	0.87	0.334	0.89	0.312
Trip information (most of car used);					
Compelling trip (1 if most of trips are related with the job, 0 otherwise)	Dummy	0.52	0.500	0.61	0.488
Weekday (1 if most of trips are spent on weekday, 0 otherwise)	Dummy	0.69	0.464	0.69	0.464
Night (1 if most of trips are spent at nighttime, 0 otherwise)	Dummy	0.29	0.452	0.29	0.454

Note: INC = Personal income.

4.5 Results and discussion

4.5.1 Transferability test between urban and rural models

Before obtaining important factors influencing WTP to reduce the risk of road accidents among urban and rural drivers. Using the transferability test (Washington et al., 2020), we must test reject or accept the null hypothesis that the influence of parameter estimates on WTP is the difference, as shown in Equation (4.14) below,

$$\chi^2 = -2[LL(\beta_{m_2 m_1}) - LL(\beta_{m_1})] \tag{4.14}$$

If we assumed m_1 to represent urban data and m_2 represent rural data, $LL(\beta_{m_2 m_1})$ is the log-likelihood at the convergence of the model containing significant parameters from rural and using data subset urban at the same time. $LL(\beta_{m_1})$ is the log-likelihood at the convergence of the estimated model using data from urban with no parameter restriction. We tested this transferability in reverse case (subset m_1 became m_2 and vice versa). To examine the level of confidence, χ^2 with a degree of freedom (set equal to the number of estimated parameters), we denoted m_1 and m_2 are the urban and rural data, respectively. The statistics revealed that χ^2 equal to 41.812 and the degree of freedom is 17; these tests resulted in a 99% confidence level, indicating that the parameters of the rural model cannot represent the urban data. Furthermore, we set m_2 to urban data and m_1 for the rest, and we reported the χ^2statistics of 71.604 and 16 degrees of freedom which indicates a 99.99% level of confidence. The results revealed that the characteristics of urban and rural drivers significantly differ. Based on this evidence, this study considered presenting factors influencing the WTP to reduce road accidents classified by urban and rural areas.

4.5.2 Overview of model evaluation

To evaluate these models, the statistical fit of various models in both urban and rural models, including five models each, namely, the binary logit model (BL), random parameter binary logit model (RPBL), correlated random parameter binary logit model (CRPBL), random parameter binary logit model with heterogeneity in means (RPBLHM), and correlated random parameter binary logit model with heterogeneity in means (CRPBLHM), is considered. Table 4.4 displays the statistical data used to compare the model advantages: McFadden ρ^2, adjusted ρ^2, AIC, AIC_c and likelihood ratio tests were used. The results demonstrated that the models with unobserved heterogeneity (RPBLHM and CRPBLHM) were significantly superior to their counterparts, and we discovered that the CRPBLHM is not significantly improved at a 90% confidence interval compared to RPBLHM (84.58% and 60.11% for urban and rural models, respectively). As per AIC_c and adjusted ρ^2 statistics, there is a slight difference between RPBLHM and CRPBLHM, with RPBLHM being slightly more accurate in both urban and rural models. However, based on the model results, we discovered that important parameters obtained from RPBLHM and CRPBLHM demonstrated no difference, in addition to the number of significant parameters (fixed parameters, random parameters, and heterogeneity), and the direction of each parameter coefficients (positive and negative) are almost the same between these two models. However, a good trade-off is an explanatory power, which CRPBLHM has more complex results, as such results could capture the direction and correlation between two random parameters. Consequently, this study considers presenting the model results obtained from CRPBLHM (consistent with Ahmed et al. (2021) and Saeed et al. (2019)), to provide relevant agencies with additional options for applying these results.

Table 4.4 Model-fit statistic, likelihood ratio test, and prediction accuracy for model superiority comparison

	Urban model					Rural model				
	BL	*RPBL*	*CRPBL*	*RPBLHM*	*CRPBLHM*	*BL*	*RPBL*	*CRPBL*	*RPBLHM*	*CRPBLHM*
Number of estimated parameter (K)	30	32	33	36	37	27	29	30	39	40
Likelihood at constant, *LL(0)*	−2427.240	−2427.240	−2427.240	−2427.240	−2427.240	−3704.568	−3704.568	−3704.568	−3704.568	−3704.568
Likelihood at convergence, $LL(\beta)$	−1679.221	−1674.587	−1674.576	−1669.609	−1668.594	−2719.181	−2718.077	−2717.956	−2697.564	−2697.208
ρ^2	0.308	0.310	0.310	0.312	0.313	0.266	0.266	0.266	0.272	0.271
Adjusted ρ^2	0.296	0.297	0.296	0.297	0.297	0.259	0.258	0.258	0.261	0.261
AIC	3418.443	3413.175	3415.151	3411.218	3411.187	5492.362	5494.154	5495.920	5473.127	5474.416
AIC_c	3418.931	3413.730	3415.741	3411.918	3411.927	5492.626	5494.457	5496.245	5473.673	5474.989
Likelihood ratio test										
	BL vs CRPBLHM	RPBL vs CRPBLHM	CRPBL vs CRPBLHM	RPBLHM vs CRPBLHM		BL vs CRPBLHM	RPBL vs CRPBLHM	CRPBL vs CRPBLHM	RPBLHM vs CRPBLHM	
Degree of freedom	7	5	4	1		13	11	10	1	
Resulting χ^2	21.256	11.988	11.964	2.031		43.946	41.738	41.504	0.712	
Level of confident	99.66%	96.50%	98.24%	84.58%		99.99%	99.99%	99.99%	60.11%	
Superior model	CRPBLHM	CRPBLHM	CRPBLHM	-		CRPBLHM	CRPBLHM	CRPBLHM	-	

4.5.3 Exploratory factor analysis of district variables

Table 4.5 shows the results of CRPBLHM for urban and rural drivers. Data analysis from the SC experiment demonstrated that travel costs, travel time, and accident rate (number of fatalities and injuries) have a significant impact on determining alternative routes for both urban and rural drivers. The minus signs on the accident rates and travel time factors show that both factors have opposing influences on drivers depending on safer alternatives; thus, it can be described that the drivers who choose alternative routes want to reduce their chances of being involved in road accidents and reduce travel times.

1) Driver's demographic: According to Table 4.5, driver's demographic factors were reported to be influenced parameters on WTP; for urban drivers, the middle age drivers (36–45 years) influence alternative because this age is working age and have their income and expenses. Because being in an accident would have a significant impact on them, they tend to take the safest route (Yang et al., 2016). The young factor was reported to have a negative influence on urban drivers' route choices. The results demonstrated that drivers with children under the age of 18 in their families possible preferred their current route because of concerns about commuting to school or not wanting to take their children on unfamiliar routes.

For rural drivers, education was reported to influence the driver's valuation; Bachelor's drivers tend to choose the alternative over other groups, consistent with Yang et al. (2016) who stated that higher educated drivers will pay more attention to safety because they have a better understanding of the consequences of road accidents. This study, however, discovered that master's drivers tend to stick to their current route because of their high self-confidence, and the nature of the work they do may be specific, and therefore changing routes will affect their work.

Marital status and age (26–35 years) influence routing decisions for urban and rural drivers, married drivers have more responsibility for safety (they may have more family members and expenses) (Antoniou, 2014; Balakrishnan and Karuppanagounder, 2020), and they must therefore reduce their road accident risks. Middle-aged drivers like marital status, have a burden of expenses and jobs, making them possibly choose alternatives for safety than younger or older drivers. This is consistent with the results of Persson et al. (2001), which said the relationship between age and WTP for road risk reductions had an "inverted-U" pattern.

2) Driving behavior: Driving behaviors and background risks seem to be related to urban drivers about WTP for safety, for example, urban drivers who have received a ticket for regularly exceeding speed limits possibly choose a safer alternative because they are aware of their risky behavior. Furthermore, drivers who often wore seatbelts were more willing to pay for road traffic safety than others because they have high safety concerns (consistent with the findings of Mon et al. (2019)).

3) Trip information: The trip purpose was reported to be a positive influence on WTP for safe road significantly for rural drivers, and the results indicated that drivers who drive for a compelling reason (work or study) tend to prefer the alternatives (Bhattacharya et al., 2007; Haddak, 2016) as drivers feel the accident affects their work and earning, and this makes them more responsible. It was discovered that urban drivers who typically drive on weekdays are more likely to prefer existing routes as this driving may be routine driving or related to work, and changing routes would impede the driving purpose. Rural drivers, however, prefer the current option because their background demonstrates that they have more experience and mileage on the road than the average urban driver, thus resulting in high self-confidence.

Table 4.5 A correlated random parameter binary logit model with heterogeneity in means for urban and rural areas

Variable	Correlated random parameter with heterogeneity in means					
	Urban			Rural		
	Parameter estimate	(t-stat)	Marginal effect	Parameter estimate	(t-stat)	Marginal effect
Constant	7.957	(18.60)		7.724	(24.69)	
Travel cost	−0.066	(−7.85)	−0.0094	−0.072	(−12.50)	−0.0128
Accident rate	−7.061	(−28.65)	−1.2733	−6.805	(−33.68)	−1.2080
Travel time	−0.089	(−13.66)	−0.0108	−0.085	(−16.08)	−0.0151
Driver's demographic;						
Marital status (married)	0.187	(2.77)	0.0313	0.130	(2.54)	0.0231
Age 26-35 years	0.407	(4.26)	0.0678	0.132	(1.73)	0.0234
Age 36-45 years	0.216	(1.84)	0.0358			
Bachelor				0.106	(1.92)	0.0189

Table 4.5 A correlated random parameter binary logit model with heterogeneity in means for urban and rural areas (Continued)

Variable	Correlated random parameter with heterogeneity in means					
	Urban			Rural		
	Parameter estimate	(t-stat)	Marginal effect	Parameter estimate	(t-stat)	Marginal effect
Master				−0.238	(−1.81)	−0.0428
Young	−0.147	(−1.80)	−0.0248			
Driving behavior;						
Ticket	0.163	(2.41)	0.0272			
Safety belt usage	0.121	(1.73)	0.0202			
Driving exceeds speed limit	0.277	(2.78)	0.0470			
Trip information (most of car used);						
Compelling trip				0.141	(2.50)	0.0250
Weekday	0.136	(1.89)	0.0228	−0.094	(−1.67)	−0.0166
Random parameter; *(normal distribution)*						
Doctoral	−6.251	(−2.99)	−0.6372			
Standard deviation	2.223	(63.69)				
Own accident	−0.546	(−1.82)	−0.0934			
Standard deviation	1.330	(63.33)				
Night				−0.202	(−1.62)	−0.0362
Standard deviation				0.580	(75.64)	
INC2				0.582	3.58	0.1012
Standard deviation				0.597	(80.00)	
Heterogeneity in means;						
Doctoral : Household size	1.775	(3.04)				
Own accident : Gender (male)	0.403	(1.92)				
Night : Household size				0.096	(2.46)	
Night : Sole earner				−0.322	(−3.25)	
Night : Own accident				0.396	(2.02)	
Night : Doctoral				−1.089	(−2.10)	
Night : Young				−0.233	(−1.67)	
INC2 : Household size				−0.083	(−1.75)	
INC2 : Sole earner				−0.344	(−3.25)	
Model statistics;						
Halton draw	1,000			1,000		
Number of observations	3,840			5,760		
Number of estimated parameters	37			40		
Log-likelihood at zero, *LL(0)*	−2427.240			−3704.568		
Log-likelihood at convergence, *LL(β)*	−1668.594			−2697.208		
Adjusted ρ^2	0.297			0.261		

4) Distribution of random parameters: Table 4.5 revealed significant mean and standard deviation of random parameters in both urban and rural models, and it was discovered that doctoral and own accidents were random indicators for urban drivers, and night and INC2 were random indicators for rural drivers. The positive coefficient of the random parameter reported that the majority of drivers (more than half) preferred the alternative route, while the remainder preferred the current route. However, a negative coefficient indicated that the majority of drivers preferred the current route over the alternative. Figures 4.2 and 4.3 depicted distributional splits (percentages) of the random parameters of the urban and rural models (orange indicated the probability below zero for the urban model (green for the rural model), and above zero was presented in grey).

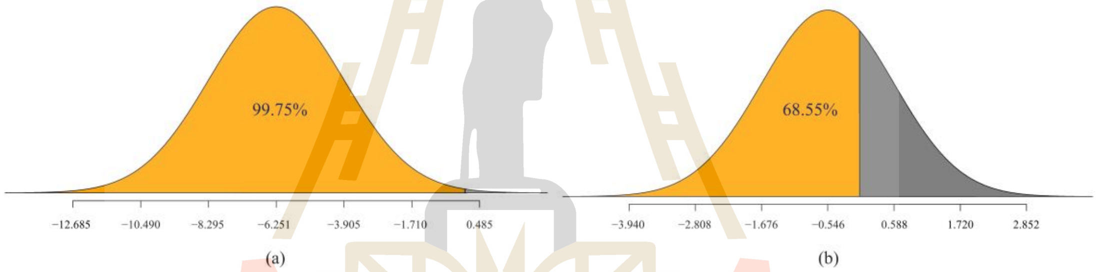

Figure 4.2 Distribution of coefficient random parameters of the urban model: (a) doctoral, (b) own accident

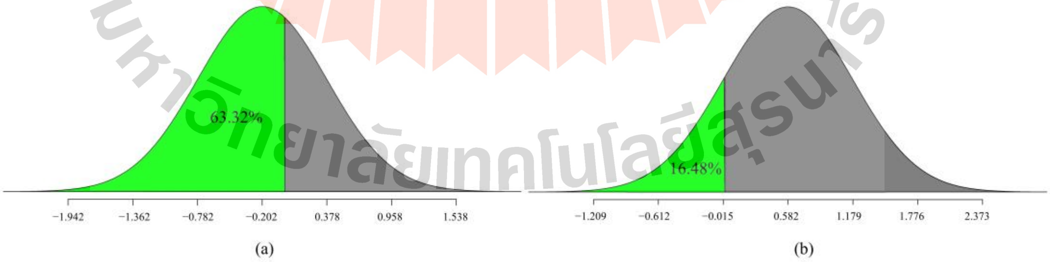

Figure 4.3 Distribution of coefficient random parameters of the rural model: (a) night, (b) INC2

5) Insight correlation of random parameter: Table 4.6 lists the diagonal, off-diagonal elements of the Cholesky matrix as well as correlation coefficients of random parameters of CRPBLHM for both urban and rural models. The correlation coefficients could represent the interaction of two (or more) random parameters, with positive coefficients (+) indicating a pair's homogeneous effect and negative coefficients (–), thus indicating the opposite influence (Fountas et al., 2021; Hooper et al., 2008). For urban drivers, the interaction of random parameters (doctoral and own accident) was reported to have a negative correlation (–0.576), indicating that unobserved characteristics captured by such variables have opposing influences on drivers' WTP. However, a positive correlation (0.984) was observed in unobserved characteristics of rural drivers, which was captured by drivers who regularly drive at nighttime (night) and stated that their income was >30,000 baht (INC2), thus indicating a homogeneous effect on WTP on road safety.

Table 4.6 Diagonal and off-diagonal elements of the Cholesky matrix, t-stat [in brackets], and correlation coefficients (in parentheses) of the correlated random parameters

Urban		
	Doctoral	Own accident
Doctoral	2.227 [2.87] (1.00)	
Own accident	–0.767 [–5.83] (–0.58)	1.086 [7.92] (1.00)
Rural		
	Night	INC2
Night	0.580 [8.47] (1.00)	
INC2	0.587 [7.73] (0.98)	0.107 [1.51] (1.00)

6) Influence of unobserved characteristics: According to Table 4.5, this study discovered heterogeneity that influences the mean of random parameters, with a significant coefficient of unobserved heterogeneity on random parameters, indicating that the mean value of the random parameter is associated with the direction of unobserved heterogeneity. In the urban model, we discovered that household size

increases the mean value of doctoral, indicating that doctoral drivers with more family members prefer the alternative over those with fewer members (Balakrishnan and Karuppanagounder, 2020). Similarly, male drivers who have been in an accident in the past are more likely than female drivers to take the safe route than female drivers (Mon et al., 2018).

Five parameters are related to the valuation of drivers who regularly drive at night for the rural model. The findings revealed that nighttime drivers' household size and accident experience will lead them to safer alternatives because increasing the number of family members resulted in more responsibility, and the accident experience would make them more aware of severity (Persson et al., 2001). Nevertheless, drivers who are sole earners, have a doctorate or are young reduce the mean of nighttime, as drivers who are sole earners are less likely to pay for safety because they have a lot of family expenses (Bhattacharya et al., 2007). Doctoral drivers who regularly drive at night prefer the existing route because higher education makes drivers self-confident, and their job appears to be specific, changing the route may cause certain problems for them, and this reason agrees with drivers who have children in the household. Furthermore, household size and sole earners significantly reduce the mean of high-income drivers, and we can conclude that if they are sole earners, they have to be mindful of expenses and more family members resulting in less intent to pay (Bhattacharya et al., 2007).

4.5.4 Estimating the value of statistical life and injury for road accidents and the value of travel time saved

Table 4.5 shows that the risk values (accident rate) are coded in the form of probability (rather than actual value) to avoid collinearity between two risk values (fatality and injury) because these two factors have the same proportion of increase or decrease in each attribute (Table 1). Consequently, we derived the WTP value to reduce fatality per person per trip from the ratio of coefficients of accident and travel cost divided by the number of fatalities (Equation (4.15)), WTP to reduce injury per person per trip (Equation (4.16)), further, VSL and VSI were obtained from Equations (4.15) and (4.16) multiplied by AADT (see Equations (4.17) and (4.18)), and VOT per hour as Equation (4.19) (Kuriyama et al., 2020; Obermeyer et al., 2015). Finally,

Table 4.7 shows VSL, VSI for road accident reduction, and VOT for urban and rural drivers.

$$WTP/fatality/trip=\frac{\beta_{accident}}{\beta_{travel\ cost}} / \text{ fatalities per trip} \quad (4.15)$$

$$WTP/injury/trip=\frac{\beta_{accident}}{\beta_{travel\ cost}} / \text{ injuries per trip} \quad (4.16)$$

$$VSL = (WTP/fatality/trip) \times AADT \times 365 \quad (4.17)$$

$$VSI = (WTP/injury/trip) \times AADT \times 365 \quad (4.18)$$

$$VOT=\frac{\beta_{travel\ time}}{\beta_{travel\ cost}} \times 60 \quad (4.19)$$

According to the findings in Table 4.7, the VSL and VSI for reducing road traffic injuries and fatalities is higher among urban drivers than rural drivers, indicating that there are certain differences between social status and drivers' attitudes towards road accidents. This leads to an increase in safety WTP, which agrees with the demographic of this study and revealed that urban drivers perceive themselves to be at a higher risk of accidents than rural drivers. Furthermore, the concept of WTP is linked to driver income, their burden, and expenses (Ainy et al., 2014; Fauzi et al., 2004). Consequently, urban drivers have greater affordability than rural drivers.

However, the overall image of the value of road safety shows that Thailand has a higher risk of road violence than other developing countries (Ainy et al., 2016; de Dios Ortúzar et al., 2000; Jomnonkwao et al., 2021; Mon et al., 2019), although Thailand is a developing country (with gross national income per capita in the upper-middle-income group); however, they are ranked eighth globally with the highest road accident fatalities (World Health Organization, 2018) or comparable to Africa. Consequently, valuing the high number of accidents along with high income resulted in a high national impact when measured in monetary terms.

Table 4.7 Estimating the value of statistical life, injury, and travel time saved

Value	Urban	Rural
WTP to reduce fatality (baht/fatality/trip)	13.28	11.81
WTP to reduce injury (baht/injury/trip)	2.21	1.97
AADT (vehicle/day)	5,691	3,938
Fatality (baht/fatality)	27,585,415	16,975,340
Injury (baht/injury)	4,597,569	2,831,619
VOT (baht/hour)	80.31	70.73

Note: WTP = willingness-to-pay; VOT = value of time; AADT = annual average daily traffic

4.6 Conclusion and further study

This study developed a modeling framework of CRPBLHM to empirically examine the VSL, VSI of a road accident, and value of travel time saved for personal car drivers in Thailand between urban and rural areas and presented factors influencing the WTP across drivers and insight correlation and unobserved characteristics among drivers. Face-to-face interviews were used to obtained questionnaire data from 1,600 Thai car drivers. There have never been previous studies on WTP to reduce road accidents that used unobserved characteristics with a correlated random parameter logit model, the current results revealed certain latent parameters that were important and overlooked, and the analysis was divided into two primary sections, including 1) VSL and VSI of road safety, and 2) factors influencing the WTP for road safety, a summary of the study results can be concluded as follows.

The results revealed that urban drivers' VSL and VSL from road accidents were significantly higher (1.63 times) than rural drivers' values, indicating that differences in the context of road users in different areas resulted in their knowledge, understanding, and awareness of road accidents differently. Consequently, the difference in WTP of road accidents was affected. However, the value of road safety at the national level remains severe compared to other developing countries, but appropriate budget allocation along with pinpoint solutions can reduce the violence. Furthermore, the VOT of urban drivers was reported to be higher (13.5%) than rural drivers with 80.31 baht per hour and 70.73 baht per hour, respectively. This confirmed how much drivers are willing to pay to reduce their time wastage in road traffic.

The results of the random parameter demonstrated that urban drivers who are doctoral and have an accident experience cause variability among drivers, and thus this group is less willing to pay for safe alternatives. However, we discovered differences in the random parameters of rural drivers compared to urban drivers; moreover, the results demonstrated that nighttime drivers and drivers with a high income were influencing factors on the WTP. This analysis captures the insight effect of unobserved characteristics because urban drivers, household size and gender of drivers can influence the mean of random parameters, causing an indirect effect on the WTP of urban drivers. Furthermore, the results show that up to five unobserved characteristics (household size, sole earner, own accident, doctoral, and young) can indirectly influence the WTP of rural drivers. The context of latent factors differs significantly between urban and rural road users.

For practical implication, these findings can be used as a management guideline for policymakers and relevant agencies in road safety, and these are useful for budget allocation in road safety improvement, provide factors associated with the WTP, and drivers' socio-demographics appear to be appropriate for strategic promotion of road safety campaigns (Alonso et al., 2021). Such data will assist agencies in focusing on unobserved characteristics of drivers (urban and rural districts) and resolving issues following area contexts.

As per the study limitations, we did not allow drivers under the age of 18 to participate in the research (because of the licensing law of Thailand), and other modes of road users are not considered. Young drivers and other road users may reflect different perspectives, attitudes, and WTP for road accident factors. Note that additional research that includes young drivers and other road users may be more representative of the population and produce different results.

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CHAPTER 5

INFLUENCE OF PSYCHOLOGICAL PERSPECTIVES AND DEMOGRAPHICS ON DRIVERS' VALUATION OF ROAD ACCIDENT: A COMBINATION OF CONFIRMATORY FACTOR ANALYSIS AND PREFERENCE HETEROGENEITY MODEL

5.1 Abstract

Property damage and loss from road traffic accidents are a major concern in developing countries; thus, studies on accident damage in such countries may include more latent factors. This study aims to examine the effect of psychological perspectives and sociodemographic status on drivers' willingness-to-pay (WTP) for road accident risk reduction, using confirmatory factor analysis (CFA) and random parameters multinomial logit model with heterogeneity in means and variances (RPMNLHMV). The CFA results from interviews with 1,650 car drivers in Thailand demonstrate that concepts of the theory of planned behavior and the health access process approach are key factors for describing drivers' behavioral intention and WTP. The RPMNLHMV results indicate that driver's demographic affected drivers' WTP to reduce road accidents, and psychological perspectives are also found to have an influence on WTP. The results also reveal unobserved characteristics that could affect drivers' WTP. The study concludes that ignoring unobserved heterogeneity in studies on WTP to reduce road accidents may lead to biased results and neglect important influential factors. Such methodological approaches offer another layer of insight into unobserved characteristics in road accident valuation. These findings could be used to provide practical insights for relevant authorities' policy development for road accident mitigation and road safety education programs in accordance with drivers' characteristics.

5.2 Introduction

Improved road safety is a factor of individuals' quality of life and national progress; therefore, many studies attempt to determine the factors to improve road safety around the world, finding them to be effective in developed countries. The issue of traffic accidents has a considerable impact in developing countries (Jadaan et al., 2018), reflected by the number of fatalities (World Health Organization, 2018) and substantial loss from road accidents at national levels. Thailand seems to be an appropriate site for investigating these factors and drivers' attitudes regarding road accident valuation, as the nation is heavily affected by traffic accidents (32.7 fatalities per 100,000 population) (Chantith et al., 2021; World Health Organization, 2018). Thailand is representative of middle-income developing countries (World Bank, 2019) and is a center of tourism and the ASEAN economy (Thailand Board of Investment, 2020). The number of traffic-related fatalities indicates that effective road safety improvement in Thailand remains incomparable to developed countries; thus, investigating drivers' perspectives regarding accident damage in Thailand may include more latent factors. In addition to demographic and environmental aspects, studies of human attitudes, risky behaviors, and psychological perspectives related to road accidents have gained increasing attention (Mekonnen et al., 2019; Tan et al., 2022; Uttra et al., 2020a). Evidence suggests that the components of accidents and related factors may be influenced by drivers' thoughts, attitudes (Tan et al., 2022), and behaviors (Han et al., 2021).

In the study of accident severity, one popular concept is to compare violence in the form of financial or economic losses. This means that if the accident is very serious, it will result in a high loss as well. Willingness-to-pay (WTP) is the monetary concept that is widely used in road risk valuation (Ainy et al., 2014). Where risk is seen as a product, people are willing to pay more if they assess the risk as very dangerous. Many previous studies used WTP for evaluating the road accident risk. Nevertheless, the majority of these studies explore the potential factors that influence individual valuation of road accidents, most of which include socio-demographics (Alberini et al., 2006; Balakrishnan & Karuppanagounder, 2020; Hoffmann et al., 2012), accident experience (Antoniou, 2014; Bhattacharya et al., 2007), or driving behavior (Mon et al., 2019; Svensson & Johansson, 2010). Nevertheless, from policymakers' perspective, examining only demographic or environmental factors may be a weak and insufficient approach for developing strategic policies to improve road safety. Consequently, understanding drivers' perspectives and risk valuations will provide policymakers with more com-prehensive insights for strategic development of such improvements. Further, the study of road safety is related to psychological or health behaviors. Several studies have examined drivers' health and risk behaviors by applying such theories; for example, the health belief model (Jomnonkwao et al., 2020; Zhang et al., 2013) and locus of control (Uttra et al., 2020b); however, these concepts are rarely used in investigating drivers' valuation of road accidents. The value of risk reduction appears to be associated with individuals' mindset or behavioral intention, as the WTP to reduce accident risk is related to behavioral intention (whether respondents intend to increase safety can be demonstrated by higher WTP) (Jomnonkwao et al., 2021). This study determines that applying two psychological concepts of the theory of planned behavior (TPB) and the health access process approach (HAPA) could describe behavioral intention to pay and can be adopted for investigating drivers' WTP.

Another aspect to be carefully considered is the analysis method. Most of the WTP studies used traditional standard regression, probit, or logit models, etc. These approaches can only indicate the affecting factors in one layer (i.e., fixed effect of parameter estimates). To explore deeper insights into the effects of factors (layer 2), the concept of unobserved heterogeneity could be applied (introduced by Mannering et al. (2016) in road safety research). The unobserved heterogeneities are the factors that do not directly relate to the dependent variable but act as hidden variables that differently influence the outcome probabilities in the model. Therefore, accounting for unobserved heterogeneity in the modeling process could produce more revealing results in WTP studies for road accident reduction.

In response to the gaps in previous research, the goals of this study are two-folds: (1) to understand Thai drivers' perspectives (using TPB and HAPA), attitudes, socio-demographic status, and experiences that may affect WTP for risk reduction; and (2) to apply a new advanced econometric and statistical approach (i.e., heterogeneity modeling) to uncover the insight into effect of relevant factors on WTP. To achieve the study purposes, we initially apply confirmatory factor analysis (CFA) to confirm the correlations between the relevant indicators of TPB and HAPA and WTP, confirming that these concepts influence drivers' intention to pay. Subsequently, the CFA results are combined with drivers' demographics for an in-depth analysis on the factors influencing drivers' WTP using the random parameter multinomial logit model with heterogeneity in means and variance (RPMNLHMV) to capture variations and unobserved characteristics across drivers, which has not been used in previous studies on WTP for road accidents. The findings provide relevant authorities and policymakers with more com-prehensive insights into relevant factors and alternatives for improving road safety in developing countries.

The remainder of this paper is structured into four sections. Section 3 details the related theories and presents a literature review. Section 4 outlines the material and methods used, and Section 5 presents the results analyses and discussion. Finally, Section 6 summarizes the research conclusions and potential directions for future study.

5.3 Literature review

5.3.1 Psychological theories

Drivers' WTP to reduce the risk of road accidents can be represented by behavioral intention. Considerable research examines behavioral intention or health changes as a form of psychological theory to determine drivers' perspectives on road safety. Consequently, we apply TPB and HAPA theories to capture drivers' perspectives and behavioral intention as key factors for analyzing their influence on WTP, which are de-tailed below.

1) Theory of Planned Behavior: The TPB examines individual attitudes and their influence on behavior change, and was developed from the concept of the theory of reasoned action (Ajzen, 1991). The theory infers that human behavior is influenced by behavioral intention by three factors of attitude, subjective norms, and perceived behavioral control (see Figure 5.1). TPB is widely used in behavior studies as it is validated to explain individuals' behavioral intention. This study applies this

concept to describe drivers' perspectives regarding these factors' influence on WTP for road accidents.

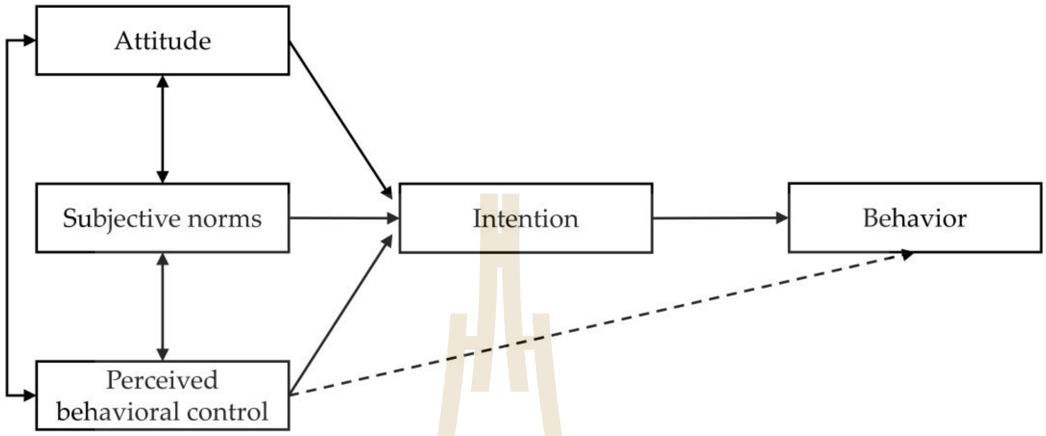

Figure 5.1 The theory of planned behavior (Ajzen, 1991)

2) Health Access Process Approach: The HAPA applies theory related to health behavior change (Schwarzer et al., 2011), referring to the replacement of usual behaviors to meet health needs. A theory was developed to describe what motivates people to change behavior and explain this process (MacPhail et al., 2014; Zhang et al., 2019). The framework of the HAPA model is divided into two main phases as shown in Figure 5.2. (1) The motivational phase is a significant aspect because every behavior change begins with intention and motivation, and is comprised of risk perception, outcome expectancies, and self-efficacy (referencing Bandura (1977)). (2) The volitional phase includes planning, maintenance self-efficacy, and recovery self-efficacy, which leads to effective action. HAPA has been applied in multiple fields of study, but has not been used to investigate drivers' valuation of road accidents. We apply the motivational phase (behavioral intention) in our study of road accident valuation in conjunction with the direction of the TPB.

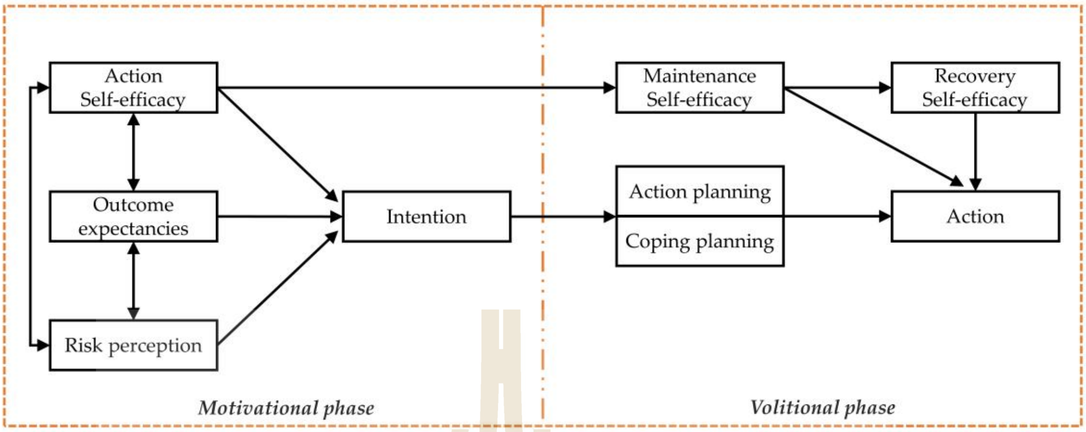

Figure 5.2 The health action process approach theory (Schwarzer, 2008)

5.3.2 Previous studies on road accident monetary valuation

Several previous studies regarding drivers' WTP for road safety improvement ap-ply logit or discrete choice models (Antoniou, 2014; de Dios Ortúzar et al., 2000; Hensher et al., 2009). The majority of these studies apply stated choice (SC) survey instruments. This approach asks respondents to consider and compare the utility of specified attributes and identify the alternatives that they consider to be the most cost effective. SC does have some limitations. As related questionnaires feature closed-ended questions, consequently, respondents are unable to indicate WTP in exact values. To address this weakness, we apply the contingent valuation method (CVM), which includes open-ended questions, allowing respondents to identify their exact WTP.

Investigating the potential factors affecting WTP with a discrete choice model is an interesting approach, as it allows exploration of the differences among a group of drivers with varying WTP. Subsequently, we construct an advanced discrete choice model with a CVM-based WTP for car drivers, classifying the WTP into three categorical variables. 1) Zero-WTP, which is a group of drivers who are unwilling to pay (or specify the value of WTP = 0); 2) below average WTP; and 3) above average WTP.

The factors associated with previous studies using WTP (20 studies in 14 countries) are presented in Table 5.1. According to the table, the majority of research only focuses on the respondents' sociodemographic data, but studies that have introduced the application of psychological theories combined with WTP analysis are rare. This study recognizes the critical role of these concepts on drivers' decision-making, integrating the TPB and the HAPA into the analysis of the factors influencing WTP based on the assumption that behavioral intention regarding risk reduction is influenced by health perspectives and intended behavior. The TPB and the HAPA can reveal drivers' perspectives and attitudes regarding road safety costs. Analyzing the factors affecting WTP to reduce road accidents is complex; therefore, we begin by confirming the components of the related theories using CFA, applying a mixed logit with unobserved heterogeneity to capture the influence of such factors on WTP, including fixed and random parameters, and unobserved characteristics.

Table 5.1 Summary of previous studies on WTP for accident risk reduction and relevant factors

Author	Factors											Method
	Country	Age	Gender	EXP	Accident	Income	Status	Education	HS	Child	Speed	Psychology	
Persson et al. (2001)	Sweden	✓		✓	✓	✓							Regression
Fauzi et al. (2004)	Malaysia	✓	✓		✓	✓	✓						Regression
Alberini et al. (2006)	Canada	✓	✓					✓					Regression
Andersson (2007)	Sweden	✓	✓	✓	✓	✓		✓					Regression
Bhattacharya et al. (2007)	India	✓			✓	✓		✓	✓				Regression
Gibson et al. (2007)	Thailand	✓	✓					✓					Regression
Andersson and Lindberg (2009)	Sweden	✓	✓	✓	✓					✓			Regression
Svensson and Johansson (2010)	Sweden	✓	✓			✓				✓	✓		Regression
Hoffmann et al. (2012)	Mongolia	✓	✓			✓		✓					Regression
Liu and Zhao (2013)	China	✓		✓		✓		✓					Binary logit
Antoniou (2014)	Greece	✓	✓		✓		✓						Ordered probit
Robles-Zurita (2015)	Spain	✓	✓	✓		✓	✓			✓			Regression
Ainy et al. (2016)	Iran	✓	✓		✓	✓	✓	✓					Regression
Haddak (2016)	France	✓	✓		✓	✓	✓	✓					Tobit model

Table 5.1 Summary of previous studies on WTP for accident risk reduction and relevant factors (Continued)

Author	Factors											Method
	Country	Age	Gender	EXP	Accident	Income	Status	Education	HS	Child	Speed	Psychology	
Yang et al. (2016)	China	✓	✓	✓		✓		✓					Mixed logit
Hoffmann et al. (2017)	China	✓				✓		✓					Regression
Mon et al. (2018)	Myanmar	✓	✓		✓	✓	✓	✓	✓		✓		Regression
Flügel et al. (2019)	Norway	✓	✓	✓		✓		✓		✓			Mixed logit
Balakrishnan and Karuppanagounder (2020)	India	✓	✓		✓	✓	✓		✓				Binary logit
Widyastuti and Utanaka (2020)	Indonesia	✓				✓				✓			Binary logit
This study	Thailand	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	TPB and HAPA	CFA and RPMNLHMV

Note: EXP = driving experience; Status = marital status; Accident = own accident; HS = household size; TPB = theory of planned behavior; HAPA = health access process approach; CFA = confirmatory factor analysis; RPMNLHMV = random parameters multinomial logit with heterogeneity in means and variances.

5.4 Materials and methods

5.4.1 Questionnaire structure

The questionnaire is structured into three main sections. Section 1: driver WTP for road accident risk reduction (using CVM), presenting an open-ended question to obtain numerical values, in which respondents were asked "What is the maximum payment you are willing to pay per 50 km-trip to use an improved highway which reduces your chance of fatality or injury from road accident by 50%?" Section 2 collects drivers' socio-demographics, including gender, age, marital status, income, and education. Accident and driving experience and the purpose of the trip were also gathered, as such information could motivate drivers' differing perspectives and attitudes. Section 3 introduces questions related to the TPB and HAPA psychological theories to elicit drivers' opinions and perspectives. The answers in this section are presented in a five-point Likert scale format (Boone & Boone, 2012), in which 5 indicates strongly agree and 1 indicates strongly disagree, and the questionnaire was validated using the Item–Objective Congruence test (IOC) (Turner & Carlson, 2003) with three road safety experts.

5.4.2 Data collection and respondent characteristics

Face-to-face interviews with respondents 18 years or older possessing driver's li-censes in Thailand were conducted to obtain data. Accurate scientific investigation re-quires that respondents are representative of the population. To ensure representativeness, we include drivers from the four main regions of Thailand (eight provinces with the highest percentage of road accident deaths in each region) via distribution of age, gender, education, income, driving experience, and other considerations, for a total of 1,650 respondents. Effectiveness of face-to-face interviews: After the initial screening, all 1,650 questionnaires were valid, so none were removed. Our survey was approved by the ethics committee of the Suranaree University of Technology (November 13, 2020; grant number IRD7-704-63-12-24) and the survey was conducted from November 20 to December 13, 2020. The driver's characteristics are presented below.

Respondents included 1,020 males and 630 females (61.8% and 38.2%, respectively), with an age range of 18–78 (range = 60, mean = 36.33, and standard deviation = 10.67), comprising 752 single drivers (45.6%) and 651 married drivers (39.5%); 48.6% had a bachelor's degree, 4.3% had a master's degree, and 0.7% had doctorates; 1,011 respondents (61.3%) indicated monthly earnings of 15,000–29,999 baht, 408 respondents (24.7%) reported incomes of 30,000 baht or above, and 14.0% for the rest. For household income, 319 respondents stated their household income was less than 30,000 baht, and 1,331 respondents stated their salary was above. Of the total 1,650 respondents, 245 (14.8%) indicated that they had been in accidents in the past. For the driver's profession, 79 respondents (4.8%) are students; 175 respondents (10.6%) are government employees; 627 respondents (38.0%) are private companies; 313 respondents (19.0%) are own businesses; and 274 respondents (16.6%) are general labor. 293 of the respondents stated that they usually use their phones while driving. 1,615 respondents have a 5-year li-cense; the rest are otherwise.

5.4.3 Modeling approaches

1) Exploratory Factor Analysis and Confirmatory Factor Analysis: We first apply exploratory factor analysis (EFA) to classify the observed indicators of relevant factors. EFA is a technique of factor analysis intended to identify underlying relationships between indicators (Norris & Lecavalier, 2010). Next, we use CFA, which was initially developed by Jöreskog (1969), to confirm the correlations among the components obtained from the EFA. The CFA is used to determine whether measures are consistent with the scholarly understanding of the nature of related factors. The purpose of CFA is to test whether the data fit research hypotheses (Kline, 2015).

2) Random Parameter Logit with Heterogeneity (in Means and Variance): We now construct the model within a discrete choice framework wherein the utility function, U_{ij}, determines the probability of WTP level *i* obtained from respondent *j* (Washington et al., 2020), as presented in Equation 5.1:

$$U_{ij} = \beta_i X_{ij} + \varepsilon \tag{5.1}$$

where β_i denotes the vector for the parameters of WTP level *I*, X_{ij} represents the explanatory variables that affected WTP, and $\mathcal{E}$ is an error component reflecting the unobserved utility component.

Individual-specific unobserved heterogeneity is allowed, and we assume that β_i has a continuous density function, $Prop(\beta_i = \beta) = f(\beta|\varphi)$, where φ

denotes the vector of parameters characterizing this function. The resulting random parameters logit probabilities are calculated with Equation 5.2 (Mannering et al., 2016):

$$P_j(i) = \int \frac{EXP(\beta_i X_{ij})}{\sum_{\forall I} EXP(\beta_i X_{ij})} f(\beta|\varphi) d\beta \tag{5.2}$$

where $P_j(i)$ is the probability of WTP level *i* associated with respondent *j*, and the other variables are as previously defined. The model is estimated using maximum likelihood estimation with logit probabilities. Accounting for the possibility of heterogeneity in the means and variances of random parameters, β_{ij} represents the parameters that vary across respondents, which are derived by Equation 5.3 (Se et al., 2021; Se et al., 2022; Washington et al., 2020):

$$\beta_{ij} = \beta_i + \Omega_{ij} Z_{ij} + \sigma_{ij} EXP(\psi_{ij} W_{ij}) \epsilon_{ij} \tag{5.3}$$

where β_i denotes the mean parameter estimate across all respondents; Z_{ij} represents a vector of explanatory variables capturing heterogeneity in means that influence WTP level *i*; Ω_{ij} is an estimable parameter vector of Z_{ij}; W_{ij} is a vector of WTP variables capturing heterogeneity in standard deviation σ_{ij}, with corresponding vector ψ_{ij}, and ϵ_{ij} is the error term.

5.4.4 Modeling approaches

This study began with a literature review to identify research gaps and weaknesses discovered in previous research and to investigate potential statistical methods and theories that could be applied to the WTP study. Next, we developed questionnaires based on review results and collected data from car drivers using face-to-face inter-views. Then, two statistical methods (CFA and RPMNLHMV) were applied in sequence to achieve the objectives. First, CFA was used to confirm the measurement indicators of TPB and HAPA. Later, we input the WTP, demographics, and CFA results into a RPMNLHMV. Finally, we presented the statistics results and discussion. The research procedure is shown in Figure 5.3.

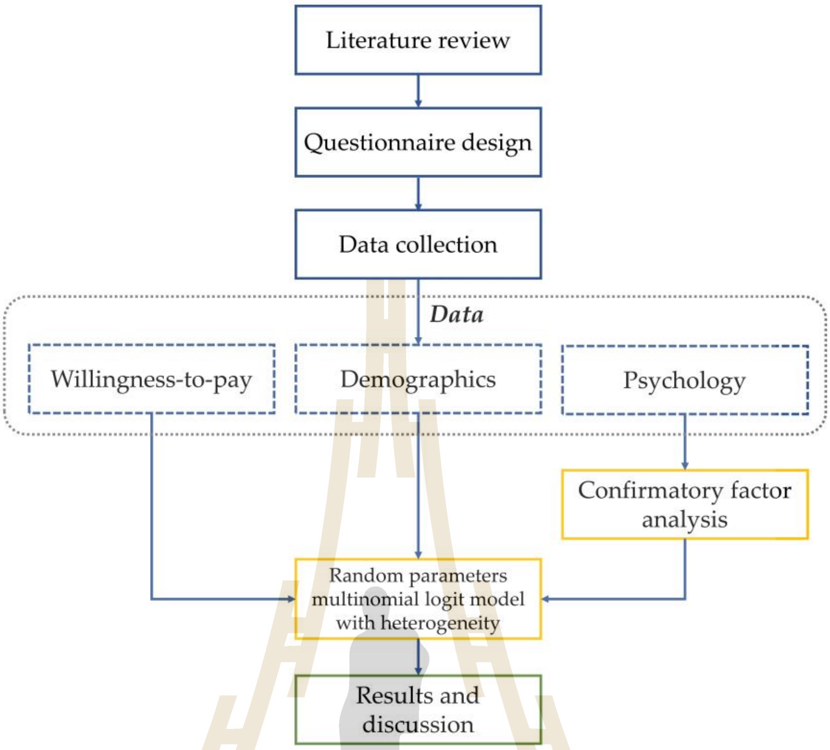

Figure 5.3 Research procedure

5.5 Results and discussion

5.5.1 Descriptive statistics and willingness-to-pay of drivers

We categorize the independent variables for statistical analysis into binary and continuous variables, representing drivers' characteristics and experiences in the mixed logit model, and Likert scale variables (ranging from 1 to 5) are used in CFA to examine the correlations between related theories and drivers' behavioral intention.

The descriptive statistics of 1,650 drivers and responses related to the TPB and HAPA are presented in Table 5.2. Prior to analyzing the CFA, we must examine the descriptive statistics of scale data to confirm the fitness of data for the analysis. The criteria of skewness is lower than an absolute of 2, kurtosis is an absolute of 7 (Kline, 2015), and the value of Cronbach's alpha should be greater than 0.6 (Hinton et al., 2014). Table 2 demonstrates that skewness and kurtosis statistics range from −0.96

to −0.08, and −1.33 to 1.44, respectively, and Cronbach's alpha ranges between 0.637 and 0.793; thus, we can conclude that our sample statistics are normal distribution and can be accepted.

Regarding variable coding, to achieve the main purpose of this study (which is to find out what factors are related to the level of WTP and to provide policymakers with practical implications for improving road safety accordingly), we decided to classify WTP into three important groups. The first group is Zero-WTP (i.e., drivers indicating WTP = 0). According to the previous studies, most of them found that some respondents indicated their WTP was equal to zero, and most were omitted from the analysis (e.g., Haddak (2016) and Andersson (2007)). However, we recognized that respondents who are unwilling to pay are still important from a policymaker's point of view and may have different attributes. So, it is necessary to separate those who specify WTP = 0 from other groups. The study therefore has to include them in the analysis to determine what factors affect unwillingness to pay. It was also discovered that lower WTP and higher WTP groups had different characteristics and perspectives. Our classification criteria for Low- and High-WTP are based on previous research. That is, a majority of them used the average WTP as a base value to estimate the total cost of road accidents (Mon et al., 2019; Svensson & Johansson, 2010). Then, they used linear regression to determine which factors are associated with high WTP (or low WTP). Therefore, it is reasonable to imply that the average WTP can be used as a reference value for WTP classification. As a result, the Low- and High-WTP were classified in this study based on the average (i.e., mean value) of overall WTP. By categorizing WTP into three levels and analyzing it with an advanced logit model, it may allow policy or decision makers to effectively implement the recommended practical implications in accordance with target groups.

Finally, we define the dependent variable (WTP) in categories in which 1 denotes drivers indicating WTP = 0 (Zero-WTP), 2 refers to the driver with a WTP greater than 0 but below all drivers' average (Low-WTP), and 3 represents the remaining driver responses (WTP ≥ overall average; High-WTP). The results reveal that 114 drivers (6.91%) had Zero-WTP for two main reasons. 1) Drivers considered paying for road safety improvement to not be their responsibility, and 2) they thought paying for road safety does not elicit demonstrable results. Furthermore, we find that 1,114 drivers (67.58%) had Low-WTP, and the remainder (25.52%) exhibited High-WTP. The values of WTP to re-duce road accident risk by 50% are approximated at 23.00 baht per 50 km-trip (SD = 16.25 baht).

Table 5.2 Descriptive statistics of drivers' socio - demographics and factors associated with the TPB and HAPA (n = 1,650)

Code	Descriptions (Binary)		Frequency	Percentage
	Demographic and factors;			
	Gender (1 if male driver, 0 otherwise)		1,020	61.8%
	Marital status (1 if married, 0 otherwise)		651	39.5%
	Age 26–35 years (1 if yes, 0 otherwise)		648	39.3%
	Age 36–45 years (1 if yes, 0 otherwise)		392	23.8%
	Age above 45 years (1 if yes, 0 otherwise)		341	20.7%
	Bachelor (1 if Bachelor, 0 otherwise)		802	48.6%
	Master (1 if Master, 0 otherwise)		71	4.3%
	Doctoral (1 if Doctoral, 0 otherwise)		13	0.7%
	INC1 (1 if 15,000 baht ≤ income < 30,000 baht, 0 otherwise)		1,011	61.3%
	INC2 (1 if income ≥ 30,000 baht, 0 otherwise)		408	24.7%
	Elder (1 if there have elder (Age ≥ 60) in the household excluding respondent, 0 otherwise)		342	20.7%
	Young (1 if there have children (Age ≤ 18) in the household, 0 otherwise)		388	23.5%
	Sole earner (1 if yes, 0 otherwise)		885	53.6%
	Own accident (1 if driver has been involved in a road accident, 0 otherwise)		245	14.8%
	Family injured (1 if family/close friends have been injured in a road accident, 0 otherwise)		468	28.4%
	Family died (1 if family/close friends have been died in a road accident, 0 otherwise, 0 otherwise)		164	9.9%

Table 5.2 Descriptive statistics of drivers' socio - demographics and factors associated with the TPB and HAPA (n = 1,650) (Continued)

Code	Descriptions (Binary)		Frequency		Percentage	
	Risk perception (1 if driver stated that his/her risk is higher than the average in Thailand, 0 otherwise)		768		46.5%	
	Ticket (orders for traffic violations) (1 if driver has ever been received a ticket, 0 never)		887		53.8%	
	Safety belt usage (1 if often or always, 0 otherwise)		560		33.9%	
	Alcohol (1 if driver has ever been drunk while driving, 0 never)		101		6.1%	
	Driving exceeds speed limit (1 if often or always, 0 otherwise)		1,448		87.8%	
	Compelling trip (1 if most of trips are related with the job, 0 otherwise)		955		57.9%	
	Weekday (1 if most of trips are spent on weekday, 0 otherwise)		1,100		66.7%	
	Night (1 if most of trips are spent at nighttime, 0 otherwise)		480		29.1%	
Code	**Descriptions (Continuous)**	**Adapted from**	**Mean**	**SD**	**SK**	**KU**
	Household size		2.96	1.38	0.31	−0.75
	Number of cars		1.19	0.46	2.00	4.33
	Annual mileage (1000 km)		22.51	11.55	0.60	0.09
	Driving experience (year)		14.11	9.63	0.72	−0.02
ATTI	**Attitude (Cronbach's alpha = 0.782)**	Wu and Chen (2005)				
A1	Paying for safe road is useful because it helps me to reduce the chance of road accidents.		4.57	0.57	−0.96	1.14
A2	Paying for safety on road usage makes me feel safer on the road.		4.56	0.57	−0.87	−0.13
A3	Most of my family will perceive me as more safety responsible if I pay more to use a safer road.		4.52	0.60	−0.96	0.33
A4	Most of my friends will perceive me as more safety responsible if I pay more to use a safer road.		4.51	0.62	−0.92	−0.03

Table 5.2 Descriptive statistics of drivers' socio - demographics and factors associated with the TPB and HAPA (n = 1,650) (Continued)

Code	Descriptions (Continuous)	Adapted from	Mean	SD	SK	KU
SUBJ	**Subjective norm (Cronbach's alpha = 0.793)**	Wu and Chen (2005),				
S1	Most of my family pays for safe road usage to reduce the chance of road accidents.		4.15	0.75	−0.28	−1.11
S2	Most of my friends pay for safe road usage to reduce the chance of road accidents.		4.18	0.75	−0.33	−1.12
S3	Most people in my community friends pay for safe road usage to reduce the chance of road accidents.		4.12	0.78	−0.22	−1.28
PERC	**Perceived behavioral control (Cronbach's alpha = 0.793)**	Wu and Chen (2005)				
P1	It is my own decision to pay for safe road usage, not depend on others.		4.05	0.77	−0.12	−1.17
P2	Risk of an accident depends on my response. If I pay for a safe road, the chance of road accidents will be decreased.		4.03	0.77	−0.07	−1.28
P3	Reducing road accidents can be my control by paying to use a safe road.		4.04	0.78	−0.08	−1.33
RISK	**Risk perception (Cronbach's alpha = 0.653)**	Ram and Chand (2016)				
RP1	I know that every time I drive, there is always a chance of road accidents.		4.16	0.75	−0.29	−1.11
RP2	I perceive that routing factors are one of the causes of road accidents.		4.15	0.78	−0.26	−1.29
RP3	I perceive that road accidents do not only depend on me.		4.14	0.75	−0.25	−1.13
RP4	I perceive the risk of road accidents is inevitable.		4.15	0.75	−0.26	−1.21
OUTC	**Outcome expectancies (Cronbach's alpha = 0.637)**	Gebbers et al. (2017)				
OE1	I think that paying for safer roads will give me the benefits I need.		4.11	0.73	−0.17	−1.09
OE2	I know that if I am willing to pay more, I will get safer.		4.08	0.72	−0.13	−1.08
OE3	I continue using safe roads with the rationale that "I will always get what I expect which is reasonable for the money I pay".		4.29	0.70	−0.46	−0.88

Table 5.2 Descriptive statistics of drivers' socio - demographics and factors associated with the TPB and HAPA (n = 1,650) (Continued)

Code	Descriptions (Continuous)	Adapted from	Mean	SD	SK	KU
SELF	*Self-efficacy (Cronbach's alpha = 0.708)*	Gebbers et al. (2017)				
SE1	When I drive, it is always easy for me to consider using a safe road.		4.50	0.62	−0.85	−0.30
SE2	Even if I drive on an unsafe route only once, I will recognize that I have more chances in a road accident.		4.50	0.62	−0.85	−0.29
SE3	Seeing others pay for safe roads I think I also can do it.		4.44	0.67	−0.78	−0.51
INT	*Intention (Cronbach's alpha = 0.732)*	Wu and Chen (2005), Venkatesh and Davis (2000), Gebbers et al. (2017)				
I1	I will pay more to use a safer road.		4.35	0.68	−0.58	−0.71
I2	I will pay for using the safer road because I believe that it could save my life.		4.30	0.72	−0.57	−0.69
I3	I will recommend my close friends to pay for safe roads to reduce the chance of road accidents.		4.48	0.63	−0.85	0.15
I4	I have planned to pay for using safe roads to reduce road accident risk.		4.51	0.61	−0.90	−0.05

Note: SD = standard deviation; SK = skewness; KU = kurtosis.

5.5.2 Exploring the factor components and correlations

1) The exploratory factor analysis of observed factors: We use EFA to define the observed indicators representing the components of each latent factor and compute the primary factors. Table 5.3 presents the EFA results, identifying 24 items as components of seven latent factors, including risk perception, intention, outcome expectancies, self-efficacy, attitude, subjective norms, and perceived behavioral control. The component loadings range between 0.560 and 0.873. The seven factors had construct reliability (CR) ranging from 0.756 to 0.893 and average variance extracted (AVE) between 0.439 and 0.735. The statistical value of AVE is at least 0.4 and CR should more than 0.7 and can be accepted in the EFA (Fornell & Larcker, 1981; Hair, 2009; Kaiser, 1974). These results confirm that all factors are suitable for CFA.

Table 5.3 Component loading of related factors

Code	Component loadings							CR	AVE
	1	2	3	4	5	6	7		
A1					0.560			0.756	0.439
A2					0.713				
A3					0.706				
A4					0.659				
S1						0.708		0.783	0.546
S2						0.736			
S3						0.771			
P1							0.833	0.893	0.735
P2							0.865		
P3							0.873		
I1		0.735						0.791	0.486
I2		0.681							
I3		0.683							
I4		0.689							
RP1	0.752							0.782	0.473
RP2	0.666								
RP3	0.633								
RP4	0.695								
OE1			0.739					0.792	0.561
OE2			0.810						
OE3			0.693						
SE1				0.731				0.767	0.523
SE2				0.703					
SE3				0.736					

2) Theoretical confirmation: Using the EFA results, this section examines the explanatory power of each item to confirm that indicators can be components of the TPB and HAPA. The CFA results using Mplus 7.2 software by Muthén and Muthén illustrates that all indicators are significant as factor components of the TPB and HAPA, with all parameters significant at the 0.01 level. Model fit statistics are χ^2 = 469.783; df = 187; χ^2/df = 2.512; CFI = 0.971; TLI = 0.957; SRMR = 0.039; and RMSEA = 0.030. These statistics are in accordance with empirical data compared to acceptance criteria. The model estimation results are presented in Table 5.4 and discussed below.

According to HAPA, RP1–RP4 are the components of risk perception, and *"I know that every time I drive, there is always a chance of road accidents"* is the highest indicator. This is followed by the three indicators of outcome expectancies (OE1–OE3), of which *"I think that paying for safer roads will give me the benefits I need"* represents the most influential factor. And the self-efficacy was measured by SE1–SE3, of which *"When I drive, it is always easy for me to consider using a safe road"* has the highest factor loading.

The latent factors of attitude in the TPB are measured by variables A1–A3, and *"Most of my family will perceive me as more safety responsible if I pay more to use a safer road"* represents the highest influential factor. This is followed by subjective norms, which is confirmed to be measured using S1–S3, and *"Most of my family pays for safe road usage to reduce the chance of road accidents"* obtained the highest factor loading. The next is perceived behavioral control, verifying that the three related variables (P1–P3) are valid measures, where *"Reducing road accidents can be my control by paying to use a safe road"* had the highest factor loading.

Finally, behavioral intention is a component of both HAPA and TPB models, and our results also validated the four indicators (I1–I4) as measures of driver intention, finding *"I will pay more to use a safer road"* had highest influential indicator.

Table 5.4 Model results of confirmatory factor analysis

Code	Description	*Estimates*	*S.E.*	*t-stat*
ATTI	*Attitude;*			
A1	Paying for safe road is useful because it helps me to reduce the chance of road accidents.	0.346	0.029	11.954
A2	Paying for safety on road usage makes me feel safer on the road.	0.481	0.029	16.504
A3	Most of my family will perceive me as more safety responsible if I pay more to use a safer road.	0.586	0.028	21.034
A4	Most of my friends will perceive me as more safety responsible if I pay more to use a safer road.	0.499	0.028	18.035
SUBJ	*Subjective norm;*			
S1	Most of my family pays for safe road usage to reduce the chance of road accidents.	0.549	0.024	23.191
S2	Most of my friends pay for safe road usage to reduce the chance of road accidents.	0.468	0.025	18.377
S3	Most people in my community friends pay for safe road usage to reduce the chance of road accidents.	0.544	0.025	22.123
PERC	*Perceived behavioral control;*			
P1	It is my own decision to pay for safe road usage, not depend on others.	0.721	0.014	50.602
P2	Risk of an accident depends on my response. If I pay for a safe road, the chance of road accidents will be decreased.	0.798	0.012	63.872
P3	Reducing road accidents can be my control by paying to use a safe road.	0.804	0.012	64.754
RISK	*Risk perception;*			
RP1	I know that every time I drive, there is always a chance of road accidents.	0.603	0.023	26.281
RP2	I perceive that routing factors are one of the causes of road accidents.	0.475	0.025	18.855
RP3	I perceive that road accidents do not only depend on me.	0.510	0.023	22.510
RP4	I perceive the risk of road accidents is inevitable.	0.550	0.023	23.665
OUTC	Outcome expectancies;			
OE1	I think that paying for safer roads will give me the benefits I need.	0.695	0.030	23.213
OE2	I know that if I am willing to pay more, I will get safer.	0.586	0.025	23.142
OE3	I continue using safe roads with the rationale that "I will always get what I expect which is reasonable for the money I pay".	0.688	0.034	20.492

Table 5.4 Model results of confirmatory factor analysis (Continued)

Code	Description	*Estimates*	*S.E.*	*t-stat*
SELF	*Self-efficacy;*			
SE1	When I drive, it is always easy for me to consider using a safe road.	0.582	0.030	19.508
SE2	Even if I drive on an unsafe route only once, I will recognize that I have more chances in a road accident.	0.568	0.030	19.135
SE3	Seeing others pay for safe roads I think I also can do it.	0.482	0.029	16.860
INT	*Intention;*			
I1	I will pay more to use a safer road.	0.777	0.020	38.722
I2	I will pay for using the safer road because I believe that it could save my life.	0.626	0.020	30.855
I3	I will recommend my close friends to pay for safe roads to reduce the chance of road accidents.	0.423	0.024	17.286
I4	I have planned to pay for using safe roads to reduce road accident risk.	0.364	0.026	14.148

As demonstrated by the results in Table 4, the indicators of each factor are appropriate for measuring TPB and HAPA significantly; therefore, we compute each indicator into main factors using beta weight, to reduce the number of factors. Finally, there are seven remaining constructs of attitude, subjective norms, perceived behavioral control, risk perception, outcome expectancies, self-efficacy, and behavioral intention.

In addition, correlations between constructs are presented in Table 5.5 to ensure that no pair of factors is overly correlated. Referencing Mukaka (2012), who asserted that correlations between relevant variables should be less than ±0.750. There is also evidence that the square roots of AVE could present a good explanation of constructs and discriminant validity, as previous studies reported that square roots of AVE of each factor should be greater than the correlation coefficients of their counterparts (Hair, 2009; Herrero-Fernández & BogdanGanea, 2022), and our results confirm that statistical values are within the acceptable range.

Table 5.5 Correlations between constructs and discriminant validity

$\sqrt{AVE}$	*INT*	*RISK*	*OUTC*	*SELF*	*ATTI*	*SUBJ*	*PERC*
INT	**0.697**						
RISK	−0.117**	**0.688**					
OUTC	−0.205**	0.002	**0.749**				
SELF	0.179**	0.089**	0.079**	**0.723**			
ATTI	0.245**	0.161**	0.134**	0.255**	**0.662**		
SUBJ	−0.116**	0.582**	−0.019	0.108**	0.116**	**0.739**	
PERC	0.323**	−0.492**	0.257**	0.124**	0.135**	−0.511**	**0.857**

Note: ** indicates that correlation is significant at 0.01 level (2-tailed). Square roots of AVE are presented **in bold** in the diagonal row.

5.5.3 Factors influencing drivers' willingness-to-pay for road accident reduction

1) Model estimation results: From the questionnaire data obtained from drivers, we have a total of 32 factors of demographic status and experience of drivers. But after we initially analyzed the model, four aspects were removed from the model, including profession of driver, phone used, type of license, and household income, because they were not found to have a significant relationship with other variables or the outcome WTP (additionally, inclusion of these factors were not found to improve the model fit statistic). Finally, 28 demographic items about drivers and 24 psychological items are left and presented in Table 5.2 for the analysis.

Table 5.6 presents the model statistics and results of the significant factors affecting drivers' WTP applying the RPMNLHMV with Nlogit6 software. We identify four characteristics that influence drivers indicating the unwillingness to pay for road safety improvement. First, married drivers tend to prefer WTP of 0, from which we can imply that married Thai drivers have more expenses, resulting in no intention to pay more. Drivers' income is also found to be an influential factor associated with WTP (Andersson, 2007; Balakrishnan & Karuppanagounder, 2020). A salary of at least 15,000 baht falls within Thailand's middle-income group; thus, drivers with adequate salaries are more likely to pay for safety rather than reluctant to pay (Bhattacharya et al., 2007) (this finding is also consistent with those of Mon et al. (2018), who discovered that middle-income drivers have a positive effect on WTP). Education is found to influence drivers' risk valuation. Drivers holding a master's degree are less likely to express Zero-WTP, presumably because higher education helps individuals to better understand the impacts of road accidents, which is consistent with Yang et al. (2016). Perceived behavioral control, a factor of TPB, is also found to have a direct effect on WTP. This factor is related to drivers' self-conception and emotions; therefore, if drivers perceive that the WTP for safety does not exceed capabilities, a resulting WTP will emerge (Jomnonkwao et al., 2021; Li et al., 2016), this is consistent with the result of Subhan et al. (2021), who stated that individuals who felt they had greater control over their finances were more likely to pay for the improvement of road safety.

Regarding Low-WTP, sole earners have a significant effect on WTP, as sole earners are more likely to express a WTP that is higher than 0, but less than the overall average. This implies that sole-earning drivers are aware of the impact of road accidents that could affect their incomes and productivity (Bhattacharya et al., 2007), recognizing WTP for safety as a superior alternative to the consequences of accidents. Nevertheless, such drivers may face challenges regarding the amount of WTP, as sole earners have considerable responsibilities and expenditures, resulting in a lower WTP.

Regarding High-WTP drivers, the results indicate that drivers who regularly travel at nighttime lead to safe behavior. The results reflect the findings of Ackaah et al. (2020), and Champahom et al. (2022), which reported that driving at night is more dangerous and could result in increased accident severity. This offers the logical explanation for the finding of the present study showing that nighttime drivers are more aware of their accident risks, which causes them to prefer a higher value of WTP. The components of HAPA reveal important insights regarding drivers' outcome expectancies toward safety improvement have a significant influence on WTP. In this context, we can assert that outcome expectancy refers to drivers' perceptions of effectiveness (Subhan et al., 2021). If drivers think that WTP for road safety improvement would effectively reduce road traffic severity, they are more likely to have a High-WTP, there is evidence from Gebbers et al. (2017) results that reveals that outcome expectancies were positively related to the intention to behave. Subjective norms are also found to have a negative influence on High-WTP drivers. This factor is related to personal beliefs regarding social trends. In other words, if a driver's intimate relations have safe road behavior, it will influence drivers to engage in the same behavior (Jomnonkwao et al., 2021). As indicated by the marginal effect value (highest compared to all other variables), the finding suggests that drivers with more normative beliefs tend to be in the Low-WTP group. This is fairly logical, and the explanation may be attributed to the fact that most of the sample populations have chosen Low-WTP (as clearly shown by the descriptive statistic in the earlier section). Therefore, people who are more likely to follow social trends are also more likely to fall into the Low-WTP group.

Table 5.6 Model results of mixed logit model with heterogeneity

Variables	Coefficients	*t-stat*	Marginal effect		
			ZW	LW	HW
Constants [ZW]	5.100	1.75			
Constants [HW]	6.136	2.29			
Non-random parameter;					
Marital status (married) [ZW]	0.574	1.70	0.0109	−0.0073	−0.0036
15,000 baht ≤ Income < 30,000 baht [ZW]	−0.953	−2.05	−0.0224	0.0153	0.0070
Perceived behavioral control [ZW]	−0.924	−2.72	−0.1428	0.0945	0.0483
Master degree [ZW]	−2.278	−1.79	−0.0014	0.0009	0.0005
Sole earner [LW]	0.551	1.79	−0.0072	0.0238	−0.0166
Night [HW]	0.649	1.75	−0.0026	−0.0111	0.0137
Outcome expectancies [HW]	0.797	2.33	−0.0452	−0.1928	0.2380
Subjective norm [HW]	−1.900	−3.84	0.1080	0.4378	−0.5458
Random parameter; (normal distribution)					
Gender (male) [LW]	0.863	0.38	0.0114	−0.0082	−0.0032

Table 5.6 Model results of mixed logit model with heterogeneity (Continued)

Variables	Coefficients	*t-stat*	Marginal effect		
			ZW	LW	HW
Standard deviation	2.360	2.05			
Attitude [LW]	−0.312	−0.55	−0.0200	0.1329	−0.1130
Standard deviation	0.430	1.90			
Annual mileage [HW]	−0.332	−2.80	0.0230	0.0192	−0.0422
Standard deviation	0.133	2.81			
Heterogeneity in means;					
Annual mileage : Young	0.063	2.27			
Annual mileage : Compelling trip	−0.047	−2.11			
Annual mileage : Intention	0.058	2.55			
Attitude : Intention	0.180	1.75			
Heterogeneity in the variance;					
Attitude : Elder	0.955	1.85			
Model statistics;					
Halton draw	1,000				
Number of observations	1,650				
Number of estimated parameters (K)	48				
Log-likelihood at zero, *LL(0)*	−1812.710				
Log-likelihood at convergence, *LL*(β)	−1205.913				
Adjusted ρ^2	0.308				
AIC$_c$	2510.765				

Note: *p < 0.1; **p < 0.05; ***p < 0.01. ZW = Zero-WTP; LW = Low-WTP; HW = High-WTP.

2) Distribution of random parameters: Table 5.6 also reveals that the significant indicators are random parameters of the models, finding that male drivers and attitude toward risk are random parameters for Low-WTP, and annual mileage is a random parameter of High-WTP drivers. The positive coefficient of random parameters indicates that the majority of drivers are more likely to fall in the reference group, while the remainder represent other groups (negative coefficients are opposites). Figure 4 presents the proportion percentage between below and above zero of each random parameter (red representing the probability of below zero, and above zero are gray). This study also revealed that most male drivers have at least a Low-WTP, indicating a higher likelihood to pay, as males perceive that their driving behavior makes them a higher risk for accidents than females (consistent with results of Balakrishnan and Karuppanagounder (2020) and Yang et al. (2016), who evinced that male drivers have a higher perception of their risk behavior, resulting in a higher WTP). Also, results from Andersson (2007) showed that female drivers were less likely to pay for safety improvement compared to male drivers. The attitude toward risk in this analysis has an extremely influential role, as drivers with high attitude scores also tend to have High-WTP. In contrast, low attitude scores could affect drivers' Zero WTP as well (Jomnonkwao et al., 2021). There is evidence from the finding of Subhan et al. (2021) which reported that attitude towards traffic safety responsibility was found to be significantly associated with the intention to pay. Interestingly, high annual mileage appears to be related to drivers' preference for lower WTP for road safety. There are two possible reasons for this result. High mileage per year makes drivers more proficient and experienced, and the greater the distance, the greater the cost, resulting in a reduced WTP per trip. This is consistent with the finding of Yang et al. (2016), who also found that highly experienced motorists tend to decrease WTP, as these groups of people are often more experienced and skilled, and they believe that life-threatening events can be avoided by themselves.

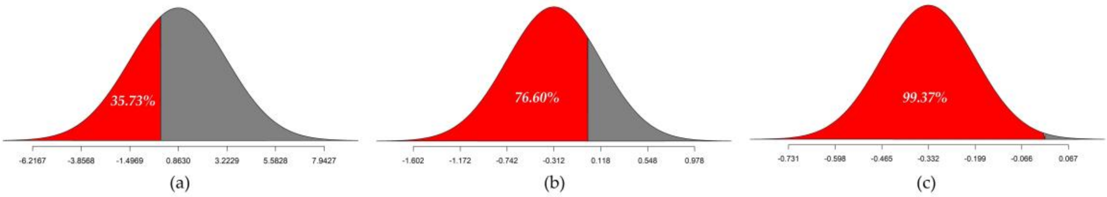

Figure 5.4 Distribution split of the random parameters. Note: (a) gender, (b) attitude, and (c) annual mileage

3) Influence of heterogeneity in the means and variances of random parameters: While previous WTP studies generally assumed that the mean and variance of the random parameters were fixed (using a standard mixed logit model), this study extensively explored the possibility that explanatory variables have a significant influence on the mean and variance of the random parameters (i.e., shifting the distribution of random parameters to the left or right and influencing the randomness of the random parameters). Therefore, after the random parameters were found in Table 6, the study tested the effect of each non-significant fixed-parameter on the mean or variance of the random parameters. As a result, some of the factors (presented below) were found to indirectly affect the outcome probabilities by influencing the mean value and variability of the random parameters (whereas these factors were not significant as fixed-parameters with direct effect). Such circumstances indicate that ignoring this deeper layer of unobserved heterogeneity would indeed result in bias and unreliable results or conclusions.

Table 5.6 also illustrates the insight characteristics for influencing random parameters, the coefficient of heterogeneity on random parameters indicate that the mean values and variance of each random parameter are influenced by unobserved heterogeneity.

Annual mileage was influenced by young members, compelling trips, and behavioral intention. In general, we determine that higher annual mileage increases drivers' driving expertise; thus, they are less likely to pay. However, behavioral intention to reduce road accidents and drivers with children will increase the awareness of accidents, resulting in a higher WTP. This is consistent with Svensson and Johansson (2010) findings that indicated drivers who have children in their family will have more road safety responsibilities, resulting in a higher WTP. Moreover, regarding the Subhan et al. (2021) result, it stated that intention plays a significant role in drivers' road safety awareness. Drivers who have a higher safety intention will result in more WTP. In contrast, drivers with compelling trips are more likely to decrease the level of WTP based on the same factor of annual mileage and proficient driving skills. Our results also infer that behavioral intention has a positive influence on drivers' attitudes toward road accidents and is found to be a factor with variation across groups of drivers. However, we found that behavioral intention in the role of unobserved characteristics can increase the means of drivers' attitudes and influence safe behavior. As a result of Subhan et al. (2021), intention and attitude toward road accidents can represent safety concerns and can influence drivers in their WTP for safety.

Furthermore, the results of heterogeneity in variance reveal that drivers with elders in the household raise the variation in attitude toward road safety improvement, as vulnerable members in the household could increase drivers' awareness of the severity of road accidents (Robles-Zurita, 2015).

5.6 Conclusions, implications, and research limitations

The study presented findings from combination of CFA and RPMNLHMV, revealing insights regarding newly introduced factors (psychological perspectives) on drivers' WTP to reduce road accidents. Our data were gathered from 1,650 car drivers across Thailand using a face-to-face interview questionnaire. This study demonstrated that traditional sociodemographic factors and those of the HAPA and TPB have influence on driver valuation. Consequently, we reveal significant results by introducing such concerns. Our main conclusions are divided into two main parts (CFA and RPMNLHMV) below.

The initial results of the CFA revealed that all observed indicators are valid measures of TPB and HAPA, and such factors are significantly associated with intention to pay for road accident risk reduction. The results of correlation demonstrated that self-efficacy, attitude, and perceived behavioral control positively correlate with behavioral intention. In contrast, factors of drivers' risk perception, outcome expectancies, and subjective norms have a negative correlation. Further, our study used these factors for in-depth analysis using a mixed logit model to identify the significance of factors' influence on WTP prediction.

Examining demographics using RPMNLHMV demonstrated that married drivers tend toward unwillingness to pay. In contrast, drivers who have middle incomes, a master's degree, are sole earners, and engage in nighttime travel had a greater than Zero-WTP for road accident reduction. Regarding psychological characteristics, the results indicated that drivers' outcome expectancies and perceived behavioral control leads to higher WTP. Conversely, subjective norms had the negative effect on WTP. In addition, three indicators of gender, attitude, and annual mileage were revealed to be random parameters influencing variations in the model. The unobserved characteristics demonstrated that young members and behavioral intention increases the mean of the random parameter, and compelling trips have the opposite effect. Finally, drivers with elder family members in their household increase the variance of attitude toward road accidents.

For policy implementation, our findings revealed the driver characteristics that can affect the WTP as well as providing important insights based on the HAPA and TPB as influences of WTP. These results can benefit relevant authorities and can be used for road safety guidance, as drivers' socio-demographics appear to be appropriate for strategic promotion of road safety education (Alonso et al., 2021b; Hawley et al., 2018). The concept of risk valuation using WTP allows policy makers to identify whether certain characteristics of drivers affect their perception of road accidents. For example, this study found male drivers tend to pay more to reduce risk. This risk may be a result of their driving behavior. Therefore, the relevant authorities should focus on this in training or educating on road risk reduction. In addition, nighttime affects the driver's perception of risk. Therefore, agencies should pay more attention to risk management at night, such as light, traffic, vision etc.

In addition to the demographics and general status, the significance of drivers' views and mindset are also demonstrated by this study. The TPB and HAPA results indicated that drivers with health awareness and plan specific behaviors are more likely to have higher risk concerns and also pay for road safety (Ram & Chand, 2016). These findings can serve as a suitable guideline for policymakers to raise public awareness and attitudes toward road safety. For example, the intention and attitude toward safety have a positive impact on drivers' risk valuation. Therefore, relevant authorities (such as the Transport Office) should focus on improving drivers' awareness of the dangers of road accidents by integrating these lessons into driver's license test programs or safety communication campaigns in order to positively improve their attitudes and behaviors toward road safety. These findings are also confirmed by the literature (Alonso et al., 2021a; Nathanail & Adamos, 2013). In addition, outcome expectancies were also found to be important to the driver's risk valuation. This result formulates the relationship between WTP and road users' expectations of the effectiveness of government efforts. In simple terms, the government should demonstrate budgeting efficiency by improving road safety. This may increase the probability of drivers' willingness to pay for safety as they perceive the value.

In terms of methodological novelty contribution, based on the authors' review, this study is the first to attempt to extend a random parameters logit model by further al-lowing the possibility that preference-level variables may have indirect influences on the outcome WTP value probabilities by shifting the means and variances of the random parameters. Evidently, in this study, variables reflecting households with children, driving to work or for work, drivers' intention, and households with the elderly were found insignificant and would be ignored using the traditional discrete choice models. However, in our heterogeneity modelling approach, these indicators were found to have an effect on the random parameter distributions that have direct influence on the out-come probabilities (for example, the indicator for the elderly has no effect on WTP, but it has a positive influence on the attitude of drivers). This study highlights the importance and necessity of accounting for unobserved heterogeneities in uncovering possible multi-layers of unobserved effects of preference-level (e.g., demographic and psycho-logical) variables on drivers' WTP for road safety. The proposed approach could offer a more flexible way to fully untangle the effect of significant variables in WTP related-studies.

Among the research limitations, our study only focuses on car drivers, and other types of road users are not included. We also did not include drivers under 18 years old in the study, following Thailand's licensing law. The inclusion of younger drivers and other road users may have differing perspectives, attitudes toward safety, and different knowledge of road safety (Lanning et al., 2018). Thus, collecting such information to represent the population more comprehensively. Moreover, including environmental factors may be beneficial to road risk valuation research (e.g., road conditions and environmental conditions). These might affect the drivers' risk perception in accordance with their driving or living area. In addition, future studies could also be conducted in multiple developing nations to provide further relevant insights and data.

5.7 Acknowledgement

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CHAPTER 6

CONCLUSION AND RECOMMENDATIONS

Damages from a road accident on a highway in Thailand remain the major issue that needs to be improved urgently. The study of the statistical value of life and injury caused by road accidents appears to be an appropriate measure that can reflect drivers' views and attitudes toward road accidents. In terms of the relevant government, the findings can give them the appropriate budget allocation and reveal which factors have the potential to affect the WTP for road accident reduction among drivers. Therefore, this study presents the results of the factors that are associated with the WTP for road accident risk reduction among 1,650 Thai car drivers. The significant findings that explored by 4 main research objectives can be summarized as follows:

6.1 The willingness to pay of drivers and total national damages from the road accident

The questionnaire results found that the average WTP of 1,650 drivers is equal to 23.00 baht (the standard deviation is 16.25). The empirical results showed the value of statistical life (VSL) from road accidents involving car drivers ranged from 25,505,238 baht to 27,305,612 baht (815,385-872,942 USD), and the value of statistical injury (VSI) was between 4,693,854 baht and 5,025,185 baht (150,059-160,652 USD). These can cause national losses from road accidents in Thailand of 147,078 million baht per year.

6.2 Influence of demographic and district factors on drivers' WTP

The factors that influence the intention and WTP of drivers are their demographic status, such as age, gender, accident experience, driving behavior, marital status, and trip purpose. according to the health belief model (HBM), the results indicated that the HBM concept can affect the drivers' health awareness, resulting in an increase in their WTP for road accident reduction.

The district-level analysis found that the different contexts of each region influenced the behavioral intention and WTP of drivers in that area. Law enforcement, government support, and the environment exert a significant impact on the intention to pay. Scholars pointed out that if drivers feel that their driving area exhibits more risk of accidents and less safety, then they will be more willing to pay for safety. On the other hand, if the authorities take care of a driving area and make it look safe and good for driving, drivers won't do anything to make sure safety.

6.3 Difference of characteristic between urban and rural drivers on valuation of road accident

The results revealed that urban drivers' VSL and VSL from road accidents were significantly higher (1.63 times) than rural drivers' values, indicating that differences in the context of road users in different areas resulted in their knowledge, understanding, and awareness of road accidents differently. Consequently, the difference in WTP of road accidents was affected. However, the value of road safety at the national level remains severe compared to other developing countries, but appropriate budget allocation along with pinpoint solutions can reduce the violence. Furthermore, the VOT of urban drivers was reported to be higher (13.5%) than rural drivers with 80.31 baht per hour and 70.73 baht per hour, respectively. This confirmed how much drivers are willing to pay to reduce their time wastage in road traffic.

The results of factors affecting the WTP revealed that urban drivers who are doctoral and have an accident experience cause variability among drivers, and thus this group is less willing to pay for safe alternatives. However, we discovered differences in the random parameters of rural drivers compared to urban drivers; moreover, the results demonstrated that nighttime drivers and drivers with a high income were influencing factors on the WTP. This analysis captures the insight effect of unobserved characteristics because urban drivers, household size and gender of drivers can influence the mean of random parameters, causing an indirect effect on the WTP of urban drivers. Furthermore, the results show that up to five unobserved characteristics (household size, sole earner, own accident, doctoral, and young) can indirectly influence the WTP of rural drivers. The context of latent factors differs significantly between urban and rural road users.

6.4 Psychological perspectives and insight effect on drivers' risk perception and valuation

The confirmatory factor analysis (CFA) found that measures of theory of planned behavior (TPB) and health access process approach (HAPA) are correlated with the intention to pay of drivers for reducing road accident risk. Thus, the findings of the preference heterogeneity model also illustrated that such psychological perspectives (TPB and HAPA) and the demographic of the driver have a direct effect on WTP and also have a hidden effect on WTP. The factors that play a role as direct influential factors include married status, incomes, education, sole earners, and night trips. Moreover, components of TPB and HAPA can affect the drivers' valuation in both direct and indirect ways (insight effect); drivers' outcome expectations and perceived behavioral control increase the WTP. Conversely, subjective norms are the opposite. The unobserved characteristics results showed the young members' intention can increase drivers' risk awareness of accidents, and drivers that have older members also have a different attitude toward road accidents.

6.5 Recommendations

The four key findings of this research revealed potential recommendations in terms of road safety improvement. Policymakers believe that the VSL, VSI, and total value of road accidents for personal car drivers in Thailand can be used as an updated budget allocation in road safety projects to appropriately reduce road accidents. Next, results from multilevel analysis also illustrated that law enforcement, support from the government, and the traffic environment of each district can affect the drivers' risk assessment and valuation, these can give the relevant authorities the guidance to improve their local road safety. For the difference between urban and rural areas, the results showed that drivers in urban areas and drivers in rural areas have different traits and risk assessments. This is because the Thai highways in urban and rural areas are not the same in terms of traffic volume, environment, or policy. The government has to focus on this concern and implement it in accordance with the local context. In addition, psychological perspectives (TPB, HBM, and HAPA) of drivers are also found to be potential factors and suitable for the study of road accident risk valuation. These ideas can show how drivers think about accidents and how they feel about them. This is helpful for organizations that want to teach drivers about road safety or include such lessons on the driving license test.

APPENDIX A

List of Publications

List of Publications

Jomnonkwao, S., **Wisutwattanasak, P.**, & Ratanavaraha, V. (2021). Factors influencing willingness to pay for accident risk reduction among personal car drivers in Thailand. PLoS ONE, 16(11), e0260666.

Wisutwattanasak, P., Jomnonkwao, S., Se, C., & Ratanavaraha, V. (2022). Influence of Psychological Perspectives and Demographics on Drivers' Valuation of Road Accidents: A Combination of Confirmatory Factor Analysis and Preference Heterogeneity Model. Behavioral Sciences, 12(9), 336.

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