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Building road safety models to improve traffic safety in Hochiminh City, Vietnam

Proefschrift voorgelegd tot het behalen van de graad van doctor in de verkeerskunde, te verdedigen door:

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Summary

Improving road safety is one of the most important public health issues and government priorities of all countries in the world, especially in emerging countries. Over the past 26 years of reformed economic development, Vietnam's road safety problems have constantly been a national challenge which not only required efforts by the Vietnamese government, but which also attracted more and more special interest within the scientific research community.

In reality, a lot of road safety related research has been carried out in recent years. However, most research simply focuses on generic issues without feasible applicable models and lack sufficiently solid data to apply these models. In addition, most of the latest research proposed subjective implementation solutions.

This thesis aims to develop comprehensive models that have a high applicability and propose efficient solutions to Vietnam's road safety problems. In general, it has a holistically systematic approach that is shown in the objectives oriented knowledge framework (Figure S1), including 5 functional layers:

- ✓ The envisioning layer essentially sets the direction and defines the thesis objectives, problems and scope to common goals of Vietnam's road safety.
- ✓ The purpose of the model design layer is to analyze and select appropriate road safety models from 3 model groups which identify different related variables and factors
- ✓ The model execution layer includes the process and practices to practically execute the designed models in real-life applications.
- ✓ All models in execution and testing will use data from the database development layer where data was collected as raw data and was consequently consolidated, analyzed and developed through many cycles of data.
- ✓ The implementation layer is the functional layer where solutions and community campaigns are developed and proposed using results from the model execution layer and database layer together with social marketing model techniques.

At the center of the thesis there are three main model groups, i.e. statistical models, data envelopment analysis (DEA) and road user behavior models. These allow us to specifically analyze road safety efficiency, predict the number of fatalities, injuries, accidents and traffic violations and finally propose road safety community campaigns to raise awareness among road users in Vietnam. There is a combination and integration across the 3 groups of models where the output of previous models is selected as input for study in the other models.

Ho Chi Minh City is selected as a representative city in a case study of the whole of Vietnam because of its diversity in terms of people, economics and culture. Three main models were applied in 24 districts and 4 clusters of districts in Ho Chi Minh City.

The below seven main groups of research activities describe in detail how the problems of road safety were defined and resolved through a systematic and scientific process:

(1) **Identifying the road safety problem:** reviewing the road safety problem in Southeast Asia and in Vietnam to identify the main causes of road accidents and possible approaches to increase road safety. The road safety result is influenced by road accident outcome levels including the number of accidents, injuries and fatalities, the severity level of road accidents, the economic cost of road accidents, transportation infrastructural faults, transportation environment, vehicle technology and road user errors.

(2) **Selecting road safety problems to discuss in the thesis**: after examining road accident situation in HCMC – the biggest city of Vietnam - road user behavior proved to be the major cause of road accidents and dangerous road accident outcomes, including number of accidents, fatalities and injuries. Therefore, road accident outcomes and road user behavior were selected to be studied in depth. The eleven impact factors of road accident outcomes are: the number of accidents, injuries, fatalities, the number of vehicle ownership; population density, average annual income per person, average car speed, number of traffic rule violations, budget for enforcement, road quality and travel demand. Road users are studied to understand their violation behavior which includes non-use of helmets in Cambodia, speeding and illegal direction change in Vietnam.

(3) **Developing database**: lacking data is a big problem in Vietnam. This thesis presents different methods, including the linear regression method, weighted method and traffic forecast method to build a complete database, which not only contains the collected raw data. The database also includes eleven derived data which are mentioned in chapter (3) for 24 districts of Ho Chi Minh City during 2001 to 2009.

(4) **Building a statistical model**: A generalized linear model is built to predict accident outcome (number of accidents, injuries and fatalities). Generalized linear regression models are predominantly used to predict road accident outcomes. These district group models clearly show the differences and similarities between district groups. These models show the impact of each district group on the result of the whole city. Weighted variables that impact on road accidents are predicted in the model. These findings will help to propose appropriate measures for eliminating road accidents.

(5) **Building DEA model**: DEA models including basic DEA, DEA Malmquist productivity and composite index are constructed to analyze road safety efficiency in each of the 24 districts of HCMC. A basic DEA model for the whole city and for each area is built to identify the best and the worst districts with regard to road safety performance, to benchmark districts and the fatality target that needs to be achieved in each district. The basic DEA model in each area has proved to be a powerful model to understand road safety efficiency in each district. Some of the worst districts in the whole country turned out to be better or best or benchmark districts of the group.

A DEA Malmquist model is used to evaluate road safety through changes in technical efficiency, technological efficiency and total productivity in the whole district and in each area for the time period of 2004 to 2009. The trend and results of the DEA Malmquist model reflect the actual situation in each district and in each year. Typical districts, including the best and worst districts as to road safety performance, as well as central district are selected to be analyzed more deeply to combine the theory and practice.

A composite index is applied to identify the share of each variable (input) to the number of fatalities (output). The result will lead to a better understanding of road safety efficiency.

(6) **Building road user behavior models:** specific studied behaviors focus on the biggest road safety problems in specific areas, i.e. non-use of helmets, which is the major cause of road accidents in Cambodia, speeding, which is the most serious problem in Vietnam and illegal direction change, which represents the highest ratio of road accident causes in Ho Chi Minh City, Vietnam.

The separate application of the theory of planned behavior (TPB) and the health belief model (HBM) prove that powerful prediction models lead to different results in case of various behaviors and different places. Basic TPB variables predict behavioral intention and behavior of helmet use and perform better than basic HBM variables. Basic HBM variables prove to give better predictions than TPB when it comes to speeding and illegal direction change behavior.

Integrated behavior models (IBM) are built by the combination of theory of planned behavior, health behavior belief and extended socio-cognitive variables. Building and examining integrated behavior models has proved to be the best behavior model for widespread application in Vietnam.

The significant contribution of variables in the predictive behavioral intention and behavior models prove to be different for different traffic violations such as helmet use, speeding, illegal direction change at various places including Phnom Penh and Ho Chi Minh City.

(7) Proposing road safety implementation: The findings of three road accident model groups would not only help policymakers and local authorities to make the right decisions with regard to road safety management, but they can also initiate valuable road safety solutions as well as community media campaigns and awareness-raising programs for road users. These community media campaigns follow social marketing theories to achieve good results. All of the solutions will help to eliminate road accidents and risky traffic behavior in HCMC.

To conclude, all the main and specific objectives of the thesis are solved through successfully building road user behavior models, predicting road accident outcomes (number of accidents, injuries and fatalities), developing a database for applying probabilistic models, DEA model to analyze road safety outcomes for improving road safety in Ho Chi Minh City. The combination of different methods and models to analyze road safety is useful for the typical transportation environment. These models are used for the first time in Vietnam in road safety analysis. Their results have proved it is possible to use scientific methods where a logical combination is made of theory and practice. These models can be widely applied throughout the country to analyze and predict road accident outcomes and road user behavior, to evaluate road safety efficiency and also to propose programs to increase road safety.

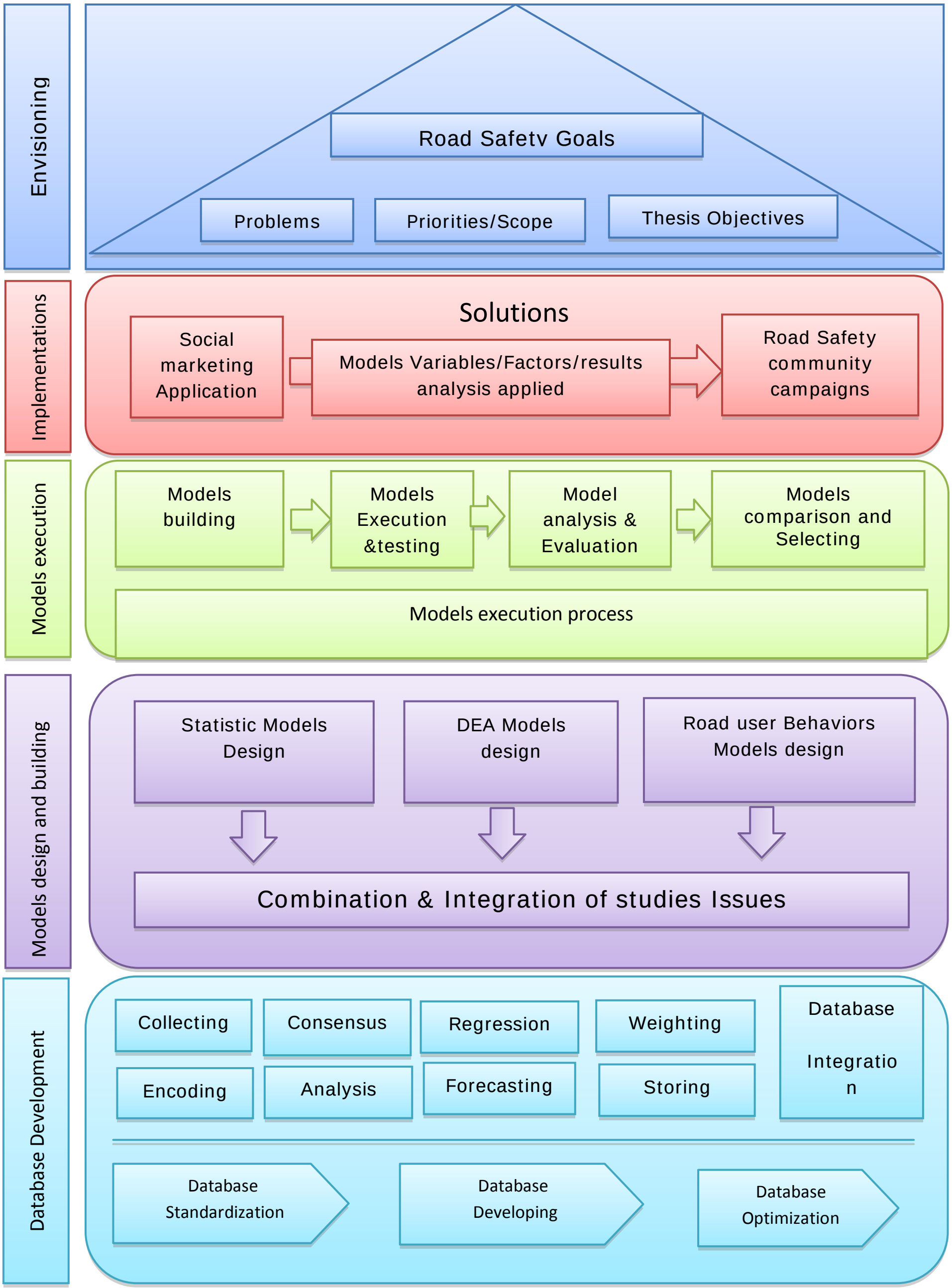

Figure S1. Thesis Knowledge Framework

List of Abbreviations

A	Average
AADT	Annual Average Daily Traffic
ACC	No of Accident
AI	Average Yearly Income Per Person
APEC	Asia-Pacific Economic Cooperation
ASEAN	Association of Southeast Asian Nations
BIC	Bayesian information criterion
BoD	Benefit of the Doubt
BT	Breaking Traffic Rule Measured for Road User's Perception
CAIC	Consistent Akaike's Information Criterion
CBA	Cost Benefit Analysis
CCR	BCC Charnes, Cooper, and Rhodes - Banker, Charnes, Cooper
CCR	Charnes, Cooper, and Rhodes
CRC	Cambodian Red Cross
DEA	Data Envelopment Analysis
DEA_MI	Data Envelopment Analysis Malmquist
DEAP	Data Envelopment Analysis Progam
DEI	'Dirty' Energy Index
DMU	Decision-Making Unit
DP DEA	Double Perspective Data Envelopment Analysis
DT	Travel Demand
EB	Budget for Enforcement Indicator
EF	Technical Efficiency
EFch	Technical Efficiency change
EFFch	Efficiency Change
EUR	Euro
F050	Federal Route 50
FA	Factor Analysis
FAT	No of Fatalities
G	Group
GDP	Gross Domestic Product
GIS	Geographic Information System
GLM	Generalized Linear Model
GOF	Goodness of Fit
HBM	Health Belief Model
HCMC	Ho Chi Minh City
HIV/AIDS	Human Immunodeficiency Virus Infection / Acquired Immunodeficiency Syndrome
IBM	Integrated Behavioral Model
ICU	Incentive Care Unit
IDC	Illegal Direction Change
INJ	No of Injuries
JICA	Japan International Cooperation Agency
Km	Kilometre
KSI	Killed And Severe Injury
LOOP	Law of One Price
LP	Linear Programming

LRM	Linear Regression Model
MLDEA	Mutiple Layer Data Evelopment Analysis
MoEYS	Ministry of Education, Youth and Sports
MRA	Multiple Regression Analysis
NRSC	National Road Safety Committee
OECD	Organisation for Economic Co-operation and Development
PC	Number of Passenger Car Unit
PD	Population Density
PDO	Property Damage Only
PMT	Protection Motivation Theory
PSI	Potential for Safety Improvement
RAD	Road Area Density
RCVIS	Road Crash and Victim Information System
RGC	Royal Government of Cambodia
RLD	Road Length Density
RS	Road Safety
SA	Satisfied Travel Demand of Road Capacity
SCM	Supply Chain Management
SFA	Stochastic Frontier Analysis
SP	Average Vehicle Speed
SPSS	Statistical Package for the Social Sciences
SSE	Error Sums of Squares
SSR	Regression Sums of Squares
SST	Total Sum of Squares
TECHch	Technological Change
TFPch	Total Factor Productivity Change
TM	Trauma Management
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action
UNESCO	United Nations Educational, Scientific and Cultural Organization
USD	United States Dollar
VMT	Vehicle Miles Traveled
WHO	World Health Organization

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Chapter 1. Introduction

1.1 Road Safety In Southeast Asia Nations

It has been apparent that the road traffic plays a very important role in economic development of nations and regions. However, with the increasing number of modes as well as number of road users, the road traffic has also impacted on people's health directly and indirectly.

Road accidents have become a global phenomenon in almost countries all over the world nowadays. Every year, more than 1.3 million people's death which is caused by road crashes around the world. Road accident has ranked as the ninth in list of death's causes across the world in 2004 (WHO 2009) and consistently one of the top three causes of death for people aged between 5 to 44 years (Peden, Scurfield et al. 2004). It is estimated that the number of deaths and injures will increase over 60% by 2020 and to reach number five on the death list, defeating HIV/AIDS to become one of the major leading causes of death over the world by 2030 (WHO 2008).

By all accounts, over 90% of world's road traffic fatalities have occurred in the low-income and middle-income countries where accounts 48% of the registered vehicles worldwide. While the rate of fatality in developed countries still remains stable, approximately 10.3 cases per 100,000 people and this rate in developing countries with low income is 21.5 cases per 100,000 people. In association of Southeast Asian nations (ASEAN), the average rate of fatality is 15.04 per 100,000 people (WHO 2009).

According to the statistics of WHO (2009) and in the comparison with other Asian countries; Vietnam belongs to the low income group and its road traffic fatality rate stands in the top six ASEAN countries whose rate is up to 16.1 per 100,000 populations. The fatality rate of Vietnam has been considered to be behind Indonesia (16.2), Laos (18.3), Thailand (19.6), Philippines (20) and Malaysia (23.6). In addition, this rate of Vietnam is estimated 1.07 times higher than the rate of other Asian countries (Figure 1.1).

In terms of the number of road traffic fatalities, Vietnam rose to the 'top' of the highest fatalities numbers in ASEAN countries, 2002. Two national groups are divided as high and low road accident risk in ASEAN countries and there is a big gap between these two groups. The high road accident risk group includes Vietnam, Indonesia, Thailand, Philippines, Malaysia and five other countries belong to the low risk one. Figure 1.2 shows that the number of fatalities fluctuated slowly in the high group, or it has a decreasing trend in most countries, with the exception of Vietnam where increased constantly to 2002 cases and reduced to 12,000 cases in 2003 during the period of 1994 – 2003 (GRSP 2006).

Beside that, traffic accidents in most ASEAN countries have been mainly caused by the 2 or 3-wheel vehicles and then over 60% of those accidents were occurred in Vietnam, Thailand and Indonesia. Traffic accidents caused by cars accounted over 20%, and then caused by others traffic means, such as pedestrians and bicyclist were 13% (Vietnam_Transportation_Police_Department 2006)

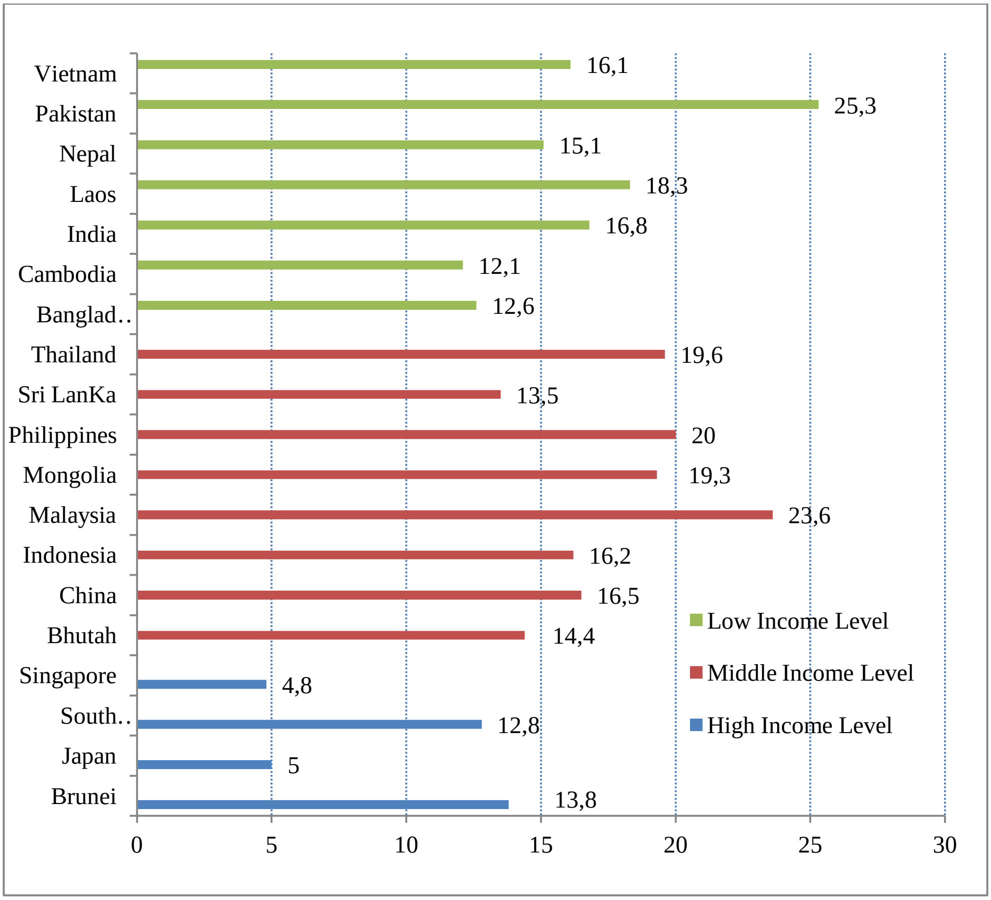

Figure 1.1 The road traffic death per 100,000 populations in Asian countries, 2008

In ASEAN, especially in Thailand, Indonesia, Vietnam where the mortality rates and the high traffic accidents have been very high, the major causes that led to traffic accidents have been mostly over-speed driving or alcohol drunk driving. Similarities among these countries are low traffic enforcement or non-traffic regulations or road users do not respect to the traffic rule. Even in Indonesia, there are no rules of limited alcoholic level in drivers' blood.

Traffic accidents are becoming not only a serious problem but also a remarkable burden for countries economy in the world. Each year, traffic accidents have costed the world economy about 520 billion USD averagely. This cost is estimately accounted about 1-1.5% and 2% of developing countries' GDP and developed countries' GDP, respectively.

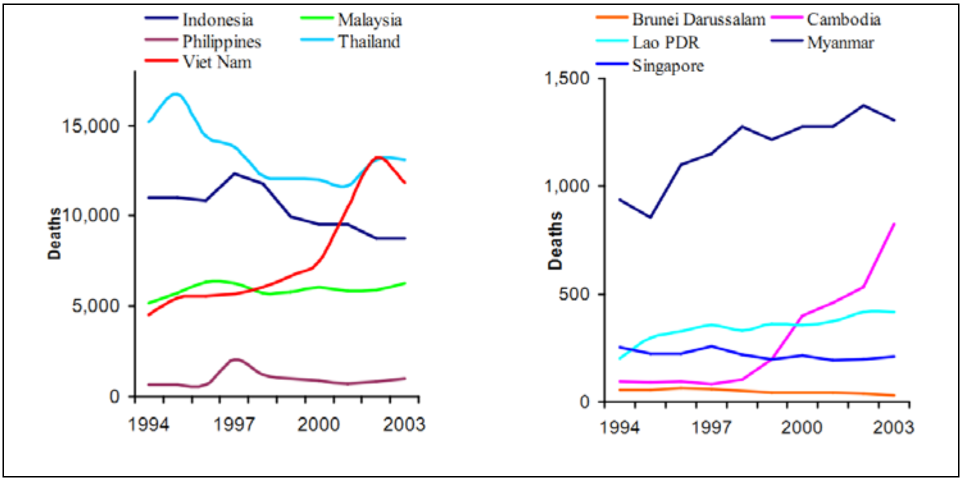

Figure 1.2 The number of fatalities of ASEAN in 1994-2003.
Source: WHO (2009)

The facts indicated that road accident has made a strongly financial, spiritual, material impacted on not only injured or killed individuals, but also their whole family. These effects include direct costs, such as the injury treatment cost, medicine cost or funeral cost and indirect cost as income loss due to leave for treatment or leave permanently for disability or death. This is really too big burden not only for each family but also for the whole society.

According to the statistics (ADB 2003; ADB-ASEAN 2003), the figure of 14,168 million USD was calculated as annual loss due to traffic accidents and it was approximated to 2.1% of Annual GDP of the ASEAN countries (GRSP 2006). The top five countries which had highest anual loss of road accident are Indonesia (6,032 million USD), Thailand (3,000 million USD), Malaysia (2,400 million USD), Philippines (965 million USD) and Vietnam (885 million USD). For GDP expression, these annual loss were changed very slightly in which Indonesia's GDP has move down to the third and Vietnam still remains at the fifth and they are accounting 2.91%, 2.45%, respectively. In the meanwhile, Cambodia (3.21% ranked No1), Myanmar (3%) and Laos (2.7%) are the three countries which have lower annual traffic accident loss but had very high ratio of GDP as showed in Table 1.1.

Table 1.1 Losses of ASEAN countries are caused by traffic accidents in 2003

Country	Annual Loss (USD million)	Expressed % of annual GDP
Brunei	65	1.00
Cambodia	116	3.21
Indonesia	6.032	2.91
Laos	47	2.70
Malaysia	2,400	2.40
Myamar	200	3.00
Philippines	965	1.20
Singapore	457	0.50
Thailand	3,000	2.10
Vietnam	885	2.45
ASEAN	14,168	2.10

Source: ADB-ASEAN (2003)

1.2 Road Safety In Vietnam

An impressive fact showed that there are approximately 30-35 people did due to road accidents everyday in Vietnam (WHO 2008). The number of road accidents, fatalities and injuries were increasing rapidly year by year from 1996 to 2003. However, it have decreased slowly since 2003 but the reducing fatal number is temporary and unstable (Figure 1.3).

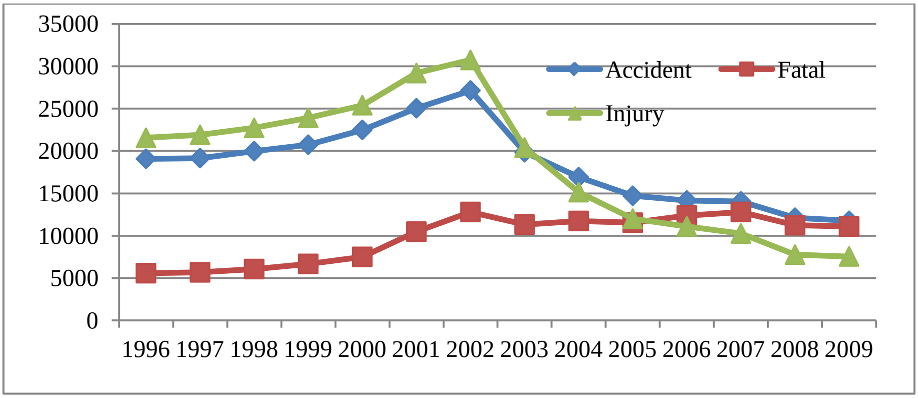

Figure 1.3 The road accident in Vietnam from 1996 to 2009.

Figure 1.4 shows the number of accident and injury rates per vehicle that were decreasing over the years because of a rapid motorization. The number of motor vehicles increased 13.5 times (4 times for cars and 15.4 for motorbikes) from 1990 to 2007. But the number of fatality per vehicle reduced insignificantly at 6.5 cases/10,000 motor vehicles (JICA and Ministry-of-Transport 2007).

Most of road accidents in Vietnam are related to faults of road users in which the 2002-2005 reported that user's speeding was the major accident cause this cause was occupied over 25% while illegal direction change and illegally crossing accounted over 17% and 15% of total road accident (Table 1.2) (NTSC 2005).

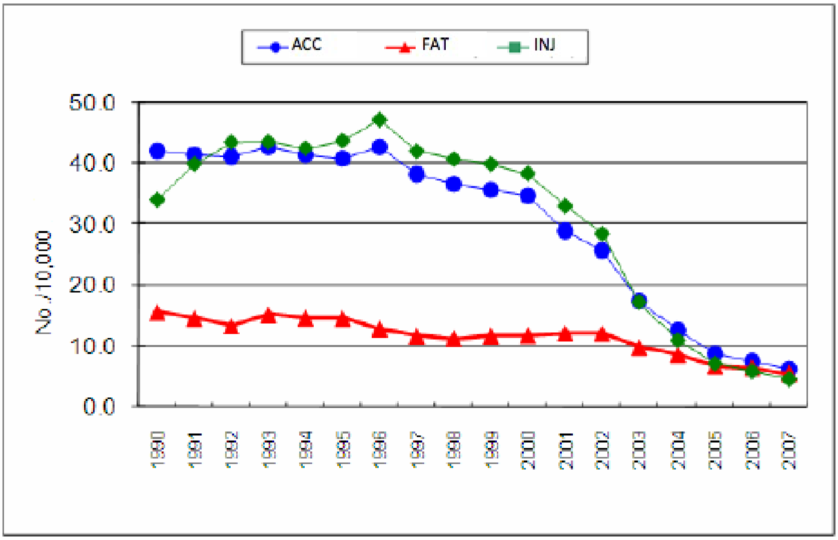

Figure 1.4 Number of accidents per 10,000 in 1990-2007

Table 1.2 Road Accidents by causes in 2002-2005

Unit: %

Road accident causes	Rate					
	2002	2003	2004	2005	2006	Average
Speeding	24.4	24.1	26	25.8	24.8	25.02
Illegal direction change	17	17.6	16.5	16.7	18	17.16
Illegal crossing	18.9	16.8	15.8	12.7	13.7	15.58
Transfer the direct without having a sign	4.1	3.4	2.4	1.6	1.7	2.64
Crossing the red traffic light	1.1	0.1	1.7	0.6	0.2	0.74
Not keep the safe distance	6.9	0.9	2.4	1.8	0.4	2.48
Reckless driving	15.9	12.1	8.1	10	8.2	10.86
Pedestrians	0.7	2.3	2.9	3.2	2.6	2.34
Others	11	22.7	24.2	27.6	30.4	23.18

1.3 Risk Factors Of Road Accident

For last years there were many studies which were carried out in countries by developing and examining various models to find, to explain and to measure factors that caused road accidents; the studies have also forecasted the road safety's evolution as well as to find risky factors leading to an increase of accident frequency and accident severity (for-Economic-Co-operation-and-Development 1997; Christens 2003; Van den Bossche and Wets 2003; Elvik and Vaa 2004; Raeside and White 2004; European-Commission 2004a; Hermans, Brijs et al. 2006a; Ohidul Haque 2010). In the reality, road safety is a complex matter that is basically affected by many factors in various ways.

The decomposition of road safety mentioned in the interaction of human – vehicle – infrastructure – environment factors (Hermans, Brijs et al. 2009a; Ohidul Haque 2010), (Figure 1.5) on the one hand and measure and comparison of risk - exposure on the other hand.

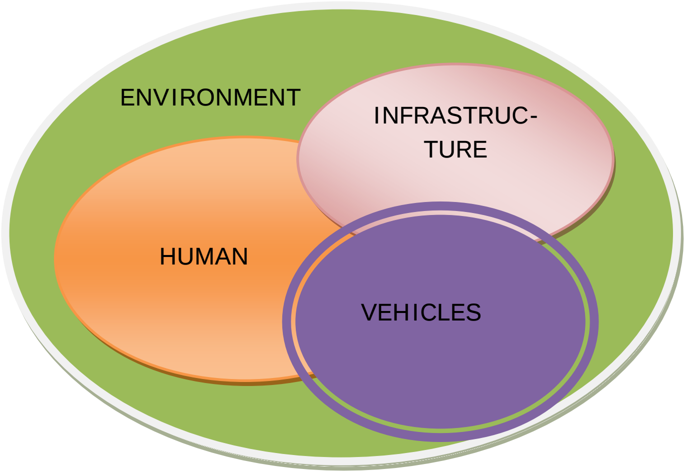

Figure 1.5 The four factor groups of road accident cause

The research has significantly focused on motor vehicle accidents prediction. In a recent report to Congress, the US General Accounting Office (GAO 2003) noted, "human factors are seen as the most prevalent, according to data, experts, and studies, in contributing to crashes, followed by roadway environment and vehicle factors" (p. 2). The human factor is considered the most contributory risk of road accident such as behavior and characteristic of road user and public that examined by age, gender breakdown (Sabey and Taylor 1980). Many road accident cases related to the failure of vehicle including types of vehicles, damage level of vehicle from different accident locations and failure of infrastructure such as types, conditions of roads. The three above components are integrated in a broader environment explored to the risk of road accident where it interacts with other factors. Environment risk is clarified as weather conditions (snow, rain, sun, frog…), time (day, night, peak period, peak off period), political and economic conditions (law related to alcohol, speed, safety action, policy or GDP, income), cultural (religion), demography (age distribution of the population, family composition), road locations such as close to schools, shopping centers, rural area (Hakim, Shefer et al. 1991; Fridstrøm, Ifver et al. 1995; Scuffham 2003; Van den Bossche and Wets 2003; Eisenberg 2004; Van den Bossche, Wets et al. 2005; Hermans, Brijs et al. 2006a; Melinder 2007). In fact, road accidents are not only causes of individual factor but also combinative factors so road accident cause should be considered associated indicators.

In order to compare the road types or different modes based safety situation among zones, regions and countries the risk and accident rates have been usually used as road safety performance comparison. Basically, a risk is defined as the expected road safety outcome given by a certain exposure (SafetyNet 2005a). The road safety outcome is usually measured by number of accidents or number of fatalities or injuries level (serious/ slight). Exposure denotes the amount of activity as amount of travel in which accidents may occur (Elvik 2007). In SafetyNet (2005a); exposure is estimated by the road length (kilometers), vehicle kilometers, person kilometers, fuel consumption, population, driver population (number of driving licenses), vehicle fleet (registered vehicles' number), number of trips, time in traffic (total spent traveling time by person). There are more indicators being considered to measure well exposure such as the different socio-economic conditions, population density, vehicles per citizen and transport mode split (Al Haji 2005). The most important risks measured road safety performance of European countries were considered as alcohol (drinking and driving, alcohol limit, enforcement and measures), speed (speed limit, speed cameras), protective system (seatbelt, helmet, enforcement sanctions, campaigns), day time running lights, vehicle, infrastructure, trauma management (emergency medical system, medical care) (European-Transport-Safety-Council 2001; Hermans, Brijs et al. 2009a). Exposure data are conducted through traffic count, travel surveys, local exposure measurements and indirect exposure estimates (fuel sale) (Organisation-for-Economic-Co-operation-and-Development 1997).

The three main factors which determine the number of people who are killed or injured in road accidents are accident risk, road safety outcome and exposure. The number of fatalities depends much on the number of vehicles (motorization level). Smeed (1968) showed that the large populations with low level of motorization have relatively low number of fatalities.

The purpose of finding main causes of road accident or having a road safety comparison is to identify the methods to eliminate the number of road accident, fatalities and injuries. Some critical ways that can help significantly reduce the number of fatalities are:

- ✓ Reducing the exposure to the risk accident (reducing the amount of travel) using safer means that lowers risk for road users.
- ✓ Reducing accident rate per given amount of travel
- ✓ Reducing accident severity by developing a protective system or a better trauma management system.

1.4 Statement Of Problem

General of road safety problems in Vietnam are:

- ✓ Traffic demand continuously increasing because of economy growth and development leads to increase number of accidents. The increasing of travel demand is because of the economic growth. Since 1999 Vietnam economy has grown rapidly and stably; the period of time that had highest growth was from 2001 to 2007 with an annual average growth rate of 7.89%. The economic growth has also constantly led to the road travel demand increase every year. The growth rate of passenger and cargo is estimated 1.5 times higher than GDP growth rate. The ratio of passenger on road and passenger-km have raised 12% and 8% per year respectively; while the road cargo has just increased 9% and 8% per year which are measured by Ton and Ton-km (ADB 2003)

- ✓ Motorization increase leads to increased number of Accidents. The increasing along with the higher income of habitant, Vietnamese have spent a lot of money for buying new vehicles to satisfy their travel demands. This issue has been obviously reflected through increasing a huge resisted private vehicle (number of motorbikes, cars) day by day. Motorization trend in Vietnam is rising with at high level in comparison with other ASEAN countries, the ratio is 148 vehicles/1000 people in 2004, it is ranked as 5th, just behind Brunei, Malaysia, Thailand and Singapore whose ratios are 684, 525, 391 and 154 vehicles/ 1000 people in that order (GRSP 2006) respectively. The rapid motorization since 1990 has substantially contributed to the higher number of road traffic accidents.

- ✓ Low infrastructure, facilities and road quality, mixed transportation types. However, Vietnam's road network including infrastructure and facility have been improved and have been constructed inadequately to meet the growth rate of transport vehicles. Beside the lack of road, the poor traffic infrastructure, the unsafe traffic environment such as very few road signs and safe areas for pedestrians, the mixed transport among car, motorbike, truck, bike… as well as the popular motorbike of mode are causes of increasing traffic conflicts, crashes, accident among vehicles with different sizes and speeds in both urban and rural areas.

- ✓ The fact of lacking of traffic regulations, rules and enforcements as well as inconsistent road safety policy and institutional system from the local authority and government are mainly causes contributed to higher road accidents situation in Viet Nam.

Specific statement of problems are identified following as:

- ✓ Solutions, proposals are too simple and weak to sufficiently address the imperative challenges of road safety due to lacking road safety database system
- ✓ Insufficient road safety programs and solutions, implementation were basically built subjectively without a scientific and fact based methods
- ✓ Although the government has invested financially a high budget in community campaigns but the road users behaviors improvement has not achieved the expected results.
- ✓ Solutions of road safety elimination have not targeted exactly to right objectives, right audiences, and right areas therefore the effectiveness and efficiency are still very low and lacking of priorities.
- ✓ Ho Chi Minh city which consist of 24 districts and sub-district is the largest and highest speed developing city of Vietnam with very high populations, diversity of cultures
- ✓ The fact of non-necessary forecasting models of number of accidents, number of fatalities and number of injuries has made authorities very passive in planning and addressing the challenges of road safety.

- ✓ Road safety policies have been regulated in inconsistent ways which lead the repetition and low-efficiency and confused road users
- ✓ Main road accidents caused by road users behaviors. In other words, road user behaviors are considered as a core reason of rapid road accidents and fatalities increase. Over 90 of road accident reasons are recorded as road user behaviors (Vietnam_Transportation_Police_Department 2006). It has been due to very low awareness of traffic rules, safety-driving behaviors many road users have not fully realized that the traffic accidents can be completely preventable.

1.5 Objectives Of Thesis

The main objective of the study is to build the road safety models for improving traffic safety in HCMC in Vietnam. In order to reach the main objective, the specific objectives are:

(1) Reviewing the theory and methodology of road safety studies in the world and its applications to the emerging countries such as Viet Nam and another South East Asia.

(2) Examining the road traffic accident situations in HCMC – the biggest city of Vietnam.

(3) Developing a database of road accident consequence impact indicators.

(4) Building statistical models to predict number of accidents, fatalities and injuries

(5) DEA model is applied to understand road safety eficiency of each district in 24 districts and in district groups through number of fatalities.

(6) Building TPB, HBM and IBM from the proposed socio-cognitive determinants of individual road user characteristic to predict their driving violations in HCMC (Vietnam) and Phnom Penh (Cambodia)

(7) Comparing and selecting the best/ suit model to predict road user risky intention and behavior among three proposed behavior models for HCMC and Phnom Penh

(8) Proposing some measures to increase traffic safety level and to prevent implicit traffic accident.

1.6 Methodology Of Thesis

The thesis consists of three main parts as following:

(1) Analytical study of current road accident consequences in HCMC Vietnam
(2) In-depth research of road user behaviors

(3) Road safety measurements and proposed community awareness driven campaigns solutions research.

There are basically three key models used in the thesis:

- ✓ Statistic models (predicting number of accident, number of fatalities and number of injuries)
- ✓ DEA models (road safety efficiency through number of fatalities)
- ✓ Road user behavior models (wearing helmet, speeding and illegal direction change)

There are nine methods are used in the thesis as statistic methods, forecast method, socio-survey method, comparison method, analysis method, non-parametric mathematical programing method, weighting score method and consensus method.

The statistic models and DEA models are mainly used in part (1), which have not covered Vietnam. These models would help to identify and clarify the factor (variables) whose weighted will make the impact to the road safety. The road safety impact measurable is basically the number of accidents, injuries and number of fatalities.

With the limited data in Vietnam, it is very important and critical to select a relevant logical model which can help analyse the current road safety situation as more prissily as possible. A database is conducted base on the four road safety concepts defined by the Police Department and Statistic Department of HCMC which includes human, infrastructure, vehicles and environment

For the part (2), road user behavior is identified to be the serious cause of accident which has caused over 98% of road accidents in HCMC. So TPB, HBM and IBM are built to predict road user' risky intention and behavior in HCMC regarding to speeding and illegal direction change behavior which are two popular driving violations in Vietnam. Beside that, all predictive variables are examined to clearly understand road user' risky behaviors in HCMC. A suit and best behavioral model is selected to propose using for predicting Vietnamese road user intention and behavior in the future. Additional, a case study of helmet wearing in Phnom Penh is studied to make a comparison between road user' risky driving intentions and behaviors of two cities having similar weather conditions and some.

The last part (3) concludes the models and results generated from part (1) and (2) will not only help the policy makers, and local authorities make right decisions of road safety management but also can initiate valuable road safety solutions as well as community media campaigns and awareness raising programs for the road users All of the this solutions will help eliminate the implicit road accident and risky traffic behaviors in HCMC.

The methodology of the thesis is described in detail in Figure 1.6

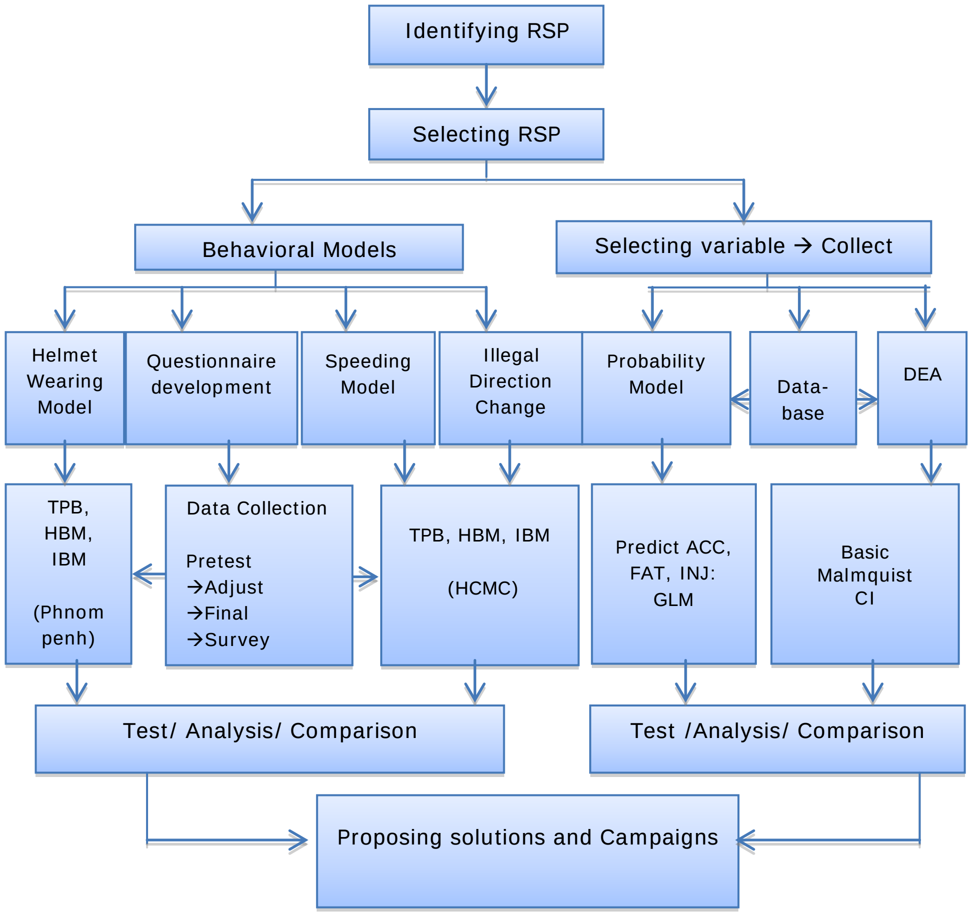

Figure 1.6 Methodology of the thesis

1.7 Organization Of Thesis

The thesis includes seven chapters in which the content of each chapter could be briefed concisely as following:

The thesis includes seven chapters in which the content of each chapter could be briefed concisely as following:

Chapter 1 introduces general road safety situation, risk factors of road accident in Southeast Asian region and in Vietnam. In addition, statement of the problem and objective of this study are presented.

Chapter 2 provides the analysis of road safety situation in Hochiminh city

Chapter 3 presents selecting road accident variables, collecting and developing a database following the proposed variables as well as general analysis of the database that would be used in the chapter 4 and chapter 5.

Chapter 4 discusses literature review of statistic models and their application to predict road accident consequence. Statistical models are built through generalized linear models (GLM) to analysis and predict road accident count (number of accident, number of fatalities and number of injuries) in 24 districts of HCMC.

Chapter 5 reviews DEA model types and the application in traffic safety. Basic DEA, DEA Malmquist productivity, composite index are established to analysis road safety efficiency, to identify road safety target, to understand the efficiency change and indicator share of the proposed variables to number of fatalities in each 24 districts of HCMC. The benchmark district in term of road safety efficiency is found and made comparisons to other worse districts for proposing better road safety in each district of HCMC.

Chapter 6 mentions behavioral theories and the application trends of behavioral models in predicting violence human behaviors. Three predictive road user behavioral models related to wearing helmet in Cambodia, speeding and IDC in Hochiminh city are presented separately in three case studies. TPB, HBM and IBM are built from the proposed socio-cognitive variables to predict the driving violations.

Chapter 7 presents the conclusion based on the analysis and running model result of three previous chapters and to provide the implementation of the proposed road safety policy measures, road safety campaigns and awareness programs to eliminate the implicit road accident and traffic risky behavior. It introduces the future research.

Chapter 2. Road Safety In Hochiminh City

2.1 Economic And Transport Development

HCMC has a total area of 2,095 square kilometers and a total population of 8.162 million (Vietnam_Statistical_Department 2009), which encompasses eight old downtown districts, six new downtown districts, six suburban districts and four rural sub-districts (Figure 2.1 and Figure 2.2). The different of topography, weather, ethnic distribution, population and colony create different cultural regions with specific characteristics of North, Central and South in Vietnam. Being considered as a major hub for economic, commerce, finance, tourist, culture and science of Vietnam, HCMC has attracted many immigrants from the whole country (accounting for 1/3). The population distribution is not equal such as 83.32% of population are living in urban area; Chinese ethnic concentrate living at districts No 5, 6, 8, 10; immigrants are from other Vietnamese provinces after 2000 living mainly at district No 7, No 9, Binh Chanh, Go Vap, Tan Binh, Thu Duc.

2.2 Road Safety And Road Accident

All types of vehicle such as car, bus, truck, taxi, bicycle and other vehicles share in the same lane which called a mixed traffic system in HCMC. Motorcycle is a popular mode for almost purpose trip such as short, long distance trip, business, picnic, work, shopping… because it is very flexible moving on the congested traffic and low infrastructure.

77.9% trips were traveled by motorbike (JICA 2002) while 3.5% and 5.9% of trip done respectively by taxi and bus. In 2009, the ratio of motorbike per $1km^2$ in HCMC was 1927 that was two times higher than Hanoi and 4.8 times higher than Danang. In the mean time, the ratio of vehicle per 1000 population was 1092 vehicle same as Hanoi but it was 1.6 times higher than the average national ratio.

The Living-Standards-Survey-in-the-Southeast (2004) reported 71% of all households owning motorcycles in Vietnam. The Houtrans person-trip survey (JICA 2002) presented that more than 90% of HCMC households owned motorcycles and that 53% owned two or more motorcycles. According to the HCMC Department of Transport and Public Works, 1,300 motorcycles are being registered and added in the city in a working day. HCMC is christened the “Pearl of the Orient” by the French, is now referred as the “motorcycle capital of the world”. The ratio of motorcycle ownership in two biggest cities of Vietnam (Hanoi is capital located in the North, and Hochiminh city is the biggest city located in the south) is highest comparing to other Asian cities (Figure 2.3)

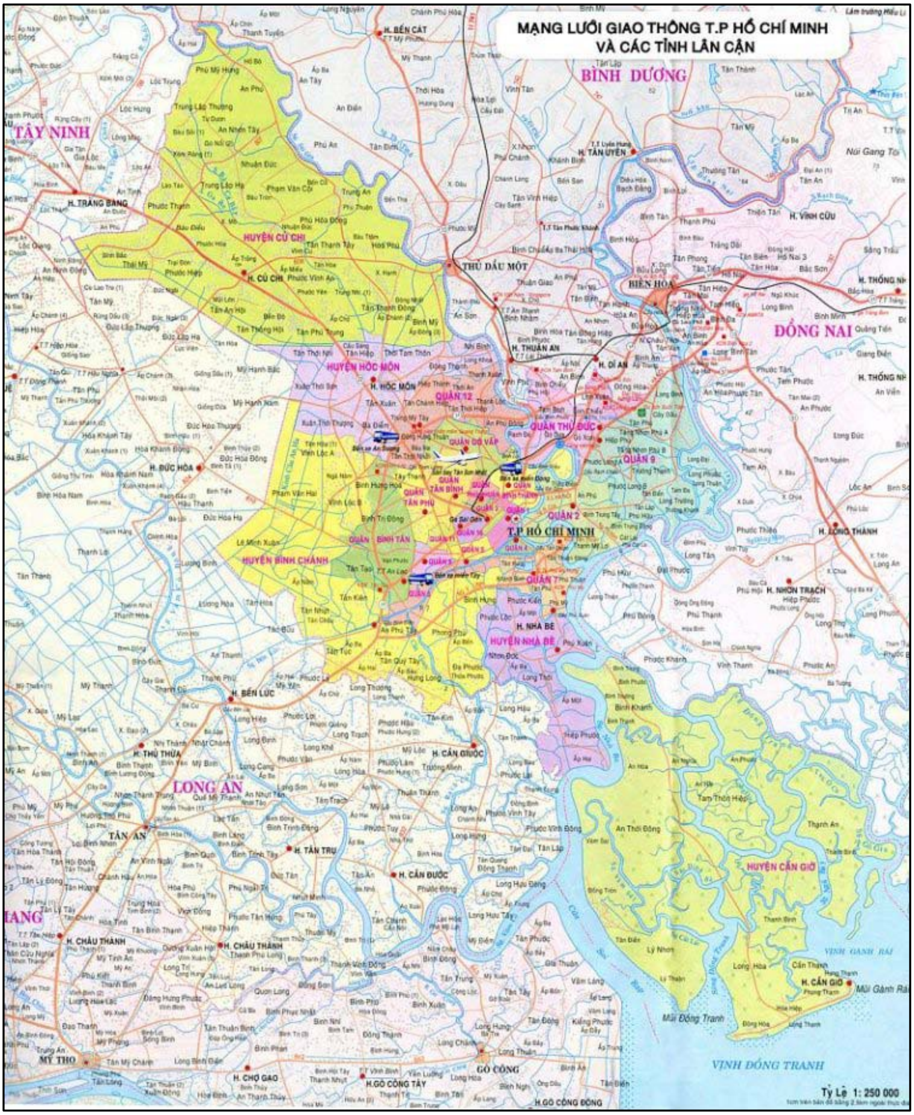

Figure 2.1 HCMC and neighbor provinces
Source: (HouseTrans 2003)

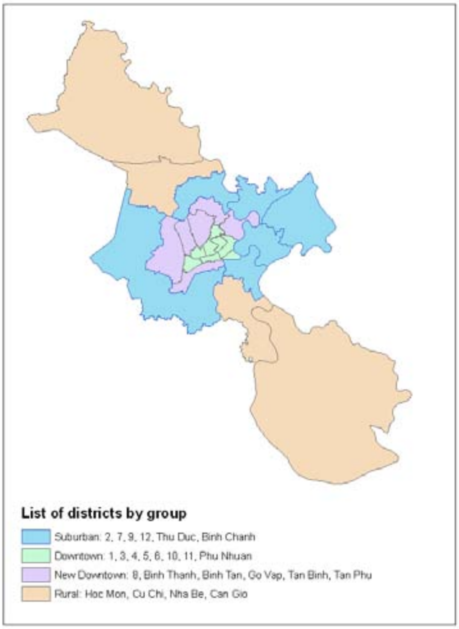

Figure 2.2 The detail location of HCMC districts and suburban districts

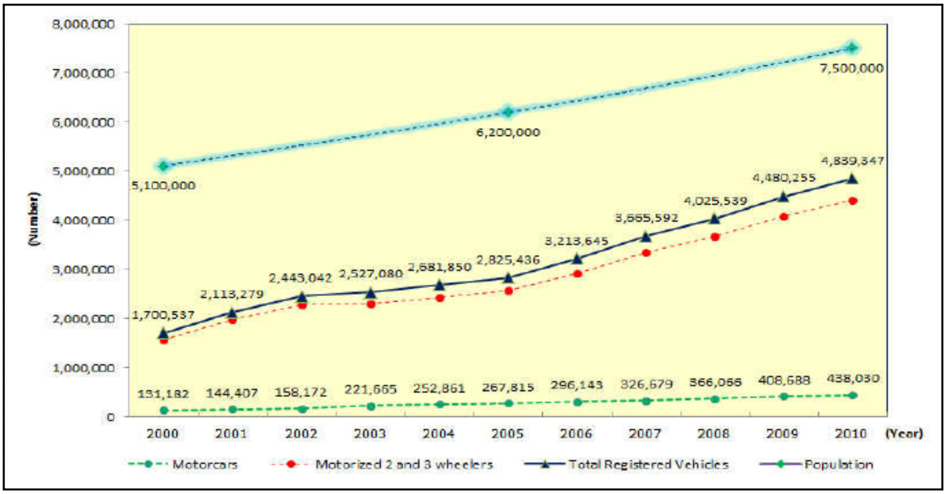

Figure 2.3 Motorcycle, car ownership and population in Hochiminh city (2000-2010) Source: HCMC_People_Committee_Office (2012)

The road accident data from 1999-2009 in all cities and provinces of Vietnam was highlighted the highest number of accidents, fatalities and injuries at Hochiminh city (accounting 9.14% of the whole country).

HCMC has the same road accident scenario with a whole country in general. The number of road injury decreased impressively from 2002 to 2008, however it increased suddenly in 2009. Besides that, the number of road accident and road fatality fall down very slowly and climb up in 2007 (according to 4% and 9% compared to 2006) (Figure 2.4).

The districts/ suburban districts are gateways of HCMC having higher number of accidents, fatalities than the others; such as Binh Chanh suburban district, Cu Chi suburban district, Thu Duc district are according to west, northeast, northwest gateways of HCMC (Figure 2.5, Figure 2.6). The old downtown districts, excluding district No 1, present lower number of accidents and fatalities than the remaining.

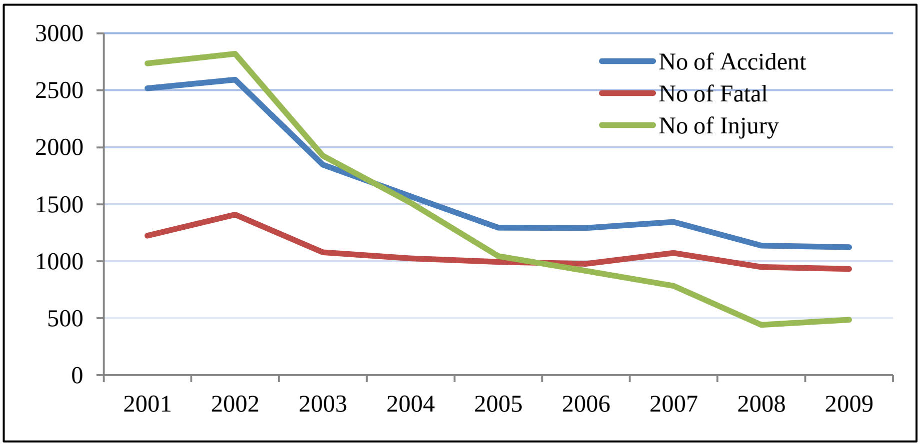

Figure 2.4 Road accident trend in HCMC from 2001-2009

✓ **Road accident by transport mode type**

Following the road accident records of the police during 9 years (2001-2009), the motorbike was caused annually highest ratio for number of accident (more than 81%), fatal (over 83%) among other road transport mean in HCMC while truck caused the second ratio for them (accounting more than 15%). The other vehicle did not contribute high ratio to number of road accident or fatalities. The ratio of pedestrian accident and death on road increased noticeably from 2004 up to 2009 (Figure 2.7, Figure 2.8). Motorbike as well as pedestrian is considered vulnerable transport means group that is an alarm to road safety situation in HCMC.

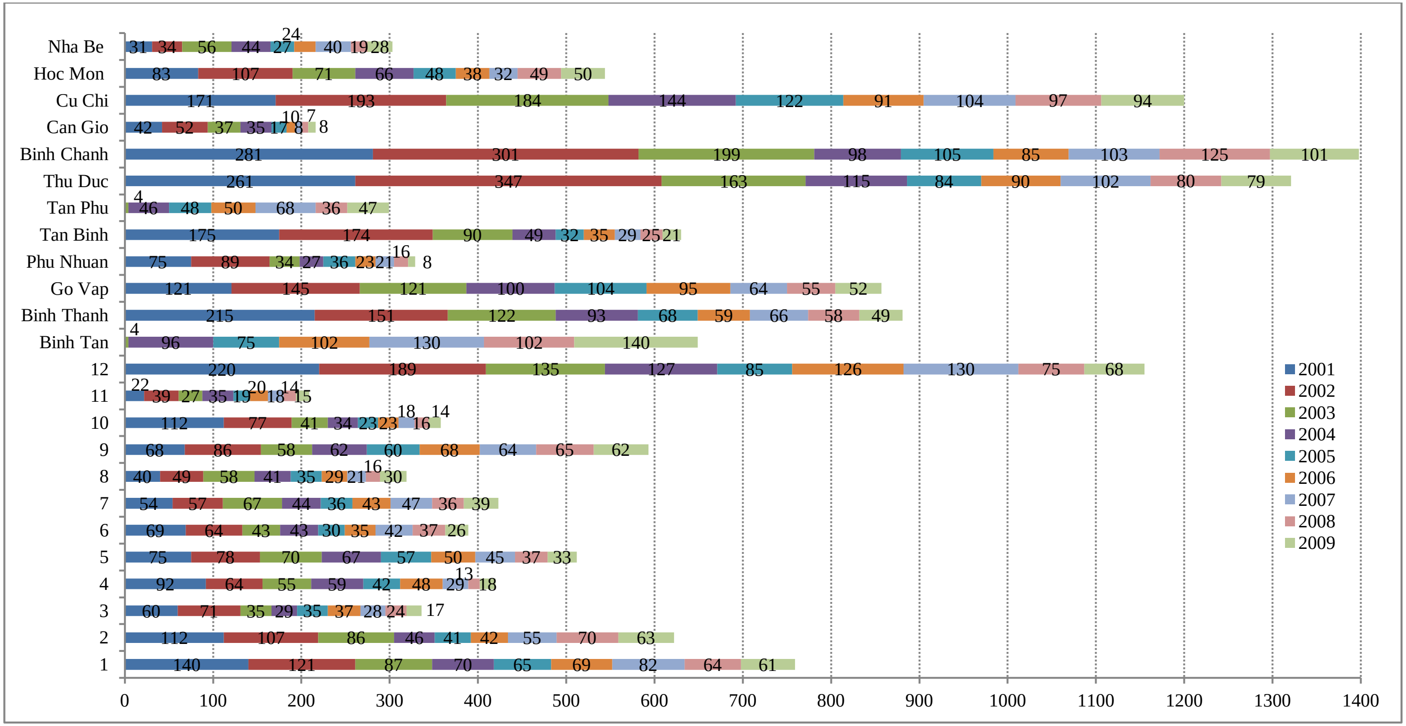

Figure 2.5 Number of road accident in each district from 2001 to 2009.

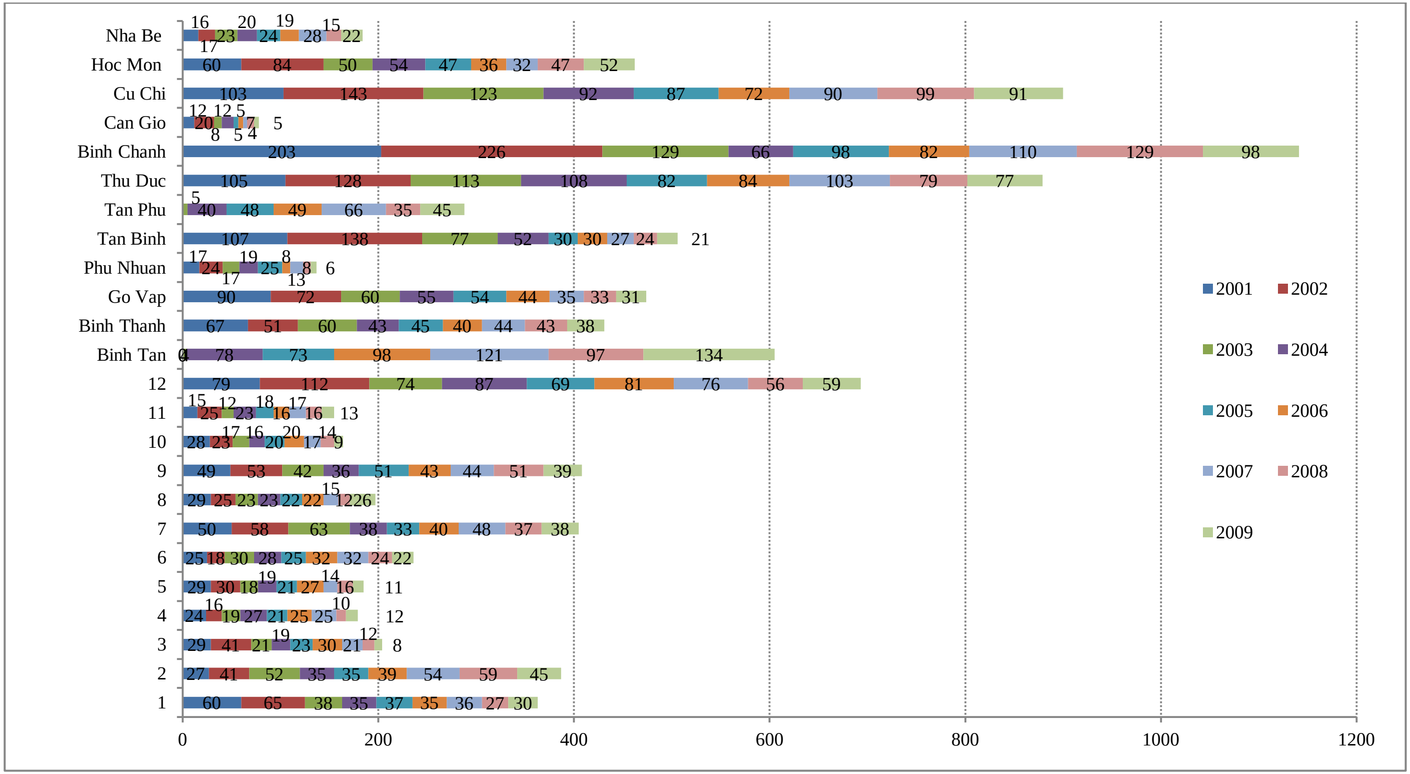

Figure 2.6 Road traffic deaths on 24 districts and suburban district from 2001-2009.

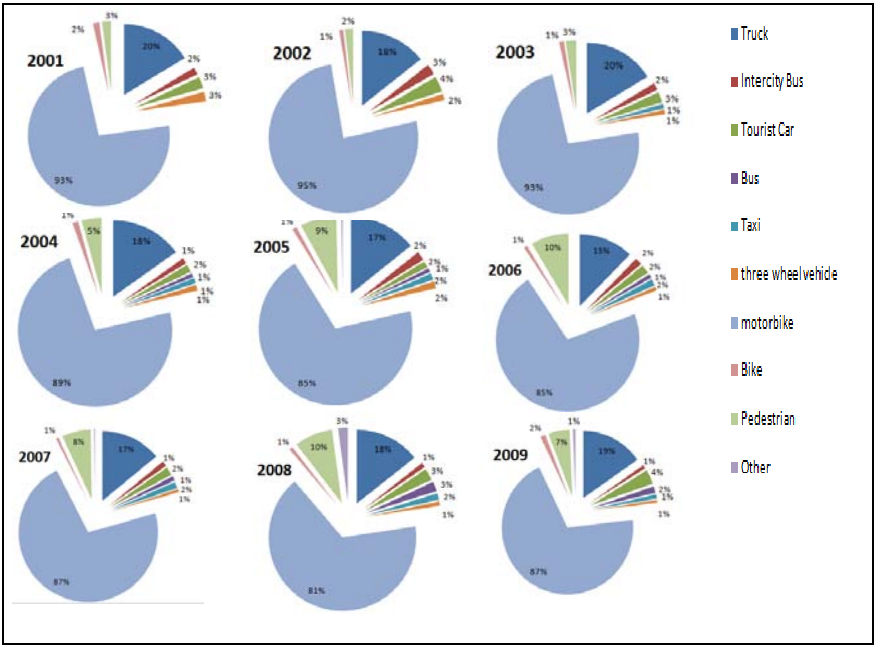

Figure 2.7 Number of road accidents by transport means.

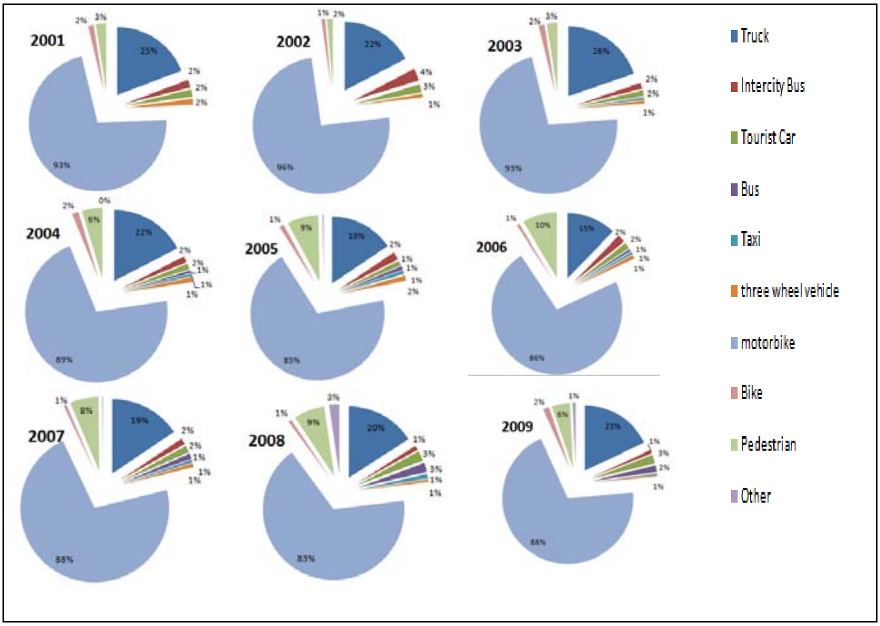

Figure 2.8 Number of fatalities by transport means.

✓ Road accident by road type

Almost road accident and death occurred on the highways and urban roads where had high traffic volume, mixed traffic and good road quality from 2001 to 2009. Road accident on urban roads decreased significantly as twice times from 68 of accident case and 64 of fatalities in 2001 to 33 of accident and 31 of fatal in 2009. Ratio of them on highway reduced slowly and unstably from 22% of accident, 25% of fatalities in 2001 to 13% of accident and 16% of fatalities. Beside that, accident and death on intersections increased from 2% of each of them to 17% of accident and 18% of fatalities during 9 years observation. After 2005, the committee of national road safety split collecting road accident of rural road type into suburban road type and rural road type. Number of road accident and fatal on suburban road climbed up fast from 3% (2006) to 18% (2009). Road accidents and fatalities on rural roads raised suddenly respectively 13% and 11% in 2009 (Figure 2.9).

✓ Road accident by age groups

Following three data collecting years (2007-2009), there were three age groups having high number of death on road, respectively 31-40 years, 19-24 years, 25-30 years, than other age groups (Figure 10). These three age groups occupied high ratio among of road fatal (60%) while they accounted for 38% of age structure of the population in 2009.

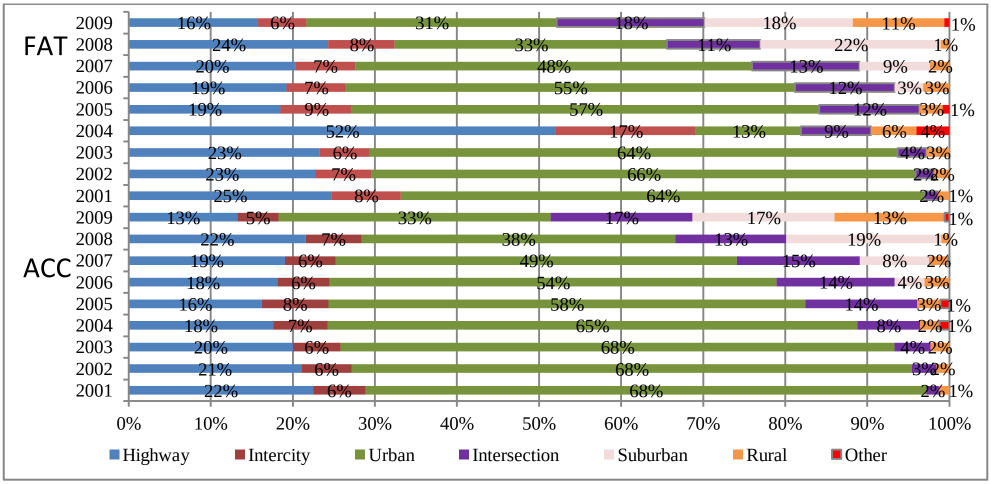

Figure 2.9 Road accidents by road type classification

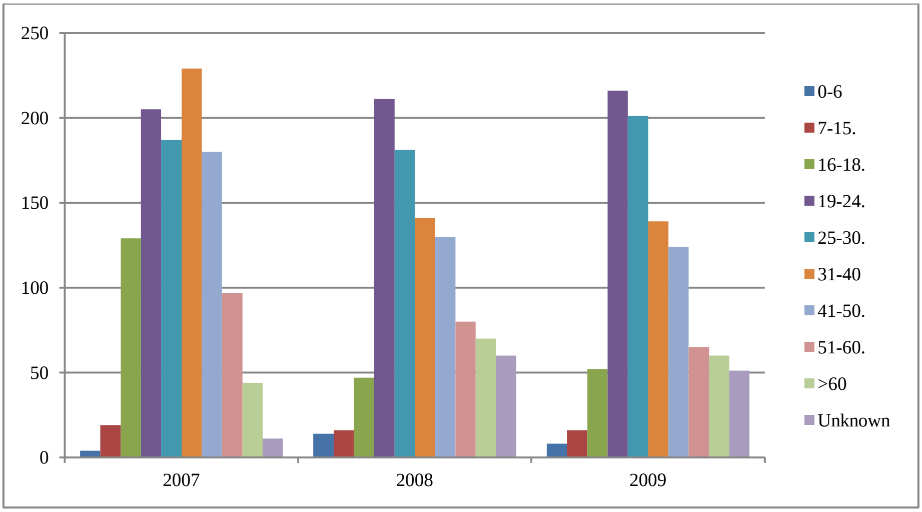

Figure 2.10 Road accident by age groups.

✓ **Road mode collisions**

The figure 2.11 shows that collisions of motorbike and pedestrian are the main cause for fatal (accounting for over 53%) in each year. The collisions between truck or car or bus and motorbike are the second cause to death (21%).

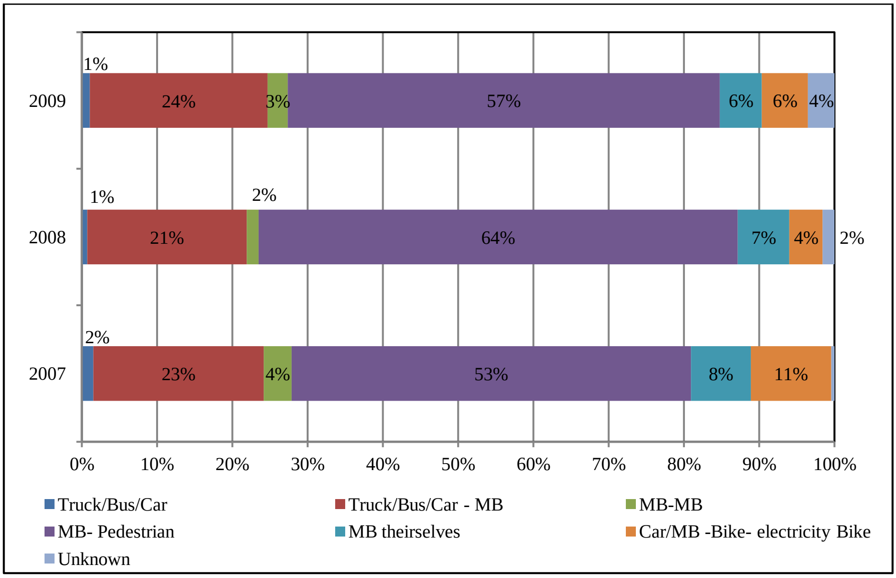

Figure 2.11 Collision among road modes caused death.

✓ Causes of road accident

Almost road accidents are identified main risk for road users, error of vehicle was very small taking 1% in 2009 while infrastructure accounted for 12% or 15% in 2001 and 2002 (Figure 2.12).

Averagely, the main causes of serious road accident are going on IDC (28%), driving on one-way road (21%), speeding (18%). The data of the figure 2.13 shows that almost cause of road accident related to road user behaviors.

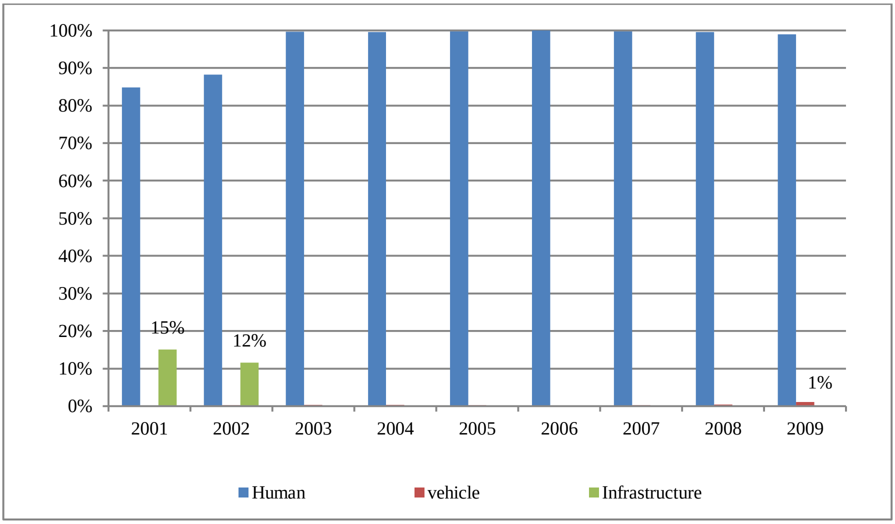

Figure 2.12 Risk of road accident

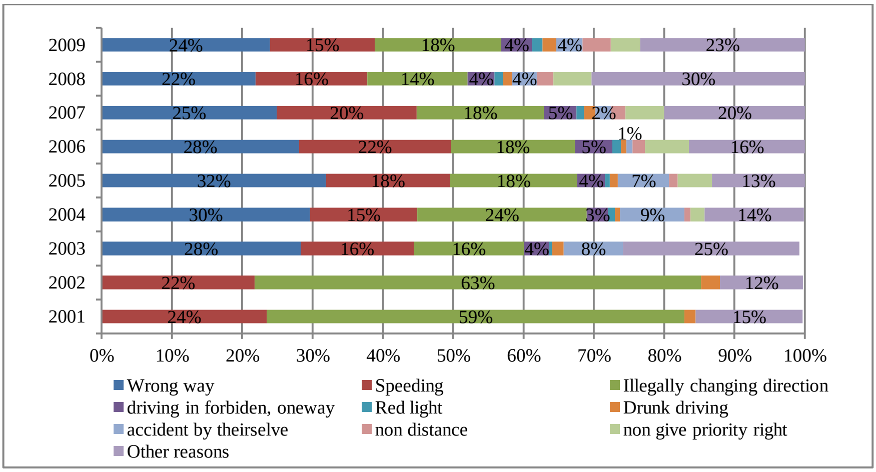

Figure 2.13 Road accident by causes

In fact, those data have not represented real causes of accident, because the road accident database is collected manually and unique; the staff is limited ability then they conclude mostly accident cause for road user behavior as breaking law traffic; almost accident cause is identified by individual factor.

2.3 Road Safety Management

Many related transportation departments do the road safety management as ministry of transport, the police, national and local road safety departments... The problems of road safety management are the low cooperation among the related departments, insufficient traffic signs, lacking of police for enforcement, lacking of infrastructure and facilities, inefficient traffic rule and law...

Some road safety awareness and educations are provided to kindergarten, schools, colleges, universities to increase road safety perception of pupils and students. Beside that, the media also is used to raise the road safety perception for road users by showing images of road accidents, advertising programs... Such as, wearing helmet policy for both motorbike driver and passenger is the most success program of the road safety campaign in Vietnam.

There are non-emergency along of the main road or highway or expressway for support road accident cases. Lacking of emergency and recuperation equipment and there is non-standard emergency in the provincial hospital (ICU - incentive care unit).

Chapter 3. Developing Road Accident Database

3.1 Selecting Road Accident Variables

Collecting appropriate road safety data which is available, reliable and comparable for data analysis is a very difficult task of all countries in the world especially Vietnam - known as a developing country. There are many indicators and variables, which are being applied in road safety models of many international studies researches and papers, such as number of accidents per year for passenger car, presence of any damage, number of accidents occurred in life time educational qualification, number of times of routine check-up of vehicles (Hashmi, Qayyum et al. 2012); number of accident, number of fatality, number of injury, number of people involved in the accident (Oyedepo and Makinde 2010), annual average daily traffic, total lanes, total of turn lanes (Maheshwari and D'Souza 2012); total of physical median, total of pedestrian crossing at the intersection, total of driveways, number of legs with extra hazards at the intersection (Noland 2003; Maheshwari and D'Souza 2012); other variables as total population, population age cohorts, per capita income, per capita alcohol consumption, seat-belt legislation and a proxy variable (Noland 2003); road geometric factors, weather conditions on the frequency of accident (Shankar, Mannering et al. 1995).

However most of them are inappropriate for applying to Vietnam due to lacking database. The research decides the data for collecting and analysing based on the past and worldwide studies, researches papers, the background of road safety in Vietnam (chapter 1) and the references of many Vietnamese experts, staff working on road safety field, and transport police whom have a lot of experiences of identifying road accident causes.

The increasing of the population of HCMC in recent years has been caused the increasing number of road user, big traffic congestions in both peak and peak off hours which are the main reasons of a huge number of road crashes. Therefore, the population density may be an impact of road accident in HCMC.

The people living standard becomes higher with each passing day, the travel demand for shopping, study, work and entertainment also increase which presents by travel coefficient. More travels raise more road accident crashes, or by another way, travel coefficients and travel density are leading more road accident (Hashimoto 2005; Mustakim, Yusof et al. 2008).

The higher living standard, the higher travel demand that are raising higher private vehicles which presents by number of car, motorbike and taxi, hence, these three factors involve to increasing number of traffic accident.

In the mean time, the roads have not developed timely which cause more traffic congestion and road crashes, it can be concluded that vehicle speed (Mustakim, Yusof et al. 2008), number of traffic congestion are impacts of road accident.

It is no double to recognize that road condition is one of factors impacting to road user travels. The wider roads would be decreased crash, on the contrary, the narrow, rough, bad roads would be difficult for traveling, higher traffic jam and increasing number of road traffic accident. The road condition includes road quality, kilometer road length, km^2 road per area unit effecting generally to number of road accident (Hashimoto 2005). Number of road traffic congestion as well as vehicle speed would impact to road accident.

The travel becomes complicated when traffic volume increases; it requests high attention, ability and cooperation of transport implementation, control, monitoring to ensure traveling safely and smoothly. The operation ability, control and monitoring of polices is the most important factor contributing to reduce number of road accident.

In general, road accident causes in HCMC are traffic law perception of road user, insufficient infrastructure (the upgrade and new construction do not meet the current traffic demand), rapid motor vehicle increasing (especially motorbike), low managing of transport and driver forces (ethnic of driver, concerning financial efficiency more than safety…), inefficiency of road traffic law education and awareness programs, un-strict enforcement and fines.

Based on these four main factors of road safety problems (mentioned in section 1.2), the sketchy above analysis and the limited database in Vietnam, the selected variables are proposed to evaluate road safety among districts and suburban districts of HCMC following four concepts of road safety causes, which show below:

- ✓ Human concept measures the following variables as Average car speed (SP), Road user's perception (BT).
- ✓ Vehicle concept presents the variable number of vehicle ownership (PC).
- ✓ Infrastructure concept uses variable as Road quality (SA) and Travel demand (DT).
- ✓ Environment concept mentions three variables as Budget for enforcement (EB), Average yearly income per person (AI), Population density (PD).

Those above-mentioned variables may be not independent with each other, some variables may depend linearity, hence, it needs selecting independent factors to number road accident.

3.2 Data Collection

The raw data is collected in 9 years from 2001 to 2009, in 24 districts/ suburban districts of HCMC. In the fact, there are 22 districts in two first years of the study. After 2003, Binh Tan was split from Binh Chanh suburban district; Tan Phu was separated from Tan Binh district. The detail information is conducted following:

- ✓ Output of road accident (dependent variables) such as number of road accident (ACC), fatalities (FAT), injuries (INJ); input of road accident such as road accident causes and road safety situations are all collected from HCMC Police Department, HCMC transport safety department.

- ✓ The remaining input data (independent variables) such as number of motorbike, car, taxi converted to PC; PD, AI, SP, BT, EB, SA, DT and the weighted of each item of integrated indicators are collected from the HCMC yearly statistic books, newspaper, projects, researches done in Vietnam and experiences of transport researchers.

Lacking of budget and ability, therefore, the authority governor offices collect some data through the central and the rural area of HCMC. Therefore, all districts in central area or rural area have the same ratio in some indicators such as habitant income. The thesis presents the different methods including linear regression method, weighting score method, consensus and traffic forecast method to build the completed database, which not only depend on the conducting raw data.

3.3 Developing Derived Data

3.3.1 Average Car Speed (SP)

Car speeds are conducted in the main roads of each district/ suburban district in 9 years, and the average are considered as presentation of speed for the whole district. The table 3.1 presents the speed is to reduce around 2-4 per year during 9 years at almost districts, because of increasing rapidly motorbikes and the main roads do not open widening or maintaining correspondingly. Contrary to those districts, the four suburban districts locate at the rural area (Can Gio, Cu Chi, Hoc Mon, Nha Be) opening new and wider some main roads and highways, hence, the average speed increases around 10-12 each year.

3.3.2 Road User's Perception (BT)

The number of traffic violations in the table 3.2 show road user's perception. The districts and suburban districts which are gateways of HCMC having higher number of breaking traffic rule than the other districts such as Binh Chanh, Binh Tan, Cu Chi, Thu Duc. The average of number of traffic rule in those suburban districts for 9 years are at least two times higher than its average (Figure 3.3).

Average speeds are higher in rural areas (Nha Be, Can Gio, Hoc Mon, Cu Chi) and the connecting area between HCMC and other provinces which having more highways (district No12, Thu Duc, Binh Chanh) and two new split districts from 2003 (Binh Tan, Tan Phu) (Figure 3.2).

Table 3.1 SP in 24 districts for 9 years

Unit: km/h

Districts	2001	2002	2003	2004	2005	2006	2007	2008	2009
1	19.637	18.958	18.302	17.669	17.058	16.468	15.898	15.348	14.817
2	16.724	16.137	15.409	14.776	14.334	13.828	13.374	12.874	12.384
3	17.090	16.456	16.002	15.586	15.165	14.708	14.231	13.885	13.127
4	18.567	18.316	17.957	17.652	17.110	16.513	16.025	15.550	15.587
5	18.971	18.266	17.791	17.316	16.151	15.649	15.056	14.620	14.164
6	20.322	19.907	19.459	19.100	18.560	17.925	17.297	16.691	16.440
7	16.378	15.571	14.834	14.203	13.652	12.973	12.133	11.591	10.878
8	17.857	17.367	16.874	16.328	15.809	15.301	14.762	14.359	13.712
9	16.629	15.743	14.917	14.214	13.650	13.141	12.612	12.141	11.390
10	16.674	16.029	15.619	15.118	14.669	14.156	13.716	13.341	12.693
11	19.892	19.114	18.540	17.988	17.535	17.087	16.654	16.291	15.112
12	41.468	40.675	40.214	38.687	37.555	36.902	36.124	35.679	35.607
Binh Tan	0	0	49.112	46.822	45.491	44.388	43.293	42.336	42.786
Binh Thanh	17.751	17.170	16.658	16.077	15.714	15.444	15.118	14.874	14.396
Go Vap	17.531	16.994	16.432	15.874	15.421	15.025	14.679	14.264	13.652
Phu Nhuan	16.129	15.903	15.689	15.446	15.174	15.056	15.166	15.058	15.500
Tan Binh	17.540	16.851	16.311	15.743	15.440	15.195	14.789	14.467	13.770
Tan Phu	0	0	46.064	43.066	43.180	41.814	40.896	39.718	36.508
Thu Duc	43.184	42.060	40.936	39.015	37.948	37.127	36.307	35.376	35.381
Binh Chanh	43.444	40.381	37.888	43.722	41.524	39.398	37.446	35.348	32.792
Can Gio	12.182	13.492	14.913	16.517	18.479	20.604	22.939	25.571	28.908
Cu Chi	15.694	17.453	19.444	21.715	24.123	26.661	29.543	32.968	36.428
Hoc Mon	15.694	17.327	19.307	21.527	23.848	26.637	29.208	31.961	33.952
Nha Be	14.374	16.021	17.852	19.671	21.934	24.421	27.134	29.692	31.499

Table 3.2 Road user's perception

Unit: case

Districts	2001	2002	2003	2004	2005	2006	2007	2008	2009
1	53692	48543	52845	53904	64025	54399	88579	111200	80392
2	42954	42927	52238	35423	40385	33112	59413	121625	83028
3	23011	28484	21260	22332	34475	29170	30247	41700	22404
4	35283	25676	33408	45434	41370	37843	31327	22588	23722
5	28764	31292	42519	51594	56145	39420	48611	64288	43491
6	26463	25676	26119	33113	29550	27594	45370	64288	34265
7	20710	22868	40697	33883	35460	33901	50771	62550	51398
8	15341	19658	35230	31573	34475	22863	22685	27800	39537
9	26079	34502	35230	47744	59100	53611	69135	112938	81710
10	42954	30891	24904	26182	22655	18133	19444	27800	18451
11	8437	15646	16400	26952	18715	15768	19444	24325	19768
12	84373	75824	82001	97798	83724	99337	140431	130313	89617
Binh Tan	0	0	2430	73926	73875	80416	140431	177225	184506
Binh Thanh	82456	60579	74105	71616	66980	46515	71296	100775	64577
Go Vap	46405	58172	73498	77006	102439	74897	69135	95563	68531
Phu Nhuan	28764	35706	20652	20792	35460	18133	22685	27800	10543
Tan Binh	67115	69806	54668	37733	31520	27594	31327	43438	27676
Tan Phu	0	0	2430	35423	47280	39420	73456	62550	61941
Thu Duc	100098	139211	99009	88557	82739	70955	110184	139000	104114
Binh Chanh	107768	120757	120876	75466	103424	67013	111264	217188	133108
Can Gio	16108	26952	16745	7884	8642	12163	10543	20862	22474
Cu Chi	65581	110889	120169	71743	112345	168538	123882	77429	111765
Hoc Mon	31832	50824	47280	29959	34568	85138	65895	42927	43127
Nha Be	11889	33883	26595	18921	43210	33013	36901	13640	34015

3.3.3 Number Of Vehicle Ownership (PC)

Number of vehilce ownership is measured totally by all motorbikes, private cars, taxi, family car (> 7 seats) of habitants. Motorbike and other vehicles are converted to passenger car unit following Vietnam vehicular converting standard (MOC 2007). The popular transport vehicle in Vietnam is motorbike in general and HCMC in particular, with average 150 cars and 1,300 motorbikes increasing per day in HCMC. Normally, the total vehicle per person was used to analyse road safety in previous researches. However in Hochiminh city (or Vietnam), the road authority agencies do not collect number of vehicle district by district. Instead of that, the total vehicle per person is identified through central and rural area of HCMC. Therefore, all districts in central area or rural area have the same ratio, it is a reason why total of vehicle ownership is selected to use in the model instead. The high number of vehicle ownership concentrates to suburban districts (Figure 3.2). Table 3.3 presents number of PC per district in each year from 2001 to 2009.

Table 3.3 Number of PC per district in each year

Unit: vehicle

Districts	2001	2002	2003	2004	2005	2006	2007	2008	2009
1	39871	41104	43786	46923	51141	55794	61025	67637	62786
2	19960	22271	25610	29195	32256	36180	40017	45352	51239
3	40415	42726	44969	47436	50987	55351	60515	65636	66607
4	37502	38664	40819	42978	47398	52787	57155	62986	63054
5	35118	36910	38471	40498	49161	53151	58811	64206	59832
6	48474	50949	54125	56969	62274	69147	75920	84816	88420
7	24008	27873	32258	36949	41856	49006	59747	69292	85041
8	64913	70348	76606	84591	93700	103681	114213	125272	142146
9	29844	34847	40677	46901	53136	59567	66460	74764	89518
10	45791	48883	51449	55447	60216	66363	72388	79263	79756
11	44574	47677	51220	54127	57794	63145	68954	75629	79543
12	38813	48915	57756	66616	76573	85295	99024	113759	141064
Binh Tan	0	0	76422	90642	103265	124270	140901	164251	201050
Binh Thanh	77938	84256	91625	99588	111364	125039	140603	155624	158485
Go Vap	64360	75266	89872	104426	119849	138090	154510	170957	181099
Phu Nhuan	33564	35845	38469	41370	44955	48862	54208	59161	61249
Tan Binh	128545	143531	77895	92440	100870	107737	120103	131808	144891
Tan Phu	0	0	77895	77895	95303	104728	116088	126452	139569
Thu Duc	47513	55095	66483	77535	88602	98957	110520	122502	155180
Binh Chanh	84679	107853	55198	70327	79744	91876	104287	122555	148120
Can Gio	11340	15566	16999	18727	20581	22824	23942	12546	13973
Cu Chi	51114	67780	75735	86051	96595	107221	120439	56330	61913
Hoc Mon	42465	57336	64422	70753	81533	95901	122442	47603	52176
Nha Be	12504	17020	18787	20828	23119	27179	34810	13674	14991

3.3.4 Budget For Enforcement (EB)

EB is measured by expenditure for road safety enforcement including salary for polices; facility investment budget for enforcement such as motorbikes, car, specific tools; budget for strengthening enforcement ability, cost of road safety control programs, cost of road safety campaigns and educations. The budget is collected from the traffic fines of road users by the polices of the previous year (Table 3.4). The high values are from rural districts (Can Gio, Hoc Mon) and new down town districts (Binh Tan, Binh Thanh, Go Vap, Tan Binh) (Figure 3.3).

3.3.5 Average Yearly Income Per Person (AI)

HCMC_Statistic-Department (2009) classifies the average yearly income per person in five groups; hence, the AI in each district in the same group is same value.

The group with highest AI consists district No 1, No 3, No 7, No 10 and Phu Nhuan. The second higher group are district No11, Binh Tan Tan Binh, Tan Phu while the third group concludes district No2, No4, No5, Binh Thanh, Thu Duc, Go Vap.

Table 3.4 EB value of each district

Unit: EUR

District	2001	2002	2003	2004	2005	2006	2007	2008	2009
1	42439.982	40643.831	40257.858	39871.562	40105.352	40346.360	40818.159	41463.623	36132.128
2	21231.986	22038.760	23657.193	24847.027	25266.453	26089.087	26746.327	27888.337	29543.019
3	43017.135	42425.719	41423.277	40229.647	39856.728	39878.481	40474.495	40098.859	38092.559
4	40026.274	38223.184	37436.577	36460.317	37068.073	38101.816	38077.155	38453.550	36098.004
5	37421.419	36628.255	35446.552	34468.495	38492.385	38306.059	39319.723	39352.408	34179.677
6	51619.706	50423.184	49828.597	48443.960	48648.624	49874.241	50711.741	51752.408	50541.561
7	25615.422	27620.648	29644.557	31444.982	32858.349	35291.210	39925.043	42348.288	48612.344
8	69211.424	69617.750	70438.572	71841.916	73256.728	74661.512	76055.870	76465.906	81163.342
9	31819.420	34631.153	37438.572	39863.384	41697.248	42944.239	44370.271	45867.743	51337.574
10	48831.986	48427.893	47227.266	47034.759	47037.278	47848.787	48247.888	48465.906	45476.228
11	47406.283	47214.127	47017.956	46035.781	45230.795	45442.424	46047.888	46057.667	45481.669
12	41462.828	48468.464	53089.780	56729.834	59937.766	61667.264	66345.865	69708.934	80770.240
Binh Tan	0	0	70202.661	77098.142	80921.560	89616.358	94145.865	100420.149	115362.261
Binh Thanh	83061.401	83454.699	84281.135	84695.076	87110.214	90125.148	93775.593	95038.908	90666.791
Go Vap	68634.556	74652.526	82680.470	88702.231	93768.561	99601.509	103170.271	104426.552	103483.126
Phu Nhuan	35821.419	35432.240	35422.611	35227.603	35258.349	35248.787	36255.870	36065.906	34843.557
Tan Binh	137049.977	142263.030	74259.854	78650.093	78851.866	77674.241	80077.155	80502.979	82714.340
Tan Phu	0	0	71602.661	72447.027	74677.798	75506.059	77580.913	77148.288	79855.901
Thu Duc	50674.538	54725.698	61108.401	65917.566	69336.145	71390.903	73871.370	74929.528	88830.133
Binh Chanh	90280.250	106909.036	50932.342	59900.187	62570.182	66380.297	69674.030	75114.889	84949.917
Can Gio	12011.995	13235.781	13227.554	13421.212	13821.284	14028.835	13643.557	12418.837	12824.606
Cu Chi	54448.835	57747.214	59397.736	62193.023	64676.692	65799.554	69111.801	55869.913	56922.367
Hoc Mon	45223.704	48667.473	50477.798	51080.604	54485.137	58601.837	70072.236	47238.760	48047.218
Nha Be	13408.853	14444.982	14643.762	15050.907	15506.421	16678.264	19952.451	13612.316	13837.242

District No 6, No8, No9, No12 consider as the fourth group. And the lowest group is suburban districts as Cu Chi, Hoc Mon, Binh Chanh, Nha Be, Can Gio (Table 3.5, Figure 3.2).

Table 3.5 AI per person in each district

Unit: EUR

District	2001	2002	2003	2004	2005	2006	2007	2008	2009
1	783.17	936.82	1083.07	1280.78	1497.84	1655.47	2071.39	2542.85	2864.59
2	286.03	346.37	375.07	417.60	491.86	504.29	644.93	802.80	845.71
3	783.17	936.82	1083.07	1280.78	1497.84	1655.47	2071.39	2542.85	2864.59
4	286.03	346.37	375.07	417.60	491.86	504.29	644.93	802.80	845.71
5	286.03	346.37	375.07	417.60	491.86	504.29	644.93	802.80	845.71
6	205.92	252.10	275.95	304.99	369.74	396.58	495.41	612.38	663.79
7	783.17	936.82	1083.07	1280.78	1497.84	1655.47	2071.39	2542.85	2864.59
8	205.92	252.10	275.95	304.99	369.74	396.58	495.41	612.38	663.79
9	205.92	252.10	275.95	304.99	369.74	396.58	495.41	612.38	663.79
10	783.17	936.82	1083.07	1280.78	1497.84	1655.47	2071.39	2542.85	2864.59
11	407.23	484.22	527.18	585.12	682.51	715.20	883.58	1071.12	1143.89
12	205.92	252.10	275.95	304.99	369.74	396.58	495.41	612.38	663.79
Binh Tan	0.00	0.00	527.18	585.12	682.51	715.20	883.58	1071.12	1143.89
Binh Thanh	286.03	346.37	375.07	417.60	491.86	504.29	644.93	802.80	845.71
Go Vap	286.03	346.37	375.07	417.60	491.86	504.29	644.93	802.80	845.71
Phu Nhuan	783.17	936.82	1083.07	1280.78	1497.84	1655.47	2071.39	2542.85	2864.59
Tan Binh	407.23	484.22	527.18	585.12	682.51	715.20	883.58	1071.12	1143.89
Tan Phu	0.00	0.00	527.18	585.12	682.51	715.20	883.58	1071.12	1143.89
Thu Duc	286.03	346.37	375.07	417.60	491.86	504.29	644.93	802.80	845.71
Binh Chanh	127.55	151.87	175.19	206.78	240.63	265.15	330.52	402.67	453.99
Can Gio	127.55	206.78	240.63	265.15	330.52	402.67	453.99	151.87	175.19
Cu Chi	127.55	206.78	240.63	265.15	330.52	402.67	453.99	151.87	175.19
Hoc Mon	127.55	206.78	240.63	265.15	330.52	402.67	453.99	151.87	175.19
Nha Be	127.55	206.78	240.63	265.15	330.52	402.67	453.99	151.87	175.19

3.3.6 Population Density (PD)

PD is a ratio between population and area of each district/ suburban district which are calculated through 9 years. The table 3.6 shows PD which is very high in the districts belongs to the downtown and tending to increase from time to time (Figure 3.2, Table 3.6).

Table 3.6 Population density in each district.

Unit: people/km^2

District	2001	2002	2003	2004	2005	2006	2007	2008	2009
1	27466.6	26322.6	26017.7	25775.8	25860.2	25972.6	26289	26662.1	23140.8
2	2180.65	2261.94	2413.48	2543.46	2586.87	2671.09	2734.04	2835.33	2995.1
3	43743.1	42988.2	41981.7	40940	40507.5	40482.1	40958.3	40650.8	38569.9
4	47774.4	45788.5	44853.1	43658.6	44322.5	45442.1	45532.3	45915.1	42976.1
5	43795.8	42789.7	41383.1	40273.1	45001.6	44791.1	45864.4	45818	39920.8
6	35901.5	35078.2	34576.5	33644.2	33854.8	34606.4	35162.2	35944.9	35036.4
7	3601.27	3886.7	4173.69	4419.58	4608.68	4967.35	5604.45	5947.63	6824.9
8	18022.4	18156.7	18345.6	18727.5	19095.5	19451.8	19829.5	19902	21114.5
9	1418.96	1540.21	1668.18	1778.13	1854.43	1913.79	1976.02	2034.07	2277.11
10	42629.5	42304.9	41313.3	41161.2	41148.6	41748.1	42142	42224.1	39724.8
11	46179.2	45916.9	45770.4	44715.4	43951	44206.2	44672.4	44834.8	44089.5
12	3991.58	4676.42	5123.29	5462.8	5780.34	5927.42	6368.31	6694.44	7761.57
Binh Tan	0	0	6809.31	7466.32	7830.13	8674.55	9101.86	9708.88	11111.5
Binh Thanh	19953.2	20052.5	20233.4	20330.5	20927.9	21631.9	22510	22798.4	21708
Go Vap	16398.1	17827.4	19751.3	21216.2	22414.7	23775.4	24618.1	24924.8	24686.8
Phu Nhuan	36625.2	36361.1	36208	35997.5	36007.4	36029.7	36990	36941	35757.6
Tan Binh	30586.1	31748	16556.7	17538.9	17617.6	17322.7	17870.6	17946.1	18444.9
Tan Phu	0	0	22361.9	22609.2	23282.4	23553.4	24160.8	24082.1	24852.2
Thu Duc	5297.53	5710.55	6393.78	6893.45	7251.44	7455.78	7705.86	7815.7	9256.91
Binh Chanh	1803.7	2135.62	1014.13	1194.49	1246.81	1322.42	1389.11	1493.76	1687.98
Can Gio	84.5784	92.5728	93.0588	94.3768	95.9874	97.402	95.5364	86.9818	89.8922
Cu Chi	628.61	664.681	683.677	715.122	742.871	754.54	792.453	644	656.758
Hoc Mon	2074.59	2233.6	2310.2	2335.76	2490.88	2680.95	3200.37	2161.94	2198.7
Nha Be	679.449	737.459	749.306	764.745	785.561	845.061	1011.96	690.694	702.612

3.3.7 Road Quality (SA)

Road quality is measured by the satisfied level between road capacity and travel demand, the research refers to other indicators related to this issue such as road surface and geometric characteristic. The road surface considers about the impact from road surface type and road surface quality to traffic flow. Besides, geometric road including road area density and road length density also effect to traffic flow. Then, getting a completed variable is necessary aggregating index to indicator and converting indicators to be a variable.

In the fact, variables have to aggregate from different indicators; hence, there are some aggregate methods presenting in the past researches, papers, projects such as the dimension analysis method, the benchmarking method, the consensus method, and the consensus method of AHP (Gozalez-Pachon and Romero 2007).

The consensus method is a quantitative method applying to aggregate indicators into variable, which weighted according to historical performance and forecast parameter for each variable model. The transport experts are asked to get their information about given indicators, aggregate variables, and weighted score of each indicator. This method is a strict process starting from establishing a transport expert group, evaluating this expert ability group, designing questions, asking – inputting and analyzing results from the expert's ideas. Otherwise, this method is used effectively to predict objects which interrupting of data in sometime or complicated forecast without the completed database. The method's result serves management orientation purpose and the other relevant additional quantitative methods.

Delphi technique is applied ranking the transport expert evaluation criteria and reaching decision consensus to predict and set weighted score of each indicator that is considered as a best method in the current data collection and management conditions in Vietnam.

This research applies consensus method and Delphi technique to identify impact levels of indicators to traffic flow and determine the weighted score of each indicator to aggregate a variable. The figure 3.1 presents the detail-weighted score for each index, indicator to aggregate data of satisfied travel demand of road capacity in 2003.

The best value of satisfied traffic demand on road capacity is equal 1; therefore, the other indicators measure by correlative efficient. Steps are to get a completed variable in the figure 3.1 presenting following:

(1) There are five type of road surface considering impact level to traffic flow, which shows in table 3.7. The road surface made by asphalt – concrete material is considered as the best road, and highest traffic ability (flow) when comparing to other road surface types, so it measured by 1 and non road measured by 0; the different ratios of other road surface arise from it.

The ratio of road surface type in 2003 shows in the table 3.8, which conducted by HCMC Transportation Department. As mentioned above, HCMC Transportation Department divided all districts/ suburban district of HCMC into five groups, hence, the districts/ suburban districts in same group having the same value. Group 1 consisted the old down town districts as district No1, No3, No4, No5, No6, No10, No11, Phu Nhuan. Group 2 was new down town area as district No8, Binh Tan, Binh Thanh, Go Vap, Tan Binh. Group 3 included districts of ring road area: district No2, No7, No9, Thu Duc, and Binh Chanh. Group 4 presented the suburban area (Hoc Mon, Nha Be). Finally, group 5 called rural area including Can Gio and Cu Chi suburban district.

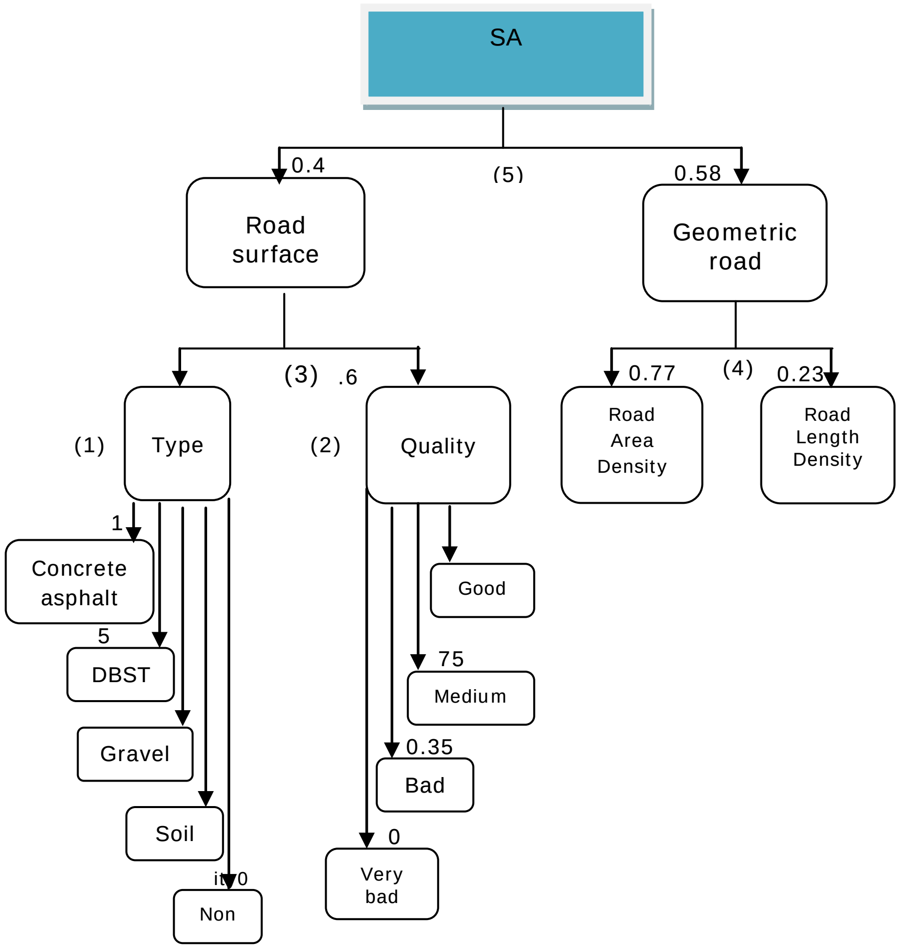

Figure 3.1 Average weighting score method

The table 3.9 presents the converting coefficient of road surface type from five types.

(2) There are four level of road surface quality: good, average, bad, very bad, as indicated in the table 3.10.

The best quality of road surface consides as 1 and very bad quality sets up 0. The table 3.11 shows impact level of road surface to the traffic flow following weighted score given by the transport expert inteview and the table 3.12 presents the converting coefficient of road surface quality.

Table 3.7 Road surface type impacts to traffic flow

No	Road surface type	Traffic ability	Score
1	Asphalt – concrete	reaching highest limitation speed, smoothy, easy driving	1
2	Double bituminous surface treatment (DBST)	A bit rough road, quite well driving, reaching averge limitation speed, driver have to pay more attention	0.75
3	Gravel	Rough road, falling down easily when driving high speed, slow speed, driving dificultly and may get crahs	0.4
4	Soil	Rough road, slow speed, driving dificultly, falling down easily because of weather	0.2
5	Non-road	Can not go	0.0

Table 3.8 The ratio (%) of road surface type in five groups in 2003

District Group	Concrete-asphalt	DBST	Gravel	Soil
Group 1	85.5	14.4	0.0	0.1
Group 2	74.4	24.9	0.1	0.6
Group 3	42.8	42.9	0.5	13.7
Group 4	15.3	62.0	3.5	19.2
Group 5	11.4	51.7	0.0	36.9

Source: HCMC_Transportation_Department (2004)

Table 3.9 Converting coefficient of road surface type from five groups.

District Group	Concrete-asphalt	DBST	Gravel	Soil	Coeeficient of road surface type
Group 1	0.8550	0.108	0	0.0002	0.9632
Group 2	0.7440	0.1867	0.0004	0.0012	0.9323
Group 3	0.4280	0.3217	0.0020	0.0274	0.7791
Group 4	0.1530	0.4650	0.0140	0.0384	0.6704
Group 5	0.1140	0.3878	0	0.0738	0.5756

Table 3.10 The percentage of road surface quality in each district in 2002.

District Group	Good	Average	Bad	Very bad
Group 1	10.3	81.1	8.1	0.5
Group 2	18.2	63.9	16.9	1.0
Group 3	2.6	62.1	21.6	13.7
Group 4	57.4	34.9	7.7	0.0
Group 5	21.8	67.4	7.7	3.2
Total	24.6	59.1	12.7	3.6

Source: HCMC_Transportation_Department (2004)

Table 3.11 The impact level of road surface to traffic flow

Level	Impact to travel flow	Weighted score
Good	Smooth road, highest speed of vehicle, easy vehicle control	1
Average	A bit rough road, high speed of vehicle, good vehicle control	0.75
Bad	Rough road, easy fall down, slow speed, difficult control	0.35
Very bad, non road	Vehicle could not go	0

There is one year (2002) having a full data of all above commented indicators in 24 districts, hence, after identify the weighted score of each indicator for 2002, the research uses the yearly investment budget of governor for constructing road network in each district, the yearly increasing ratio of road surface type, road length density, road area density to estimate a full database for 9 years in each district.

Table 3.12 The converting coefficient of road surface quality

District Group	Good	Average	Bad	RSQ efficient
Group 1	0.1030	0.6082	0.0283	0.7395
Group 2	0.1820	0.4792	0.0591	0.7203
Group 3	0.0260	0.4658	0.0756	0.5674
Group 4	0.5740	0.2617	0.0269	0.8626
Group 5	0.2180	0.5055	0.0269	0.7504

(3) The best road surface type is made by asphalt – concrete materials, if they are downgraded which may decrease strongly to the vehicle movement; therefore, the road surface quality has bigger impact than road surface type. The both impacts are evaluated by weighted scores in the table 3.13.

Table 3.13 Weighted score of road surface type and quality to traffic flow

Indicators	Features	Weighted score
Road surface quality	Big impact to traffic flow	0.6
Road surface type	Normal impact to traffic flow	0.4

Source: Transport experts interview

(4) In order to identify the impact of geometric road to vehicle movement, the research consider road wide and road length. The table 3.14 indicates the effect among road area density (RAD), road length density (RLD) and traffic flow.

Table 3.14 The weighted score for RAD and RLD

Geometric road	Content	Weighted score
RAD (Km2/km2)	The larger RAD is easier for transport move, it may decrease crashes	0.77
RLD (km/km2)	The longer RLD is to increase movement space for vehicle, it may decrease crashes	0.23

The table 3.15 presents the ratio of road area density and road length density in each district, the converting coefficients of each indicators and the geometric road coefficient.

(5) The best value of satisfied traffic demand on road capacity is equal 1, the weighted score of road surface and road geometric road coefficients are aggregated in 0.42 and 0.58 respectively (Table 3.16).

The interpolation method and consensus method are applied to predict a full database of satisfied traffic demand on road capacity for 9 years through data of annual investment and maintain budget of road of the government, annual increasing ratio of new road construction are applied to interpolation (Table 3.17).

Table 3.15 The Coefficient of geometric road

Districts	RAD (km^2/km^2,)	RLD (km/km^2,)	Converting Coefficient of RAD	Converting Coefficient of RLD	Geometric road Coefficient
1	17.6	9.41	0.6776	0.1680	0.8456
2	0.5	0.49	0.0193	0.0087	0.0280
3	12.9	7.82	0.4967	0.1396	0.6363
4	6.2	4.61	0.2387	0.0823	0.3210
5	23.1	12.88	0.8894	0.2300	1.1194
6	9.7	6.58	0.3735	0.1175	0.4910
7	0.8	0.73	0.0308	0.0130	0.0438
8	2.6	2.66	0.1001	0.0475	0.1476
9	0.4	0.36	0.0154	0.0064	0.0218
10	9.7	6.22	0.3735	0.1111	0.4846
11	8.8	6.20	0.3388	0.1107	0.4495
12	0.7	0.51	0.0270	0.0091	0.0361
Binh Tan	0.3	0.35	0.0116	0.0063	0.0179
Binh Thanh	3.3	2.67	0.1271	0.0477	0.1748
Go Vap	2.7	2.23	0.1040	0.0398	0.1438
Phu Nhuan	6.3	5.16	0.2426	0.0921	0.3347
TanBinh	3.0	2.20	0.1155	0.0393	0.1548
Tan Phu	3.0	2.20	0.1155	0.0393	0.1548
Thu Duc	0.6	0.54	0.0231	0.0096	0.0327
Binh Chanh	0.3	0.35	0.0116	0.0063	0.0179
Can Gio	0.04	0.05	0.0010	0.0009	0.0019
Cu Chi	0.4	0.54	0.0154	0.0096	0.0250
Hoc Mon	0.6	0.69	0.0231	0.0123	0.0354
Nha Be	0.2	0.26	0.0077	0.0046	0.0123

Table 3.16 Value of road quality in each district

Districts	Road surface coefficient	Geometric road coefficient	Value of satisfied traffic demand of road capacity
1	0.8290	0.8456	0.8595
2	0.6521	0.0280	0.3491
3	0.8290	0.6363	0.7521
4	0.8290	0.3210	0.5902
5	0.8290	1.1194	1.0000
6	0.8290	0.4910	0.6775
7	0.6521	0.0438	0.3572
8	0.8051	0.1476	0.4890
9	0.6521	0.0218	0.3459
10	0.8290	0.4846	0.6742
11	0.8290	0.4495	0.6562
12	0.6521	0.0361	0.3532
Binh Tan	0.8051	0.1438	0.4870
Binh Thanh	0.8051	0.1548	0.4927
Go Vap	0.8051	0.1548	0.4927
Phu Nhuan	0.8290	0.1748	0.5152
TanBinh	0.8051	0.3347	0.5850
Tan Phu	0.8051	0.0327	0.4300
Thu Duc	0.6521	0.0179	0.3439
Binh Chanh	0.6521	0.0250	0.3475
Can Gio	0.6805	0.0354	0.3674
Cu Chi	0.6805	0.0179	0.3584
Hoc Mon	0.7857	0.0123	0.4096
Nha Be	0.7857	0.0019	0.4042

Daily traffic value is high on a very central district (district No1), connecting districts between down town and rural area (Tan Phu, Tan Binh), connecting district between HCMC and other provinces (Binh Chanh) (Figure 3.3)

Table 3.17 Road quality

District	2001	2002	2003	2004	2005	2006	2007	2008	2009
1	0.7846	0.8595	0.9415	1.0315	1.1300	1.2378	1.3560	1.4855	1.6273
2	0.3187	0.3491	0.3824	0.4189	0.4589	0.5027	0.5507	0.6033	0.6609
3	0.6865	0.7521	0.8238	0.9025	0.9887	1.0831	1.1865	1.2998	1.4239
4	0.5388	0.5902	0.6465	0.7083	0.7760	0.8500	0.9312	1.0201	1.1175
5	0.9129	1	1.0954	1.2001	1.3147	1.4402	1.5777	1.7284	1.8934
6	0.6185	0.6775	0.7421	0.8130	0.8907	0.9757	1.0689	1.1710	1.2827
7	0.3261	0.3572	0.3912	0.4286	0.4696	0.5144	0.5635	0.6173	0.6763
8	0.4464	0.489	0.5356	0.5868	0.6428	0.7042	0.7714	0.8451	0.9258
9	0.3157	0.3459	0.3789	0.4151	0.4547	0.4981	0.5457	0.5978	0.6549
10	0.6155	0.6742	0.7385	0.8091	0.8864	0.971	1.0637	1.1653	1.2765
11	0.599	0.6562	0.7188	0.7875	0.8627	0.945	1.0353	1.1341	1.2424
12	0.3224	0.3532	0.3869	0.4239	0.4644	0.5087	0.5573	0.6105	0.6688
Binh Tan	0	0	0.5335	0.5845	0.6403	0.7014	0.7684	0.8418	0.9221
Binh Thanh	0.4497	0.4927	0.5397	0.5912	0.6477	0.7095	0.7773	0.8515	0.9328
Go Vap	0.4497	0.4927	0.5397	0.5912	0.6477	0.7095	0.7773	0.8515	0.9328
Phu Nhuan	0.4703	0.5152	0.5643	0.6183	0.6773	0.742	0.8128	0.8905	0.9755
TanBinh	0.534	0.585	0.6408	0.702	0.7691	0.8425	0.9229	1.0111	1.1076
Tan Phu	0	0	0.471	0.516	0.5653	0.6193	0.6784	0.7432	0.8142
Thu Duc	0.3139	0.3439	0.3767	0.4127	0.4521	0.4952	0.5425	0.5943	0.6511
Binh Chanh	0.3172	0.3475	0.3807	0.4171	0.4569	0.5005	0.5483	0.6006	0.658
Can Gio	0.3354	0.3674	0.4025	0.441	0.4831	0.5292	0.5797	0.6351	0.6957
Cu Chi	0.3272	0.3584	0.3926	0.4302	0.4713	0.5162	0.5655	0.6195	0.6787
Hoc Mon	0.3739	0.4096	0.4486	0.4915	0.5385	0.5899	0.6462	0.7079	0.7755
Nha Be	0.369	0.4042	0.4428	0.4851	0.5314	0.5822	0.6378	0.6987	0.7654

3.3.8 Travel Demand (DT)

Total daily trip is forecasted following the four steps of the classical urban transportation planning system model by (HouseTrans 2003) as trip generation, trip distribution, modal choice and route assignment. The gravity - attractive model and the trip distribution model are applied to estimate number of daily trip.

- ✓ The gravity and attractive model is linear regression models showing below:

  Gravity model: $G_i = \sum a_k x_{ki} + C$

  Attractive model: $A_{ji} = \sum b_k x_{kj} + D$

  where, x_{ki} : Variable of zone i; x_{1i} : population; x_{2i} : number of workers at workplaces; x_{3i} : number of student and pupil at school;

  a_k, b_k : parameter, C, D: constant.

- ✓ The trip distribution model has classified into two types such as in city and intercity models to predict number of trip. The local travel model:

$T_{ii} = I_{ii} G_i A_i$; where, T_{ii} : number of local trip in zone I; I_{ii} : ratio of local trip in zone i

The intercity trip model estimates number of local trip by separated model and the gravity model was developed to calculate number of intercity trip as: ; $T_{ij} = \kappa \frac{G_i^{\alpha} A_j^{\beta}}{d_{ij}^{\gamma}} \quad (i \neq j)$

where, T_{ij} : number of intercity trip between i and j; d_{ij} : constrain object between i and j; k, α, β, γ : parameters.

Table 3.18 shows the regression result of daily trip number in each district/ suburban district and figure 3.3 presents their trends in all studied districts.

Table 3.18 Travel deman in each district/ suburban district.

Unit: (1,000 trips/day)

District	2001	2002	2003	2004	2005	2006	2007	2008	2009
1	2387.3	2467.1	2549.6	2634.9	2723	2814.1	2908.2	3005.5	3106
2	431.9	483	540.2	604.1	675.7	755.7	845.1	945.2	1057.1
3	1448.8	1484.2	1520.4	1557.4	1595.4	1634.3	1674.2	1715.1	1756.9
4	896.4	887	877.6	868.4	859.2	850.1	841.2	832.3	823.5
5	1732.3	1758.1	1784.3	1810.9	1837.9	1865.3	1893.2	1921.4	1950
6	1850.8	1833	1815.3	1797.8	1780.4	1763.2	1746.2	1729.3	1712.7
7	552	584	617.9	653.8	691.7	731.9	774.3	819.3	866.8
8	1659	1670	1681.1	1692.2	1703.4	1714.7	1726.1	1737.5	1749
9	667.9	717	769.8	826.4	887.2	952.5	1022.6	1097.8	1178.6
10	1406	1421	1436.1	1451.4	1466.9	1482.5	1498.3	1514.3	1530.4
11	995.2	992	988.8	985.6	982.5	979.4	976.3	973.1	970
12	737.2	785	836	890.2	948	1009.6	1075.1	1144.9	1219.3
Binh Tan	0	0	841.48	896.04	962.69	1029.69	1101.36	1178.08	1260.10
Binh Thanh	2200.6	2189.9	2179.2	2168.5	2157.9	2147.4	2136.9	2126.4	2116
Go Vap	1322.5	1377.9	1435.5	1495.6	1558.2	1623.4	1691.4	1762.2	1835.9
Phu Nhuan	770.9	769	767.2	765.4	763.5	761.7	759.9	758.1	756.3
Tan Binh	3125	3192.9	3262.3	3333.2	3405.7	3479.7	3555.3	3632.6	3711.5
Tan Phu	0	0	3262.3	3333.2	3405.7	3479.7	3555.3	3632.6	3711.5
Thu Duc	1229.2	1279	1330.8	1384.6	1440.7	1499.1	1559.8	1622.9	1688.7
Binh Chanh	1789.3	1913.9	2047.1	2189.7	2342.1	2505.1	2679.5	2866.1	3065.6
Can Gio	214.5	219	223.5	228.1	232.8	237.6	242.5	247.5	252.6
Cu Chi	865.3	949.1	1041	1141.7	1252.3	1373.5	1506.4	1652.3	1812.2
Hoc Mon	754.5	789	825.1	862.8	902.3	943.5	986.6	1031.7	1078.9
Nha Be	221.9	244	268.2	294.9	324.3	356.5	392	431	473.8

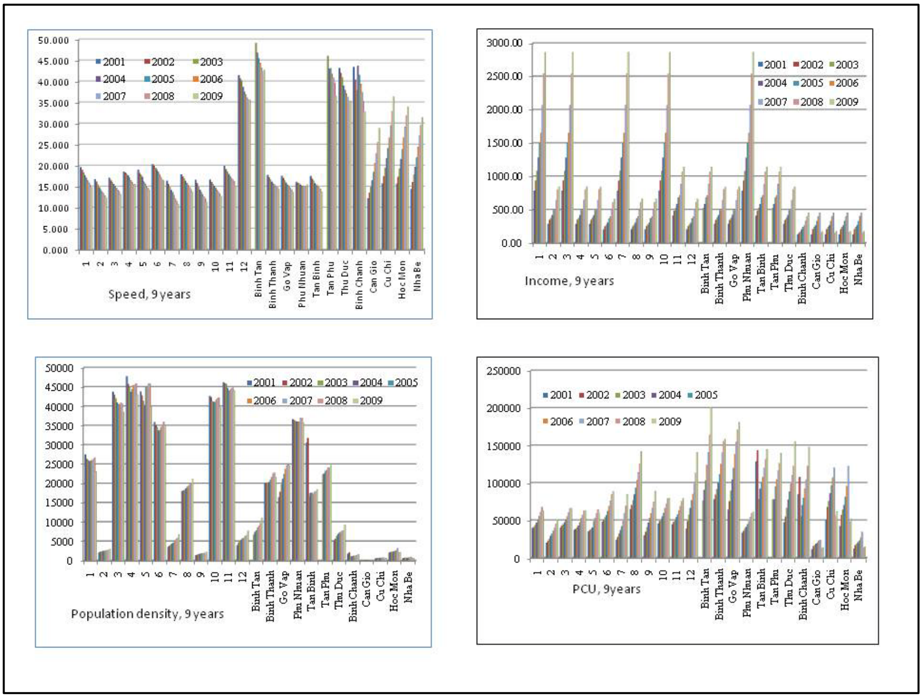

Figure 3.2 All variables values of 24 districts for 9 years (1)

Figure 3.3 All variables values of 24 districts for 9 years (2)

3.4 Pearson Correlation Test

In general, the results show almost the correlations between independent and dependent variables in all districts and the correlation among independent variables are significant at 0.01 and 0.05 level (Table 3.19). All correlation directions between dependent variables (ACC, FAT, INJ) and independent variables (eight selected variables) are significant explainable in HCMC.

PD, AI, SA have negative significant correlations to ACC, INJ, FAT that mean increasing PD (too crowded for moving), increasing AI (people care more on their health and safety, as well as more opportunities to choose better and safer vehicle), higher road quality (road capacity is higher leading the decreasing number of accident and then transport safety is improved) could reduce ACC, FAT, INJ.

Positive correlation between three dependent variables and other variables show that increasing independent variables make increasing dependent variables. The correlation between BT variable and other three dependent variables are positive that mean increasing BT variable (punishment due to violation caused by poor awareness) lead to increasing traffic accident consequences. SP variable have positive correlation in most of figures, showing that high traffic flow or high speed could cause increasing ACC, FAT, INJ. Traffic enforcement (EB) enhancing also force people to follow traffic law but the budget is contributed from the traffic violations then the number of accident is increasing.

DT and PC are positive significant with both ACC and INJ, that mean increasing travel demand and car ownership would lead increasing risk of ACC and FAT. But they are negative significant to INJ, showing that high traffic flow (DT) and car ownership could cause decreasing INJ.

Table 3.19 Variable Correlations

	ACC	FAT	INJ	PD	AI	SA	DT	PC	EB	BT	SP
ACC	1	.857**	.910**	-.286**	-.297**	-.335**	.138*	.190**	.282**	.651**	.449**
FAT		1	.627**	-.429**	-.254**	-.339**	.195**	.382**	.314**	.761**	.583**
INJ			1	-.205**	-.342**	-.364**	-.035*	-.043*	.204**	.391**	.224**
PD				1	.395**	.665**	.274**	.031*	.087*	-.349**	-.307**
AI					1	.570**	.186**	.103*	.074*	-.087*	-.219**
SA						1	.406**	.220**	.054*	-.067*	-.187**
DT							1	.567**	.372**	.248**	.194**
PC								1	.596**	.557**	.320**
EB									1	.276**	.303**
BT										1	.520**
SP											1

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

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

There is a significant correlation between independent and dependent variables. Above correlations show appropriate relationship between factors. It means that dependent and independent variables were chosen appropriate for building forecast model.

3.5 General Analysis Of Variables

3.5.1 Dependent Variables

Three dependent variables (ACC, FAT, INJ) are count numbers to not follow the normal distribution (Figure 3.4, 3.5, 3.6).

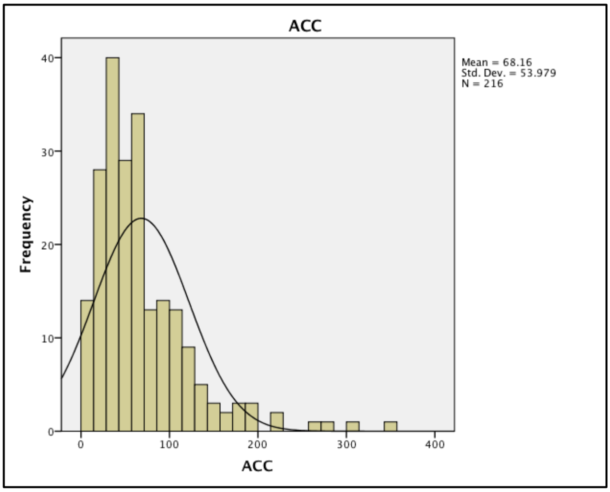

Figure 3.4 Number of accident distribution for 2001- 2009 of all districts in HCMC.

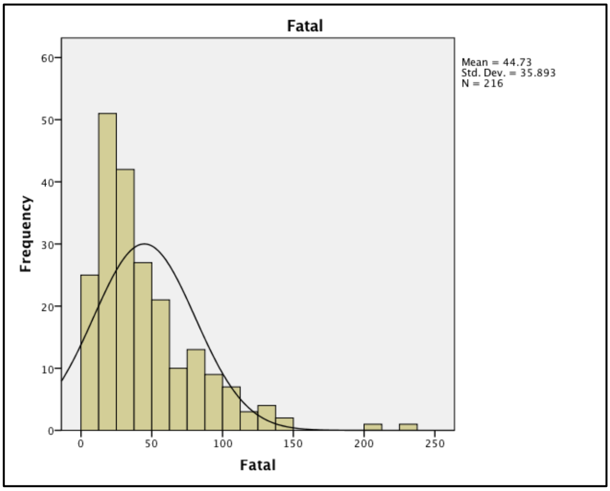

Figure 3.5 Number of fatalities distribution for 2001- 2009 of all districts in HCMC

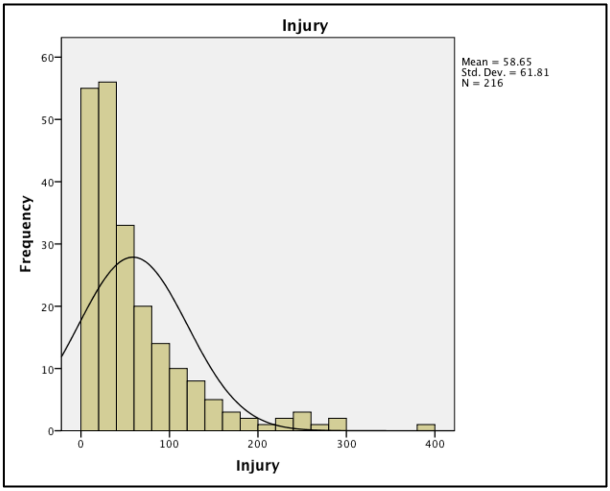

Figure 3.6 Number of injuries distribution for 2001- 2009 of all districts in HCMC

3.5.2 Independent Variables

The general analysis of variables are considered by the statistics values including the minimum, maximum, mean, standard error and variant values of data (2001 - 2009, all districts) that present in the following tables from 3.20 to 3.23.

The incoherent data set may be followed Regular, Binomial, Negative Binomial, Poisson or Metaphysics Distributions. The results shows: (1) the data is quite limited that including from 7 to 9 numbers, so it is very difficult to find the correct distribution rule; (2) almost the data has too large value of the standard error, the variant comparing to the mean value. The discrete data leads a very difficult to analysis.

Table 3.20 Average statistical results of PD and AI variables

District	PD					AI				
	MIN	MAX	MEAN	SD	VAR	MIN	MAX	MEAN	SD	VAR
1	23100	27500	25900	1100	1221800	780	2860	1640	680	465440
2	231	275	259	011	12218	286	846	524	188	35439
3	38600	43700	41200	1400	2068400	780	2860	1640	680	465440
4	43000	47800	45100	1300	1759400	286	846	524	188	35439
5	39900	45900	43300	2200	4755200	286	846	524	188	35439
6	33640	35940	34870	750	562730	206	664	397	152	23180
7	3600	6820	4890	990	984420	780	2860	1640	680	465440
8	18000	21100	19100	900	894950	206	664	397	152	23180
9	1419	2277	1829	248	61366	206	664	397	152	23180
10	39720	42630	41600	830	695200	780	2860	1640	680	465440
11	43950	46180	44930	790	616760	407	1144	722	245	59989
12	4000	7800	5800	1100	1119200	206	664	397	152	23180
Binh Tan	6800	11100	8700	1400	1834700	527	1144	801	220	48620
Binh Thanh	20000	22800	21100	1000	1033700	286	846	524	188	35439
Go Vap	16400	24900	21700	3000	8864600	286	846	524	188	35439
Phu Nhuan	35760	36990	36320	410	171560	780	2860	1640	680	465440
Tan Binh	17000	32000	21000	6000	32054000	407	1144	722	245	59989
Tan Phu	22360	24850	23560	820	674260	527	1144	801	220	48620
Thu Duc	5300	9300	7100	1100	1266700	286	846	524	188	35439
Binh Chanh	1010	2140	1480	330	107110	128	454	262	107	11400
Can Gio	84.58	97.40	92.26	4.06	16.52	128	454	262	107	11400
Cu Chi	628.6	792.5	698.1	52.9	2796.9	128	454	262	107	11400
Hoc Mon	2070	3200	2410	330	107770	128	454	262	107	11400
Nha Be	679.4	1012.0	774.1	97.1	9423.9	128	454	262	107	11400

Table 3.21 Average statistical results of SA and DT variables

District	SA					DT				
	MIN	MAX	MEAN	SD	VAR	MIN	MAX	MEAN	SD	VAR
1	0.7846	1.6273	1.1615	0.2719	0.0739	2387	3106	2733	232	53803
2	0.3187	0.6609	0.4717	0.1104	0.0122	432	1057	704	202	40659
3	0.6865	1.4239	1.0163	0.2379	0.0566	1448.8	1756.9	1598.5	99.4	988.57
4	0.5388	1.1175	0.7976	0.1867	0.0349	823.5	896.4	859.52	23.53	553.76
5	0.9129	1.8934	1.3514	0.3163	0.1001	1732.3	1950.0	1839.3	70.3	4939.1
6	0.6185	1.2827	0.9156	0.2143	0.0459	1712.7	1850.8	1781.0	44.6	1989.0
7	0.3261	0.6763	0.4827	0.1130	0.0128	552	867	699	102	10321
8	0.4464	0.9258	0.6608	0.1547	0.0239	1659.0	1749.0	1703.7	29.0	843.8
9	0.3157	0.6549	0.4674	0.1094	0.0120	668	1179	902	165	27153
10	0.6155	1.2765	0.9111	0.2133	0.0455	1.4060	1.5304	1.4674	0.0402	1.6123
11	0.5990	1.2424	0.8868	0.2076	0.0431	970	995.2	982.54	8.12	65.94
12	0.3224	0.6688	0.4773	0.1117	0.0125	737	1219	961	156	24198
Binh Tan	0.5335	0.9221	0.7131	0.1296	0.0168	841	1260	1038	140	19640
Binh Thanh	0.4497	0.9328	0.6658	0.1558	0.0243	2116.0	2200.6	2158.1	27.3	745.8
Go Vap	0.4497	0.9328	0.6658	0.1558	0.0243	1323	1836	1567	166	27453
Phu Nhuan	0.4703	0.9755	0.6962	0.1630	0.0266	756.3	770.9	763.56	4.70	22.16
Tan Binh	0.5340	1.1076	0.7906	0.1850	0.0342	3125	3711	3411	189	35834
Tan Phu	0.4710	0.8142	0.6296	0.1144	0.0131	3262	3711	3483	150	22422
Thu Duc	0.3139	0.6511	0.4647	0.1088	0.0118	1229	1689	1448	148	21987
Binh Chanh	0.3172	0.6580	0.4696	0.1099	0.0121	1790	3070	2380	410	169590
Can Gio	0.3354	0.6957	0.4966	0.1162	0.0135	214.5	252.6	233.12	12.28	150.91
Cu Chi	0.3272	0.6787	0.4844	0.1134	0.0129	865	1812	1288	305	93303
Hoc Mon	0.3739	0.7755	0.5535	0.1296	0.0168	755	1079	908	105	10957
Nha Be	0.3690	0.7654	0.5463	0.1279	0.0164	221.9	473.8	334.1	81.3	6604.7

Table 3.22 Average statistical results of PC and EB variables

District	PC					EB				
	MIN	MAX	MEAN	SD	VAR	MIN	MAX	MEAN	SD	VAR
1	40000	68000	52000	10000	90671000	36100	42400	40200	1600	2652700
2	20000	51000	34000	10000	99613000	21200	29500	25300	2500	6387700
3	40000	67000	53000	9000	85516000	38100	43000	40600	1400	1957400
4	38000	63000	49000	10000	90906000	36100	40000	37800	1100	1231400
5	40000	6000	50000	10000	109050000	34200	39400	37100	1900	3544200
6	50000	90000	70000	10000	192690000	48400	51800	50200	1100	1176500
7	20000	90000	50000	20000	372090000	26000	49000	35000	7000	50196000
8	60000	140000	100000	20000	610930000	69000	81000	74000	4000	13432000
9	30000	90000	60000	20000	338600000	32000	51000	41000	6000	31656000
10	50000	80000	60000	10000	148020000	45480	48830	47620	980	968420
11	40000	80000	60000	10000	135750000	45230	47410	46210	760	583360
12	40000	140000	80000	30000	955550000	40000	80000	60000	10000	122600000
Binh Tan	100000	200000	100000	0.0	1642200000	70000	120000	90000	10000	201320000
Binh Thanh	80000	160000	120000	30000	822600000	83000	95000	88000	4000	18347000
Go Vap	100000	200000	100000	0.0	1561900000	70000	100000	90000	10000	156420000
Phu Nhuan	34000	61000	46000	10000	90758000	34840	36260	35510	430	181270
Tan Binh	80000	140000	120000	20000	479930000	70000	140000	90000	30000	642850000
Tan Phu	80000	140000	110000	20000	477200000	71600	79900	75500	2700	7313200
Thu Duc	0.00	200000	100000	0.0	1058100000	50000	90000	70000	10000	117520000
Binh Chanh	60000	150000	100000	30000	707120000	50000	110000	70000	20000	267500000
Can Gio	11000	24000	17000	4000	17739000	12010	14030	13180	620	386680
Cu Chi	50000	120000	80000	20000	508500000	54000	69000	61000	5000	22433000
Hoc Mon	40000	120000	70000	20000	591250000	45000	70000	53000	7000	52332000
Nha Be	13000	35000	20000	7000	45777000	13400	20000	15200	1900	3704500

Table 3.23 Average statistical results of variables of BT and SP

District	BT					SP				
	MIN	MAX	MEAN	SD	VAR	MIN	MAX	MEAN	SD	VAR
1	48543	111200	67509	20148	405950000	14.8170	19.6370	17.1283	1.5555	2.4197
2	33112	121625	56789	30000	732170000	12.3840	16.7240	14.4267	1.3884	1.9276
3	21000	42000	28000	6000	41100000	13.1270	17.0900	15.1389	1.2072	1.4574
4	23000	45000	33000	7000	56046000	15.5500	18.5670	17.0308	1.0964	1.2021
5	30000	60000	50000	10000	115970000	14.1640	18.9710	16.4427	1.6142	2.6056
6	30000	60000	30000	10000	143550000	16.4400	20.3220	18.4112	1.3252	1.7562
7	20000	60000	40000	10000	167670000	10.8780	16.3780	13.5792	1.7473	3.0531
8	15000	40000	28000	8000	58188000	13.7120	17.8570	15.8188	1.3283	1.7643
9	26079	110000	60000	30000	657680000	11.3900	16.6290	13.8263	1.6200	2.6244
10	18133	43000	26000	7000	54238000	12.6930	16.6740	14.6683	1.2389	1.5348
11	8437	27000	18000	5000	25453000	15.1120	19.8920	17.5792	1.4001	1.9602
12	75824	140000	100000	20000	450400000	35.6070	41.4680	38.1012	2.1213	4.5001
Binh Tan	2430	200000	100000	100000	3693100000	42.3360	49.1120	44.8897	2.2574	5.0959
Binh Thanh	50000	100000	70000	10000	199270000	14.3960	17.7510	15.9113	1.0442	1.0903
Go Vap	50000	100000	70000	20000	261050000	13.6520	17.5310	15.5413	1.2110	1.4665
Phu Nhuan	11000	36000	25000	8000	60217000	15.0560	16.1290	15.4579	0.3638	0.1323
Tan Binh	30000	70000	40000	20000	244750000	13.7700	17.5400	15.5673	1.1217	1.2583
Tan Phu	2430	73456	46071	21834	476710000	36.5080	46.0640	41.6066	2.7924	7.7978
Thu Duc	70955	139211	103763	21922	48058000	35.3760	43.1840	38.5927	2.7330	7.4691
Binh Chanh	100000	200000	100000	0.0000	1650100000	32.7920	43.7220	39.1048	3.4304	11.7680
Can Gio	8000	27000	16000	6000	38920000	12.1820	28.9080	19.2894	5.3608	28.7383
Cu Chi	70000	170000	110000	30000	904970000	15.6940	36.4280	24.8921	6.6947	44.8188
Hoc Mon	30000	90000	50000	20000	280520000	15.6940	33.9520	24.3846	6.1178	37.4275
Nha Be	10000	40000	30000	10000	106300000	14.3740	31.4990	22.5109	5.7330	32.8674

3.5.3 Relation Between Independent And Dependent Variables

The relations between eight independent variables and three dependent variables are significant explainable in HCMC road safety situation. Some interesting findings are found:

(1) Higher average yearly income per person makes lower number of accident/ fatalities and injuries (Figure 3.7). In general, the people living in the central districts (old new down town) have higher AI than the suburban and the rural districts. The number of accidents, fatalities, injuries occur frequently in the rural and suburban districts (connecting between central districts and neighbor provinces) than the old and new downtown districts. Higher income makes people caring their health than before so they travel more careful; contributing more to develop road, road quality and vehicle quality.

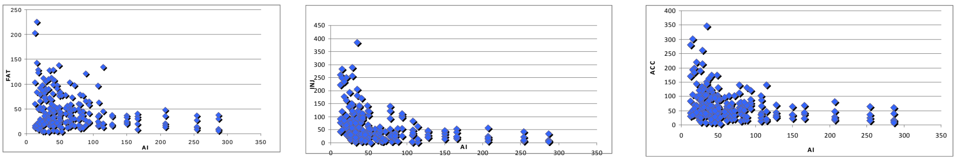

Figure 3.7 Relationship between AI and ACC, FAT, INJ

(2) Figure 3.8 shows PD scatter in three groups: low PD - rural area, higher PD - suburban area and highest PD - downtown area. Road users drive often faster, unsafe in the suburban and the rural areas. The road quality in the rural area is worst compare to the suburban and downtown areas. ACC, FAT, INJ happen more frequently in the low PD area - the rural areas than the suburban and the downtown areas.

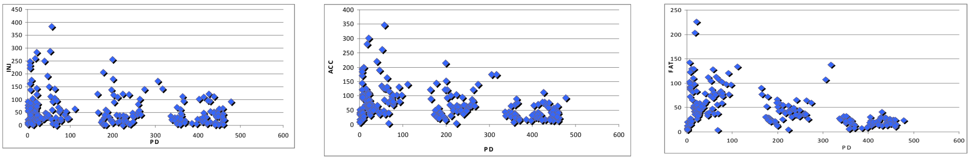

Figure 3.8 Relationship between PD and ACC, FAT, INJ

(3) Figure 3.9 presents low SP at the suburban area and high SP at the rural area making more FAT, INJ and ACC. But higher speed leads more FAT, INJ and ACC. The suburban area is the connecting districts between the downtown areas and the neighbor provinces of HCMC, there are big traffic congestions with differential vehicle mixed in the same lane. Road users drive usually dangerously to save the time on the road that why low speed but high FAT, INJ and ACC. Regarding the rural areas, low traffic volume, higher speed, driving faster and unsafely, low road user' perception are contributing more FAT, INJ and ACC.

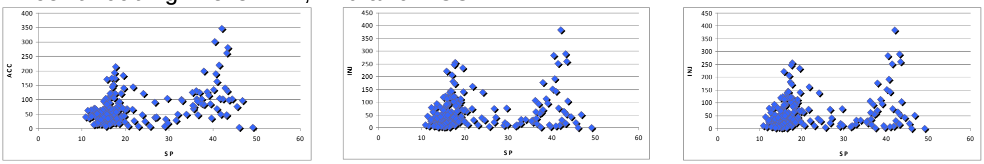

Figure 3.9 Relationship between SP and ACC, FAT, INJ

(4) DT in the suburban area leads higher ACC/ FAT/ INJ than in the downtown and the rural areas (Figure 3.10). DT in the downtown area is higher than in the suburban and in the rural areas.

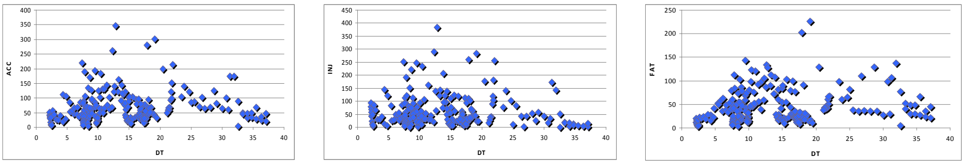

Figure 3.10 Relationship between DT and ACC, FAT, INJ

(5) Number of traffic violations are high in the rural area and decreasing in to the suburban and the downtown areas. But highest ACC, FAT, INJ occur on the suburban district area because of huge traffic volume, the mixed traffic vehicle, low road user' perception (that mentioned in (3)) (Figure 3.11).

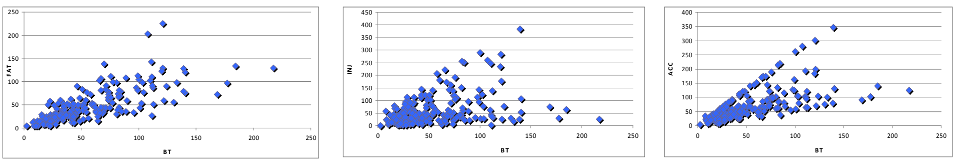

Figure 3.11 Relationship between BT and ACC, FAT, INJ

Chapter 4. Statistic Models

4.1 Introduction

The most important thing in building statistical regression model is to establish the mathematical model that describes the relation between happened events based on the rule of certain probabilistic distributions. In model analysis progress, it is necessary to carry out some statistical tests with respect to parameters, so the name of statistical model is used for including procedures of choosing probabilistic distributions and model tests.

In the traffic accident and road safety field, the observed data are the counts, so the discrete distributions is used in order to describe the change rules of data. Discrete probabilistic distributions in statistology are Regular, Poisson, Binomial, Negative Binomial, Bernoulli, Metaphysics distributions. To predict the observed data such as frequence of accident, injury, fatality in traffic safety, firstly the research checks if the observed data is followed by Poisson or Negative Binomial distributions. Secondarily the research proposes using the appropriate model (the generalized linear model) to estimate accident consequences in HCMC. Beside that, road accident prediction models and some important distributions are reviewing briefly in order to find out a suit model for the current database.

4.2 Literature Review

4.2.1. Variable Distribution Functions For Road Accident Prediction Models

In term of traffic safety analysis and road accident prediction models, road accident consequences are selected as output of the ananlysis or the dependent variables; relevant factors affecting the road accident consequences are selected as input of the analysis or independent variables or explanatory variables. The selecting and checking variable distribution type of the dependent and explanatory variables play an important role since they will determine type of the accident prediction model.

Road accident consequences can be assessed by the accident rate (AR), that called continuous numbers (Hashmi, Qayyum et al. 2012), or accident frequency (AF) called discrete counts, integer, non-negative number (Khan, Shanmugam et al. 1999; Turner and McClure 2004; TARC 2009). AR is the ratio of the number of accidents per vehicle or per traveling miles at a specific location or in a specific road segment (Wang 1989; Rakh, Arafeh et al. 2010), or severity level of the accident by weight score, the risk assessment of areas by black spots (Mustakim and Fujita 2011; Zou 2012). AF is the number of accidents/ fatalities/ injuries in the unit of time (year, month or period) or in a specific road/ highway or area. Explanatory variables are the traffic flow and geometric characteristics of the road, weather conditions (Usman, Fu et al. 2011), vehicle speed (A.Baruya 1998; Taylor, Baruya et al. 2002), number of traveled miles (P.Jovanis and Chang 1986)

If the road accident consequence variables are continuous numbersc and following normal distribution such as accident rates, severity of the accident; the linear regression model can be proposed to predict the road accident model by Sharad Maheshwari et al (2005), La Torre, Quaranta et al (2007), Olugbenga J. et al (2010), N.Hashmi et al (2012).

If the road accident consequence variables are discrete, non-negative, integers counts; such as the frequency of accidents; Poisson, Negative Binomial (NB), Zero-Inflated Poisson, Gamma distributions are applied to check the type of variable distributtion before selecting suitable road accident prediction models. The most common distribution for checking road accident variables are Poisson and NB distributions. The condition of Poison distribition is the average number of accidents must be equal to the variance.

In fact, road accident consequence data often exhibits over-dispersion meaning the variance is greater than the mean. So NB distribution is proposed to use popularly for the road accident prediction models as Mountain et al. (1996); Milton and Mannering (1998); Brüde et al. (1998); Mountain et al. (1998); Karlaftis and Tarko (1998); Persaud and Nguyen, 1998; Turner and Nicholson (1998); Heydecker and Wu (2001); Carson and Mannering (2001); Noland (2002) , Z. Sawalha et al (2003); Miaou and Lord (2003); Amoros et al. (2003); Hirst et al. (2004); L.Hiselius (2004) Abbas (2004); Young-jun Kweon et al (2004) Lord et al. (2005a); Parajuli et al (2006) ;El-Basyouny and Sayed (2006); Lord (2006); Kim and Washington (2006); S.C. Wong et al (2007) Lord and Bonneson (2007); Lord et al. (2009); Malyshkina and Mannering (2010b); Daniels et al. (2010); Cafiso et al. (2010a); M.Garnowski et al (2012). NB regression model has the same form of linear predictor and logarithm link function as Poisson regression models, except response dependent variable (Y) follows a NB distribution.

4.2.2 Road Accident Predictive Models

Multiple linear regression model was used popularly for predicting road accident consequences such as predicting number of driving accidents, expecting number of accidents per year for passenger car (Hashmi, Qayyum et al. 2012), number of accident (Oyedepo and Makinde 2010), estimating average number of accidents in specific period at signalized intersections (Maheshwari and D'Souza 2012), mortality rate, accident rate and fatality rate La Torre, Quaranta et al (2007). The condition of building mutiple linear regression is the dependent variables have to be continuous data.

If dependent variable are count number with non-negative discrete integer value, the use of linear regression model had unsatisfactory statistical properties (Miaou 1994). Accidents are discrete events and accident counts are nonnegative integers, Poisson regression is the most suitable models (Vogt and Bared 1998). Poisson distribution was implicated to solve the traffic problems (Gerlough 1955).

Poisson distribution has its probability being exponential function, a link function of the logarithm form is used for converting exponential to linear that called model Generalized linear model (GLM). Jovanis and Chang (1986) was considered as the first authors using the Poisson model to predict the number of accidents depended on the travel mileage and the hours of snowfall in Indiana Toll Road. Joshua and Garber (1990) analyzed the relationship between the number of accidents of large trucks and the highway geometric characteristics in Virginia using Poisson regression. The results showed that Poisson regression is proposed as a superior alternative to conventional linear regression but the disadvantages of this model can not handle overdispersion and underdispersion; negatively influenced by the low sample mean and small sample size bias.

If the data occurs overdispersion meaning that the variance is greater than the mean, NB regression models are used for predicting road accident consequences. NB regression models have the same form of linear predictor and logarithm link function as Poisson regression models, except dependent variable (Y) follows a NB distribution that called GLM using NB distribution.

NB regression model was applied popularity to predict accident frequency from road geometric factors (Shankar, Mannering et al. 1995; Poch and Mannering 1996; Garnowskia and Manner 2011), weather conditions (Shankar, Mannering et al. 1995), other demographic variables (Noland 2003), traffic-related elements (Poch and Mannering 1996), traffic flow (Hiselius 2004), average daily traffic (Garnowskia and Manner 2011), speed limit (Kweon 2004).

Noland (2003) showed infrastructure improvements did not reduce effectively number of fatalities and injuries. The demographic changes in age cohorts, increased seat-belt use, reduced alcohol consumption and increased in medical technology had accounted for a large share of fatalities reductions.

Poch and Mannering (1996) identified important interactions between geometric and traffic-related elements with accident frequencies. These findings provided a good approach to estimate benefits for reducing road accident from the various improvements at intersections.

Combination of applying NB regression to predict road frequency from traffic volumes and basic entity characteristics, Bishnu Parajuli, Bhagwant Persaud et al. (2006) applied new safety performance functions for interchanges, ramps and ramp terminals for Ontario freeways to overcome the limitations of conventional screening methods.

Hiselius (2004) applied both Poison and NB models to find the accident rate decreases when the homogeneous vehicle environment. Accident rate did not change or increase while studying vehicle separately (homogenous vehicle, car and truck). But the result for truck study was opposite direction, the truck increase leaded reducing accident rate.

To identify factors caused accidents on German Autobahn connectors, Garnowskia and Manner (2011) used the NB model basing a data set of 197 ramps for a period of 3 years (2003-2005). The three different types of ramps are investigated separately, and the average daily traffic was found as the most significant variable in all models and the geometric variables was significant variable.

Kweon (2004) studied speed limit impacting to numbers of fatalities, injuries, crashes and property-damage-only (PDO) crashes by the specifications of fixed-effects and random-effects Poisson and NB regression over 6,000 Washington State highway segments. It was found that the "10 mph speed limit" increase would lead to raise risky 78% and 24% of fatalities and injuries, respectively. Speed limit influenced negatively significant to total crashes (and property-damage-only crashes) that meant more serious road accidents.

Through previous mentioned studies, NB regression showed its predictive power of road accident models. The Modal Theory of the distribution, predictive model will mentioned more detail.

4.3 Modal Theory

4.3.1 The Poisson Distribution

Poisson distribution is a discrete probability distribution that expresses the probability of a given number of events occurring in a fixed interval of time or space; it arises when counting a number of events across time or over an area. The probability of an event within a certain interval does not change over different intervals and in one interval is independent of the probability of an event in any other non-overlapping interval.

Poisson regression models is the probability of discrete events such as traffic accidents according to the Poisson process as follows (Hashimoto 2005):

$$\Pr ob(n_i) = \frac{\lambda^{ni} \exp(-\lambda)}{n_i!} \text{, and } \quad \lambda = \exp(\beta x) \qquad (4.1)$$

Expected value (mean): $E(n_i) = \lambda$ (4.2)

Variance: $Var(n_i) = \lambda$ (4.3)

Where,

n_i is the target number of events on section i over a period of time t ;

λ is expected mean number of events;

x is a vector representing the independent variables of section i ; and

β is a vector representing parameters to be estimated;

Note that :

$$Var(n_i) = E(n_i) = \lambda \qquad (4.4)$$

According the definition and above mentions, the number of crashes (events) occurred in a fixed interval of time can obey Poisson distribution. So that, the Poisson regression model is a natural first choice for modeling for road accidents data in many researches and studies.

But the Poisson regression model can be applied when the mean and variance of the crash counts have to be equal.

4.3.2 The Negative Binomial Distribution

The NB distribution is probability distribution with trials k being minimum to make appearance of one event in r times. NB distribution is also applying popularly as Poisson distribution in lots of studies for predicting road crashes.

Notation: NB (r,p) , p€(0;1) (4.5)

Probability distribution function:

$$P(X = k) = C_{k-1}^{r-1} p^r (1-p)^{k-r}, \text{ while } k \geq r \quad (4.6)$$

Mean value: $$E(X) = \frac{r(1-p)}{p} \quad (4.7)$$

Variance: $$Var(X) = \frac{r(1-p)}{p^2} \quad (4.8)$$

$$Var(X) = \frac{1}{p} E(X) > E(X) \quad (4.9)$$

Note that:

When the count data has greater variance than the mean, NB distribution is an excellent alternative of Poisson distribution.

From Poisson model, NB model is raised following:

$$\lambda = \exp(\beta x_i + \varepsilon_i) \quad (4.10)$$

Where,

λ is expected mean number of events on section i ;
β is a vector representing parameters to be estimated;
x_i is a vector representing the an independent variable on section i ;
ε_i is error term, where $\exp(\varepsilon_i)$ has a gamma distribution with mean 1 and variance α
.

The resulting probability distribution is as follows:

$$\Pr ob(\frac{n_i}{\varepsilon}) = \frac{\exp[-\lambda_i \exp(\varepsilon_i)][\lambda_i \exp(\varepsilon_i)]^{ni}}{n_i!} \quad (4.11)$$

Integrating ε out of the expression produces the unconditional distribution of n. The formulation of this distribution is:

$$\Pr ob(n_i) = \frac{\Gamma(\theta + n_i)}{\Gamma(\theta) n_i!} u_i^{\theta} (1 - u_i)^{\theta} \quad (4.12)$$

Where, $u_i = \frac{\theta}{\theta + \lambda}$; and $\theta = \frac{1}{\alpha}$

The corresponding likelihood function is:

$$L(\lambda_i) = \prod_{i=1}^{N} \frac{\Gamma(\theta + n_i)}{\Gamma(\theta) n_i!} u_i^{\theta} (1 - u_i)^{\theta} \quad (4.13)$$

N is the total number of sections.

4.3.3 Generalized Linear Model

The general linear model can be expanded to become the generalized linear model by adding specified link function in order to take the dependent variable have linear relation to the factors and covariates. GLM uses statistical models such as linear regression for normally distributed responses, logistic models for binary data, log-linear models for count data and allows the dependent variable to have a non-normal distribution.

Let Y is the random variable that represents the accident frequency at a given location during a specific time period, and let y_i is a certain realization of Y. The mean of Y, denoted by λ, is itself a random variable (Kulmala 1995). The explanatory variables of the model involves X_1, X_2,... X_k, such as population density, traffic volumes, highway geometrics, vehicle speed… and so on.

GLM uses a link function to generalize the connection between the dependent and the independent variables:

$$\eta_i = g(\lambda_i) = b_i X_i \qquad (4.22)$$

In the case of the dependent variable has exponential function form of independent variables, the logarithmic function is normally used as link function.

$$\eta_i = \ln(\lambda_i) = \ln(E(y_i)) = b_i X_i \qquad (4.23)$$

When the model will take on form:

$$E(Y) = \exp \sum_{i=1}^{k} b_i X_i \qquad (4.24)$$

Where:

E(Y) is the dependent variable, in this case the expected number of accidents
b_i are parameters to be estimated by the model
X_i is the independent variables

The model design with a sum of bX terms is characteristic for linear models.

4.3.4 Multicollinear Issue

Multicollinear is the issue in regression. Multicollinear is a phenomenon in which many independent variables are depended each other. Two type of collinear phenomena are the perfect and the non- perfect collinear. Perfect collinear occures when between two variables there is an exact linear relationship as $x_{2i} = \measuredangle_0 + \measuredangle_{01} x_{1i}$, with $\measuredangle_0$ and $\measuredangle_{01}$ being parameters with determined values . The non-perfect collinear is a phenomenon of high correlation between the two variables.

The multicollinear phenomenon:

(1) Model with high R^2 values, while the value of t statistics is very low.
(2) Using the correlation matrix between the independent variables. Correlation coefficient of 0.6 or more is high, of 0.9 or more is very high.
(3) Using the adding regression model , if the R^2 of it is higher than in the main regression model then the multicollinear occurs in main regression model
(4) Using the formal detection-tolerance , or the variance inflation factor (VIF).

$$\text{tolerance} = 1 - R_j^2 ; VIF = \frac{1}{\text{tolerance}} \qquad (4.25)$$

If the tolerance is less than 0.20 or 0.10; or VIF of 5 or more is high multicollinear phenomenon, if VIF> = 10, the model occurs very high multicollinear.

To deal with the multicollinear phenomenon:

(1) Based on the a priori information, the previous research on similar issues under research.
(2) Collecting more data can surmount the multicollinear phenomenon
(3) To remove variable causing multicollinear from model. Choose variables being less statistically significant at first. (this is relative).
(4) Combining the data of time-series and the cross data can overcome the phenomenon of multicollinear.
(5) Using differential model

4.4 Data And Methods

(1) Selecting data (variables) for the predictive road accident model: dependent variables are ACC, FAT, INJ that predicted from eight selected independent variables as PD, SP, BT, PC, SA, DT, EB, AI (Section 3.1, 3.3). The study areas are in 24 districts of HCMC for 9 years.

(2) Checking distribution of road accident consequences: statistic results show the ACC, INJ, FAT of all districts do not fit the Poisson regression because of occurring over-dispersion that is the greater variance value than their mean values (Table 4.1). An alternative distribution is negative binomial distribution that can be used instead to predict the road accident models.

Table 4.1 Mean and Variance value of dependent variables

Content	ACC	Fatal	Injury
Mean	68.16	44.73	58.65
Variance	2913.715	1288.339	3820.516

(3) Checking multi-collinear phenomenon: PD and SA have very high correlation (larger than 0.6), these variables would affect to the significant result model when input two variables in the same time (Table 3.20). To avoid the multicollinear phenomenon, the database is divided into two separate data set then inputting to the predictive model for selecting the best predictive ACC, INJ and FAT models. One data set does not include PD variable and the remaining data set does not consist of SA variable. The data set makes a better model will be selected to input to the predictive models for the four groups. The results will show and discuss in section 4.3.3.

(4) Three predictive road accident models regarding ACC, FAT and INJ models of all districts are estimated (SPSS.20) by GLM which following negative binomial distribution. The first dataset (without PD) and the second dataset (without SA) are entered in turn to select a better model. The third dataset is a dataset making a better model of the first two steps, without a big insignificant variable of a better previous model. Best predictive models with an appropriate dataset are proposed to select. Aikaike' information Criterion (AIC) is used to select a better model, the value is in smaller is better form.

(5) In order to identify and select the power predictive models in each district group, the GLM models are estimated following negative binomial distribution. The dataset creating a best predictive model in step (4) are selected to predict the road accident models for each district group. The district groups are classified into four groups, which have similar social – cultural – economic development and traffic characteristic that divided following HouseTrans (2003):

- ✓ Group 1: Old downtown area (old central districts) are district No1, 3, 4, 5, 6, 10, 11, Phu Nhuan (16)
- ✓ Group 2: New downtown area (new central districts) includes district No8, BinhTan (13), Binh Thanh (14), Go Vap (15), Tan Binh (17), Tan Phu (18).
- ✓ Group 3: Suburban area presents district No2, 7, 9, 12, Thu Duc (19), Binh Chanh (20).
- ✓ Group 4: Rural area are Hoc mon (23), Nha Be (24), Cu Chi (21), Can Gio (22) district

The model result may give the difference of road accident causes among district groups and the whole HCMC. They would help the governor authority making suitable and better decision for improve road safety in HCMC.

4.5 Results And Discussions

4.5.1 All Districts

Table 4.2 presents the results of predictive road safety models (ACC, FAT and INJ) for the whole city by using the GLM.

In the first of two steps, the predictive ACC model of the dataset without PD variable is better than without SA variable (AIC is smaller is better). SP variable is contributed highest insignificant to the better predictive ACC model, so it would be withdrawn on the third step. The AIC has a smallest value in the third step but it is not a big value comparing to the better model without PD variable and it does not improve predictive power or β value. Then, the dataset without PD variable is proposed to use for predicting ACC model. The most significant and important variable of the ACC model is BT ($\beta = 30.778$, $p<0.000$) followed by PC ($\beta = 8.547$, $p<0.003$), DT ($\beta = 5.596$, $p<0.018$).

Similar with the predictive ACC model trend, the best predictive FAT is selected from the dataset without PD variable (first step). The FAT model is predicted form three significant variables as BT ($\beta = 22.157$, $p<0.000$), SA ($\beta = 8.072$, $p<0.004$), DT ($\beta = 4.127$, $p<0.043$).

Regarding the INJ model, the best predictive model is based from the dataset without SA and DT variables due to the smallest AIC (2099.907) and the significant of almost variables (except PD variable).

Table 4.2 Road accident model results

Model	Factor	(-PD) β	Sig	(-SA) β	Sig	(-PD-SP) β	Sig
ACC	(Intercept)	164.929	0	178.377	0	207.484	0
	AI	2.657	0.103	8.018	0.005	2.392	0.122
	DT	5.596	0.018	2.677	0.102	5.297	0.021
	PC	8.547	0.003	9.947	0.002	8.315	0.004
	EB	2.344	0.126	3.349	0.067	2.163	0.141
	BT	30.778	0	31.026	0	35.61	0
	SP	0.521	0.471	0.212	0.646		
	SA	3.114	0.078			2.848	0.092
	PD			0.171	0.679		
	AIC	2196.606		2199.391		2195.121	
FAT	(Intercept)	107.761	0	110.499	0	108.445	0
	AI	0.06	0.806	1.329	0.249		
	DT	4.127	0.042	2.762	0.097	4.171	0.041
	PC	0.446	0.504	1.109	0.292	0.453	0.501
	EB	0.555	0.456	2.001	0.157	0.552	0.457
	BT	22.157	0	16.958	0	22.087	0
	SP	0.415	0.52	0.467	0.494	0.483	0.487
	SA	8.072	0.004			10.851	0.001
	PD			3.58	0.058		
	AIC	2005.528		2009.539		2003.588	
INJ		-PC		-SA		-SA, -DT	
	(Intercept)	107.761	0	239.762	0	239.791	0
	AI	0.06	0.806	31.713	0	31.95	0
	DT	4.127	0.042	0	0.994		
	PC	0.446	0.504	38.312	0	42.681	0
	EB	0.555	0.456	10.709	0.001	10.904	0.001
	BT	22.157	0	47.956	0	48.49	0
	SP	0.415	0.52	8.411	0.004	8.432	0.004
	PD			2.636	0.104	3.078	0.079
	SA	8.072	0.004				
	AIC	2100.883		2100.327		2099.907	

The goodness of fit, omnibus test of all selected models present in the Appendix I.

Almost contributed variables explain positive significantly to predict ACC, FAT and INJ. BT is the most important variable due to the contribution of this factor to predict three road accident models. DT is the second important variable to estimate road accident consequences through ACC and FAT while PC is a variable to predict both ACC and INJ. The remain variables predict different model (FAT or INJ) like higher road quality may lead higher FAT. The interesting finding is better road quality (SA) will lead increasing number of fatalities. That is explained because of better road quality leading people higher speeding as well as inattention driving. Another interesting finding is more budget of traffic enforcement will lead increasing number of injuries. Because the budget of traffic enforcement is collected from the traffic fines of road users by the polices of the previous year, that means more traffic violations getting more budget.

The GLM is applied in each divided group of HCMC (4 groups) to clarify more detail contribution of all variables to the prediction road accident consequences.

4.5.2 Each District group

The datasets of the selected models in section 4.4.1 are entered to predict road accident (ACC, FAT, INJ) models by district group. The dataset without PD variable is used to predict ACC and FAT models while the dataset without SA and DT variables is entered to estimate INJ model.

Table 4.3 shows the selected dataset without PD variable contributing to predict ACC and FAT in the group 2 only. Otherwise, the dataset without SA and DT variables contribute significantly to predict INJ in the group 1 and group 2.

The most significant and important variable of the ACC model in group 2 is DT ($\beta = 10.943$, $p<0.001$), BT ($\beta = 9.569$, $p<0.002$) and AI ($\beta = 9.027$, $p<0.003$). Continuing with the FAT model in group 2, predicts four positive significant variables as DT ($\beta = 9.541$, $p<0.002$), AI ($\beta = 5.17$, $p<0.03$), SP ($\beta = 3.831$, $p<0.05$), BT ($\beta = 6.828$, $p<0.009$). For predicting INJ model, only PC and BT are positive significant in the group 1 while EB, BT, SA has positive significant in the group 2.

4.6 Conclusions

4.6.1 Variable Findings

Basing on the above results, there are three findings presenting below.

The first finding is to confirm the valid and useful proposed variables in predicting number of accident, fatality and injury in the whole HCMC. Half proposed variables are predicted significantly ACC and FAT models, especially almost variables are estimated significantly INJ model in the whole country by GLM.

The second finding is predicting inefficiently road accident models of different areas. The proposed dataset estimates only road accident models in the new downtown area (Group 2).

The third finding is the important and different role variables contributing to predict different road accident models of HCMC. BT is the most important predictor of all road accident models (ACC, FAT, INJ) and DT is the second important variable to estimate FAT and INJ model. Road quality (SA) has positive impact to FAT. That is explained because of better road quality leading people higher speeding as well as inattention driving. Budget of traffic enforcement will lead increasing number of injuries. Because the budget of traffic enforcement is collected from the traffic fines of road users by the polices of the previous year, that means more traffic violations getting more budget.

Table 4.3 Predictive road accident models by district group.

Model	Factor	Group 1		Group 2		Group 3		Group	
		β	Sig	β	Sig	β	Sig	β	Sig
ACC	(Intercept)	4.663	0.031	0.569	0.451	19.73	0	3.73	0.053
(-PD)	AI	1.289	0.256	9.027	0.003	0.018	0.894	0.783	0.376
	DT	1.99	0.158	10.943	0.001	0.04	0.841	1.981	0.159
	PC	2.248	0.134	0	0.992	0.008	0.931	0.81	0.368
	EB	0	0.988	1.113	0.291	0	0.998	0.064	0.801
	BT	2.158	0.142	9.569	0.002	2.013	0.156	0.435	0.509
	SP	0.362	0.547	3.055	0.081	0.23	0.631	0.034	0.854
	SA	1.547	0.214	2.79	0.095	1.259	0.262	0.123	0.726
	AIC	690.729		537.1		608.345		367.388	
FAT	(Intercept)	4.663	0.031	1.164	0.281	13.807	0	0.168	0.682
(-PD)	AI	1.289	0.256	5.17	0.023	0.108	0.742	2.441	0.118
	DT	1.99	0.158	9.541	0.002	0.238	0.626	2.692	0.101
	PC	2.248	0.134	0.007	0.934	0.076	0.782	1.354	0.245
	EB	0	0.988	1.075	0.3	0.019	0.891	0.21	0.647
	BT	2.158	0.142	6.828	0.009	0.725	0.394	0.749	0.387
	SP	0.362	0.547	3.831	0.05	0.102	0.749	0.026	0.872
	SA	1.547	0.214	2.192	0.139	0.866	0.352	0.716	0.398
	AIC	602.252		501.71		576.534		337.464	
INJ	(Intercept)	2.581	0.108	0.149	0.7	62.746	0	21.979	0
(-SA	AI	0.514	0.473	0.193	0.66	1.495	0.221	1.314	0.252
_DT)	PC	19.462	0	0.311	0.577	9.511	0.002	0.119	0.731
	EB	0.025	0.874	11.341	0.001	3.75	0.053	0.068	0.794
	BT	4.706	0.03	7.697	0.006	0.618	0.432	1.61	0.204
	SP	0.014	0.904	0.413	0.521	1.107	0.293	0.111	0.739
	PD	0.128	0.72	10.328	0.001	0.163	0.687	0.058	0.81
	AIC	658.479		536.647				365.532	

The increasing number of car ownership will contribute more traffic congestion (low speed) as well as increasing number of accident and injury. Average yearly income per person is a significant factor to predict INJ model while significant effect of average car speed (SP) in predicting INJ models.

4.6.2 Proposing Measures

The proposing measures are mentioned from the significant predictors of road accident models. The governor authority should consider all the proposing measures to improve road safety in HCMC.

BT finding shows that people awareness is poor and should be focus as the most important thing to reduce number of accidents, number of fatalities and injuries. The city authority is requested to conduct an traffic safety education campaign and propagandize for enhancing people’s awareness of traffic safety and people’s behavior of obeying traffic law.

Following DT findings, it is required for enhancing road network and control system in the whole country. DT shows number of trip as natural need which couldnot be cut off. Therefore the city authority required for improving old roads, building new roads, enhancing traffic control, warning and raising driver’s awareness in order to reduce the number of fatalities and injuries as shown in the model.

Controlling speed (SP) in the rural and suburban areas should consider seriouly. SA variable show limited road capacity that could meet the travel demand and then cause traffic accident in most of districts in the city. The city authority could focus on building road network to improve traffic safety.

EB variable has increased number of injuries in the whole country. Therefore control system and signal system should enhanced within those groups to reduce cost of traffic safety enforcement. Moreover, EB variable also presents the punishment fee amount, then it is required to conduct propagandization, caimpainge, and traffic law education to improve people’s awareness and then to reduce number of traffic law violation.

PC variable increase making reduction of accident and injury in the whole city. Therefore, people’s awareness and transport facility should be enhanced for the suburban area (group 3).

4.6.3 Limited And Future Research

The limitation of this study is limited database, so it do not enough to develop road accident models for each district group. Developing enough data samples for predictive road accident model by area, and ipust spatial and temporal dummy variables should be considered in the near future research.

Chapter 5. Data Envelopment Analysis Method

5.1 Introduction

Data Envelopment Analysis (DEA) is non-parametric mathematical programming method for estimation of the frontier (envelope) of data. DEA is a piecewise - linear convex hull approach for frontier estimate proposed by (Farrell 1957). However, the method did not receive wide attention until the published paper by Charnes et al. (1978) which named DEA. The primary idea of DEA is to measure the relative efficiency of decision-making unit (DMU). In 1984, Banker, Charnes et al. extended the Charnes, Cooper, and Rhodes (CCR) model to accommodate technologies. The Charnes, Cooper, and Rhodes - Banker, Charnes, Cooper (CCR-BCC) models and the generic approach DEA provide a good method to estimate relations between multiple inputs and multiple outputs without considering weight and unit measurement. For each DMU, the efficiency score was defined as the ratio of weighted sum of multiple output to weighted sum of multiple input (Cooper, Seiford et al. 2000), the model is formulated maximum to determine which DMU is efficient as much as possible. It means that maximizing outputs and minimizing inputs could be considered as much as better for efficient DMU.

Wei (2001) introduced the history, presents status of data envelopment analysis (DEA) as well as the extension of some DEA models. It was firgured out that mathematics, economics and management science were the main forces in the DEA development, optimization provided the fundamental method for the DEA research, and the wide range of applications enforced the rapid development of DEA.

Hayes (2005) presented briefly the important contents in DEA models and the extensions including prior valuations such as discretionary and non-discretionary variables, categorical variables, prior restrictions on weights, relationships between weights on variables, prior assessments of efficient units and substitutability of variables.

Some definitions on efficiency and relative efficiency, DEA model and CCR model in input - and output - oriented versions, each in the form of a pair of dual linear programs were mentioned by Cooper, Seiford et al. (2011).

DEA is accepted as an efficiency method using popularly in worldwide' science researches that consists of 3,203 publications from 2,152 different authors and different fields (Tavares 2002). Besides that, the development of computer software for solving the DEA linear programming (LP) problems made it considerably easier to use in practical applications. Because it requires very few assumptions, DEA has also opened up possibilities for use in cases which have been resistant to other approaches because of the complex (often unknown) nature of the relations between the multiple inputs and multiple outputs involved in DMUs.

While statistic models have basically had ability to predict accident consequences (number of accident, fatalities and injuries), and just help to identify factors impacting to the accident consequences in the whole country or in each district group (chapter 4), the DEA has proved itself as a really effective model with its ability to compare the road safety efficiency among districts and areas and to determine the benchmarking district for the whole city or whole district groups. This advantageous method has been very useful to help improve the road safety in Vietnam especially if the budget is very limited. Obviously, with a limited Government's budget, it is almost impossible to simultaneously address the road safety issues in all districts of HCMC. Therefore as a more efficient way to address the road safety issues, the investment would be focusing on the districts or areas where have the worst performance of road safety performent. Otherwise, statistic method could not classify which district is the best or the worst performer of road safety or it could not make comparison among districts or district groups.

In addition, DEA proves a strong model to analyse and assess for a wide range of data, so this method has been applied to analyse, to evaluate and to compare the traffic safety situations in the different zones (areas/ countries/ districts).

5.2 DEA Applications

5.2.1 DEA Application In Other Science Fields

DEA was developed and applied popularly in lots of fields worldwide such as Macro-economic, Sustainable Development, Economic Freedom, Human Development, Road Safety and so on (Puyenbroeck 2010). (Rebba and Rizzi 2003) applied DEA to measure the efficiency of 85 acute hospitals in Veneto, a Northern region of Italy. The empirical analysis helped to verify the precise role of weight restrictions and of demand in the measurement of hospitals' efficiency scores.

Banker and Morey (1986) evaluated means of mathematical programming formulations, the relative technical and scale efficiencies of decision making units (DMUs) when some of the inputs or outputs were exogenously fixed and beyond the discretionary control of DMU managers. DEA developed on both efficiency evaluation and estimation of efficient production frontiers. Authors also employed the model to provide efficient input and output targets of fast food restaurants.

In the study of Bampatsou and Hadjiconstantinou (2009), DEA was used not only to develop an efficiency index which combined economic activity, CO2 emissions and energy consumption of the production process in the 31 countries of Europe for the year 2004, but also to make estimates about the margins of long term increasing or decreasing in the consumption levels of exhaustible energy resources of a selected sample (Switzerland, Greece, United Kingdom, and Luxembourg) of European countries (out of 31) which belonged to the high income group of OECD members. The study concluded that each country could achieve better technical efficiency when its increased economic activity was combined with improved ecological performance. The noticed analysis showed the developed economies to tend stabilizing their environmental degradation through time (Switzerland), as the GDP (per capita GDP) increases, ensuring satisfactory margins for the increase in the consumption of the ‘dirty’ energy index (DEI) in the long term, and thus contributing to sustainable economic development. This fact was significant different in countries showing either intense deterioration (Greece) or temporary improvement (United Kingdom, Luxemburg) in the pollution levels without any indications of a temperate stabilization of environmental degradation.

Gavirneni presented a powerful analysis technique (DEA) to evaluate the relative efficiencies of various business units in the presence of a multinational chemical company, with six manufacturing plants located all over the world. The objective was to match customer demands with plant capacities at the lowest possible cost by multiple measures of performance (e.g., labor cost, material cost, etc.).

Mishra and Patel (2010) used DEA to evaluate efficiently the supply Chain Management (SCM). DEA had adopted as a systematic and integrative approach to manage the operations and relationship among different parties in supply chain. The study had investigated how quality management could be employed in SCM to improve performance in the whole supply network. This study developed an application guideline for the assessment, improvement, and control of quality in SCM by using DEA. Quality improvement was for all supply chain processes leading to cost reductions as well as service enhancement.

5.2.2 DEA Application With Other Techniques

An introduction of DEA and some important methodological extensions improved its effectiveness as a productivity analysis tool by Talluri (2000). Some concepts of efficiency score and DEA model proposed by Charnes, Cooper et al. (1978) that considered benchmarking in DEA, Performance Ranking, Weight Restrictions, Efficiency Changes Over Time, Other DEA Models. The author concluded advantages of DEA approach and some noted points as some critical factors; the efficiency scores could be very sensitive to changes in the data and depending heavily on the number and type of input and output factors and the size of the data set.

On the other hand, lost of different methods and models were combined with DEA to get a good analysis such as scoreboard approach, constructing a composite indicator, the archetypical composite indicator, some additional guidelines for CI’s, a stepwise exposition of BoD (benefit-of-the-doubt), benchmarking, dynamic analysis, robustness and sensitivity analysis; imprecise (original) data; least favorable weights (Puyenbroeck 2010).

Toloo and Nalchigar introduced the importance of exploitation, utilization of data that called data mining. Many data mining techniques had also been presented in various applications, such as association rule mining, sequential pattern mining, classification, clustering, and other statistical methods. A new methodology was proposed for prioritizing association rules that are valuable patterns deriving from large databases. Besides that, using a method of a non-parametric linear programming technique as DEA was proposed for ranking the units.

Vu (2005) estimated technical efficiency obtained from both DEA and stochastic frontier approach using household survey data for rice farming households in Vietnam. A bootstrap method is used to provide statistical precision of DEA estimator. Technical efficiency is modeled as a function of household and production factors. The results from the deterministic, semi-parametric and parametric approaches indicate that among other things, technical efficiency is significantly influenced by primary education and regional factors. In addition, scale efficiency analysis indicates that many farms in Vietnam are operating with less than optimal scale of operation, especially in the Center region.

The first time, DEA and SFA (Stochastic Frontier Analysis) methods were applied on the Measurement of Operating Efficiencies for 27 International Container Ports, from 1999 to 2002 by (Lin and Tseng 2005). The operating efficiency of a port was the critical element for its competitiveness in the international market, since more than 80 of the global international trade was conducted by way of maritime transportation. The result showed that Hong Kong port demonstrated the best performance in each model. Besides that, three hypotheses for port performance, including the geographical location of port, port administrative structure, and national economic growth rate were performed. The operating efficiencies were not significantly difference between two first hypotheses but the last hypothesis presented significant difference in DEA model.

Nadimi and Jolai (2008) combined two techniques DEA and Factor Analysis (FA) to data reduction in DMUs. FA method was a statistical method basing on the correlation analysis of multi-variables. The FA/DEA method had been proposed as data reduction and classification technique, which could be applied in DEA technique for reduction input –output data. Numerical results revealed that the new approach was a good consistency in ranking with DEA.

Huang, Lin et al. (2008) studied to elucidate how governmental officials could solve the problems surrounding municipal solid waste management in Metropolitan-Manila. Cost-benefit analysis (CBA) and DEA were applied to determine the benefits and cost / input and output technical efficiency of alternative projects, which afforded financial data information that evaluators can use for economic decision-making regarding MSW projects. Results of this study suggested that the thermal process technology was less efficient than resource recovery using DEA. Nevertheless, the net benefits of resource recovery exceeded those of the thermal process technology by CBA.

Novaes and Paiva (2010) introduced the application of real estate pricing DP DEA – Double Perspective Data Envelopment Analysis to solve the LOOP (Law of One Price) arbitrage. A general equilibrium model of real estate values was developed to analyze price variation over digital map, and applied to urban area of the city of Joinville. The DP-DEA made use of two encapsulating surfaces that enfold in an n-dimensional space, all the observed data. Real estate units from the point of view of either the seller or the buyer presented an “efficient” price. Value of the remaining units could be assessed by taking the envelopments as frameworks, under an output- oriented or an input-oriented DEA model. The LOOP/DP-DEA was the market value that estimated between the two encapsulating surfaces, which minimized the median obsolete deviation of whole distribution. The power of real estate locational value assessment using DP-DEA was then compared with the usual MRA-Multiple Regression Analysis using a real case of land data. All computational generated results and data were subsequently geocoded on GIS - Geographic Information System. The computational Price line Map was easily visualized in a real estate value chart, that could enhance accuracy when compared to a conventional methodology, and a tool for immediate updates and testing the effects of new development over urban areas.

5.2.3 Applying DEA In Traffic Safety

The weight of the individual indicator in the construction process of a composite road safety performance indicator was mentioned by Hermans, Van den Bossche et al. (2008). In that study, five commonly used weighting methods were investigated. They were factor analysis, analytic hierarchy process, budget allocation, DEA and equal weighting. These methods were applied to combine six safety performance indicators for ranking road safety in 21 European countries and their advantages and disadvantages were discussed. DEA confirmed a valuable and helpful method for development of a road safety index.

Outcome indicators of road safety such as number of fatalities, crashes and the inputs including alcohol-drugs, speed, protective system, vehicle, infrastructure, trauma management are applied by DEA method to evaluate road safety (Hermans, Brijs et al. 2009a). The efficiency of road safety was the score between total of weighted outputs and total weighted inputs. The optimal score equaled to one would present the efficient country. Inefficient country had score more than one. Obtaining realistic and acceptable weights was based on the expert opinions such as the assignation on contribution of six risk factors to road safety. From DEA results, an overall ranking of the countries can be made based on their optimal road safety score. Next, for inefficient countries with an index score larger than one, the country-specific weights could identify the sources and the amount of inefficiency in each indicator. For each inefficient country, another country in the data set can be taken as a benchmark. Based on the indicator values of the benchmark country and a country-specific adjustment factor, useful targets could be set for the inefficient country and the achievement towards in the future. The data from 21 countries involving six inputs and two outputs were collected and computed. It is affirmed that DEA was a very suitable method in evaluating road safety of a country and in comparing the road safety situations among countries. Hence each country would have their own priority policies to aim restricting risk factors and improving the road safety in order to become as good as the benchmark country.

Combination of basic DEA method and Malmquist index was used to estimate the road safety situation of 26 EU countries which measures of exposure including the number of inhabitants, passenger cars, and passenger-kilometers travelled (Shen, Hermans et al. 2010). Malmquist productivity index measured the productivity change over time and was presented into two components: the change in efficiency and the technical change. The decomposition of the DEA-MI showed that the bulk of the improvement was attained through the adoption of new road safety technologies or strategies, rather than through the relatively inefficient countries catching up with those efficient ones.

Shen, Hermans et al. (2010) presented a trauma management (TM) index which is considered as a key method to avoid death and disability for reducing the severity and injury. The most optimal TM index score, including 17 TM performance indicators related to emergency medical services and permanent medical facilities, was computed for 21 European countries. Besides that, not only DEA but also multiple-layer DEA (MLDEA) model were explored and developed to reflect the hierarchical structure of the indicators. The weights assigned to the indicators of each layer of the hierarchy are deduced to provide insight into the critical aspects of the prevalent TM system. A country was evaluated in accordance with the index score, and a particular set of benchmark countries was identified for those countries with relatively poor performance. The developed MLDEA model was concluded to provide useful results.

In the same road safety study series, Shen, Hermans et al. (2012) presented the primary DEA model, dual DEA model, and advantages of DEA to estimate the overall optimal road safety efficiency score for each of 26 EU countries in the considered time. Selected risk indicators for evaluating road safety were the number of fatalities per million inhabitants, the number of fatalities per million passenger cars, and the number of fatalities per 10 billion passenger kilometers travelled (pkm). Although, one country (A) with optimal weights had a score not equal to one, but its weights created a score of one for another country (B), then second country (B) could become the benchmark for the first country (A) to improve its road safety performance. From calculated results following the dual model, the dual weights of each country were determined by the sample country, hence the target numerical value would be defined. The target fatalities were always smaller than fatalities in reality. It proved each less performing country could learn from benchmark country on priority policies concerning risk factors in road safety.

5.3 DEA Methods In The Research

The application of original DEA, DEA-based Malmquist (DEA-MI) method and composite index may be useful and powerful methods for the road safety analysis with wider and different scale data that may not suit in the other methods, especially for Vietnam case.

5.3.1 Selecting Inputs – Output

As usual, road safety efficiency has been mainly measured by accident consequences as number of accidents, number of fatalities through statistic models as mentioned above (chapter 4). It is obviously admited that reduction of number of fatalities (FAT) is the top priority of road safety performance improvement. Hence, number of fatalities (FAT) is considered as the output of road safety performance to study in this chapter.

Eight indicators are selected as inputs. They are PD, SP, BT, PC, SA, DT, EB, AI (mentioned in Chapter 3). Different inputs will be used in the different DEA methods in this chapter.

To evaluate the efficiency (basic DEA and DEA-MI methods), four exposure indicators are considered as the inputs: PD, DT, AI, PC.

All eight indicators are combined in the composite index method.

All the data (inputs and output) are showed in Chapter 3. The period is considered for applying DEA methods in 2004 – 2009 because of separating districts of HCMC in 2003 (mentioned in Section 3.2).

In order to identify and to compare the efficiency of 24 districts in 6 years, the studied area is divided into four groups (same as chapter 4), which have similar social - cultural – economic development and traffic characteristics. So the efficiency of road safety is mentioned both per district and per group by basic DEA and per district over time by DEA-MI.

5.3.2 Basic DEA Modeling

The basic DEA is applied to consider the efficiency in each district, in each year separately to find the best district as benchmark for other districts having lower efficiency. Basic DEA also identifies the target number of fatality in single district in terms of improving road safety.

In terms of road safety efficiency (RS_e), considering an n DMUs set (DMU set for 24 districts), the efficiency score of a particular DMU_o is denoted as h_o. The output is considered as the result of road safety (number of fatalities, s=1) and m different inputs (m=4) or factors having impacts on safety outcome. An efficient DMU is concerned to have as lower as posible safety outcome and possible higher inputs. Therefore, the minimization model of the ratio of weighted output and weighted input was applied (Hermans, Brijs et al. 2009a). It means to minimize the total weighted output values of district 0 (h_0) and to set the total weighted input values equal to one.

$$RS_e = \min h_0 = \sum_{r=1}^{s} u_r \, y_{r0} \qquad (5.1)$$

$$st \quad \sum_{i=1}^{m} v_i \, x_{i0} = 1,$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i \, x_{ij} \geq 0; \quad j = 1, \ldots, 24$$

$$u_r, v_i \geq 0; \qquad r = 1 \qquad i = 1, \ldots, 4$$

where y_{rj}: rth output of DMU_j
x_{ij}: ith input of DMU_j
u_r : the weight given to output r
v_i : the weight given to input i.

A road safety (RS) score equal to one indicates an efficient district. If the RS score is larger than one, it is an inefficient district. However, for applying DEAP version 2.1, the maximum model is used with the efficiency score of a particular DMU_o is denoted as E_0, that is described following:

$$RS_e = \max E_0 = \sum_{i=1}^{m} v_i x_i$$

$$st \quad \sum_{r=1}^{s} u_r y_{ro} = 1,$$

$$\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} \leq 0; \quad j = 1, \ldots, 24$$

$$u_r, v_i \geq 0; \quad r = 1 \quad i = 1, \ldots, 4$$

The most important thing of DEA application is to know which DMU (district) does better than the others. Hence, using DEAP2.1 for running the model, a RS score equal to one presents an efficiency district that can be considered as a benchmark district and a RS score less than one presents an inefficient district.

The target score is the ratio in percent of number fatality that the district needs to reduce in each year. Target score is determined using following formula (Wong SC, NN et al. 2006):

$$Score = \frac{real.fatality - t\arg et.fatality}{real.fatality} \times 100\% \qquad (5.2)$$

- ✓ When the real fatality = target fatality, then the Score = 0%, technical efficiency TE=1
- ✓ When the real fatality > target fatality, then the Score > 0%, technical efficiency TE<1
- ✓ When the target fatality = 0%, then the Score =100, technical efficiency TE = 0

5.3.3 DEA-based Malmquist Index Method

The DEA-based Malmquist (DEA-MI) index method is used to identify the change of indexes as well as to evaluate the development of road safety over a time period (t = 6 years). DEA-MI index method provides a comprehensive knowledge on the development tendency of road safety in each district and all districts in a long period to identify the best and worst. The fomulation of DEA-MI was modified by Shen (2009) that presents following:

$$MI_0 = \frac{h_0^{t+1}(x_0^{t+1}, y_0^{t+1})}{h_0^t(x_0^t, y_0^t)} \left[\frac{h_0^t(x_0^{t+1}, y_0^{t+1})}{h_0^{t+1}(x_0^{t+1}, y_0^{t+1})} \frac{h_0^t(x_0^t, y_0^t)}{h_0^{t+1}(x_0^t, y_0^t)} \right]^{1/2} \qquad (5.3)$$

The results of DEA-MI from the period t to t+1 present through Technical Efficiency change (EFch), Technological change (TECHch) and Total Factor Productivity change (TFPch) that are determined following (Shen, 2009):

$$EFch = h_0^{t+1}(x_0^{t+1}, y_0^{t+1}) / h_0^t(x_0^t, y_0^t) \qquad (5.4)$$

$$\text{TECHch} = \left[\frac{h_0^t(x_0^{t+1}, y_0^{t+1})}{h_0^{t+1}(x_0^{t+1}, y_0^{t+1})} \frac{h_0^t(x_0^t, y_0^t)}{h_0^{t+1}(x_0^t, y_0^t)}\right]^{1/2} \qquad (5.5)$$

$$TFPch = TECHch \; x \; EFch \qquad (5.6)$$

Where

x_0^t, y_o^t: inputs and output of the DMU_0 at any given point in time t

x_0^{t+1}, y_o^{t+1}: inputs and output of the DMU_0 at any given point in time t+1

h_0^t, h_0^{t+1}: efficiency score of DMU_0 at any given point in time t or t+1

EFch results in DEA-MI are the same value in basic DEA through 6 years. DEA-MI provides Technological change (TECHch) and Total Factor Productivity change (TFPch) compared to basic DEA.

5.3.4 DEA-based Composite Index

DEA is used to develop a composite index for each district to obtain its own indicator weights and the relative performance following Shen, Hermans et al. (2010). The composite index combines the information from 8 indicators on 1 value (value between 0-1). Using Lingo to run the optimum model:

$$\mathrm{CI_c} = \max \sum_{i=1}^{m} v_i \, x_{i0}$$

Subject to $\quad \sum_{i=1}^{m} v_i x_{ij} \leq 1 \qquad j = 1, \ldots, 24 \qquad (5.7)$

$$v_i \geq \epsilon \qquad i = 1, \ldots, 8$$

$$\sum_{i=5}^{8} v_i \; x_{ij} \leq v_4 x_{4j} \leq \sum_{i=1}^{3} v_i x_{ij} \qquad (1)$$

To run the maximum optimization model, BT (x_2), SP (x_3), PD (x_5), PC (x_7), DT (x_8) variables have to change the direction while SA (x_1), EB (x_4), AI (x_6) keep the same value as input to the model. The constraint (1) of the formulation (5.5) follows from the important level of in the target hierarchy for road safety that presents in figure 5.1 (Wegman et al. 2005). The final outcome is FAT while intermediate outcomes are SA, BT, SP; policy output is EB; and policy inputs are PD, AI, PC, DT.

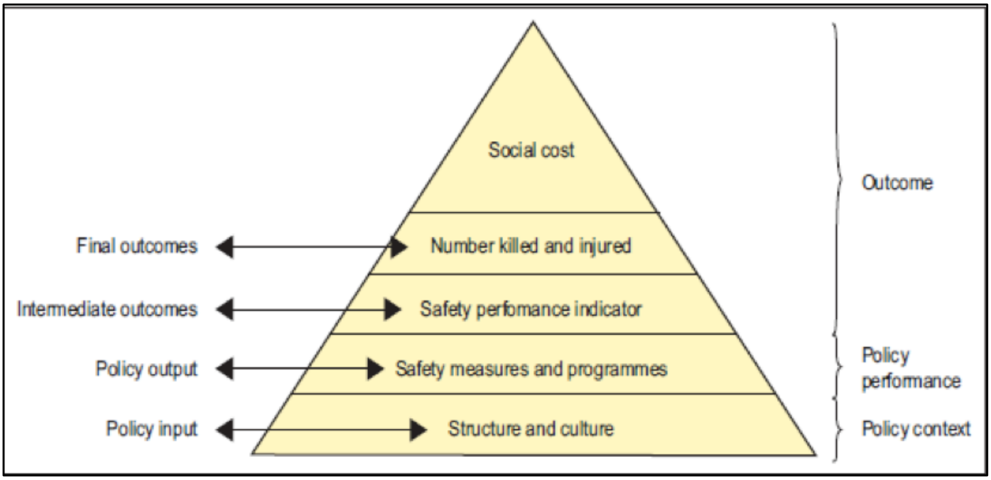

Figure 5.1 Target hierarchy for road safety
Source: Wegman et al. (2005)

5.4 Results

5.4.1 Basic DEA

A. Average Technical Efficiency

The technical efficiency (EF) results of 24 districts per year is presented in Table 5.1. By making EF comparisons on each district by years and the whole city by each year, the specific district or year to be the best and the worst performing can be found. Then the best district of the city is chosen for organizing benchmark and it is called benchmarking district.

EF values in each district jump up and down through studied years, it means lots of changes in each district. Mean[1] is the annual average EF in each district for 6 years of HCMC, therefore they may never equal to one. Mean[1] is divided into three ranges with three equal intervals for helping to identify differences or similarities among district groups. Phu Nhuan is presented as the best district with the highest average EF (0.94) in the whole cities as well as in the first EF value range (>0.8). Go Vap district is the first position of the second EF value range (0.33 – 0.8) with the annual average EF of 0.5333. District No2 is the worst with the lowest annual average of EF (0.1777 <0.33).

Figure 5.1 also presents 25%, 33.3% and 41.67% of districts belonging respectively to three EF value ranges.

Table 5.1 Technical efficiency in each district in each year

No	District	2004	2005	2006	2007	2008	2009	Mean[1]
1	1	0.806	0.8	0.723	0.711	0.756	0.471	0.7112
2	2	0.234	0.263	0.186	0.147	0.11	0.126	0.1777
3	3	0.9	0.912	0.518	0.861	1	1	0.8652
4	4	0.629	0.864	0.404	0.556	0.994	0.601	0.6747
5	5	1	1	0.654	1	0.843	0.807	0.8840
6	6	0.694	0.822	0.511	0.433	0.509	0.438	0.5678
7	7	0.421	0.606	0.201	0.284	0.241	0.219	0.3287
8	8	1	1	0.802	1	1	0.536	0.8897
9	9	0.357	0.252	0.231	0.216	0.151	0.228	0.2392
10	10	1	1	0.715	1	0.846	0.964	0.9208
11	11	0.756	1	0.646	0.88	0.627	0.599	0.7513
12	12	0.209	0.262	0.172	0.174	0.196	0.234	0.2078
13	Binh Tan	0.319	0.336	0.208	0.16	0.165	0.147	0.2225
14	Binh Thanh	0.641	0.595	0.546	0.424	0.348	0.415	0.4948
15	Go Vap	0.517	0.521	0.514	0.58	0.496	0.572	0.5333
16	Phu Nhuan	0.842	0.8	1	1	1	1	0.9403
17	Tan Binh	0.684	1	1	0.987	1	0.82	0.9152
18	Tan Phu	0.877	0.641	0.618	0.402	0.689	0.376	0.6005
19	Thu Duc	0.196	0.256	0.193	0.146	0.151	0.197	0.1898
20	Binh Chanh	0.359	0.228	0.273	0.187	0.148	0.168	0.2272
21	Can Gio	0.434	1	0.747	0.968	0.269	0.299	0.6195
22	Cu Chi	0.254	0.261	0.244	0.176	0.11	0.091	0.1893
23	Hoc Mon	0.356	0.407	0.436	0.503	0.147	0.111	0.3267
24	Nha Be	0.289	0.237	0.234	0.18	0.196	0.098	0.2057
	Mean[2]	0.5739	0.6276	0.4907	0.5406	0.4997	0.4382	

Mean[1]: The Eff mean of each district over 6 years
Mean[2]: The Eff annual average of all districts in each year

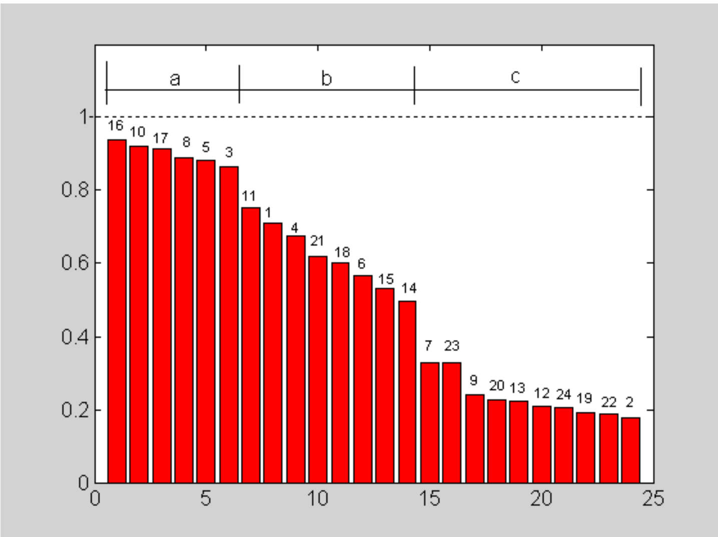

Figure 5.2 Ranking the annual average of EF for 9 years (Mean[1]) of districts

The first EF value range may consider the best performing-group including six districts: Phu Nhuan (16), 10, 8, 5, 3, Tan Binh. These districts have crowded population density but the roads are rather organized with sufficient signals, without heavy trucks (showed in Figure 3.2, Figure 3.3).

The second EF value range consists eight districts including district No 11, 1, 4, 6, Tan Phu (18), Go Vap (15), Binh Thanh (14), Can Gio (21) that values from 0.4948 to 0.6747. There are high population density and narrow roads in the old districts (districts 4, 6) and the new districts have some wider roads but limited good roads as Binh Thanh (14), Go Vap (15) and Tan Phu (18) districts so the traffic flow is a bit higher and a bit difficult to move compared to the first group.

The last range shows the lowest EF values including ten districts. They are disitrict No7, No2, No9, No12, Binh Chanh (20), Binh Tan (13), Cu Chi (22), Nha Be (24), Thu Duc (19), Hoc Mon (23) with the value ranging from 0.1777 to 0.3287. The traffic control system (signal, traffic light…) is lacking with the old, narrow roads and too crowded, especially for districts 2, Binh Chanh (20), Hoc Mon (23), Nha Be (24); the traffic control systems are weak, in some other regions the while population is too crowded.

B. Technical Efficiency In Groups

Considering technical efficiency by groups is carried out in order to find out the strong and the weak points in each group of district based on some similar characteristics in the same group.

Figure 5.2 presents the EF value of group 1 is one in some years. They are Phu Nhuan district (16) in four years (2006, 2007, 2008, 2009), district No5 and district No10 in three years (2004, 2005, 2007), district No3 in two years (2008, 2009). The remaining districts have EF value less than one including district No1, 4, 6, 11. The lowest EFs are in district 4 in the year 2006, district 6 in the year 2007, 2008 and 2009.

In terms of the average, the annual average of EF in each district for 6 years shows the highest value is obtained by Phu Nhuan district (16), followed by district No10 and No5; the lowest is district No6, followed by No4 and No1 (Figure 5.2). There is a big gap between the benchmark district of this group which is Phu Nhuan (16) and the worst district as No6 after year 2006. District No 6 is considered as downtown area, it is a bit far from the central and nondeveloped like other districts of this group. 2005 is a noted year because of highest EF value in all districts of group 1, then reducing strongly in 2006 and raising up a bit in 2007, and decreasing finaly a bit in 2009.

Figure 5.3 shows big differences among districts and the changing up and down unpredictably in group 2 in terms of technical efficiency. The districts that have technical efficiency equal to 1 include district No8 for five years from 2004 to 2008 and Tan Binh district for five years from 2005 to 2009.

The efficiencies of all districts seem to have tendency to reduce gradually, with the benchmark and lowest efficient districts: Tan Binh (17) and Binh Tan (13). Binh Tan was splited from Binh Chanh province from 2003, it has low infrastructure, nondevelopment compared to other districts in Group 2.

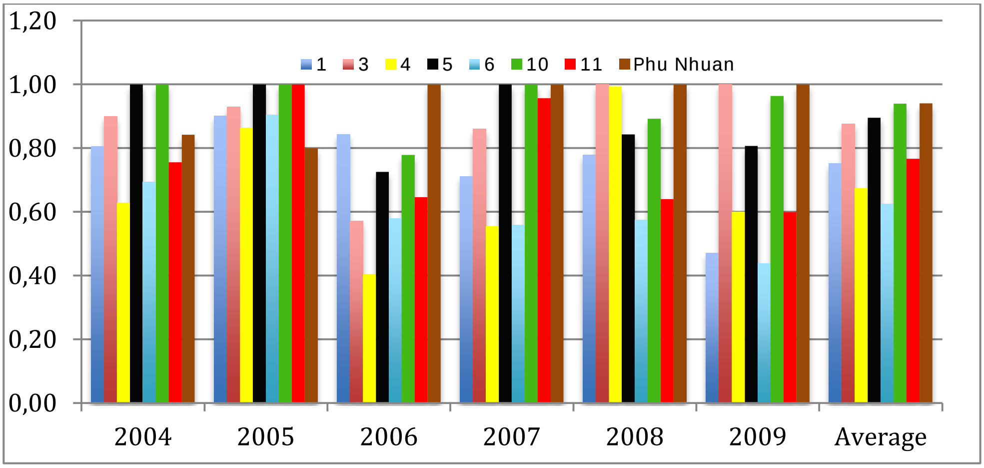

Figure 5.3 EF of districts in-group 1 per year

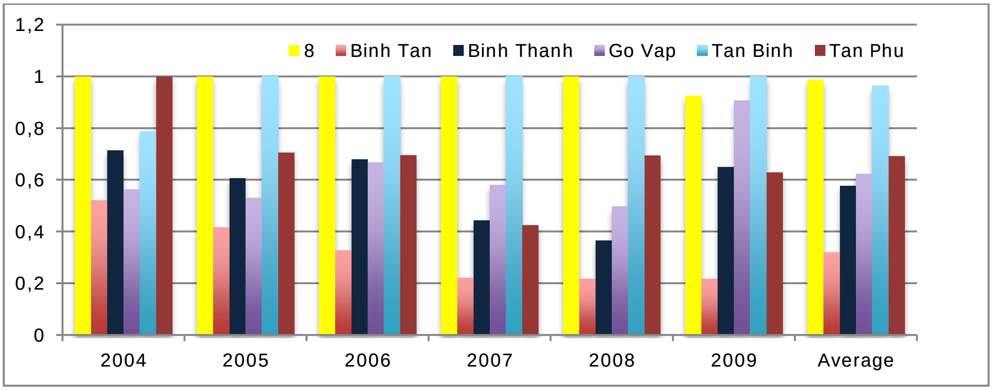

Figure 5.4 EF of districts in-group 2 per year

Group 3 is consided as suburban area of HCMC, the efficiencies are very high in all districst for 6 years. The suburban area is the connection area between HCMC and neighbouring provinces with lots of heavy trucks traveling on the low quality roads (Figure 5.4). The tendency of the all-relative efficiencies increases gradually, that fits to same road characteristics. District no7, Binh Chanh are benchmark districts for the whole group with EF =1 in all studied years.

Group 4 indicates as the rural area; Figure 5.5 shows that Can Gio, Hoc Mon suburban district have EF values reaching one for the whole period. The remaining districts have low efficiency, but still lightly higher than districts ingroup 2. Traffic volume is low in the rural area and none improvement traffic conditions. EF value of Cu Chi (22) decreased rapidly and being lowest at 2007 and a bit increasing afterward. Nha Be (24) has a better EF value than Cu Chi. Its gets the lowest value in 2007 and becomes one at 2008.

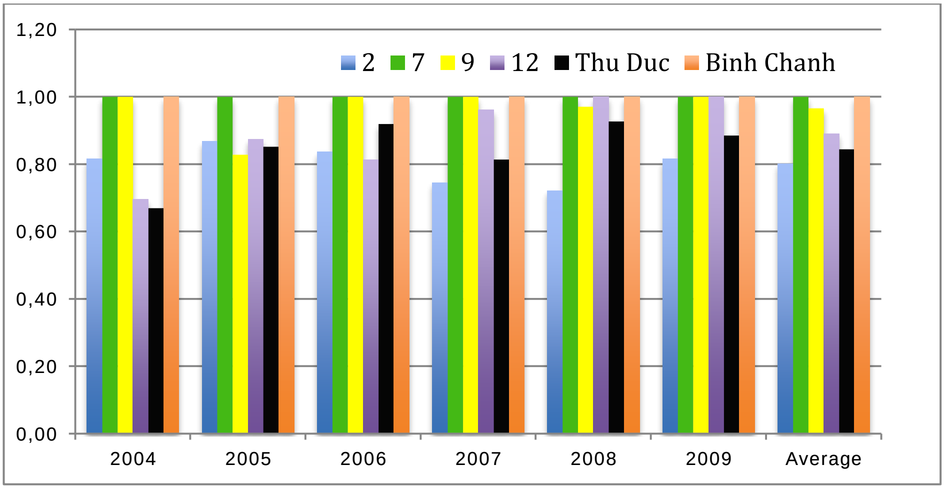

Figure 5.5 EF of districts in-group 3 per year

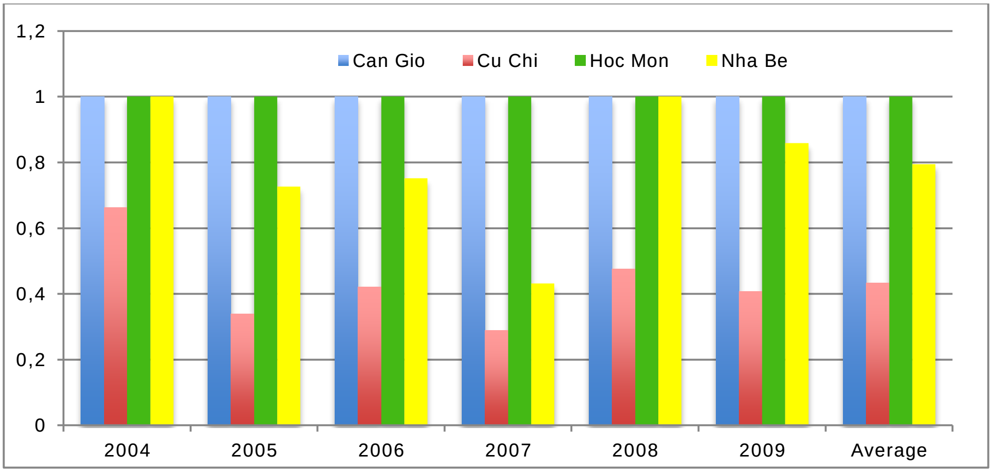

Figure 5.6 EF of districts in-group 4 per year

C. Target Fatality

The target fatality in each disitrict per each year is presented in the Table 5.2 based on the formula (5.2, 5.3).

Following the formula (5.3), calculating an example for reduction of fatalities percentage (Score) of district No1 in 2004 presents following:
Real.fatalitiy = number of fatalities of district No1 in 2004 = 35.
District No1 in 2004 has two target districts as district No10 and No 5.
Target = weight of target districts in 2004 (District No10: 0.712; district No5: 0.885)
Fatality = number of fatalities of district No10 (16) and district No5 (19) in 2004

$$Score = \frac{35 - (0.712\ x\ 16 + 0.885\ x\ 19)}{35}\ x\ 100\% = 19\%$$

Table 5.2 Reduction of fatality percentage in each district to reach the target

Unit: %

No	District	2004	2005	2006	2007	2008	2009	Mean [1]
1	1	19	20	28	29	24	53	28.83
2	2	77	74	81	85	89	87	82.17
3	3	10	9	48	14	0	0	13.50
4	4	37	14	60	44	1	40	32.67
5	5	0	0	35	0	16	19	11.67
6	6	31	28	49	57	49	56	45.0
7	7	58	39	80	72	76	78	67.17
8	8	0	0	20	0	0	46	11.00
9	9	64	75	77	78	85	77	76.00
10	10	0	0	28	0	15	4	7.83
11	11	24	0	35	23	37	40	26.50
12	12	79	74	83	83	80	77	79.33
13	Binh Tan	68	66	79	84	83	85	77.50
14	Binh Thanh	36	94	45	58	65	58	59.33
15	Go Vap	48	48	49	42	50	43	46.67
16	Phu Nhuan	16	20	0	0	0	0	6.00
17	Tan Binh	32	0	0	1	0	18	8.50
18	Tan Phu	12	36	38	60	31	62	39.83
19	Thu Duc	80	74	81	85	85	80	80.83
20	Binh Chanh	64	77	73	81	85	83	77.17
21	Can Gio	57	0	25	3	73	70	38.00
22	Cu Chi	75	74	76	82	89	91	81.17
23	Hoc Mon	64	59	56	50	89	89	67.83
24	Nha Be	71	90	77	82	80	90	81.67

Mean[1]: The annual average of fatality reduction percentage of all districts for 6 years

Following the formula (5.3), calculating an example for reduction of fatalities percentage (Score) of district No1 in 2004 presents following:
Real.fatalitiy = number of fatalities of district No1 in 2004 = 35.
District No1 in 2004 has two target districts as district No10 and No 5.
Target = weight of target districts in 2004 (District No10: 0.712; district No5: 0.885)
Fatality = number of fatalities of district No10 (16) and district No5 (19) in 2004

$$Score = \frac{35 - (0.712\ x\ 16 + 0.885\ x\ 19)}{35}\ x\ 100\% = 19\%$$

The target fatality is an important efficiency index. The reduction percentage of fatality number is necessary; it indicates how many fatalities or how many percentage of fatality need to be reduced to get the target number in each district. In other words, the difference between the real and target number expresses the loss of fund (money, material...), people lives that each district or the local authority must consider to eliminate the accident consequences.

Regarding the whole districts, Table 5.2 shows the highest fatality reduction percentage at districts located in the suburban and the rural area such as district No2, No9, Nha Be (24), Cu Chi (22), Thu Duc (19) (from 75% to 85%). Additional, the lowest fatality reduction percentage presents at districts of the downtown and the new downtown area accounting for 6% to 12%, followed by district No3, No5, No8, Tan Binh (17), No10, Phu Nhuan (16).

Table 5.3 Reduction of number fatality in each district group to reach the target

Unit:%

Group	District	2004	2005	2006	2007	2008	2009	Mean [1]
G1	1	19	10	16	29	22	53	25
	3	10	14	43	14	0	0	13
	4	37	14	60	44	1	40	33
	5	0	0	27	0	16	19	10
	6	31	10	42	44	43	56	38
	10	0	0	22	0	11	4	6
	11	24	0	35	4	36	40	23
	Phu Nhuan	0	20	0	0	0	0	3
G2	8	0	0	0	0	0	8	1
	Binh Tan	48	58	67	78	78	78	68
	Binh Thanh	29	39	32	56	63	35	42
	Go Vap	44	47	33	42	50	9	38
	Tan Binh	21	0	0	0	0	0	4
	Tan Phu	0	29	30	57	31	37	31
G3	2	18	13	16	25	28	18	20
	7	8	0	0	0	0	0	1
	9	3	17	0	0	3	0	4
	12	30	13	19	4	0	0	11
	Thu Duc	53	15	8	19	7	12	19
	Binh Chanh	0	0	0	0	0	0	0
G4	Can Gio	0	0	0	0	0	0	0
	Cu Chi	34	66	58	71	52	59	57
	Hoc Mon	78	0	0	0	0	0	13
	Nha Be	0	27	25	57	0	14	21

The large percentage reduction in target fatalities is often impossible for the authority to make right decisions. Then identifying the target fatalities in each group will be more helpful and realistic. The table 5.3 shows the small differences in the new and old downtown districts (group 1 and 2) when considering the whole country; while the target fatalities needed to reduce are very large in the suburban and rural area (group 3 and 4) than compairing to the whole country. In the suburban area (group 3) district no2 and Thu Duc need to reduce averagely 20%, 19% per year while they are 82% and 81% respectively in the un-divided analysis. District no7 and Binh Chanh do not need to reduce when focusing in the group. Group 4 is in the same situation as group 3, the average number of fatilites in each year of Nha Be, Hoc Mon consider decreasing 21% and 13% when they are 62% and 68% with the whole country.

For evaluating in more detail road safety efficiency in time series, DEA-based Malmquist is applied in the next section.

5.4.2 DEA-based Malmquist Index

DEA-based Malmquist index constructs an efficiency frontier to all samples using DEA and computing the distance of individual observations from the frontier to measure the productivity change of DMUs over time. DEA-based Malmquist index evaluates road safety situation through all districts over a period of 6 years. The typical districts in HCMC are selected to examine the application in the real road safety efficiency.

A. Average DEA-based Malmquist Index

The results of Malmquist Indexes change including the Technical Efficiency change (EFch), Technological change (TECHch) and Total Factor Productivity change (TFPch) are presented in Appendix II.

Regarding the mean over six year (Figure 5.6), EFch of almost districts usually are less than 1 excluding some efficiency district such as 3, 12, Phu Nhuan (16), Tan Binh (17).

The TECHch of all districts is more than 1, that proves the efficiency and improvement of technology investment. The best TECHch is in district 7 and Phu Nhuan (16), while the remainings are nearly equivalent value.

The TFPch means over six years of each district (i.e Mean[1]) are considered to identify the difference between districts over time period (Figure 5.8). The order of efficiency districts are Phu Nhuan (16), 12, Go Vap (15), 3, Tan Binh (17), Thu Duc (19), Can Gio (21), 10, 7, 4, 11, 5, 9, 1, Binh Thanh (14), 2, 6, Nha Be (24), Cu Chi (22), Binh Tan (13), 8, Hoc Mon (23), Binh Chanh (20), Tan Phu (18). The best progress has beenmade in Phu Nhuan district with the highest TFPch Mean[1] (1.387); the worst improvement is district Tan Phu (18) with the lowest TFPch Mean[1] (1.0023). They are considered as typical districts on improvement level in the city.

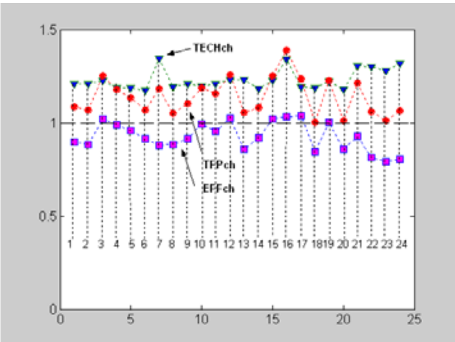

Figure 5.7 Mean[1] of EFFch, TECHch and TFPch over six years of each district

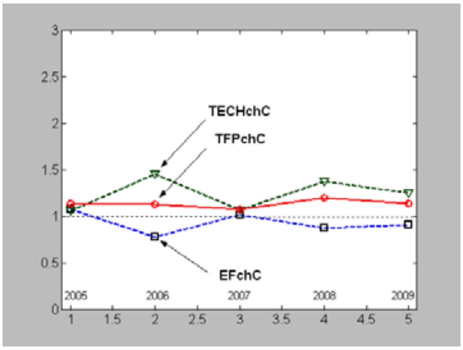

Figure 5.8 The average change of efficiency, technology and total factor productivity

For the annual mean of all districts in each year (Figure 5.7), the EFch improved more than 1 in two years 2005, 2007 but it was less than 1 in 2006, 2008, 2009. It means the technical efficiency is not improved, especially for 2006 with the lowest EFchC of 0.7761. It is noted that the 14th APEC conference organized in Vietnam in 2006 attracted lots of tourists and businessman while the infrastructure improved unfollowing. Beside that, the heavy traffic congestion because of many road excavations of the drainage system reconstruction that started in 2006 and did for several years. The separated lanes for each vehicle type and new one-ways were implemented in the selected roads in 2007 possibly contributed to increase EFch more than 1.

The technological change of HCMC (TECHch) is more than 1 over the considered period. The main factors of the technological change are technology investments, reconstruction and widening roads and bridges; such as new Tan Thuan bridge construction, completed Truong Chinh road widening in 2006, new Khanh Hoi bridge construction, new Calmette bridge construction and Nguyen Van Troi bridge and road widening in 2008. The total factor productivity changes (TFPch) of HCMC from 2005 up to now are more than 1 that proves the improvement of the road safety situation in HCMC.

5.4.2 DEA-based Malmquist Index In Typical District

Through the general analysis (section 5.4.1), this section selects five typical districts with the featured characteristics to evaluate deeply road safety in the technical efficiency, technology efficiency and the productivity change. Choosing typical districts is based on two factors: (1) performance on EFch, TECHch and TFPch, (2) good input factor (Rank of the first and second as presented in the Table 5.4, 5.5). Those districts are No1, No2, No5, Phu Nhuan, Tan Phu. The main reasons to select those districts are that district No1 is considered as the most central and important area of HCMC in terms of the economic, political and cultural situation; Phu Nhuan district has the best index values in both DEA and Malmquist approaches. District No2 has the worst EFch value while district No5 has a medium productivity change; Tan Phu has the less improvement than other districts.

Table 5.4 The order of districts following input factors

District	PD	AI	DT	PC	FAT
1	8	1	3	17	12
2	18	10	20	22	17
3	5	2	10	16	6
4	1	11	19	19	7
5	3	12	6	20	4
6	7	16	7	12	10
7	17	3	22	18	13
8	12	17	8	5	7
9	20	18	16	15	16
10	4	4	12	13	3
11	2	6	17	14	4
12	16	19	15	9	20
Binh Tan	14	7	14	2	24
Binh Thanh	11	13	5	3	15
Go Vap	10	14	9	1	14
Phu Nhuan	6	5	21	21	2
Tan Binh	13	8	1	4	11
Tan Phu	9	9	2	6	19
Thu Duc	15	15	11	7	21
Binh Chanh	21	20	4	8	23
Can Gio	24	21	24	24	1
Cu Chi	23	22	13	10	21
Hoc Mon	19	23	18	11	17
Nha Be	22	24	23	23	9

Note: For the FAT, DEA and DEA-MI indexs rank 1 is the best and 24 is the worst.
For input factors rank 1 is the highest value and 24 is the lowest value

Table 5.5 Rank of the results by DEA and Malmquist Index method

Method	DEA – Order of district			Malmquist Index- Order of district			
	EF	Score	Typical	EF	TECH	TFP	Typical
1	8	8	Central	8	13	14	Central
2	24	24	Worst	24	14	16	
3	6	6		6	10	4	
4	9	9		9	20	10	
5	5	5		5	21	12	Medium
6	12	12		12	24	17	
7	15	15		15	1	9	
8	4	4		4	18	21	
9	17	17		17	15	13	
10	2	2		2	16	8	
11	7	7		7	12	11	
12	20	20		20	8	2	
Binh Tan	19	19		19	7	20	
Binh Thanh	14	14		14	22	15	
Go Vap	13	13		13	9	3	
Phu Nhuan	1	1	Best	1	2	1	Best
Tan Binh	3	3		3	17	5	
Tan Phu	11	21		11	19	24	Worst
Thu Duc	22	18		22	11	6	
Binh Chanh	18	10		18	23	23	
Can Gio	10	22		10	4	7	
Cu Chi	23	16		23	5	19	
Hoc Mon	16	23		16	6	22	
Nha Be	21	11		21	3	18	

A. District No1 – Center District

District No1 is located at city center connecting between district 2, 3, 4, 5, Binh Thanh, Phu Nhuan that concentrates almost headquarter offices and the administrative – cultural – commercial and financial offices of the city (Figure AI.1). District 1 has the narrow road network with lots of one-ways. Comparing the input data of other districts, district No1 ranks the eighth of PD, the seventeenth of PC, the first position of AI, and the third of DT. The high living level, lots of buying demand and travels are disadvantages/ weak points of transport efficiency.

Figure 5.8 indicates that EFch was less than 1 in 2006 and improving in 2008 and reducing strongly in 2009. The TECHch improved in 2006, 2008, 2009 (maximum level at 1.439) so they made TFPch increasing in these years. Because some roads and bridges were under-construction and widening as new Calmette bridge (2008), new Khanh Hoi bridge (2009) that connects district 1 to district 4; and new Nguyen Van Cu bridge (2009) connects district 1, 5 to district 4, 8. The East-West boulevard was build along Ben Nghe canal (9/2009). However since the number of personal car increased a lot in the year 2009, it made reducing EFch as well as TFPch.

Although the road and bridge network of district 1 is quite good, but the numerous people pass through the central area, the traffic efficiency is not higher and lower than some other districts.

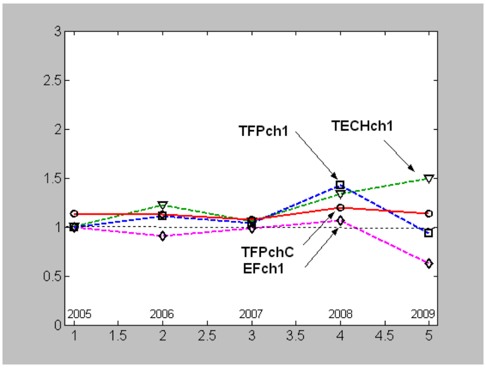

Figure 5.9 The indexes change of district No1

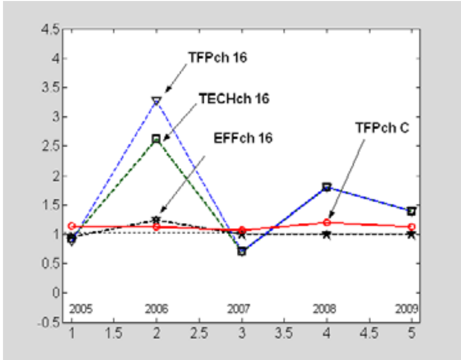

Figure 5.10 The indexes change of Phu Nhuan district (16)

B. Phu Nhuan District - The Best Performing-District

Phu Nhuan (16) district is located among district 3, Binh Thanh (14), Go Vap (15) and Tan Binh (17) that connects to other important places (shopping centrals, international airport…) by the main and large roads with the heavy traffic volume (Phan Dinh Phung, Hai Ba Trung, Nguyen Kiem, Phan Dang Luu, Hoang Van Thu, Nam Ky Khoi Nghia, Nguyen Van Troi) (Figure AI.2). Beside that, the remaining roads connecting to the resident areas are narrow but well organized with the good traffic light system and without trucks.

Phu Nhuan district has the highest EFch in the whole city as well as in group 1. Besides, Phu Nhuan also is best performing-district on the TFPch. That why this district is selected as a benchmarking district for remaining districts in group 1 in almost all studied years.

Figure 5.9 shows EFch gained maximum at 1.250 in 2006 and be equal 1 in the remaining years. TECHch changes strongly with maximal value of 2.6260 in 2006, and minimum value of 0.7090 in 2007. The high TECHch is because of the better road network than other ditricts as well as providing lots of new buses from the city governor. The TECHch influenced directly the TFPch. TFPch has a wide range value with a maximal value of 3.282 in 2006 and a minimum value of 0.7090 in 2007. For three years from 2007 to 2009, TFPch has the same value of 1 because TFPch = TECHch×EFch.

C. District No5 – The Average Performing-District

District No5 is selected to typical analysis because the TFPch value (1.1351) is nearly the same on that of the whole city (1.1344).

Regarding TECHch, district 5 has an average perfoming efficiency with a value bigger than 1 in the whole period except for the initial year of the study (2005). The technology investment as reconstruction and widening of the roads are done usually and regularly. District 5 is located between districts No1, No3, No10, No11 and No8 that concentrates lots of Chineses living very long time ago so the houses and roads had built and developed well such as Tran Hung Dao, Hung Vuong, Nguyen Chi Thanh, Nguyen Trai, Nguyen Van Cu, Le Hong Phong, Ly Thuong Kiet, Le Dai Hanh streets (Figure AI.3).

EFch of district 5 has a big change from the minimum value of 0.6540 in 2006 and maximum value of 1.5290 in 2007. EFch influenced strongly to TFPch, the TFPch has the same trend of EFch with the minimum value of 0.7930 in 2006 and the maximum value of 1.958 in 2007. In 2008, the EFch reduced to lead down the TFPch, otherwise, the TFPch in 2009 increased following the raising of the TECHch. A low traffic demand (DT) is advantage to improve EFch as well as TFPch in the studied time (Figure 5.10).

D. Tan Phu District - The Worse Performing-District

Tan Phu district (18) has the lowest of TPFch (1.0023) so it is selected to be the typical district for detail analys of the road safety efficiency. The TECHch is always more than 1 (some old roads have been opended widening) but the EFch is very low and less than 1 in the whole of period (Figure 5.11).

It is proved by the fact, these widening roads are not satisfied to the traffic volume. Tan Phu district was established from 2003, and locating between districts 6, 11, 12, Binh Tan, Tan Binh (Figure AI.5). High PD, high PC, and heavy DT that point at the 9th, the 6th and the 2nd respectively, while no new road is constructed. Thus, although TECHch is improved but the technology investment is still too small so it is imposible to prevent the weakness on EFch.

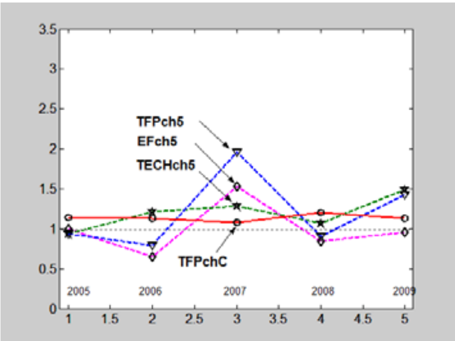

Figure 5.11 The indexes change of district No5

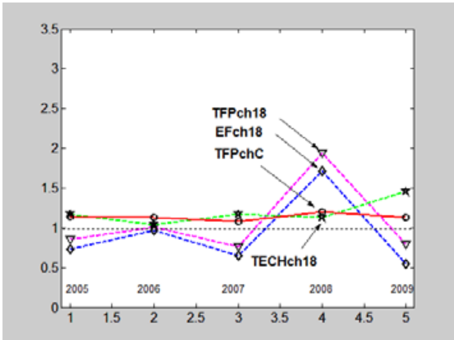

Figure 5.12 The indexes change of Tan Phu (18) district

E. District No 2 – The Worst Performing-District

District No2 is covered by Saigon river and connecting between district no1, no4, no7, and no9 (Figure AI.4). The main highway (Hanoi highway) connects this district to Dong Nai provinces and other North provinces with a huge traffic volume of heavy trucks, buses and cars. The other roads as Luong Dinh Cua, Tran Nao, Nguyen Duy Trinh, Cau Giong Ong To, Nguyen Thi Dinh, Cat Lai were opening widening and constructing newly. The population concentrates mostly in the east and northeast of Hanoi highway, the remaining area are sparse population and wilderness. Low road user perception and weak road quality are two main reason causing low EFch.

5.4.4 Composite Index Score

All eight variables including PD, SP, BT, PC, SA, DT, EB, AI are considered as the composite index method to identify the impact of each variable to the overall composite index. The average composite iindex in each district per year and whole 6 years peridos, the correlation between composite index and number of fatalities are presented in the Appendix II (Table AII.7)

Table 5.6 presents percentage of eight indicator shares in each district of the survey area. In terms of the average, SA and SP account for a large share in the index (26% of each indicator), followed by EB index (24%). Other indicators have a small share in the number of fatalitites.

Table 5.6 Average Composite Index Share for 2004 -2009

Unit: %

Group	District	PD	AI	SA	DT	PC	EB	BT	SP	Total	Mean FAT
G1	1	0	15	62	1	0	19	1	3	100	34
	3	0	11	45	0	0	11	3	30	100	19
	4	0	0	31	7	4	12	7	38	100	20
	5	0	3	73	2	5	14	0	3	100	18
	6	0	2	39	0	11	23	6	20	100	28
	10	0	20	17	0	0	23	15	25	100	16
	11	0	3	48	6	2	18	18	5	100	18
	Phu Nhuan	0	7	1	3	1	17	26	45	100	14
	AG1	0	8	40	2	3	17	10	21	100	
G2	8	0	2	7	4	6	23	2	56	100	20
	Binh Tan	0	6	44	15	0	36	0	0	100	101
	Binh Thanh	0	4	6	0	7	28	1	54	100	43
	Go Vap	0	5	1	8	0	33	0	53	100	42
	Tan Binh	0	6	22	0	4	34	7	27	100	31
	Tan Phu	0	8	42	0	7	38	6	0	100	48
	AG2	0	5	20	5	4	32	3	32	100	
G3	2	0	0	0	0	12	12	5	70	100	45
	7	0	8	0	0	2	10	3	76	100	39
	9	0	0	0	1	9	11	0	78	100	44
	12	0	3	36	18	0	37	0	6	100	72
	Binh Chanh	1	1	23	0	25	36	1	12	100	98
	Thu Duc	0	5	34	12	0	37	0	12	100	89
	AG3	0	3	16	5	8	24	2	42	100	
G4	Can Gio	16	1	6	2	0	20	56	0	100	7
	Cu Chi	3	2	38	3	9	38	0	7	100	89
	Hoc Mon	1	0	33	10	10	34	5	5	100	45
	Nha Be	7	0	26	6	16	23	17	6	100	22
	AG4	7	1	26	5	9	29	20	5	100	
	Average	1	5	26	4	5	24	8	26	100	

SA has impact through 21 districts and the highest share in district No5 (73%), followed by district No1 (62%), No11 (48%) and No3 (45%). Those districts are in the central (the old downtown) that are huge traffic congestions compared to the other central districts in general and to all districts in HCMC in particular.

Regarding to SP indicator, district no9, no7 and no2 have a high share accounting for 78%, 76% and 70%, respectively. These districts are in the suburban area, district no 9 and No2 have built new highways that connect the central (the old and new downtown) to the neighbour provinces of HCMC and district No7 has built lots of big wide roads. The CI scores are presented in the Appendixes AI (Table AI.9).

EB contributes a similar value of share at all districts, the suburban district and rural districts have the higher share than the old and new downtown district such as Tan Phu (38%), Cu Chi (38%), Thu Duc (37%), Binh Chanh (36%), Hoc Mon (34%), Binh Tan (36%), 12 (37%).

PD has a highest impact to rural area, especially for Can Gio (16%). Other district has non impact from PD to number of fatalities.

BT has a highest share in Can Gio (56%) and Phu Nhuan (26%) districts. AI has higher impact in the old downtown districts, especially for district No10 (20%), No1 (15%), No3 (11%) than the other groups. PC has higher impact in the rural and suburban districts than the remaining.

5.5 Conclusions

5.5.1 DEA Model Findings

Applied Technical Efficiency EF (un-divided group) identifies benchmark as well as worst districts. Combination with range evaluation could rank the best districts, average and weak districts to understand road safety efficiency of districts. District group help to find out the benchmark and worst districts in same characteristic in the same group.

Deduction rate of number fatalities to approach the target in each district and each district group are presented to get the efficient road safety.

DEA-based Malmquist index low technical efficiency (EFch), but high investment on technology such as widening and opening new roads, bridges, improving light traffic system (TECHch) that identify the efficiency/ inefficiency of total traffic improvement (TFPch) in each district.

DEA-based Malmquist index in each district group is evaluated and compared by EFch, TECHch and TFPch among them to help the authority provide different and appropriate methods (concentrate to technical of technology) for improving road environment to get road safety efficiency.

Composite Index indicates the different important level and weight of each input variable in the index value as well as different district.

The DEA analysis results significance between the theory and the practice. DEA method is examined the reliability through real transport situation in HCMC. The current transport situation evaluates into two aspects (1) The real situation through input variables, (2) the real and current change of transport situation in term of technical or technology as opening, widening, investment road and bridges in HCMC.

5.5.2 District Findings

There are differences among districts of the different groups. The best road safety efficiency is the old downtown area (group 1), followed by the new downtown district area (group 2), then the suburban districts (group 3), and the rural districts (group 4).

There is a big change of benchmarking district from the whole country to group. Without group classification, the worse districts like 7, 9, 2, 12, Hoc Mon, Binh Chanh, Binh Thanh are performing not that well. But when identifying road safety efficiency in group, district No7, Binh Chanh, no9, Hoc Mon become benchmarking of followed group.

For both group and un-divided group classification, Phu Nhuan – a central district - is considered as the best district; district No2 – a suburban district and Cu Chi – a rural sub-district that connect central districts to neighbor provinces of HCMC - and Tan Phu – a new split district are the worst districts among all the districts in HCMC.

In term of EF, the worst districts in each group is district 6 – far from the central HCMC and very crowded compared to other old downtown districts - in the old downtown districts, Binh Tan - a new split district - in the new downtown districts, Cu Chi – rural district. The benchmarking district is Tan Binh of group 2, district No7 – a develop district with a modern, organized and high quality of life resident area with lot of trees and Binh Chanh – rural area in the suburban district group, Can Gio - home of Can Gio Mangrove Forest, a biosphere reserve listed by UNESCO and Hoc Mon of rural districts.

For the time series from 2004-2009, in term of un-divided group, the best road safety efficiency is in year 2008 and the worst is year 2007. The efficiency road safety in each group is different, the best year are 2007, 2008, 2009, 2006 while the worse efficiency year are 2005, 2009, 2007, 2008 in different group: the old downtow districts, the new downtown districts, the suburban districts and the rural districts, respectively.

Continuosing with TFPch, the best district by group are Tan Binh in the new downtown area, district 12 in the suburban district and Can Gio in the rural districts. The worse districts are district 1 in the old down town, Tan Phu in the new downtown, Binh Chanh in the suburban districts and Nha Be in the rural districts.

Some districts (Tan Phu, Thu Duc, Binh Chanh) have the low EF (basic DEA), low EFch (Malmquist) and high SA indicator share (IC) that present the real road network situation because of narrow, incapacity, low quality roads, non-satisfying traffic demand, or the high traffic density in some special events.

Some districts (Phu Nhuan, No7) have the high EF (basic DEA), high EFch (Malmquist) and low SA indicator share (CI) that means significantly with the investment of widening, opening roads and bridges, organized traffic flow (rearranging one-way direction, split lane for individual vehicle type, traffic control).

The high target percentage of number of fatalities, low TECHchs are significance with the districts or district groups that have low technology investment and non-efficiency of TFPch (Tan Phu). Contrary to that, the district has efficiency TECHch that have road safety improvement (Phu Nhuan).

Composite Index results show SA, EB, SP are the most important impact of road safety (number of fatalities) that complete significantly to the practice. The good capacity road, increasing traffic enforcement, reducing speed will clearly reduce number of fatalities. BT is an average impact to number of fatalities, but it should get more concern because of low perception and awareness of road users.

5.5.3 Proposing Measures

The suburban and rural areas (group 3 and 4) should receive more concern as increasing road user behavior perception, than the old and new downtown area group 1 and 2).

To improve road safety in general and number of fatalities in particular through applying DEA methods, some measures should proposed concentrating into the worst performance districts (district 2, 6, Binh Tan, Binh Chanh, Tan Phu, 1, Nha Be). They are re-arranging individual lane for individual vehicle type, organizing more one-way direction lane, applying intelligent traffic system (green wave) in the main road/ street, upgrading and widening roads and bridges, constructing light bypasses through the intersections of huge traffic volume and high population density to reduce number of fatalities, using GPS for the traffic control system, installing traffic warning and notice to support road user minimizing accident. Some awareness and education should propose in those districts to improve the road user perceptions.

Chapter 6. Behavioral Model To Road Safety

6.1 Behavioral Theory

6.1.1 Precede - Proceed Model

Originally proposed by Green first time in 1980 in health section (Green 1980) and extended many times afterward to encompass the wider environmental, policy and organizational factors (Green 1991), PRECEDE – PROCEED is a participatory model for community-orientation. This model has an effective framework that provides health program planners, policy makers, and evaluators with a capability to analyze the situation and design a health program efficiently by offering a comprehensive structure for assessing health and quality of life needs and for designing, implementing, and evaluating health promotion and other public health programs to meet those need (Green 2005).

In 1999 more dimensions have been added into health promotion planning from international experiences which were taken in Canada, Europe, China, Australia, Singapore, Japan, and Africa (Green and Kreuter 1999). In The 4th edition in 2005, Green was had proposed a process that has been applied, tested, studied, extended, and verified widely today in community, school, clinical, and workplace (Green 2005).

The model's objecties are basically to explain health-related behaviors and environments, and to design and evaluate the interventions needed to influence both the behaviors and the living conditions that influence them and their consequences. The 3 main phases of this model is presented in the figure 6.1.

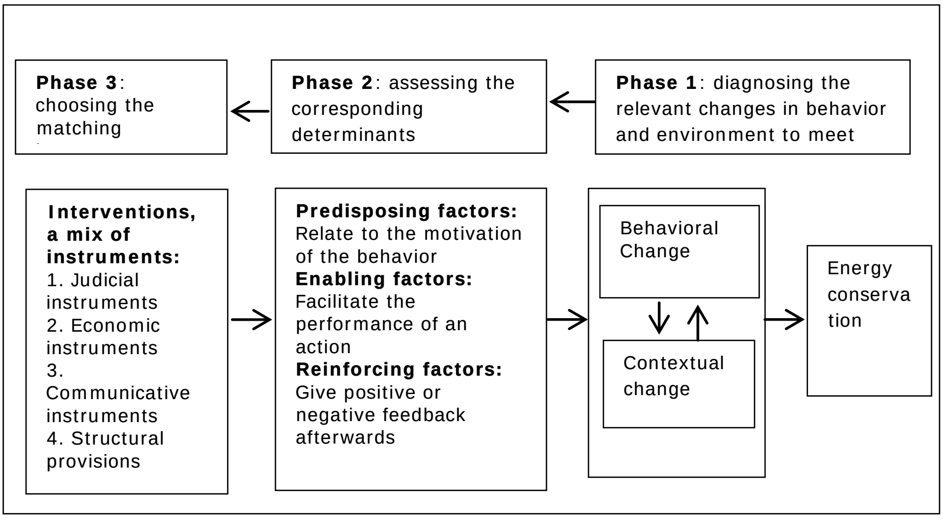

Figure 6.1 Precede-proceed model presented by (Green and Kreuter 1999)

Another premise behind PRECEDE-PROCEED is that a change process should focus initially on the outcome, not on the activity. Many organizations set out to create community change without stopping to consider either what effect their actions are likely to have, or whether the change they're aiming at is one the community wants and needs. In 2005 the model is extended with eight phases (Green 2005) as shown in figure 6.2. that were almost quitely changed.

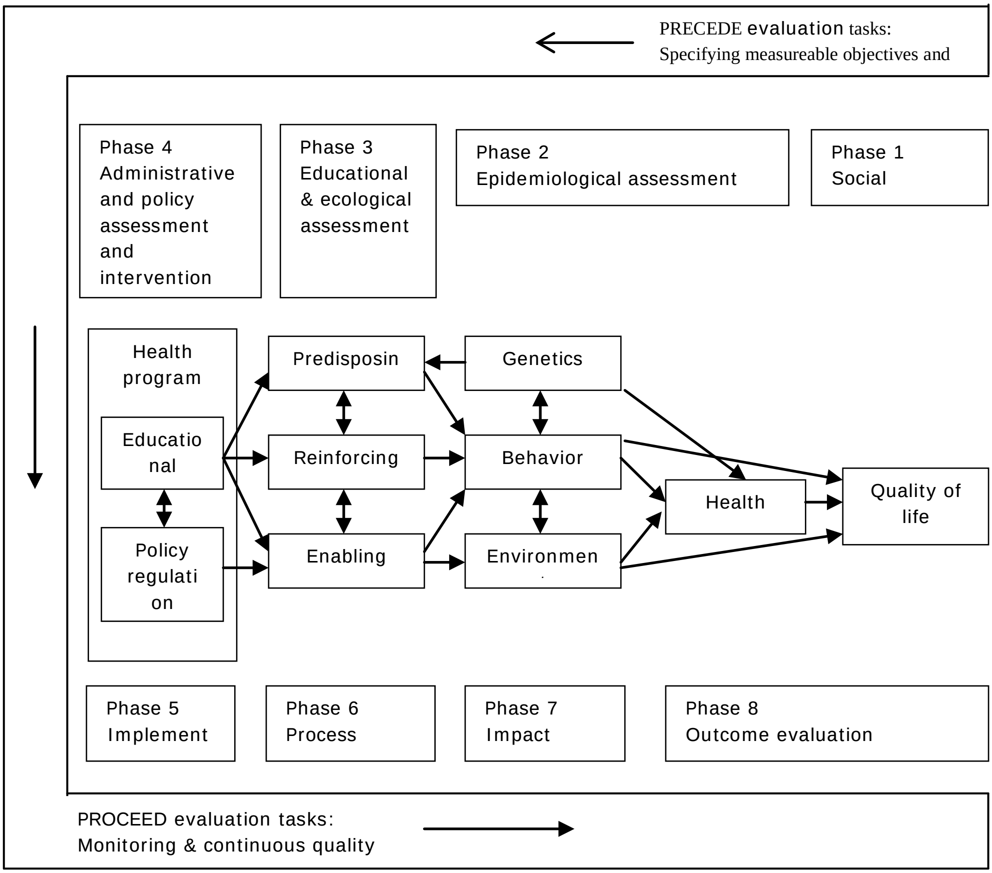

Figure 6.2 Precede – Proceed model (Green 2005)

6.1.2 Reason's Swiss Cheese Model

Reason (1990) proposed Swiss Cheese Model from the idea of multiple slices (human system) of Swiss cheese, stacked together, side by side that described the interaction between latent failures. It is widespread acceptance in approaching human errors.

Figure 6.7 (CAST, 2009) presents the hypothetical breakdown of a latent failure in the decision-making process leading up to unsafe act following Swiss Chesee Model. An error (a rural road in rainy weather) may allow a problem to pass through holes in the same places (hole 1: wet pavement, hole 2: lack of enforcement, hole 3: lack vehicle maintenance, hole 4: road user drink alcohol, hole 5: injunctive behavior, hole 6: pressure from other road users) of all slices (slice 1: structure and organizational influence, slice 2: legal influence, slice 3:

technical influence, slice 4: individual influence, slice 5: social influence, slide 6: unsafe act) to create an accident (consequence). It proves these holes have opportunities to be a process of fall through six slices. Otherwise, each slice of cheese is an opportunity to stop an error. Each slice can protect against expected and unexpected errors and that is understood as “defensive layers” in the process. Six slices are considered in the model that clarify more detail factor groups of road accident causes (mentioned in section 1.3). This model help to propose measures for decreasing the risk of accident from all impacts. In term of road safety, minimizing risk is better than maximizing road safety (Shinnar, 2007).

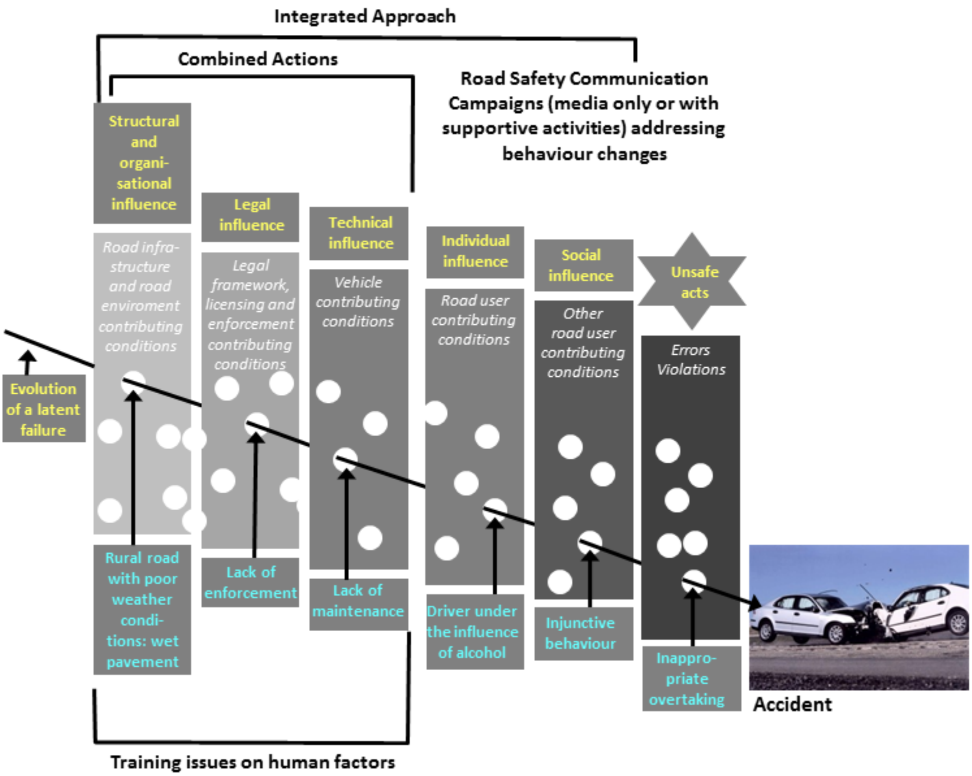

Figure 6.3. Applying Swiss cheese model for road accident.
Source: CAST, 2009

6.1.3 Motivational Models

In this part there are 4 main models to predict behaviors reviewed for motivational models:

- ✓ The theory of reasoned action (TRA)
- ✓ The theory of planned behaviors (TPB)
- ✓ Protection Motivation Theory (PMT)
- ✓ Health Belief Model (HBM)

The theory of reasoned action (TRA) is a model for the prediction of behavioral intention, attitude and behavior that was defined the first time by Ajzen (Icek Ajzen 1980) (figure 6.4). TRA was derived from a research of (Martin Fishbein 1975), that started out as the theory of attitude, which led to the study of attitude and behavior. The key purpose of TRA is to predict and understand motivational influences on behavior.

By adding perceptions of behavioral control as predictor of intentions and behaviors the theory were extended. It enhances the prediction of behavioral intention and behaviors.

The predictions of behavioral intention and behaviors are basically proceeded through a process of analysis of evaluation of outcome and subjective norms which includes 5 elements as following: beliefs toward an outcome, attitude, belief of what others think, what expert think, and motivate to comply with others.

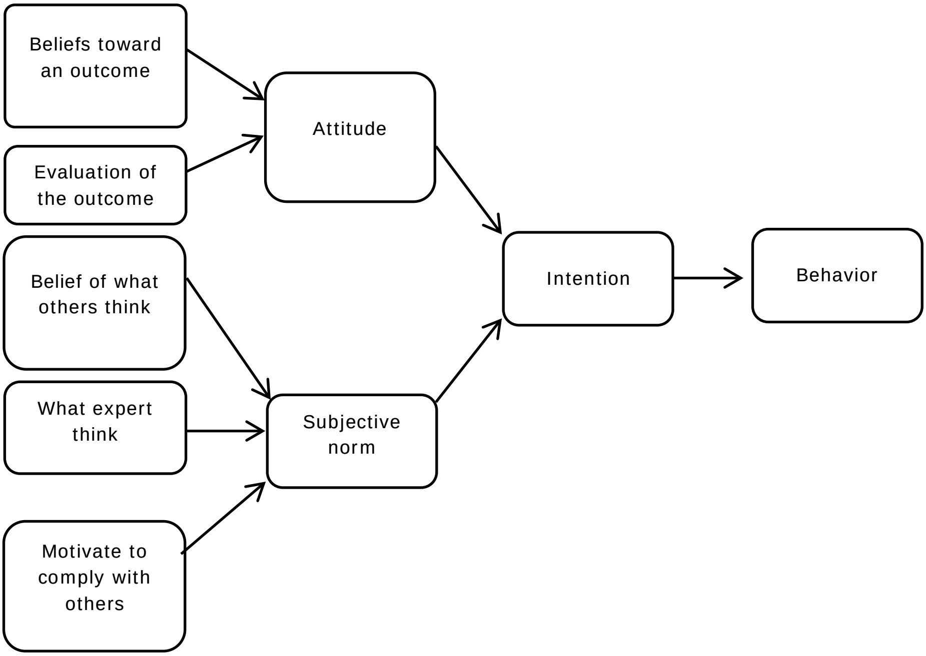

Figure 6.4 TRA model by (Ajzen 1980)

In 1991, (Ajzen 1991) revised the TRA model into the **theory of planned behavior** (TPB) with extension of perceived behavioral control to the model since the research indicated that when people have the intention of carrying out a behavior , but the actual behavior is threated because of lacking confident or control over behavior (Figure 6.5).

Protection Motivation Theory (PMT): In 1975, Roger proposed the PMT model with aim of understanding of fear appeal to by providing conceptual clarity (Rogers 1975). The extended version of Protection Motivation Theory was revised by with an emphasis on the cognitive processes mediating behavioral change.

In the PMT model there are two appraisal processes of threat appraisal and a process of coping appraisal. The appraisal of the health threat and the appraisal of the coping responses result in the intention to perform adaptive responses (protection motivation) or might lead to maladaptive responses.

The PMT model has proposed that the intention to protect one self rely on four key factors (Figure 6.6). Protection motivation is considered as the result of the threat appraisal and the coping appraisal in which the Threat appraisal is the estimation of the chance of contracting a disease or vulnerability the seriousness or severity. Coping appraisal are response efficacy and self-efficacy. Response efficacy is the individual's expectancy that carrying out recommendations can remove the threat. Self-efficacy is the belief of people's ability to execute the recommend courses of action successfully.

The Protection Motivation Theory can be used for influencing and predicting various behaviors. In addition, the PMT model can be used in health-related behaviors. The main features of application are reducing alcohol use, enhancing healthy lifestyles, (Boer, Seydel 1996).

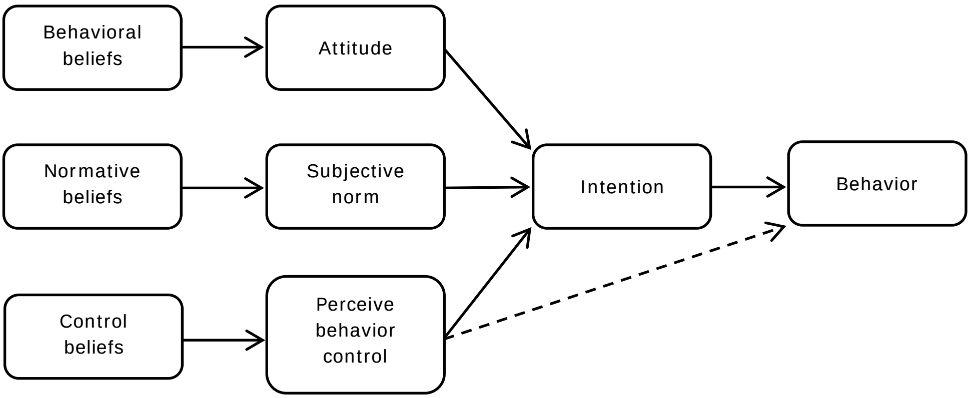

Figure 6.5 TPB model by (Ajzen 1991)

The **Health Belief Model** has its origins in the early 1950s and was developed by the U.S. Public Health Service in order to better understand the widespread failure of people to accept disease preventives or screening tests for the early detection of asymptomatic disease (Janz and Becker, 1984). (Rosenstock 1966; Rosenstock 1974) also developed the health belief model to explain human behavior and to assist the design of campaigns. The idea of this model is avoiding a negative health consequence and motivate for taking a positive action to preserve or promote health. It has since then been applied to a wide variety of health-related problems. The variables and construction of the health belief model are presented in the Figure 6.7. The model considers six main factors that impact to an individual behavior (speeding/ not wearing helmet) related their health (CAST 2009):

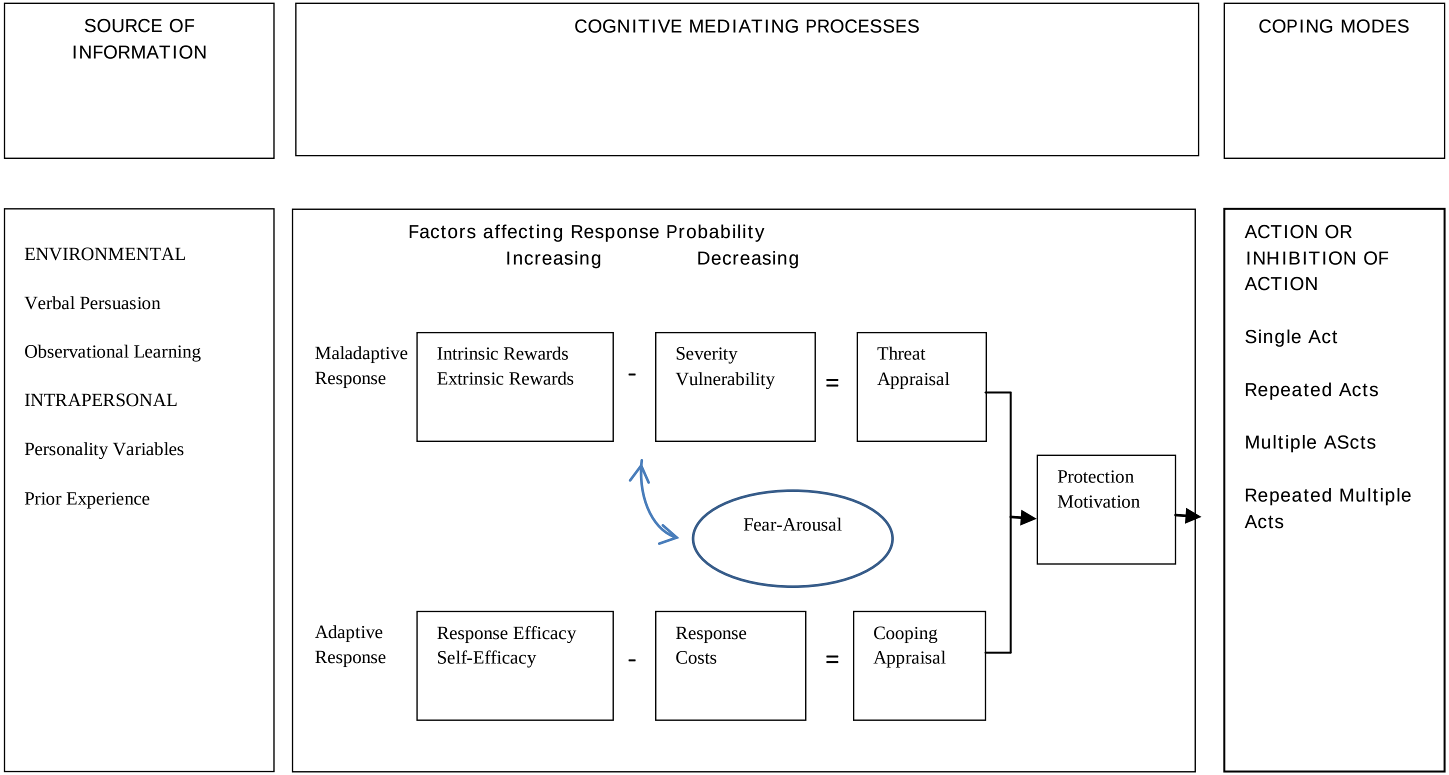

Figure 6.6 Protect motivation theory (adapted from Roger, 1983

1. Perceived susceptibility describes the people feel of the health hazard or the negative consequence of a dangerous behavior

2. Perceived severity presents the serious of these consequences

3. Perceived threat is associated between perceived susceptibility and perceived severity with a health hazard or a given behavior.

4. Perceived barriers includes tangible and intangible factors that decrease likelihood of action

5. Perceived benefit consists tangible and intangible factors that increase likelihood of action

6. Cues to actions are the internal (unpleasant memories of the given behavior...) and the external (advise from others, information in the media, education program...) to motivate readiness for behavior change or raise likelihood of action.

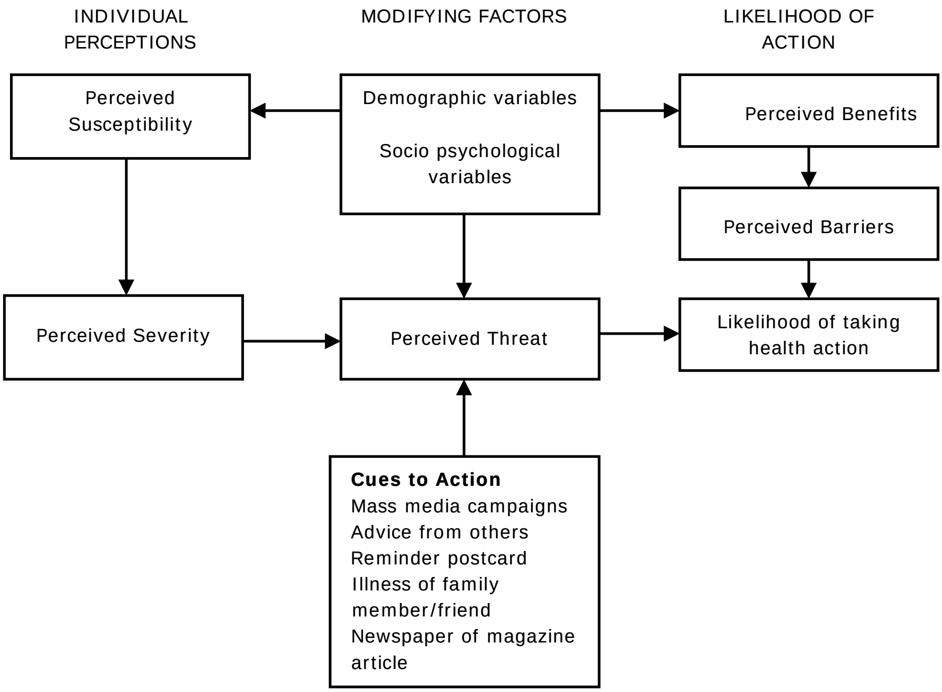

Figure 6.7 Health belief model by (CAST 2009).

6.2 Case 1: Socio-cognitive Determinants Of Motorcycle Helmet Use Among Young And Adults In Cambodia: An Integrated Behavioral Model

6.2.1 Abstract

This study adopted a socio-cognitive perspective towards the examination of helmet use in a sample of Cambodian young adults. Two theoretical models, i.e., Health Belief Model and Theory of Planned Behavior were estimated separately as well as within a combined framework that included two additional norm-related variables, i.e., descriptive- and personal norm. Based on the results, four important conclusions can be drawn. Firstly, the sample investigated in this study is clearly favorably disposed towards the use of helmets while riding. Secondly, in decreasing order, helmet use behavior was found to be determined by the following five key-determinants: perceived behavioral control over a specific set of inhibiting situational factors (i.e., mostly when driving short distances, at night, or when dressed up to go out), perceived behavioral control in general, perceived susceptibility, personal norm, and behavioral intentions. Thirdly, in terms of predictive power, the TPB performed substantially better than the HBM. Finally, even though the integrated behavioral model implemented in this study showed that different theories can complement each other in the explanation of motorcycle helmet use, it should not be overlooked that, besides being comprehensive, models should also be parsimonious.

6.2.2 Introduction

Even though prior research on the effectiveness of safety helmets is not always conclusive and to be interpreted with care, (e.g. Curnow 2005; Elvik 2011), there are serious indications that helmets can reduce the frequency an GRSP (2006) severity of head and brain injuries (e.g., McDermott 1993; Maimaris 1994; Rowland 1996; Thompson 1996; Lawrence 2002; Deutermann 2004; Keng 2005; DeMarco 2010); Notwithstanding, helmet wearing rates remain too low, especially in developing countries (Peden 2004). In a paper published by Li (2008) the focus was on the South-East Asian and Pacific regions, and it was mentioned that a lack of helmet use had been reported by 31 of motorcyclists in Thailand, 46 in Malaysia, and 45 in Indonesia. This study fits within this stream of research and will look at motorcycle helmet use in Cambodia.

6.2.3 Background

The number of traffic deaths in Cambodia is very high and rapidly increasing since the mid 1990s. In 2010, a total of 18.287 casualties were officially reported. Among them 1.816 were fatalities, 6.718 severe injuries and 9.170 slight injuries. Compared to 2009, the number of fatalities further increased by 6% (Cambodia 2010). The majority of those fatalities (78%) are vulnerable road users with the situation for motorcyclists being particularly worrying. Motorbikes account a very high share in the registered vehicle fleet (83%) and motorcyclists rank highest in terms of casualties (72%). Over a period of five years (Sullman, Gras et al.), the number of motorbike fatalities has increased dramatically by 61% (Cambodia 2010). Of special interest for this study is that, 73% of motorcycle fatalities suffered head injuries with 85% of the victims concerned not wearing helmets (Cambodia 2010). A closer look at the problem shows that non-use of helmets prevails among passengers and children. Besides that, adolescents and young adults would be particularly vulnerable. In general, traffic casualties for people aged between 15 and 24 years old are disproportionately high when compared to other age groups. In 2010, 15 to 24 year old ones accounted for the highest share (26%) of total motorbike casualties (Cambodia 2010).

6.2.4 Objectives

The primary objective of this paper is to study helmet use among young adult motorcyclists in Cambodia. More in particular, we attempt to gain further insight into the psychological mechanisms behind the use of motorcycle helmets. As indicated by Ritter (2011), such an in-depth approach is welcome since most evidence compiled focuses on the injury mitigating capacities of helmets, while less is known about the underlying behavioral motivations of helmet use. Others have likewise emphasized the need for greater integration of social sciences and behavioral theories within the field of injury prevention (Thompson 2002; Gielen 2003).

Different from prior papers where socio-psychological theories have been used to explain and predict motorcycle helmet use, this study will propose and empirically verify a so-called integrated behavioral model (e.g., Montaño 2008; Klöckner 2009; Davies 2002; Chen 2011). Such an integrated behavioral model is based on the idea that it is fruitful to combine socio-cognitive constructs drawn from different theories (Armitage 2000; IOM 2002; Elliott 2010). More in detail, the model in this study will bring together variables from the Theory of Planned Behavior (Ajzen 1991) and the Health Belief Model (Rosenstock 1974), since these are the two most frequently used models by previous studies on helmet use.

Throughout the next section we review the literature concerned. More in detail, we list up and classify different factors that have been identified as potential determinants of helmet use, we highlight typical differences between users and non-users, and we comment on how behavioral models have been used in previous studies. After that, we discuss applications of the HBM and TPB on helmet use and integrate these two theories into a single overall model, together with two additional norm-related concepts, i.e., descriptive- and personal norm. We continue with the methodological aspects of the study that was conducted to empirically verify this integrated behavioral model. Besides discussing the obtained results, we come to the road safety implications, and in addition to the study's limitations, we propose an agenda for future research. A final conclusion will summarize the most important findings.

6.2.5. Literature Review

A. Determinants Of Helmet Use

Within the literature on bicycle and motorcycle behavior, numerous potential determinants for helmet usage have been identified. In general, these relate to the driving context, trip-specific aspects, vehicle properties, and driver/passenger characteristics (for some good overviews, we refer to

Thompson 2002; O'Callaghan 2006; Gkritza 2009; Kakefuda 2009; Ranney 2010; Ritter 2011; Ross 2011.

With respect to the importance of driving context, the use of helmets has been found to vary in function of (1) the time conditions (time of the day, day of the week, period within the riding season) (Nakahara 2005; Hung 2008; Li 2008; Gkritza 2009), (2) roadway conditions (pavement surface, type of roadway, roadway environment)(Gkritza 2009), (3) climate and weather conditions (sunshine, temperature, level of precipitation, cloudiness)(Gkritza 2009), (4) traffic conditions (high vs. low traffic density)(Rodgers 1995), and (5) the presence of cues to action, such as a (universal or partial) mandatory helmet law (Lee 2005; Coben 2007; Houston 2007; Houston 2008; Mayrose 2008; Hill 2009; Karkhaneh 2011) educational campaigns (Ashby 1998), school/company regulations(Ichikawa 2007), enforcement (Cambodia 2010) or helmeted co-driver/passenger role models (Lajunen 2001; Fuentes 2010).

Besides that, helmet usage is influenced by variables related to the trip itself. As such, research indicates people decide to use the helmet (or not) depending on (1) the travel distance (Everett 1996; Page 1996), (2) the number of passengers (Xuequn 2011), and (3) route purpose (commuting vs. recreation) (Kakefuda 2009). With respect to vehicle-related properties, helmet usage rates have been reported to vary in function of registration status (Xuequn 2011).

Finally, helmet use has been related to different driver/passenger characteristics. Basically, these can be subdivided into six categories, i.e., (1) variables related to personal driving history such as driving experience or frequency (Ritter 2011) and (in-)direct accident involvement (Fullerton 1991; Coron 1996; Ranney 2010; Ross 2010); (2) variables related to the commission of other forms of risky driving such as speeding, driving while intoxicated, not wearing the car seatbelt, use of unapproved head protection devices such as a skull cap or a beanie, or not always wearing protective gear while riding (Lin 2003; Germeni 2009; Gkritza 2009; Ranney 2010); (3) socio-demographic variables such as age and gender, education, income, socio-economic status and household composition (Gkritza 2009; Dellinger 2010; Donate-López 2010; Ranney 2010; Ritter 2011); (4) exposure to some form of motorcycle education and/or training (Savolainen 2007), (5) helmet ownership (Ross 2010) and; (6) so-called socio-cognitive variables drawn from several well known theoretical models within the field of traffic and health psychology, but mostly from the Theory of Reasoned Action/Theory of Planned Behavior, and the Health Belief Model (Trifiletti 2005). Since socio-cognitive determinants of voluntary helmet use are the central focus of attention in this paper, we will discuss these more in detail under a separate section (cf. section 5). We continue with a closer view on what earlier studies found to be the most important differences between helmet users and non-users.

B. Users vs. Non-users

In terms of correlates for helmet use vs. non-use, there are no fundamental differences between bicyclists on the one hand and motorcyclists on the other. In a U.S. study reviewing barriers for helmet use among undergraduate bicyclists, Ross (2010) mentioned cost, short distances, lack of knowledge regarding helmet efficacy, negative peer pressure, concerns about ridicule, physical discomfort and inconveniences such as disruption of physical appearance, and vision impairment. Hill (2009) reported almost identical barriers for helmet use in a study on motorcyclists in Viet Nam, namely, cost, uncertainty about quality and efficacy in terms of injury prevention, aesthetic objections such as stupid and unfashionable looks, messing up face make-up and stylish hair, functional discomfort under the form of restricted vision and hearing, and practical obstacles such as hot and heavy, difficult to store and likely to be stolen. Li (2008) observed and interviewed a sample of 2.325 Chinese motorcyclists and found the common perception among non-users to be that helmets are only needed when riding on highways (95.9), not always comfortable (71.3), and that helmets could block vision (38.5). A recent study by Orsi (2012) on motorcycle riders' perception of helmet use found the two most common complaints to be related to noisiness and the helmet visor.

In contrast, positive correlates of undergraduates' helmet use are past personal injury or hospitalization due to a bicycling accident, a cycling-related injury to a close friend, long distances, helmet ownership, perceived vulnerability to injury, perceived ability of helmets to prevent head injury, and having peers who routinely wear bicycle helmets (Ross 2010). O'Callaghan (2006) also looked at helmet use among adolescent cyclists and proposed similar findings. Users typically would be more convinced that wearing a helmet protects their head in an accident. Also, users seem to agree that significant others such as best friends or other cyclists wear and approve helmets. In addition, users are more inclined to think that wearing a helmet is the right thing to do. Next to that, they believe more strongly that helmet use can be stimulated by personal principles and morals, by feelings of safety and pride or guilt, regret and disappointment in case of non-use, and by increased self-confidence, enforcement, and secure storage opportunities.

Of particular interest with respect to helmet use, is that several studies found wearers not always to be driven primarily by safety-related motives. For instance, Hill (2009) noticed that Vietnamese motorcyclists often use a helmet, not because of the perceived protection offered, but rather by a desire to avoid being fined by the police or by fear to (permanently) lose family income due to an accident. Li (2008) confirmed this for Chinese motorcyclists. Wearing helmets was not to prevent or alleviate head injury, but to cope with police.

Ross (2010) (p. 30) summarized the comparison between users and non-users as follows: helmet wearers generally (1) have lower perceived exemption from harm, (2) higher perceived danger from (Deutermann)cycling, (3) higher perceived severity, (4) more emotional benefits from using helmets, (5) more safety benefits related to using helmets, (6) less cost barriers, (6) less personal vanity and discomfort barriers, and (Deutermann) experience friends, family, parental rules in childhood and media influences more as a positive cue to action.

Before bringing together a selection of these different helmet use correlates into an integrated behavioral model, the next section will touch upon how some influential behavioral theories have been used in previous studies.

C. Prior Use Of Behavioral Models

Within health psychology, individual differences with respect to all sorts of health behaviors have been explained in function of socio-demographic factors such as age, gender, income, etcetera. These socio-demographic factors however, are very difficult (if not impossible) to influence. Therefore, the search started for more readily changeable psychological variables that could account for the differences in health behavior that were previously attributed to socio-demographics. Special attention thereby went to social cognitive variables, giving rise to a number of behavioral models referred to as social cognition models (Norman 2006). According to Armitage (2000) social cognition models can be further subdivided into motivational models (i.e., models that focus on the motivational factors that underpin individuals' decision to perform (or not) a health behavior), behavioral en-action models (i.e., models focused on bridging the gap between motivation and behavior) and multi-stage models (i.e., models that delineate processes that facilitate behavioral en-action and provide maintenance strategies). A detailed review of the literature on unintentional injury prevention performed by Trifiletti (2005) indicates that motivational models clearly predominate in the area of motor- and bicycle injury prevention. More in detail, the TRA, TPB and HBM are the most popular theoretical models.

According to Glanz (2008), motivational models can be used in many different ways, for instance, in function of (1) the purpose they serve and (2) the way in which they are implemented.

In terms of usage purposes, when serving a descriptive purpose, motivational models function as a source of inspiration for the identification and assessment of socio-cognitive key-correlates of behavior. Typically, data for these socio-cognitive constructs is gathered in an attempt to gain primary insight into the specific behavioral problem under study (e.g., Lajunen 2001; Ross 2010). When serving an explanatory purpose, the function of motivational models is different in a sense that the focus is not primarily on the socio-cognitive constructs themselves, but on whether and/or how these structurally relate to each other and to behavior. Put differently, rather than purely describing a specific behavioral problem, the intention is to understand the underlying psychological mechanism (e.g., Arnold 1994; O'Callaghan 2006; Ranney 2010; Ross 2011). When used for a comparative purpose, the main goal is to find out which from a variety of motivational models has the highest predictive power and accordingly, can be assumed to offer the best explanatory framework for the behavioral problem under study (e.g., Lajunen 2004; Quine 2006; Ambak 2010).

In terms of implementation, motivational models within the helmet literature have been replicated in various ways, going from partial implementation (i.e., only a fragment of the original model is replicated) (e.g., Ranney 2010) over full implementation (i.e., the original model is fully replicated) (e.g., Trifiletti 2005) for an overview) to extended or integrated implementation (i.e., a set of variables drawn from different motivational models is integrated into a single overall model) (e.g., Sissons-Joshi 1994; O'Callaghan 2006; Quine 2006; Kakefuda 2009). With respect to the latter however, it is important to notice that the most recurrent practice is to select one specific motivational model (for instance, the TPB) as a reference framework and to extend it with one or a few additional variables (often being habit or past behavior), rather than starting from different motivational models from which the most important variables are distillated (e.g., Fishbein 2001) and then amalgamated into a single overall framework, as proposed by Davies 2002, Figueroa 2002, and Montaño 2008. Recent applications of this approach can be found in studies performed by Klöckner 2009 and Chen 2011. Klöckner 2009 proposed an integrated model for car use, bringing together the TPB, the Norm Activation Model and Habit. Chen (2011) combined the Theory of Planned Behavior, the Technology Acceptance Model, and Habit into an overall framework to better understand switching intentions to public transport among motorcycle- and car commuters.

As already indicated, this study proposes an integrated model with variables drawn from the Theory of Planned Behavior and the Health Belief Model. This integrated model will be used for explanatory purposes, i.e., to better understand the psychological process behind motorcycle helmet use. In addition to that, the predictive power of the integrated model will be compared to that of the two original models.

6.2.6 Theoretical Background

A. Health Belief Model

The HBM has its origins in the early 1950s and was developed by the U.S. Public Health Service in order to better understand the widespread failure of people to accept disease preventives or screening tests for the early detection of asymptomatic disease (Janz 1984). It has since then been applied to a wide variety of health-related problems. Within the field of traffic safety, the HBM has been implemented recurrently to explain and predict the use of preventive safety devices such as seat belts (e.g., Şimşekoglu 2008), child safety seats (e.g., Chang 1989, Deutermann) cycling helmets (e.g., Lajunen 2004; Quine 2006; Ambak 2010).

Essentially, the HBM considers “healthy” or “safe” behavior in function of two basic mechanisms, i.e., threat perception and behavioral evaluation (Rosenstock 1974; Becker 1975). Threat perception is to be understood as a function of perceived susceptibility (i.e., the estimated likelihood of being involved into a motorcycle crash without wearing a helmet) and perceived severity (i.e., the anticipated seriousness of the consequences of a motorcycle crash without wearing a helmet). Behavioral evaluation consists of two sets of beliefs, namely, perceived benefits (i.e., the assumed advantages of wearing a helmet, such as reduced injury risk), and perceived barriers (i.e., the expected disadvantages of wearing a helmet, such as inconvenience or discomfort). Another important cognitive component in the HBM are the so-called cues to action (i.e., any internal or external triggers increasing the readiness to wear a helmet such as unpleasant memories, advice from media or others, etcetera) (Sheeran 1996). Since its apparition, this model has been further modified several times through the addition of other variables such as health motivation and self-efficacy (Champion 2008).

Originally, the HBM suggested that its variables should be used primarily to predict the probability or likelihood that a certain prevention-oriented behavior (i.e., helmet use) will occur. However, some years later, Rosenstock and his colleagues speculated that behavioral intentions might be a mediating variable between the HBM variables and behavior. This assumption was retained and empirically supported by others later on (Quine 2006). Even though there still is debate on how the different HBM variables influence each other or combine to affect behavior, Quine (2006)(p. 76) propose treating them as separate influences, which would be in line with Rosenstock's discussion of the model. Across different research areas and behaviors, findings for the HBM variables in terms of predictive importance are quite mixed (e.g., Becker 1974; Janz 1984; Harrison 1992).

As for perceived susceptibility, summary results seem to indicate that this variable is important overall, but especially in cases where the focus is on preventive health behavior rather than sick-role or unsafe behavior(Champion 2008). Within the literature on helmet use, (Sissons-Joshi 1994) found it to be the only significant predictor for the intention to wear a helmet. Yet, this is contrary to findings reported by Lajunen (2004); Quine (2006) and Ambak (2010), who found no such effect on behavioral intentions. As for models with behavior itself as dependent variable, significant effects for perceived susceptibility were established by Arnold (1994). This however deviates from other studies (e.g., Sissons-Joshi 1994; Quine 2006).

With respect to perceived severity, results are more consistent. Champion (2008) state that, even though it is strongly related to sick-role or unsafe behavior, overall, this variable is the least powerful predictor for preventive action taking. Most studies confirm that perceived severity has no significant influence, neither on helmet use intentions, nor on behavior (e.g., Arnold 1994; Gielen 1994; Sissons-Joshi 1994; Quine 2006; Ambak 2010). There are a few exceptions however. Lajunen (2004) for instance, found perceived severity to be a significant predictor for the intentions to wear a helmet and Witte (1993) established important influences of threat perceptions on bicycle helmet-related attitudes, intentions and behavior.

Perceived benefits are overall considered to be a powerful predictor. Interestingly, their effect is stronger when the focus is on sick-role or unsafe behavior rather than on preventive health behavior (Champion 2008). Results coming from the literature on helmet use do not seem to be conclusive. Although it is a well-supported fact that helmet users can be discriminated from non-users in function of how they score the potential benefits (and barriers) of wearing a helmet (e.g., O'Callaghan 2006; Kakefuda 2009; Ross 2010), studies where the strength of perceived benefits as predictors of helmet use intentions and behavior has been investigated do not always find it to be an important determinant. Sissons-Joshi (1994), Lajunen (2004) and Ambak (2010) for example, found no significant effects for intentions to use a helmet and Lajunen (2001) demonstrated that perceived safety benefits were significant predictors for helmet ownership, but not for helmet use behavior itself. Different results were obtained by Arnold (1994) and Quine (2006) who identified perceived benefits as the strongest predictor for both helmet use intentions and behavior.

Turning to perceived barriers, Champion (2008) (p. 50) summarized that existing evidence suggests this variable is the most powerful single predictor across all studies and behaviors. In general, studies on helmet use indeed seem to support the importance of perceived barriers. Lajunen (2004) found it to be the strongest predictor of helmet use intentions. Others have also reported significant effects on intentions (e.g., Quine 2006) and behavior (e.g., Arnold 1994). Contrary to that, Ambak (2010) did not find significant effects for perceived barriers as a determinant of helmet use intentions.

Finally, since cues to action have not yet been studied systematically, neither conceptually, nor empirically, findings for this variable are to be taken as exploratory at best (Champion 2008). Depending on its operationalization, mixed results have been found. For instance, studies focusing on the potential of a compulsory helmet law as a cue to action all together found substantial to strong positive effects on helmet use behavior with increases ranging from 5 to 54 (e.g., Karkhaneh 2006; Karkhaneh 2011). Different from that, another frequently investigated cue to action, i.e., (in)direct accident involvement, shows much less consistent results. While Arnold (1994) found it to be the strongest predictor of helmet use, other studies were not able to detect any significant effects on helmet wearing intentions or behavior (e.g., Dannenberg 1993; Sissons-Joshi 1994; Everett 1996; Lajunen 2001; Quine 2006).

B. Theory of Planned Behavior

Undisputedly, the TPB (Ajzen 1988) and its predecessor, i.e., the Theory of Reasoned Action (Fishbein 1975) are the most influential motivational models within the literature on helmet use (Trifiletti 2005). In general, the TPB posits that an individual’s behavior (in this case, the use of a helmet) is dependent upon so-called intentions (i.e., the personal willingness or preparedness to use a helmet), with the latter being determined by three socio-cognitive factors, i.e., attitude, subjective norm and perceived behavioral control.

An attitude can be defined as a person’s overall evaluation of the targeted behavior and expresses for instance the extent to which one likes or dislikes using a helmet. Attitudes are based on so-called behavioral beliefs, i.e., a set of salient beliefs about the potential consequences of performing a certain behavior (or not). These behavioral beliefs are also referred to as ‘outcome expectancies’ and can be positive (a helmet protects me from getting seriously injured) or negative (a helmet is inconvenient and unfashionable). Conceptually, behavioral beliefs are equal to the HBM variables ‘perceived benefits and barriers’ (Lippke 2008). However, an important difference with the HBM is that according to the TPB, perceived benefits and barriers do not directly influence intentions or behavior (Ajzen 1980).

Subjective norm stands for the extent to which one takes into account (or not) the opinion of important reference groups (like family or friends) with regard to the use of a helmet. A person’s beliefs about whether other people think s/he should be wearing a helmet or not are known as normative beliefs. These normative beliefs thus constitute the basis of the variable subjective norm.

Perceived behavioral control refers to the subjective probability that one is capable of wearing a helmet. This perceived behavioral control in turn, is dependent upon so-called control beliefs, i.e., the degree to which one thinks being able to resist to certain contextual factors that might prevent a helmet from being used (such as for instance when traveling for a short distance or when having no opportunity to store a helmet). Besides an indirect effect on behavior (i.e., through intentions), perceived behavioral control can have a direct effect on behavior as well.

The hypothesized key-relationships within the TPB have received wide empirical support within the literature on helmet use (Ross 2011). Even though this is not always the case (e.g., Quine 2006), most studies find attitude to be a significant predictor of the intentions to wear a helmet (e.g., Otis 1992; Berg 2001; Lajunen 2004; Ambak 2010). As for subjective norm, different social reference groups, going from family and parents (e.g., Witte 1993; Lajunen 2001; Fuentes 2010) to friends (e.g., Gielen 1994; O'Callaghan 2006; Quine 2006; Fuentes 2010), passengers (e.g., Gkritza 2009), and other (Deutermann) cyclists (e.g., O'Callaghan 2006) have been found to have a significant positive and/or negative influence on both helmet use intentions and behavior. With regard to perceived behavioral control, both direct and indirect (i.e., through intentions) effects on helmet use behavior have been reported (e.g., Lajunen 2004; O'Callaghan 2006; Quine 2006). Finally, the core assumption that helmet use behavior is largely driven by the underlying intentions to do so (or not), has also been supported (e.g., O'Callaghan 2006; Quine 2006; Ambak 2010).

Even though both the HBM and the TPB have been found to predict helmet use behavior quite well, there are indications that the TPB has greater predictive power (with less redundancy) than the HBM. Three helmet-related studies directly comparing the two theories found the TPB to be the best performing model (e.g., Quine 1998; Lajunen 2004; Ambak 2010). Notwithstanding, it would be interesting to join the two models into a single overall framework. By listing up several manners in which the two models could further complement each other, Quine (2006) (p. 79-80) implicitly provide a solid theoretical argument in favor of such an integrated approach. Strengths of the TPB are that, besides taking into account a person's rational arguments to use a helmet (or not), it encapsulates any eventual pressure coming from the social environment as well as the estimated control over contextual factors that might facilitate or hinder helmet usage. An important addition from the HBM would be that, besides the purely rational aspect of making choices, threat-specific variables such as perceived susceptibility and severity represent a well recognized emotional side of health- and safety-related decision-making. Also different from the TPB, the HBM takes into account the role of any potential cues to action. Even though strictly taken, the TPB does not exclude such cues to action, it seriously attenuates their significance by assuming they influence behavior only indirectly, i.e., through their effect on behavioral and normative beliefs. Throughout the following section, we describe the integrated model that will be tested in this study.

C. Integrated Behavioral Model

Figure 6.8 pictures the integrated behavioral model as it will be empirically verified.

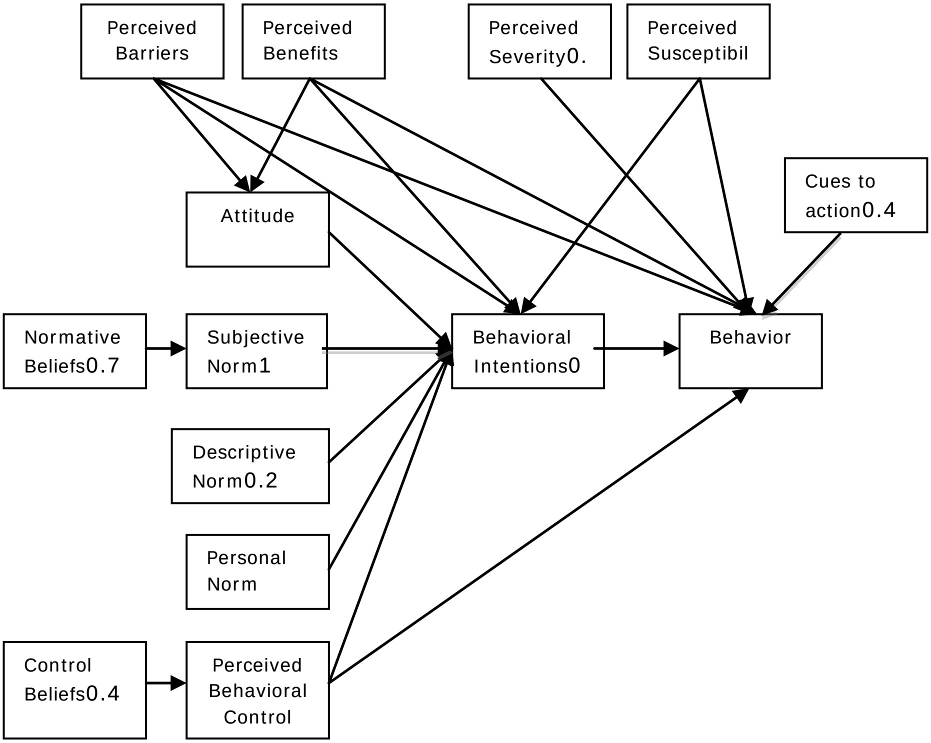

Figure 6.8 Hypothesized Integrated Behavioral Model for Helmet Use

Four things are important to notice with respect to this model. Firstly, since Rosenstock's assumption that the effect of the original HBM variables on behavior itself could possibly be mediated by behavioral intentions has received empirical support, we have linked the five HBM constructs (i.e., perceived benefits and barriers, perceived susceptibility and severity, and cues to action) to both intentions and behavior. Secondly, in line with (Quine 2006), we treat the two variables related to threat perception (i.e., perceived susceptibility and severity) and behavioral evaluation (i.e., perceived benefits and barriers) as separate factors. Thirdly, as already discussed, in this model, the HBM variables "perceived benefits and barriers" are to be considered as identical to the TPB variables "positive and negative behavioral beliefs". This explains why the concepts 'perceived benefits and barriers' have also been linked with the variable "attitude". Finally, besides the variables contained by the original HBM and TPB models, two more concepts have been incorporated, i.e., descriptive norm and personal norm.

Descriptive norm stands for perceptions about whether important social referents will carry out the behavior themselves and influences behavioral intentions by informing a person about the extent to which the behavior is typical (Norman 2005; Elliott 2010). Several studies on helmet use (e.g., Gielen 1994; Sissons-Joshi 1994; Fuentes 2010) support the finding reported in a meta-analysis by Rivis (2003) that descriptive norm is a significant predictor of intention, and often even a stronger one than subjective norm. To illustrate, in a sample of 965 Finnish high school students, Lajunen (2001) found the number of friends using a helmet (i.e., an item typically related to the concept “descriptive norm”) to be more strongly related to helmet use than the dependency on friends’ opinion about helmet use (i.e., an item more related to the concept “subjective norm”).

Contrary to subjective and descriptive norm, personal norm refers to the motivation to perform a behavior according to one’s own personal value system. As Parker (1995) explain, the underlying idea is that before an individual engages in a certain behavior, he will consider the potential consequences for his self-image. In case of conflict with a set of deeply engrained moral values, anticipated regret will refrain a person from carrying out the behavior. Even though to the best of our knowledge, the predictive power of personal norm in combination with the other two norm-related concepts (i.e., subjective and descriptive norm) has not yet been investigated in the literature on helmet use, there are reasons to expect that it is an important determinant of helmet-related intentions and behavior. For instance, not only do helmet users typically more than non-users consider wearing a helmet spontaneously as the right thing to do (e.g., O’Callaghan 2006), a study by Manstead (1995) reported that 10 to 15 of traffic behavior could be explained by the variable personal norm. In light of the above mentioned insights, we added descriptive- and personal norm to the model as two determinants of the intentions to wear a helmet.

6.2.7 Methodology

A. Design and procedure

To test the integrated model for helmet use, a single group cross-sectional survey design was developed. The study was conducted during spring, 2009. A total of 344 motorcyclists were randomly approached on a series of pre-selected locations such as supermarkets and gas stations, spread across different areas of Phnom Penh city (i.e., the capital of Cambodia). Professionals working for Handicap International - Belgium and a team of trained master students from the Department of Sociological Sciences collected the data by means of a structured face-to-face interview. Participants first gave their formal consent and were informed about anonymous and confidential treatment of the data. Next, they self-reported on a series of items related to their personal helmet use. The whole procedure took approximately 20 minutes.

B. Participants

Taking into account missing values, the sample studied included 50% males (n = 172) and 47.7% females (n = 164). Mean age was 22.56 (SD = 3.47) with 88.6 of the sample (n = 305) being between 16 and 26 years old. Among the interviewees, 86% (n = 296) were single, 66.6% (n = 229) were high school/university students, and 64.2% (n = 221) had no personal income. Interestingly, 94.5% (n = 325) of the persons interviewed declared they had a helmet vs. 4.1% (n = 14) who said they did not.

C. Questionnaire development

Questionnaire development went through six-steps. Firstly, a detailed literature review was conducted to identify good measurement items for the various HBM- and TPB-concepts that were included in the integrated model. Secondly, a series of in-depth interviews were conducted with key stakeholders, such as the National Road Safety Committee (NRSC), the Cambodian Red Cross (CRC), the Japan International Cooperation Agency (JICA), the Coalition for Road Safety (a local non-governmental organization), the Ministry of Education, Youth and Sports (MoEYS), and the Office of the Municipal Traffic Police, in order to get an overview of the road safety situation in Cambodia in general, and with respect to helmet usage more in particular. Thirdly, the results of the interviews and the literature search were discussed in a focus group consisting of a selected mix of representatives of the stakeholder parties mentioned above, and members of the research team. This exercise resulted in a first list of candidate items for the questionnaire to be developed. In a next step, through intense discussions with Cambodian natives, members of the research team verified the questionnaire's so-called conceptual equivalence, i.e., the identity of theoretical constructs that can be interpreted differently across cultures, so that possible misunderstandings could be avoided (e.g., Harkness et al., 2003). After that, the interview questionnaire was pre-tested in situation on a small-scale random subsample (n = 10).

Finally, before its definite implementation, based on the outcome of this pre-test, the basic format as well as some interview instructions were slightly modified and the interview procedure further improved to minimize the influence of the interviewer. In addition, formulation of items in the questionnaire was more specifically adapted to the local Cambodian situation and some statements were rephrased in order to make them more understandable to Cambodians.

D. Questionnaire

The final questionnaire contained two main sections. The first section focused on background variables such as age, gender, education, income, marital status and helmet ownership. The second section contained a total of 46 items measuring the set of 14 socio-cognitive constructs included by Figure 1. Table 1 gives an overview of these constructs, as well as the items and the scales used to assess them. For each construct, mean values as well as scores for S.D. and Cronbach's α as a test for reliability are reported.

E. Data analysis

Data were analyzed with SPSS 18.0. As a starting point, for each of the measured constructs, respondent scores on the different items per construct were averaged into a composite index. These composite indexes served as input for subsequent analyses.

In first instance, a two-tailed Pearson correlation test was carried out in order to be able to identify potential predictors of behavioral intentions and behavior (Table 6.2).

In second instance, before concentrating on the integrated behavioral model, we focused on the two original models, i.e., the HBM and the TPB. More in detail, for the HBM, two multivariate regression analyses were performed, i.e., a first one with behavioral intentions as dependent variable and a second one with behavior as dependent variable (Table 6.3). The hypothesized determinants entered the regression simultaneously in order to be able to estimate their respective contribution in the prediction of behavioral intentions and behavior. The same analyses were done for the TPB (Table 6.4), but in addition, we explored the power of the individual items used to measure the different belief-concepts (i.e., perceived benefits/barriers, normative beliefs and control beliefs) in predicting attitude, subjective norm and perceived behavioral control respectively (Table 6.5).

In third instance, for the integrated behavioral model, two series of hierarchical regression analyses were executed, i.e., a first one with behavioral intentions as dependent variable (Table 6.6) and a second one with behavior as dependent variable (Table 6.7).

6.2.8 Results

A. Descriptives

As can be derived from the mean values reported in Table 6.1 and 6.2, respondents are overall more strongly convinced that wearing a helmet has certain benefits than that the proposed potential disadvantages would be meaningful barriers refraining them from using a helmet while driving (perceived benefits: mean = 4.31, SD = 0.60 vs. perceived barriers: mean = 2.18, SD = 0.90). As for normative beliefs, all together respondents think that a series of important social referents support the use of helmets (mean = 4.02, SD = 0.74), albeit that the perceived support among friends (mean = 2.92, SD = 1.40) is remarkably lower compared to the other reference groups (i.e., parents: mean = 4.12, SD = 1.10; partner: mean = 4.26, SD = 1.12; most Cambodian people: mean = 4.26, SD = 0.70). Regarding control beliefs, a mean value of 3.38 (SD = 0.87), suggests that respondents do not consider it always to be that easy to wear a helmet under situational circumstances that might stimulate them not to do so. The situations most difficult to resist are when travelling a short distance (mean = 2.49, SD = 1.40), at night (mean = 2.67, SD = 1.50), and when dressed up to go out (mean = 2.70, SD = 1.41) (Table 6.1).

In terms of attitude, results indicate respondents are overall very positively oriented towards using a helmet (mean = 4.31, SD = 0.73). With respect to subjective norm, a mean score of 4.26 (SD = 0.85) shows respondents strongly agree their social environment favours wearing a helmet. Interestingly, compared to subjective norm, both the degree to which respondents really see other important social referents (in this case, friends) using a helmet (i.e., descriptive norm: mean = 3.72, SD = 1.03), as well as the extent to which respondents consider it as a personal moral obligation to wear a helmet (i.e., personal norm: mean = 3.94, SD = 0.85), are somewhat lower. Turning to, perceived behavioral control, respondents are quite confident they are able to resist influences that might prevent them from using a helmet (mean = 3.99, SD = 1.00).

Table 6.1 Concepts and scales

Concepts	Items	Scoring	M	S.D.	N
Perceived Benefits (α= .58)	Wearing a helmet protects me from getting head injured in accident.	1= disagree : 5= agree	4,68	0,61	344
	Wearing a helmet protects me from dust/wind/rain.	1= disagree : 5= agree	3,89	1,04	344
	Wearing a helmet protects me from getting into trouble with police.	1= disagree : 5= agree	4,33	1,04	344
	Wearing helmet will better protect me from serious head injury.	1= disagree : 5= agree	4,36	0,85	344
Perceived Barriers (α= .60)	Wearing a helmet is uncomfortable when it is hot.	1= disagree : 5= agree	2,35	1,24	344
	Wearing a helmet is not fashionable.	1= disagree : 5= agree	1,68	1,14	344
	Wearing a helmet makes it difficult to hear and see traffic.	1= disagree : 5= agree	2,50	1,24	344
Normative Beliefs (α= .56)	My parents think that I should never drive without wearing a helmet.	1= disagree : 5= agree	4,12	1,10	341
	My friends think that I should never drive without wearing a helmet.	1= disagree : 5= agree	2,92	1,40	339
	My partner thinks that I should never drive without wearing a helmet.	1= disagree : 5= agree	4,26	1,12	286
	Most Cambodian people consider it is advisable to wear a helmet.	1= disagree : 5= agree	4,64	0,70	342
Control Beliefs (α= .85)	How hard is it for you to wear a helmet when only travelling a short distance?	1= hard to do : 5= easy to do	2,49	1,39	340
	How hard is it for you to wear a helmet when driving slowly?	1= hard to do : 5= easy to do	3,05	1,36	342
	How hard is it for you to wear a helmet when it is hot?	1= hard to do : 5= easy to do	4,01	1,07	342
	How hard is it for you to wear a helmet when driving at night?	1= hard to do : 5= easy to do	2,67	1,50	340
	How hard is it for you to wear a helmet when you are in a hurry?	1= hard to do : 5= easy to do	3,94	1,14	342
	How hard is it for you to wear a helmet when you are dressed up for going out?	1= hard to do : 5= easy to do	2,70	1,41	340
	How hard is it for you to wear a helmet when driving in the city?	1= hard to do : 5= easy to do	3,71	1,10	341
	How hard is it for you to wear a helmet when driving outside the city?	1= hard to do : 5= easy to do	4,43	0,91	340
Attitude (α= .83)	If I wear a helmet while driving, it would be un/safe.	1= unsafe : 5= safe	4,08	1,04	342
	If I wear a helmet while driving, it would be un/pleasant.	1= unpleasant : 5= pleasant	4,27	0,92	342
	If I wear a helmet while driving, it would be ir/responsible.	1= irresponsible : 5= responsible	4,51	0,70	342
	If I wear a helmet while driving, it would be un/embarrassing.	1= embarrassing: 5= unembarrassing	4,36	0,82	342

Table 6.1 Concepts and scales (continuous)

Concepts	Items	Scoring	M	S.D.	N
Subjective Norm	People who are important to me would want me to wear a helmet while driving.	1= disagree : 5= agree	4,26	0,85	341
Perceived Behavioral Control (α= .88)	I believe I have the ability to wear a helmet.	1= disagree : 5= agree	3,88	1,11	342
	I can wear a helmet even if the other do not.	1= disagree : 5= agree	4,14	1,08	342
	I can wear a helmet even if there is no police on the street.	1= disagree : 5= agree	3,94	1,21	342
Descriptive Norm (α= .73)	Most of my friends wear a helmet when driving in the city.	1= disagree : 5= agree	3,34	1,25	339
	Most of my friends wear a helmet when driving outside the city.	1= disagree : 5= agree	4,08	1,08	336
Personal Norm (α= .56)	I consider myself as someone who always wear a helmet.	1= disagree : 5= agree	3,83	1,21	343
	Not wearing a helmet makes me feel guilty.	1= disagree : 5= agree	4,07	1,08	342
	There is no excuse for not wearing a helmet.	1= disagree : 5= agree	3,92	1,22	338
Perceived Severity (α= .73)	Being injured in an accident due to not wearing a helmet could lead to long-term health problems, costs and income losses.	1= disagree : 5= agree	4,38	0,85	342
	My whole life might change due to not wearing a helmet.	1= disagree : 5= agree	4,30	0,86	342
Perceived Susceptibility (α= .70)	Not wearing a helmet in the city is very risky.	1= disagree : 5= agree	3,87	1,17	341
	Not wearing a helmet outside the city is very risky.	1= disagree : 5= agree	4,08	1,11	341
	I worry about having a serious head injury without wearing a helmet.	1= disagree : 5= agree	4,07	1,03	340
Cues to action (α= .80)	More traffic police enforcing the helmet law would stimulate me to wear a helmet more often.	1= disagree : 5= agree	4,38	0,84	342
	Higher fines for violating the helmet law would stimulate me to wear a helmet more often.	1= disagree : 5= agree	4,47	0,91	342
	If more people would wear a helmet, then I would also wear a helmet more often.	1= disagree : 5= agree	4,32	0,85	342
Behavioral Intentions (α= .89)	I intend to wear the helmet the next time I drive my motorcycle.	1= disagree : 5= agree	4,11	1,00	341
	My intention from now on to never drive without wearing helmet is very large.	1= disagree : 5= agree	4,29	0,85	342
	I am willing to wear a helmet more often in the future.	1= disagree : 5= agree	4,29	0,87	338
Behavior (α= .85)	How often do you wear a helmet when you drive in the city?	1= never : 5= always	3,70	1,12	341
	How often do you wear a helmet when you drive outside the city?	1= never : 5= always	4,38	0,91	339
	How often do you wear a helmet in general?	1= never : 5= always	4,04	1,00	339

Table 6.2 Pearson correlation matrix*

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. PBe														
2. PBa	0.03													
3. NB	0.37[b]	-0.03												
4. CB	0.20[b]	-0.29[b]	0.32[b]											
5. ATT	0.43[b]	-0.13[a]	0.51[b]	0.55[b]										
6. SN	0.28[b]	-0.08	0.42[b]	0.39[b]	0.58[b]									
7. PBC	0.31[b]	-0.17[b]	0.47[b]	0.70[b]	0.79[b]	0.54[b]								
8. DN	0.24[b]	-0.19[b]	0.13[a]	0.41[b]	0.38[b]	0.28[b]	0.47[b]							
9. PN	0.40[b]	-0.02	0.43[b]	0.48[b]	0.63[b]	0.47[b]	0.64[b]	0.24[b]						
10. PSe	0.29[b]	-0.03	0.43[b]	0.41[b]	0.58[b]	0.55[b]	0.60[b]	0.26[b]	0.48[b]					
11. PSu	0.20[b]	-0.13[a]	0.35[b]	0.45[b]	0.57[b]	0.47[b]	0.60[b]	0.34[b]	0.47[b]	0.64[b]				
12. CA	0.35[b]	0.05	0.28[b]	0.15[b]	0.48[b]	0.36[b]	0.34[b]	0.14[a]	0.48[b]	0.48[b]	0.41[b]			
13. BI	0.34[b]	-0.05	0.41[b]	0.55[b]	0.70[b]	0.50[b]	0.77[b]	0.33[b]	0.59[b]	0.56[b]	0.51[b]	0.41[b]		
14. B	0.25[b]	-0.23[b]	0.36[b]	0.80[b]	0.65[b]	0.47[b]	0.78[b]	0.45[b]	0.59[b]	0.50[b]	0.58[b]	0.30[b]	0.66[b]	
Mean†	4.31	2.18	4.02	3.38	4.31	4.26	3.99	3.72	3.94	4.34	4.01	4.39	4.23	4.04
SD	0.60	0.90	0.74	0.87	0.73	0.85	1.00	1.03	0.85	0.76	0.86	0.73	0.83	0.89

*P values are as follows: [a]$p < 0.05$; [b]$p < 0.01$; [c]$p < 0.001$

†Scores range between 1 and 5

In relation to perceived threat, respondents agree that the consequences of having an accident without wearing a helmet are serious (perceived severity: mean = 4.34, SD = 0.76) and that they are not excluded from the risk of being involved in such an event (perceived susceptibility: mean = 4.01, SD = 0.86). In addition, increased police controls, higher fines and more people wearing a helmet are considered as potentially effective means to stimulate helmet usage (cues to action: mean = 4.39, SD = 0.73). Finally, through the scores for both behavioral intentions (mean = 4.23, SD = 0.83) and behavior (mean = 4.04, SD = 0.89), respondents self-declare they (are willing to) wear a helmet as a preventive measure against any serious personal harm.

In sum, these results suggest the sample questioned is overall favourably disposed towards the use of motorcycle helmets.

6.2.9 Health Belief Model

Table 6.3 summarizes the results for the regression analyses with the HBM variables as hypothesized determinants of behavioral intentions (cf. upper part) and behavior (cf. lower part).

Table 6.3 Regression analyses for prediction of behavioral intentions and behavior (HBM)

Regression of behavioral intentions on HBM-variables*						
Variables entered	B	SE B	β	t	p	$sr^{2†}$
PERCEIVED BENEFITS	.227	.063	**.167**	3.582	**.000**	**.024**
PERCEIVED BARRIERS	-.025	.040	-.028	-.633	.527	.001
PERCEIVED SEVERITY	.343	.066	**.314**	5.232	**.000**	**.051**
PERCEIVED SUSCEPTIBILITY	.213	.055	**.223**	3.851	**.000**	**.028**
CUES TO ACTION	.124	.058	**.111**	2.141	**.003**	**.008**

*N= 334, R^2= 0.39

†sr^2= the squared semi-partial correlation coefficient. This coefficient equals the R-square change value from the regression when a variable is added or removed.

Regression of behavior on HBM-variables*						
Variables entered	B	SE B	β	t	p	sr^2
PERCEIVED BENEFITS	.185	.067	**.126**	2.741	**.006**	**.013**
PERCEIVED BARRIERS	-.175	.042	**-.178**	-4.147	**.000**	**.031**
PERCEIVED SEVERITY	.234	.069	**.199**	3.385	**.001**	**.020**
PERCEIVED SUSCEPTIBILITY	.422	.058	**.411**	7.222	**.000**	**.093**
CUES TO ACTION	-.009	.062	-.007	-.138	.891	.000

*N= 337, R^2= 0.41

Overall, the five HBM variables accounted for 39% of the total variance in behavioral intentions. Examination of the beta weights for the significant variables indicated perceived severity was the most important predictor (β = .31, p< 0.001), followed by perceived susceptibility (β = .22, p< 0.001), perceived benefits (β = .17, p< 0.001), and cues to action (β = .11, p< 0.01). The effect of perceived barriers was in the expected direction, but not statistically significant (β = -.28, p = .527).

Looking at the model with behavior as outcome variable, the overall predictive power of the HBM variables was slightly higher (R^2 = 0.41) only this time, the results for the individual variables were different from what was obtained for the model with intentions as dependent variable. The strongest predictor of behavior was perceived susceptibility (β = .41, p< 0.001), followed by perceived severity (β = .20, p = 0.001), perceived barriers (β = -.18, $p < 0.001$), and perceived benefits (β = .13, $p < 0.01$). Cues to action did not significantly contribute to the prediction of behavior (β = -.01, p = .891).

6.2.10 Theory Of Planned Behavior

Table 6.4 contains the results for the regression analyses with the TPB variables as hypothesized determinants of behavioral intentions (cf. upper part) and behavior (cf. lower part).

As can be derived, the three assumed TPB predictor variables together accounted for 62% of the total variance in behavioral intentions with perceived behavioral control as the most important factor (β = .55, $p < 0.001$), followed by attitude (β = .23, $p < 0.001$). Interestingly, subjective norm had no significant contribution in the prediction of intentions (β = 0.06, p = .145).

Table 6.4 Regression analyses for prediction of behavioral intentions and behavior (TPB)

Regression of behavioral intentions on TPB-variables*						
Variables entered	B	SE B	β	t	p	sr^2
ATTITUDE	.264	.065	**.233**	4.058	**.000**	**.019**
SUBJECTIVE NORM	.061	.041	.062	1.461	.145	.003
PERCEIVED BEHAVIORAL CONTROL	.457	.046	**.551**	9.853	**.000**	**.112**
*N= 336, R^2= 0.62						
Regression of behavior on TPB-variables*						
Variables entered	B	SE B	β	t	p	sr^2
BEHAVIORAL INTENTIONS	.169	.058	**.158**	2.894	**.004**	**.010**
PERCEIVED BEHAVIORAL CONTROL	.580	.048	**.651**	11.961	**.000**	**.169**
*N= 334, R^2= 0.61						

With regard to behavior, the two hypothesized TPB determinants explained 61% of the total variance with perceived behavioral control (β = .65, $p < 0.001$) as a stronger predictor than behavioral intentions (β = .16, $p < 0.01$). In addition to the prediction of helmet use intentions and behavior, we examined the extent to which the individual items used to measure the four belief-based concepts in the TPB (i.e., perceived benefits/barriers, normative beliefs, and control beliefs) were able to predict their hypothesized dependent variables, i.e., attitude, subjective norm and perceived behavioral control respectively. Table 6.5 gives an overview of the three regression analyses that were conducted to this end with results for attitude in the upper part, subjective norm in the middle, and perceived behavioral control at the bottom.

Overall, the four perceived benefits and the three perceived barriers included in the questionnaire accounted for 28% of the variance in attitude, which is rather low. The two most important predictors were benefit-specific beliefs both related to the helmet's perceived capacity of decreasing the severity (β = .33, $p < 0.001$), and the susceptibility (β = .25, $p < 0.001$) of getting injured in case of an accident. The idea that wearing a helmet is not fashionable was the only perceived barrier that made a significant contribution to the prediction of attitude (β = -.14, $p < 0.01$).

Continuing with subjective norm, the four sources of social influence selected for this study only accounted for a collective 22% of explained variance. The two significant predictors were parents (β = .26, $p < 0.001$) and other Cambodians in general (β = .23, $p < 0.001$). Maybe somewhat surprisingly, the opinion of friends (β = 0.5, p = .386) and partners (β = .11, p = 0.60) did not make a significant contribution to the prediction of subjective norm.

Table 6.5 Regression analyses for prediction of attitude, subjective norm, and perceived behavioral control (TPB)

Regression of **attitude** on perceived benefits and barriers*						
Variables entered	B	SE B	β	t	p	sr^2
Wearing a helmet protects me from getting head injured in accident.	.292	.060	**.247**	4.853	**.000**	**.051**
Wearing a helmet protects me from dust/wind/rain.	.036	.037	.052	.982	.327	.002
Wearing a helmet protects me from getting into trouble with police.	.037	.036	.053	1.021	.308	.002
Wearing helmet will better protect me from serious head injury.	.286	.045	**.333**	6.356	**.000**	**.087**
Wearing a helmet is uncomfortable when it is hot.	-.016	.030	-.027	-.530	.597	.001
Wearing a helmet is not fashionable.	-.087	.032	**-.137**	-2.708	**.007**	**.016**
Wearing a helmet makes it difficult to hear and see traffic.	-.024	.032	-.040	-.744	.457	.001
*N= 342, R^2= 0.28						

Regression of **subjective norm** on normative beliefs*						
Variables entered	B	SE B	β	t	p	sr^2
My parents think that I should never drive without wearing a helmet.	.204	.049	**.261**	4.204	**.000**	**.050**
My friends think that I should never drive without wearing a helmet.	.029	.033	.048	.867	.386	.002
My partner thinks that I should never drive without wearing a helmet.	.090	.048	.114	1.885	.060	.010
Most Cambodian people consider it is advisable to wear a helmet.	.289	.073	**.226**	3.982	**.000**	**.045**
*N= 279, R^2= 0.22						

Regression of **perceived behavioral control** on control beliefs*						
Variables entered	B	SE B	β	t	p	sr^2
How hard is it for you to wear a helmet when only travelling a short distance?	.053	.048	.074	1.418	.157	.003
How hard is it for you to wear a helmet when driving slowly?	-.003	.043	-.004	-.062	.951	.000
How hard is it for you to wear a helmet when it is hot?	-.028	.045	-.030	-.616	.538	.000
How hard is it for you to wear a helmet when driving at night?	.036	.031	.054	1.164	.245	.002
How hard is it for you to wear a helmet when you are in a hurry?	.308	.040	**.349**	7.778	**.000**	**.075**
How hard is it for you to wear a helmet when you are dressed up for going out?	.074	.034	**.105**	2.157	**.032**	**.006**
How hard is it for you to wear a helmet when driving in the city?	.348	.049	**.380**	7.032	**.000**	**.061**
How hard is it for you to wear a helmet when driving outside the city?	.106	.052	**.097**	2.036	**.043**	**.005**
*N= 334, R^2= 0.60						

Contrary to attitude and subjective norm, perceived behavioral control was predicted quite well by means of the eight control beliefs questioned (R^2 = 0.60). Four items were identified as significant predictors with the most important one being the condition of driving inside the city (β = .38, $p < 0.001$), closely followed by being hurried (β = .35, $p < 0.001$), being dressed up to go out (β = .11, $p < 0.05$), and driving outside the city (β = .10, $p < 0.05$).

6.2.11 Integrated Behavioral Model

Table 6.6 gives a summary of the hierarchical regression analysis for the prediction of behavioral intentions. More in detail, the three predictors proposed by the TPB (i.e., attitude, subjective norm, and perceived behavioral control) entered at step one. These variables entered the regression first because prior analyses indicated they were more powerful predictors of intentions than the variables proposed by the HBM (cf. section 6.2.9 and 6.2.10). Descriptive norm and personal norm entered at step 2, since these variables are seen as meaningful additions to the original TPB. Finally, the HBM variables (i.e., perceived benefits/barriers, perceived severity/susceptibility, and cues to action) entered at step 3.

Table 6.6 Hierarchical regression analysis for prediction of behavioral intentions*

	B	SE B	β	t	p	sr^2
STEP 1						
ATTITUDE	.253	.067	**.223**	3.758	**.000**	**.017**
SUBJECTIVE NORM	.052	.042	.053	1.230	.220	.002
PERCEIVED BEHAVIORAL CONTROL	.470	.048	**.565**	9.814	**.000**	**.116**
R^2= .62						
R^2 change= .62						
F change= 170.61 ($p < 0.001$)						
STEP 2						
ATTITUDE	.219	.068	**.193**	3.207	**.001**	**.012**
SUBJECTIVE NORM	.041	.042	.042	.972	.332	.001
PERCEIVED BEHAVIORAL CONTROL	.443	.052	**.533**	8.521	**.000**	**.086**
DESCRIPTIVE NORM	-.020	.031	-.025	-.639	.523	.000
PERSONAL NORM	.109	.046	**.113**	2.391	**.017**	**.007**
R^2= .63						
R^2 change= .01						
F change= 3.26 ($p< 0.05$)						
STEP 3						
ATTITUDE	.167	.072	**.147**	2.318	**.021**	**.006**
SUBJECTIVE NORM	.017	.044	.017	.379	.705	.000
PERCEIVED BEHAVIORAL CONTROL	.457	.056	**.549**	8.224	**.000**	**.079**
DESCRIPTIVE NORM	-.016	.032	-.020	-.517	.605	.000
PERSONAL NORM	.065	.048	.067	1.346	.179	.002
PERCEIVED BENEFITS	.057	.055	.042	1.034	.302	.001
PERCEIVED BARRIERS	.044	.032	.049	1.380	.169	.002
PERCEIVED SEVERITY	.077	.057	.070	1.361	.174	.002
PERCEIVED SUSCEPTIBILITY	-.014	.047	-.015	-.303	.762	.000
CUES TO ACTION	.076	.049	.067	1.549	.122	.003
R^2= .64						
R^2 change= .01						
F change= 2.18 ($p= 0.56$)						
* N= 322						

Overall, the ten variables accounted for 64% of the total variance in behavioral intentions. At step one, attitude, subjective norm, and perceived behavioral control were found to explain already 62% of the total variance in intentions. Only attitude ($\beta = .22$, $p< 0.001$) and perceived behavioral control ($\beta = .57$, $p< 0.001$) made significant contributions. At step 2, addition of descriptive norm and personal norm further increased the value for R^2 by no more than 1%. Besides attitude ($\beta = .19$, $p = 0.001$) and perceived behavioral control ($\beta = .53$, $p< 0.001$), personal norm made a significant contribution to the prediction of intentions ($\beta = .11$, $p< 0.05$). At step three, the total variance explained went up to 64%, which is a very small increase given the number of variables (i.e., five) added to the model. Important to notice is that none of the HBM variables made a significant contribution to the prediction of intentions. In addition to that, personal norm was no longer a significant predictor (β = 0.67, $p = .179$). The only significant contributions were made by two TPB variables, i.e., perceived behavioral control (β = .55, $p < 0.001$) and attitude (β = .15, $p < 0.05$).

Table 6.7 gives a summary of the hierarchical regression analysis for the prediction of behavior. At step one, the two predictors proposed by the TPB (i.e., perceived behavioral control and behavioral intentions) entered the regression. The HBM variables are also hypothesized to determine behavior, but were found to be less powerful predictors than the two TBP variables (cf. section 6.2.9 and 6.2.10). Therefore, the five HBM variables entered at step 2. Even though Ajzen and Fishbein (1980) consider attitude and subjective norm to be related to behavior indirectly (i.e., through intentions), Table 2 shows that these two concepts correlate quite strongly with behavior (attitude: $r = 0.65$, $p < 0.01$; subjective norm: $r = 0.47$, $p < 0.01$). In addition to that, there is the well-known theorists workshop organized by the National Institute of Mental Health (NIMH), where it came out that "…whereas some would argue that some variables (e.g., attitude, perceived norms) influence behavior only indirectly (i.e., through their influence on intention), others would argue for both a direct and an indirect effect of a given variable on behavior." (Fishbein et al., 2001, p. 14-15). The same counts for the variables descriptive norm and personal norm. Both significantly correlate with behavior (descriptive norm: $r = 0.45$, $p < 0.01$; personal: $r = 0.59$, $p < 0.01$), and previous studies have argued they are antecedents proximal to behavior (e.g., Davies et al., 2002; Klöckner and Matthies, 2009; Lajunen and Räsänen, 2001). As a consequence, the variables attitude, subjective norm, descriptive norm, and personal norm were entered at step three. Finally, at step four, control beliefs also entered the regression. Despite Ajzen and Fisbein's (1980) contention that belief-related concepts influence behavior only indirectly, Table 2 indicates that control beliefs was the strongest correlate of behavior ($r = 0.80$, $p < 0.01$). Besides that, a study on recycling behavior in 317 UK households performed by Davies et al. (2002) found a belief-based measure for perceived behavioral control to have significant effects on both intentions and behavior.

Overall, the twelve variables accounted for 75% of the total variance in behavior. At step one, perceived behavioral control (β = .65, $p < 0.001$) and behavioral intentions (β = .15, $p = 0.01$) were found to explain 60% of the variance in behavior. Addition of the five HBM variables at step two slightly increased the R^2 to 63% with significant contributions made by the two TPB variables, i.e., perceived behavioral control (β = .54, $p < 0.001$) and behavioral intentions (β = .15, $p < 0.01$) and two of the HBM variables, i.e., perceived susceptibility (β = .20, $p < 0.001$) and perceived barriers (β = -.11, $p < 0.01$). At step three, the R^2 increased by no more than 2. Interestingly however, the two additional norm-related variables, i.e., descriptive norm (β = .11, $p < 0.01$) and personal norm (β = .17, $p = 0.001$) made significant contributions to the prediction of behavior, besides the two TPB variables perceived behavioral control (β = .41, $p < 0.001$) and behavioral intentions (β = .14, $p < 0.05$), and the two HBM variables perceived susceptibility (β = .18, $p < 0.001$) and perceived barriers (β = -.11, $p < 0.01$). Finally, addition of control beliefs at step four substantially increased the R^2 by 10%, with control beliefs as the most important predictor of behavior (β = .47, p< 0.001), followed in decreasing order by perceived behavioral control (β = .18, p< 0.01), perceived susceptibility (β = .15, p< 0.001), personal norm (β = .11, p = 0.01), and behavioral intentions (β = .11, p< 0.05). To summarize, figure 6.9 brings together the most important results that came out of the analyses.

Table 6.7 Hierarchical regression analysis for prediction of behavior

STEP 1	B	SE B	β	t	p	sr^2
BEHAVIORAL INTENTIONS	.156	.60	**.147**	2.603	**.010**	**.009**
PERCEIVED BEHAVIORAL CONTROL	.580	.50	**.654**	11.594	**.000**	**.172**
R^2= .60						
R^2 change= .60						
F change= 233.16 (p < 0.001)						
STEP 2						
BEHAVIORAL INTENTIONS	.164	.060	**.154**	2.714	**.007**	**.009**
PERCEIVED BEHAVIORAL CONTROL	.479	.054	**.541**	8.920	**.000**	**.095**
PERCEIVED BENEFITS	.039	.056	.027	.694	.488	.001
PERCEIVED BARRIERS	-.105	.034	**-.109**	-3.054	**.002**	**.011**
PERCEIVED SEVERITY	-.059	.060	-.050	-.991	.323	.001
PERCEIVED SUSCEPTIBILITY	.206	.049	**.201**	4.175	**.000**	**.021**
CUES TO ACTION	-.019	.051	-.016	-.380	.704	.000
R^2= .63						
R^2 change= .04						
F change= 5.98 (p< 0.001)						
STEP 3						
BEHAVIORAL INTENTIONS	.146	.060	**.137**	2.442	**.015**	**.007**
PERCEIVED BEHAVIORAL CONTROL	.366	.065	**.413**	5.677	**.000**	**.037**
PERCEIVED BENEFITS	-.019	.058	-.013	-.331	.741	.000
PERCEIVED BARRIERS	-.103	.034	**-.107**	-3.031	**.003**	**.010**
PERCEIVED SEVERITY	-.045	.060	-.038	-.742	.459	.001
PERCEIVED SUSCEPTIBILITY	.182	.049	**.177**	3.710	**.000**	**.016**
CUES TO ACTION	-.065	.052	-.054	-1.242	.215	.002
ATTITUDE	.025	.076	.021	.330	.742	.000
SUBJECTIVE NORM	.006	.046	.005	.122	.903	.000
DESCRIPTIVE NORM	.091	.033	**.106**	2.726	**.007**	**.008**
PERSONAL NORM	.172	.051	**.166**	3.362	**.001**	**.013**
R^2= .65						
R^2 change= .02						
F change= 4.36 (p< 0.01)						
STEP 4						
BEHAVIORAL INTENTIONS	.116	.051	**.109**	2.296	**.022**	**.004**
PERCEIVED BEHAVIORAL CONTROL	.158	.058	**.179**	2.743	**.006**	**.006**
PERCEIVED BENEFITS	-.019	.049	-.013	-.386	.700	.000
PERCEIVED BARRIERS	-.032	.029	-.034	-1.097	.273	.001
PERCEIVED SEVERITY	-.046	.051	-.039	-.896	.371	.001
PERCEIVED SUSCEPTIBILITY	.154	.041	**.151**	3.716	**.000**	**.011**
CUES TO ACTION	.016	.045	.013	.359	.720	.000
ATTITUDE	.017	.064	.014	.259	.796	.000
SUBJECTIVE NORM	-.003	.039	-.003	-.079	.937	.000
DESCRIPTIVE NORM	.053	.028	.062	1.885	.060	.003
PERSONAL NORM	.111	.044	**.107**	2.549	**.011**	**.005**
CONTROL BELIEFS	.474	.043	**.467**	11.028	**.000**	**.099**
R^2= .75						
R^2 change= .10						
F change= 121.61 (p< 0.001)						
* N= 316						

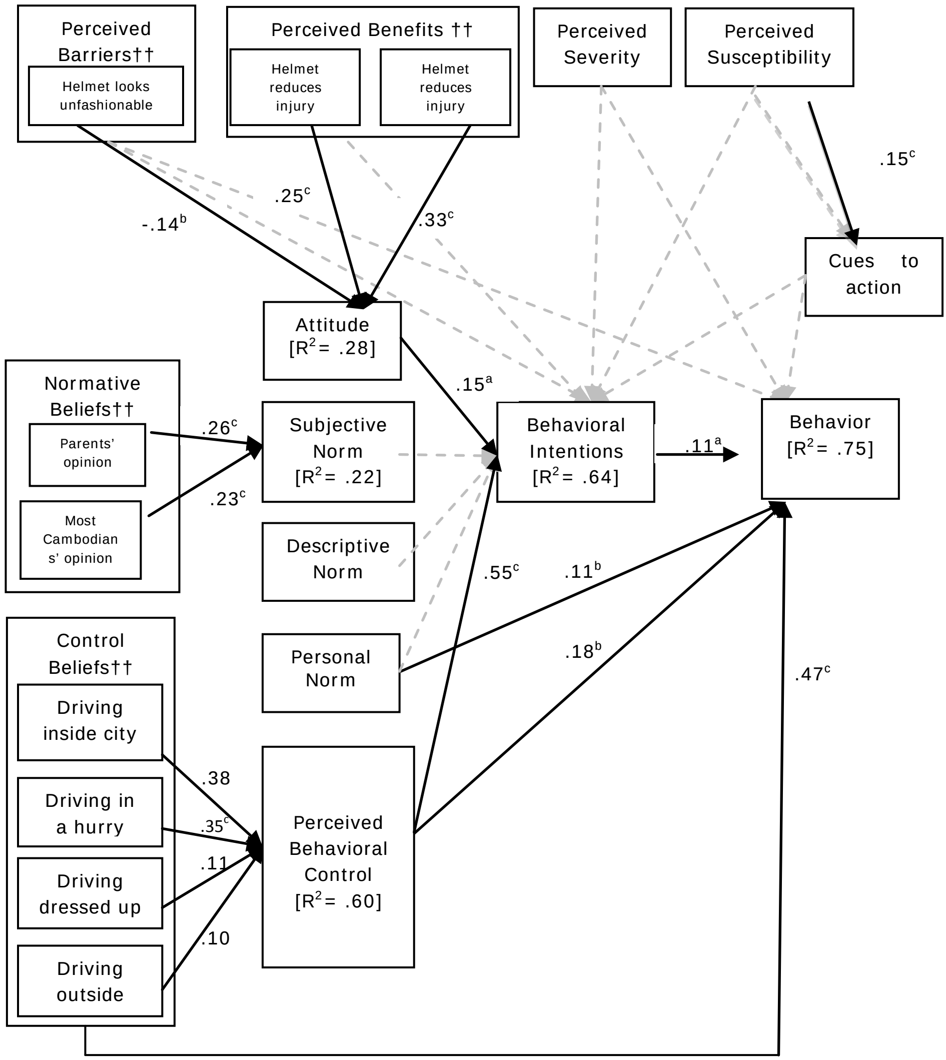

Figure 6.9 Results for the Integrated Behavioral Model for Voluntary Helmet Use

6.2.12 Discussion

A. Descriptive Findings

The descriptive results obtained for the different socio-cognitive concepts included in the questionnaire are useful in a sense that they give us more detailed insight into the sample's current overall disposition towards the use of motorcycle helmets. In general, it can be concluded that the Cambodian young adults that participated in this study are very positive towards wearing a helmet. Besides the fact that 94.5% actually owns a helmet, the aggregate mean values for the majority of the variables examined were very close to or even above 4 on scales from 1 to 5, with values of 5 systematically standing for a helmet-supportive opinion (cf. Table 2). To put it in terms of a well-known multi-stage model, i.e., the Transtheoretical Model of Change (e.g., Prochaska and DiClemente 1983), within the overall process of moving motorcyclists towards a voluntary and systematic use of helmets, this sample of Cambodian young adults can be situated somewhere between the stages of action (i.e., individuals are actively engaged in implementing the desired behavior) and maintenance (i.e., individuals are attempting to maintain the desired behavior).

More in particular, respondents declared they see more benefits than barriers to the use of a helmet, which explains their overly positive attitude. The only serious potential barrier would be the helmet's unfashionable look. The most important perceived benefit is the helmet's ability to decrease both the severity of and susceptibility to personal injuries in case of an accident. With respect to the latter, it is interesting to see that driving without a helmet is clearly recognized as dangerous, both in terms of how serious the consequences of an eventual accident might be like as the extent to which one is vulnerable to personal harm. Turning to the social environment, it can be seen that several important reference groups (i.e., parents, partners, friends, Cambodians in general) favour helmet usage, even though this is somewhat less the case for peers. Also positive in terms of safety, is that the use of a helmet is almost felt to be some kind of intrinsic moral obligation.

Even though respondents are quite confident in their overall ability to wear a helmet, they admit there are some specific situations in which it is not always that easy to use it (i.e., mostly when driving short distances, at night, or when dressed up to go out). Irrespective of the fact that interviewees support the usefulness of more traffic police enforcement, higher fines and a higher amount of people actually wearing a helmet as cues to undertake the right action, the self-reports for both intentions and behavior suggest that study participants are already in the stage of actively implementing the desired behavior, and therefore strictly taken do not really need to be persuaded anymore of the need to start wearing a helmet.

Overall, these findings confirm the socio-cognitive properties that have been considered previously by others as characteristic for convinced helmet users (e.g. Hill et al., 2009; O'Callaghan and Nausbaum, 2006; Ross et al., 2010). Besides that, the results obtained in this study reflect the positive trend in terms of helmet use that can be established over the last few years in Cambodia. To deal with the growing trend in road crashes and fatalities, from 2004 up to now, the Royal Government of Cambodia (RGC) decided to encourage and support a variety of governmental and non-governmental stakeholders active in the field of road safety, with special attention for motorcycle helmet use. Through the National Action Plan, the National Road Safety Policy, and the Motorcycle Safety Helmet Wearing Action Plan, school-based awareness raising programs were implemented, new regulations and penalties on helmet wearing were proposed, and a road traffic accident victim information system was developed. Following the 2009 publication of a law making helmet wearing for motorbike drivers compulsory, the percentage of motorbike fatalities that suffered from head injuries has dropped from 84% in 2007 to 73% in 2010 (RCVIS, 2010).

B. Theoretical Findings

In total, this study examined the role of seven socio-psychological mechanisms behind motorcycle helmet use. According to the HBM, self-protective health behavior can be explained best in function of the following three phenomena: (1) threat perception (i.e., an emotion-oriented aspect of helmet-related decision making), (2) behavioral evaluation (i.e., a rational assessment of helmet-specific costs and benefits), and (3) cues to action (i.e., strategies to activate the readiness to wear a helmet). The TPB also considers behavioral evaluation to be important, but has a different view on its operationalization and its structural relationship with behavior (e.g., Quine et al., 2006). Besides that, the TPB recognizes the importance of two other psychological factors, namely, (4) subjective norm (i.e., a more explicit type of social influence where social referents function as role models through the direct expression and reinforcement of their helmet-related opinions), and (5) perceived behavioral control (i.e., the personally estimated ability to resist to contextual factors that might hinder helmet use). Since we know from social learning theory that individuals adopt or change behaviors not only through direct experience and positive/negative feedback offered by others, but through self-reinforcement, or through indirect or vicarious experiences of others being reinforced (or not punished) for particular behaviors (e.g., Bandura, 1986), we decided to pay attention also to the role of (6) descriptive norm (i.e., a more implicit type of social influence where social referents function as role models through the observation of their behavior by others). Finally, we explored the extent to which helmet use is determined by (Deutermann) personal norm, i.e., a form of anticipated regret caused by a conflict between the potential consequences of not wearing a helmet and a set of deeply engrained moral principles (Parker et al., 1995). Findings with respect to these different socio-psychological mechanisms will now be summarized and discussed.

Threat perception: The HBM considers threat perception as a function of two specific components, i.e., perceived severity and perceived susceptibility. Previously performed studies overall find that perceived susceptibility is important especially when the focus is on preventive health behavior (as in this study), while perceived severity is the least powerful predictor for preventive action taking (e.g., Becker, 1974; Champion and Skinner, 2008; Harrison et al., 1992; Janz and Becker, 1984). When looking at the prediction of helmet use behavior, results obtained in this study confirm that perceived susceptibility is the more important threat-related factor. Both within the model where the HBM was estimated separately as within the model where it was combined with the TPB and two additional norm-related concepts, perceived susceptibility was the most important significantly contributing HBM variable. This is in line with findings reported by Arnold and Quine (1994). However, the picture is somewhat different when looking at the prediction of helmet use intentions. Within the integrated model, neither of the two threat-related variables made a significant contribution, which corresponds to a couple of earlier studies (e.g., Ambak et al., 2010; Quine et al., 1998). Also, estimation of the HBM as a separate model showed perceived severity to be more important than perceived susceptibility as a predictor of intentions, reflecting what was found by Lajunen and Räsänen (2004).

Together, these findings suggest that the role of threat perception as a psychological mechanism in the explanation of helmet use is to be considered with care. In the prediction of helmet use intentions, the influence of perceived threat is of minor importance compared to other psychological factors (i.e., attitude and perceived behavioral control) and mainly driven by its severity component (i.e., the estimated seriousness of the consequences of having an accident when not wearing a helmet). Different from that, in the prediction of helmet use behavior itself, threat perception, and more specifically, its susceptibility component (i.e., the estimated probability of occurrence of a motorcycle crash without wearing a helmet), is a factor that should not be neglected. Inspection of the squared semi-partial correlations shows perceived susceptibility has a unique contribution of 9.3% in the prediction of behavior in the model where the HBM is separately estimated (cf. Table 6.3). Even though this coefficient drops to 1.1% in the model where the HBM is combined with the TPB and the two additional norm-related concepts, it remains the second most important significant predictor of behavior (cf. Table 6.7).

Behavioral evaluation: The HBM defines behavioral evaluation as a rational process where the perceived benefits of wearing a helmet are weighed against the perceived barriers. Prior research overall found perceived benefits of self-protective measures to have stronger effects when focusing on unsafe behavior while perceived barriers would be the most powerful predictor within the HBM across a large number of studies and a wide variety of behaviors (e.g., Becker, 1974; Champion and Skinner, 2008; Harrison et al., 1992; Janz and Becker, 1984). Results obtained in this study are not in line with these findings and suggest there is not much consistency in the way these two variables operate. With respect to the prediction of helmet use intentions, perceived barriers was not found to be a significant predictor, neither in the model where the HBM was estimated separately (cf. Table 6.3), nor in the integrated model (cf. Table 6.6). Even though perceived barriers had a significant effect on helmet use behavior when the HBM was estimated separately, its unique contribution was not that high (sr^2 = .031) and clearly below the value obtained for perceived susceptibility (sr^2 = 0.93). Within the integrated model, the unique contribution of perceived barriers was low (sr^2 = .010) and not significant anymore when control beliefs entered the regression (cf. Table 6.7). Taken as such, these results corroborate what was found by Ambak et al., but deviate from findings reported by Arnold and Quine (1994), Quine et al. (1998) and Lajunen and Räsänen (2004).

The findings for perceived benefits are close to what we established for perceived barriers. Perceived benefits was a significant predictor of helmet use intentions in the model where the HBM was estimated separately, but its unique contribution was limited (sr^2 = .024) and not significant within the integrated model (cf. Table 6). The same counts for the prediction of helmet use behavior: perceived benefits had a significant but small unique contribution in the separately estimated HBM model (sr^2 = .013), but not in the integrated model (cf. Table 7). This is in line with several previously performed studies on helmet use where the HBM was implemented (e.g., Ambak et al., 2010; Lajunen and Räsänen, 2001, 2004; Sissons-Joshi et al., 1994). Thus, the behavioral evaluation mechanism as it is operationally defined by the HBM (i.e., as a purely rational cost-benefit analysis) and structurally related to behavior (a direct relationship between perceived benefits/barriers and behavior is hypothesized) does not receive much support in this study.

Interestingly, the behavioral evaluation mechanism as it is approached by the TPB (i.e., as an expectancy-value process where perceived benefits and barriers, understood as a set of salient outcome expectancies, are also evaluated, resulting in an overall attitude) and structurally related to behavior (it is hypothesized that perceived benefits/barriers → attitude → behavioral intentions → behavior) performs better. Perceived benefits and barriers indeed had significant effects on attitude, albeit the overall variance explained was rather low (R^2 = .28). Attitude in turn, was the only significant predictor of behavioral intentions besides perceived behavioral control, even though its unique contribution was low, both in the model where the TPB was separately estimated (sr^2 = .019) as within the integrated model where the TPB was combined with the HBM and two additional norm-related concepts (sr^2 = .006). Finally, behavioral intentions were found to be a significant, but rather weak predictor of behavior, both within the separately estimated TPB (sr^2 = .010) as in the model together with the HBM and descriptive- and personal norm (sr^2 = .004). Two possible explanations can be found for the weaker performance of behavioral intentions. Firstly, as argued by Davies et al., (2002, p. 98), behavioral intentions are an expression of support for the behavior, and not a commitment to act. Prior research indeed shows that intentions are not always indicative of behavior (e.g., Chandon et al., 2005; Davies et al., 2002; Wong and Sheth, 1985). The extent to which people are willing to implement intentions would already make an important difference to whether or not people undertake self-protective actions (e.g., Gollwitzer, 1999; Gollwitzer and Sheeran, 2006). Secondly, especially for younger people, engagement in risky behaviors (such as not wearing a helmet while riding) often is not a matter of planning or premeditation, but of finding yourself in a situation in which the opportunity to perform such behaviors is presented and/or facilitated (e.g., Gibbons et al., 1998). In other words, the issue is more what you are willing to do (i.e., behavioral willingness) than what you plan to do (i.e., behavioral intentions).

Behavioral evaluation thus is a psychological mechanism that is to be taken into account when studying helmet use, even though there are more important psychological factors in the prediction of helmet use behavior. Next to that, results obtained in this study provide more support for the way in which the TPB approaches the behavioral evaluation process. While the HBM posits that perceived benefits and barriers are antecedents proximal to behavior, our results indicate they are rather to be considered as distal factors, as hypothesized by the TPB. More specifically, perceived benefits and barriers become relevant through their overall evaluation (i.e., attitude). The latter in turn, affects behavior indirectly, i.e., through behavioral intentions.

Cues to action: As indicated by Champion and Skinner (2008, p. 62), little is known about the relative impact of cues to action because the concept has not been identified clearly enough before. Findings in the literature on helmet use are mixed. For instance, Ambak et al. did not find significant effects on helmet use intentions while Lajunen and Räsänen (2004) did. This study examined the following three cues to action: more police enforcement, higher fines, and more people wearing a helmet. Although participants in this study recognized the potential of these items to stimulate the use of a helmet (cf. Table 1), cues to action was not an important variable in the prediction of helmet use intentions or behavior. The only model where cues to action had a significant effect was the one where behavioral intentions were predicted by the HBM variables (cf. Table 6.3). Its unique contribution however was low (sr^2 = .008).

Subjective norm: The total absence of any significant effect for subjective norm might be a surprising finding given the large number of studies where the use of helmets was found to be influenced by social reference groups (e.g., Fuentes et al., 2010; Gielen et al., 1994; Gkritza, 2009; Lajunen and Räsänen, 2001, 2004; O'Callaghan and Nausbaum, 2006; Quine et al., 2006; Witte et al., 1993). Yet, as indicated by Courneya et al. (2006, p.198-199), while direct effects of the TPB variables attitude and perceived behavioral control on intention have been well documented, results for subjective norm are much less consistent. On the one hand, there is literature suggesting subjective norm is not as important as a determinant of future intentions when compared with attitude and perceived behavioral control (e.g., Godin and Kok, 1996; Shepperd et al., 1988; Van den Putte, 1991). On the other hand, an extensive review performed by Quine et al. (2006) resulted in various studies where subjective norm was found to be the better predictor of behavioral intentions.

Across these different studies, three factors are frequently mentioned that seem to affect the extent to which behavioral intentions are influenced by social norms, i.e., (1) the type of behavior under study, (2) the degree to which people are sociable, and (3) the way in which subjective norm is measured (e.g., Armitage and Conner, 2001). More in detail, subjective norm appears to be an important determinant in cases where the target behavior can be qualified as social (i.e., performed in the presence of others, susceptible to prevailing moral standards, or with potential consequences for others), or when people executing the behavior are sociable (i.e., sensitive to the opinions of those who are important to them). Interestingly, subjective norm seems less influential when measured by a single-item instead of a multiple-item scale.

Returning to the topic under study here, qualifying helmet use as individual or social behavior is open for discussion. Even though prior research shows the use of helmets to be determined by social influences such as role modeling and peer-, partner-, or parental reinforcement, helmets are a prototypical self-protective safety measure in a sense that the potential consequences of (not) using it are primarily for the individual. With respect to the sociability of the sample examined in this study (i.e., Cambodian young adults), it is important to notice that research into cultural identity has found (South-East) Asian cultures to be highly collectivistic. Collectivism is a personal or social orientation that emphasizes the good of the group, community or society over and above the individual. In collectivistic cultures, people's self-image is typically defined in terms of "we" rather than "I" and the role of norms and values shared by parents and family is of particular importance (e.g., Hofstede, 2001). As a consequence, in a Cambodian sample, we would expect the opinions of socially closer reference groups to be a more important determinant. Yet, this is not what was found. The analysis for normative beliefs (cf. Table 6.5) indicated that parental opinions as well as the opinions of Cambodian society at large have a significant but rather small unique contribution in the prediction of subjective norm (parents: sr^2 = .050; most Cambodian people: sr^2 = .045). The fact that subjective norm itself is without significant effects could mean that, even though respondents have an idea about what important social referents think of wearing a helmet, they are not inclined to take these opinions as compelling directives for their own behavior. In line with Armitage and Conner (2001), we think a plausible explanation for the overall weak performance of subjective norm can be found in the use of a single- instead of a multiple-item measure that was formulated in general terms (i.e., “people important to you”), rather than referring to a specific reference group (such as parents, or peers).

Perceived behavioral control: Most prior studies on helmet use where the TPB has been implemented found support for both direct and indirect (i.e., through intentions) effects of perceived behavioral control on behavior (e.g., Lajunen and Räsänen, 2004; O’Callaghan and Nausbaum, 2006; Quine et al., 2006). This study clearly confirms these findings. Perceived behavioral control was the most important predictor of behavioral intentions, making significant unique contributions both within the model where the TPB was estimated separately (sr^2 = .112) as in the model where the TPB was combined with the HBM and the two additional norm-related variables (sr^2 = .079). With respect to the prediction of behavior, perceived behavioral control even made a higher unique contribution than behavioral intentions in the model where the TPB was separately estimated (perceived behavioral control: sr^2 = .169; behavioral intentions: sr^2 = .010). In the combined model, perceived behavioral control also had the highest unique contribution in the prediction of behavior (sr^2 = .037), even though this coefficient substantially dropped when control beliefs entered the regression (cf. Table 6.7).

The finding that control beliefs have a higher predictive influence than perceived behavioral control is not surprising. Manstead and Parker (1995) already recommended that, besides a direct measure for perceived behavioral control, studies implementing the TPB would do best in incorporating a belief-based measure as well that contains a set of known situational control factors which facilitate or inhibit the behavior in question. Davies et al. (2002) indeed found a belief-based measure for perceived behavioral control to supersede the direct measure for perceived behavioral control and to substantially improve the predictability of the TPB. According to Manstead and Parker (1995), a possible explanation might be that a belief-based measure containing specific control factors takes the measurement of perceived behavioral control away from rather general statements (such as ‘having the ability to wear a helmet’) to more exact situations (such as ‘wearing a helmet when travelling a short distance’). Considering these results, it can be concluded that the subjective estimation of personal control over specific situational factors that might facilitate or hinder the use of a helmet is the most important psychological process to take into account in this study.

Descriptive norm: As in the meta-analysis performed by Rivis and Sheeran (2003), several studies found that descriptive norm is a significant predictor of helmet use intentions, and often even a stronger one than subjective norm (e.g., Fuentes et al., 2010; Gielen et al., 1994; Lajunen and Räsänen, 2001; Sissons-Joshi et al., 1994). The results obtained in this study are only partially in line with these findings. Descriptive norm indeed made a significant contribution to the prediction of behavior, contrary to subjective norm. The unique contribution however was low (sr^2 = .008) and not significant anymore when control beliefs entered the regression (cf. Table 6.7). In addition, descriptive norm was not a significant predictor of the intentions to wear a helmet (cf. Table 6.6).

A first possible reason for the rather weak performance of descriptive norm might be that this study adopted a health promotion-oriented focus. There are indeed indications that descriptive norm is less important as a determinant in health promotion-oriented studies compared to studies where the focus is on health risk behavior (e.g., Rivis and Sheeran, 2003).

Another potential explanation might be that the items used to measure descriptive norm applied to friends. The fact that friends were not important either in the analysis for subjective norm (cf. Table 6.5), could indeed suggest that this specific social reference group has no fundamental impact on the positive decision to use a helmet in this group of respondents. Results might have been different if we would have focused on the non-use of helmets.

Thus in the present context, the limited extent to which people experience social influence arises from the perceived typical behavior of important social referents (i.e., descriptive norm), rather than from expectations about whether one will receive social disapproval or not (i.e., subjective norm).

Personal norm: As indicated by Davies et al. (2002, p.47), personal norm was defined originally by Heberlein (1975) as a set of strongly internalized moral attitudes, which though derived from socially shared norms, are distinct in that the consequences of violating or upholding them are tied to one's self-concept. Even though to the best of our knowledge, the role of personal norm in the prediction of helmet use has not yet been investigated before, the importance of this variable as a predictor of intentions and behavior has been empirically supported in various studies both outside as within the field of traffic safety (for an overview, see Davies et al., 2002). While Manstead and Parker (1995) could relate personal norm to the commission of driving violations in general, De Pelsmacker and Janssens (2007) identified personal norm as a significant predictor of self-reported speeding behavior. More recently, Elliott and Thomson found the two basic components of personal norm (i.e., moral norm and anticipated regret) to contribute to the explanation of intentions to speed.

This study indicates personal norm is a predictor to take into account when studying helmet use. Next to the classical TPB variables, personal norm made a small but significant unique contribution to the prediction of behavioral intentions (sr^2 = .007), until the HBM variables entered the regression (cf. Table 6.6). Also with respect to the prediction of helmet use behavior, personal norm was found to make a small but statistically significant contribution (cf. Table 6.7). Even in the model where the most powerful predictor (i.e., control beliefs) was added to the regression, the unique contribution of personal norm (sr^2 = .005) remained significant.

Thus, in light of how personal norm is traditionally defined, we can conclude that helmet use intentions and behavior are under the influence of socially shared norms to the extent that violating or upholding these norms has negative consequences (such as feelings of guilt or regret) or positive implications (such as feelings of security or pride) for one's self-concept.

C. Comparative findings

This study examined variables coming from both the HBM and the TPB in two different constellations, namely, within their original setting (i.e., as separately estimated HBM- and TPB-models) as well as within an integrated framework (i.e., a combination of the two original models, together with descriptive- and personal norm).

Looking at the results for behavioral intentions, it can be concluded overall that variables from the original TPB perform best in terms of predictive power. Comparison of the proportion of variance explained in behavioral intentions shows that the original TPB scores substantially better than the HBM (R^2 for TPB = 0.62 vs. R^2 for HBM = 0.39). Results obtained for the integrated behavioral model further support the predominance of original TPB variables as predictors of the intentions to use a helmet. Compared to the original TPB, the more complex model combining the three hypothesized TPB variables with the five HBM variables and the two additional norm-related concepts only explained 2 more (R^2 for integrated behavioral model = 0.64), and the two only variables making a significant contribution were both TPB variables, i.e., attitude and perceived behavioral control.

The prediction of helmet use behavior is also predominated by variables of the original TPB. While the hypothesized TPB variables alone explained 61 of the variance in behavior, the predictive power of the five HBM variables was at 41. Results for the integrated behavioral model (R^2 = 0.75) show that, out of the five significantly contributing variables (i.e., control beliefs, perceived behavioral control, perceived susceptibility, personal norm, and behavioral intentions), three variables (i.e., control beliefs, perceived behavioral control, and behavioral intentions) come from the original TPB, with control beliefs and perceived behavioral control being the two most important predictors.

Together, these results confirm previous studies on helmet use where the predictive utility of the TPB was found to be superior to that of the HBM (e.g., Ambak et al., 2010; Lajunen and Räsänen, 2004; Quine et al., 1998). Purely in terms of predictive power, one could argue that for the prediction of helmet use behavior, the integrated model (R^2 = 0.75) is to be preferred over the original TPB (R^2 = 0.61). However, one should be careful in comparing different theories and models with each other: "… very little can be said about which theory is the best one. To achieve this would first require that we determine the criteria for comparing theories. Maybe one theory is better for a special population, another theory is more appropriate for a single behavior but not for other behaviors or in changing multiple behaviors." (Lippke and Ziegelmann, 2008, p. 708-709). Based on recommendations coming from various philosophers of science, Prochaska et al. (2008) proposed the following hierarchy of criteria for assessing the quality of theories: clarity, consistency, parsimony, testability, empirical adequacy, productivity, generalizability, integration, utility, practical usefulness and impact. From the perspective of parsimony alone already, one could question whether the integrated model is to be preferred over the less complex TPB. Indeed, while the integrated model needs 12 variables to explain 75% of the variance in behavior, the TPB is able to explain 61% by means of two variables only. In addition to that, the higher R^2 for the integrated model is mostly attributable to control beliefs, which strictly taken is also a variable belonging to the TPB. With comparable situations in mind, Lippke and Ziegelmann (2008) argue that the variance explained gained by adding variables should not outweigh the parsimony principle. As they put it more explicitly: “theories have to be comprehensive but also parsimonious, in other words, clear and simple.” (Lippke and Ziegelmann, 2008, p. 706).

Notwithstanding, at several occasions already, it has been asserted that the combination of theories is appropriate and promising in further understanding health- and safety-related behaviors (e.g., Armitage and Conner, 2000; Champion and Skinner, 2008; Michie et al., 2008; Montaño and Kasprzyk, 2008). As a result, an increasing number of empirical studies following a more holistic-oriented combinatory approach is being published in diverse areas going from HIV/STD-prevention (for an overview, see Montaño and Kasprzyk, 2008), sports and physical exercise (e.g., Chatzisarantis et al., 2008; Hagger and Armitage, 2004), or household recycling (e.g., Davies et al., 2002), to transport (Chen and Chao, 2011; Klöckner and Matthies, 2009), and more recently also traffic safety (e.g., Elliott and Thomson, 2010). The integrated model in this study can certainly be criticized on several of the quality criteria proposed by Prochaska et al. (2008). Nevertheless, to some extent, it was able to demonstrate one of the main motives behind a combinatory approach, namely that different theories can complement each other in the explanation of health- and safety-related behaviors.

6.2.13 Road Safety Implications

In this study socio-psychological theories were used to examine helmet use among Cambodian young adults. Through reference to the work of Glanz and Rimer (1995), Trifiletti et al. (2005, p.299) explain the practical benefits of using socio-psychological theories and models as follows: “Theories and models can be useful in planning, implementing and evaluating interventions. Theories and models help program planners and researchers go beyond basic unchangeable risk factors (e.g. gender, socioeconomic status) to answer why, what and how people can change their behavior. Theories (and model) can be used to guide the search for reasons WHY people are or are not following public health and medical advice, or not caring for themselves in healthy ways. They can help pinpoint WHAT you need to know before developing or organizing an intervention program. They can provide insight into HOW you shape program strategies to reach people and organizations and make an impact on them. They also help you identify WHAT should be monitored, measured and or compared in the program evaluation.” Indeed, based on the outcome of this study, several interesting observations can be made with respect to why Cambodian young adults are using a motorcycle helmet (or not) and what needs to be taken into account by policy makers and planners of future intervention programs.

A. Current Status

A first important finding is that the initiatives undertaken by the Cambodian government to increase voluntary helmet use, seem to have positive effects. Not only does 94.5 of the Cambodian young adults questioned in this study actually own a helmet, there are clear indications that they are overall favourably disposed towards the use of motorcycle helmets. Not only do they see more benefits than barriers to the use of a helmet, they clearly recognize riding without a helmet as dangerous, both in terms of how serious the consequences of an eventual accident might be like as the extent to which they think this might lead to personal harm. In addition to the fact that several social reference groups think the use of a helmet is important, respondents declare they share this opinion and experience the non-use of a helmet as in conflict with their self-identity. Even though respondents are quite confident in their overall ability to wear a helmet, they admit there are some specific situations in which it is not always that easy to use it (i.e., mostly when driving short distances, at night, or when dressed up to go out). The self-reports for both intentions and behavior suggest that the Cambodian young adults interviewed in this study are already in the stage of actively implementing the desired behavior.

The fact that respondents already seem to have gone through the earlier stages of the behavioral change process (i.e., pre-contemplation, contemplation, and preparation) implies that policy makers and intervention program planners would do best in re-orienting their current approach accordingly. Gradually, the focus should shift towards other target variables and different change processes and methods than the ones that have been prioritized before (e.g., DiClemente and Prochaska, 1982; Prochaska et al., 1992; Weinstein, 1988). As indicated by Prochaska et al. (2008), in early stages, people mainly apply cognitive, affective and evaluative processes to further progress. Change methods that are typically used go from consciousness raising (i.e., finding and learning new facts, ideas, and tips that support the healthy behavior change) and dramatic relief (i.e., the initial experience of negative emotions (fear, anxiety, worry) that go along with unsafe behavioral risks, followed by reduced affect or anticipated relief if appropriate action is taken) to environmental reevaluation (i.e., realizing how the presence or absence of a personal behavior affects one's social and /or physical environment and being aware that one can serve as a positive or negative role model for others) and self-reevaluation (i.e., realizing that the behavior change is an important part of one's identity as a person) (e.g., Kidd et al., 2003). Yet, in later stages, people rely more on commitments, conditioning, contingencies, environmental controls, and support for progressing towards maintenance and termination (Prochaska et al., 2008). This will be further discussed in section 9.3.

B. Key-determinants

Based on the results from the regression analyses, five key-determinants can be identified that should be taken into account by policy makers and intervention program planners in their effort to stimulate helmet use among Cambodian young adults. The most important factor clearly is the subjective estimation of personal control over specific situational factors that might facilitate or hinder the use of a helmet (i.e., control beliefs). Even though respondents indicate they are quite confident in their ability to wear a helmet in general (i.e., perceived behavioral control), they admit there are some specific situations in which it is not always that easy to use it (i.e., mostly when driving short distances, at night, or when dressed up to go out). These contextual circumstances thus require special attention and further insight should be gained into why more precisely the use of a helmet in these situations is problematic. Also, effective and easy to implement countermeasures should be offered so that enough coping appraisal is elicited to confront these situations (e.g., Witte, 1992).

More than the seriousness of the consequences of having an accident when not wearing a helmet, a third key-factor is the extent to which respondents think they are vulnerable to danger when riding without a helmet. Acknowledgement of the idea that one can never fully exclude the chance that something dangerous might happen, should be further sustained because of several reasons. For instance, it should be avoided that Cambodian young adults become optimistically biased in their personal risk assessments or that they get overconfident in their driving skills (e.g., Arnett, 2002; Weiner, 1986).

A fourth important factor, is the level up to which respondents experience the consistent use of a helmet as a personal norm that has to be respected in order to avoid unpleasant conflicts with one's self-concept. Further integration of helmet use into Cambodian young adults' self-identity is an important step towards increased levels of self-determination, which is a crucial factor in the process of developing voluntary safe behavior (e.g., Deci and Ryan, 1985).
Finally, through the results for behavioral intentions, this study indicates helmet use is significantly dependent also on the motivation to do so, even though the contribution of this factor is rather weak. Since good intentions do not automatically translate into the desired behavior, people should be stimulated to implement their helmet use intentions (e.g., Gollwitzer, 1999). Influencing these five key-determinants appropriately is an important future challenge for policy makers and intervention program planners.

C. Future Policy Recommendations

The set of key-determinants discussed above is close to the advanced stages of the behavioral change process (i.e., action and maintenance) and requires other change methods than those used in the earlier stages (Prochaska and DiClemente, 1982). Overall, this study identifies two primary challenges for policy makers and intervention program planners. Firstly, Cambodian young adults should become more consistent in their use of a helmet, meaning they should be stimulated to wear a helmet under any kind of circumstances. Secondly, Cambodian young adults should maintain doing so, implying that the potential for relapse should be minimized as much as possible. Self-liberation, counter-conditioning, stimulus control, reinforcement management, helping relationships, and social liberation are change methods deemed appropriate for the achievement of these goals (Patten et al., 2000; Prochaska et al., 1992; Prochaska and Velicer, 1997; Velicer et al., 1998).

Self-liberation is focused on the belief that one can change and the commitment and re-commitment to act on that belief. Besides techniques such as personal resolutions or public testimonies, Sniehotta (2009) emphasizes the value of simple action procedures (i.e., insight into when and where to wear a helmet) and coping plans (i.e., anticipative insight into how obstacles or hindering factors can be avoided or overcome).

Counter-conditioning includes substituting alternatives for problem behaviors. In the context of helmet use, desensitization (i.e., learning to mitigate the harmful effects of negative thoughts such as for instance the fear that helmets make you look silly, stupid or unfashionable in the eyes of others) and assertion training (i.e., learning to resist to negative pressure exerted by peers) could be particularly interesting counter-conditioning techniques.

Stimulus control relates to removing or countering stimuli that elicit problem behavior and adding prompts for healthier alternatives. Re-engineering is an often cited strategy to get rid of hindering physical features, such as the lack of facilities to safely store a helmet or the often rather unattractive design of the helmet itself (e.g., Hill et al., 2009; Hung et al., 2008). Reinforcement management refers to rewarding one's self or being rewarded by others for making changes. Procedures for increasing reinforcement and the probability that positive responses will be repeated can go from formalized contingency contracts to overt incentives or covert reinforcement (i.e., the use of positive, vivid and rewarding imagery to stimulate helmet use). Reinforcement management can also include punishment, albeit that self-changers rely more on positive encouragement and rewards when it comes to continuation of the desired behavior (Prochaska et al., 2008). Indeed, a mandatory helmet law can be effective when the objective is to stimulate initiation of helmet use, but its long-term successfulness is dependent upon a complex set of critical factors going from a necessary shift in motorcyclists' mentality, to strong and unified support by government and mass agencies, comprehensive and coordinated legislation and regulation, mobilization of police and civil inspectors to enforce, and strategic use of the media (e.g., Hill et al., 2009).

Helping relationships is a change method often used in health areas related to substance abuse (drugs or alcohol addiction) or eating disorders (bulimia or anorexia nervosa), and is primarily aimed at being open and trusting about problems with people who care. In the context of helmet use, an individual's social network can be helpful more particularly in modeling and reinforcing the desired behavior. Peer (group) counseling is a well-known technique where based on communication, empathy and understanding, people in the stage of (recently) using a helmet can gain recognition and increase self-confidence in the continuation of that behavior.

Social liberation stands for helmet use advocacy, i.e., the extent to which helmet use is identified, framed and treated as an important health issue within society. In this respect, Hill et al., (2009) demonstrated how strategic and coordinated use of print and electronic media is important, given the fact that media significantly contribute to processes such as policy agenda setting, information delivery, propaganda and socialization, promotion, and the formation of public acceptance.

Besides helmet use consistency and maintenance, two other important future challenges should be mentioned that apply more specifically to developing and middle income countries in South East Asia, i.e., (1) the widespread circulation of poor quality helmets, due to the (illegal) importation of sub-standard helmets, counterfeits of popular brands, or the use of inappropriate materials, and (2) the improper use of helmets by motorcyclists while riding (e.g., Peden et al., 2002). These problems have been reported for countries like Viet Nam (Hill et al., 2009), China (Li et al., 2008; Xuequn et al., 2011), Thailand (Nakahara et al., 2005), Malaysia (Kulanthayan et al., 2001) and Indonesia (Conrad et al., 1996). It is evident these issues have to be resolved if road safety policy with respect to helmet use wants to be effective in further bringing back the number of injuries and deaths among motorcyclists.

6.2.14 Limitations And Future Research

A number of methodological issues have to be taken into account when interpreting the results of this study. Firstly, self-report measures were used, which are potentially vulnerable to several forms of answering bias (Af Wåhlberg 2009). Yet, specifically looking at the TPB, there is growing support for its predictive validity with respect to objective behavior measures (e.g., Armitage, 2005, 2008; Conner et al., 2007; Elliott et al., 2007). Secondly, this study was based on a correlational design. As indicated by Elliott and Thomson this allows the identification of predictors of intentions and behavior, but does not permit conclusions about cause and effect relationships since the latter would require experimental research. Interestingly however, Elliott and Thomson (2010, p. 1603) mention several experimental studies that found the relationships hypothesized by the TPB to be causal (e.g., Beale and Manstead, 1991; Elliott and Armitage, 2009; Jones et al., 2005; Webb and Sheeran, 2006). Thirdly, in terms of external validity, the focus of this study was very specific, both in terms of nationality (i.e., Cambodia) as in terms of age (i.e., young adults) and road user behavior (i.e., motorcycling). Therefore, the results of this study should not be automatically applied to other populations. Future research can take several directions. For instance, the integrated behavioral model examined in this study could be validated in other populations and with respect to different forms of road user behavior. Unavoidably, this requires the measurement instrument used in this study to be thoroughly revised. Next to that, it would be relevant to explore the usefulness of other theoretical models or concepts in explaining and predicting the voluntary use of helmets. Another interesting issue would be to investigate the extent to which the findings reported in this study replicate in a sample of typical non-users.

6.2.15 Conclusion

This study adopted a socio-cognitive perspective towards the examination of helmet use in a sample of Cambodian young adults. Two theoretical models, i.e., HBM and TPB were estimated separately as well as within a combined framework that included two additional norm-related variables, i.e., descriptive- and personal norm. Based on the results, four important conclusions can be drawn. Firstly, the sample investigated in this study is clearly favourably disposed towards the use of helmets while riding. This reflects the positive trend in terms of helmet use that can be established over the last few years in Cambodia, probably under impulse of a series of well-coordinated awareness raising and educative programmes. Secondly, in decreasing order, helmet use behavior was found to be determined by the following five key-determinants: perceived behavioral control over a specific set of inhibiting situational factors (i.e., mostly when driving short distances, at night, or when dressed up to go out), perceived behavioral control in general, perceived susceptibility, personal norm, and behavioral intentions. Policy makers and practitioners are advised to take these factors into account when planning future interventions aimed at increasing or maintaining the use of motorcycle helmets. Thirdly, in terms of predictive power, the TPB performed substantially better than the HBM in predicting helmet use intentions and behavior. Finally, even though the integrated behavioral model implemented in this study showed that different theories can complement each other in the explanation of motorcycle helmet use, it should not be overlooked that, besides being comprehensive, models should also be parsimonious.

6.3 Case 2: Towards Optimal Socio-cognitive Factors Of Speeding Behavior Model In Ho Chi Minh City, Vietnam

6.3.1 Abstract

Speeding is one of the most important factors affected to road accidents. This study aims to develop an integrated behavior model to predict speeding characteristic of people using the public transportation system in Ho Chi Minh City (HCMC), Vietnam. Here, 415 motor drivers were interviewed in 24 districts of the HCMC to measure their characteristic factors: perceived benefits, perceived barriers, cognitive attitude, affective attitude, personal norm, descriptive norm, subjective norm, perceived behavior control, situation specific personal behavior control, perceived severity, perceived susceptibility, cues to action, behavior intention and behavior with respect to speeding. These parameters were used as input variables in differing models where an appropriate model was found as an optimal model predicting closely speeding behavior in the HCMC, known as integrated behavior model (IBM). The results show that the behavior intention of each participant is strongly correlated to four parameters which are the cognitive attitude, perceived behavior control, situation specific personal behavior control and perceived susceptibility. Based on the results, we also found that predictive intention and behavior from the IBM are better than that in two other models, theory of planned behavior (TPB) and health belief model (HBM).

6.3.2 Introduction

Recently, traffic accident analysis and prevention have attached much attention due to their urgent need for any countries to save the civil life, especially developing countries. There are a number of methods and models using for data analysis and modeling in which they were trying to resolve a problem of the life, traffic accident prevention. To realize such problems in feasible way, a better understanding of influent factors affected to the traffic accident is indispensable and those factors were being optimized in order to figure out the most important factor affected directly to the accident behavior of each participant in a particular area.

Different methods were being applied in differing investigation purposes and geographic areas. In this paper, characteristic of each participant is to be explored by using TPB, HBM and IBM which were applied to study a specific localization, HCMC of Vietnam. The reasons for choosing the HCM city are, (1) the HCMC is the biggest city of Vietnam where population is of 7,396,446 and population density of 9,141/km^2 in 2010 (HCMC_People_Committee_Office 2012); (2) the transportation system in the HCMC is a complex system which spreads onto 2,095 km^2–area with 12 districts and 12 district towns (HCMC_People_Committee_Office 2012); (3) the HCMC also has the highest mortality rate of 16.1 per 100,000 population and larger than 35 deaths per day. The mortality level in this area was higher than the average value of other areas in Vietnam (15.6) and also higher than that of the other Asian countries (NTSC 2005; WHO 2009).

In particular, there is a complicated method in using traffic system in the HCMC where all types of vehicles sharing a lane line, so-called a mixed traffic system. This is one of key reasons causing crashes within those vehicles and subsequently getting accidents with injuries or deaths. Moreover, many types of transportation in differing sizes and speeds are also used the same lane line with a low infrastructure quality. Another factor which highly induced to road accident is illegally crossed over a transportation lane line by other participants. Among those factors and based on current circumstances of the HCMC and other cities in the South-East Asian, the road user behavior was assumed to be the most important factor affected directly to the recorded road accident (>90% of recorded road accidents (Almec 2009), whilst other factors are minor influences such as vehicle and infrastructure errors in ranges of 0.39-1.33% and 0-0.26%, respectively. Thus, such behavior needs to be investigated in details in specific circumstances and location. The HCMC is an excellent example/area to be concerned and is to be discussed in the following sections.

6.3.3 Objectives

Of the road user behavior and other factors given above, speeding behavior is the most relevant factor and it is to be discussed intensively in this work. Here, the speeding behavior was assumed to be related to socio-cognitive behavior of road users. Particularly, the original TPB model and HBM were used firstly to estimate some socio-cognitive outcome variables from the estimated processes, which were then used as key parameters to predict speeding intention and behavior of road users. Moreover, a correlation of the examined socio-cognitive variables was also analyzed to predict cognitive and effective attitudes which are affected to speeding behavior. Speeding intention and behavior of road users were also predicted through integrated social cognition model where those factors can be used to propose an implication program to increase the perception of respecting and/or preventing speeding via appropriate traffic safety education programs or so. Thus, in the following sections the concepts and main characteristics of road users (drivers) behavior are explained in detail.

6.3.4 Literature Review

A. Determinants Of Speeding

Speeding is defined as an excessiveness of normal speeding limit for the prevailing rule of the road in a specific area. Speed limit can be different in differing road and vehicle types or areas in a country where road users have to follow those particular regulations. In fact, speeding behavior is a factor depending on person to person (drivers). Recently, a number of researchers have been studying on speeding behavior to identify and understand speeding determinants of drivers. As one of participations of studies of the road user behavior in Cambodia and Vietnam, i.e., Cambodian helmet wearing behavior (Section 6.2), this paper is intensively focused into determinants of speeding where they are related to the driving context, trip-specific aspects, vehicle properties and driver/passenger characteristics.

Regarding to the driving context, the speeding behavior depends on vary issues, such as (1) the time conditions at differing time periods (Arnett, Offers et al.

1997), at late night (Musselwhite 2006), at rush-hours (Liu 2007); (2) roadway conditions (Musselwhite 2006), differing between urban and rural road systems (Charles Goldenbeld 2007; Liu 2007), the road curves (Charlton 2004), tunnel-roads (M.P. Manser 2007); (3) climate and weather conditions (Mats Haglund 2000); (4) traffic conditions, i.e. traffic volume (Elvik 2005), traffic lights (Liu 2007), transportation environment (M.P. Manser 2007); (5) cues to action, i.e. enforcement (Assum 1997; Finn Jørgensen 2005), knowledge of fines (Charles Goldenbeld 2007), restriction and speedometer (Miguel Angel Recarte 2002), cellphone task (Charlton 2004). Besides, speeding is particularly related to trip-specific aspects: (1) travel time, i.e. saving time (R. Fullera, Stradlingb et al. 2009), time pressure (Gabany, G. et al. 1997); (2) number of passengers (Miguel Angel Recarte 2002); (3) vehicle properties i.e. vehicle types (Liu 2007).

Road users (drivers) characteristics were considered under the influences of speeding behavior, those variables are related to personal driving history, i.e. driving experiences (Finn Jørgensen 2005; Charles Goldenbeld 2007), frequency (Mats Haglund 2000); other forms of risky driving behavior, i.e. drunk cases (Beullens and Bulck 2008); forms of driving education and/or in specific circumstances of using music/video/media viewing and reading newspaper (Beullens and Bulck 2008), driver training (R. Fullera, Stradlingb et al. 2009); socio-demographic variables such as gender (Arnett, Offers et al. 1997; Gabany, G. et al. 1997; Mast, Sieverding et al. 2007; Beullens and Bulck 2008), locations (Wendy Wrapsona 2006; Charles Goldenbeld 2007) and age (Arnett, Offers et al. 1997; Gabany, G. et al. 1997; Finn Jørgensen 2005; Charles Goldenbeld 2007; Liu 2007; Mast, Sieverding et al. 2007); socio-cognitive variables that were mentioned in a numbers of behavioral models, known as Theory of Reasoned Action (TRA), Theory of Planned Behavior (TPB), Health Belief Model (HBM). In those studies, attitudes of drivers were considered and reflected via a number of states such as mood (Arnett, Offers et al. 1997; Mast, Sieverding et al. 2007), hurry (Musselwhite 2006), sensation seeking, habit, norm, in attention, perception (Gabany, G. et al. 1997; Wendy Wrapsona 2006; Mast, Sieverding et al. 2007). In this paper, they are continuously discussed and detailed in the following sections.

B. Speeder And Non-speeder

Although many drivers are aware of the negative impact of speeding or exceeding the speeding limit, but a number of drivers do. However, it is very difficult to clarify clearly between speeder and non-speeder. Some people always drive faster than speed limit and some people always respect speed limit. People can drive faster than the speed limit in certain circumstances (in a hurry, late at night, peak-off hours…). Generally, the speeding behavior is decided in balances of safety, time saving benefits, pleasure, sensation seeking and driving experience of each driver.

A large difference of the driver opinion between the preferred speed and the perceived safety speed limit, and a high positive correlation of drivers between number of speeding ticket and speeding times which were investigated by (Charles Goldenbeld 2007). In these studies, drivers preferred driving with speed is higher than the posted speed limit (about 10%) in either urban and rural roads corresponding to 4-5 km/h faster than the speed limit. Arnett, Offers et al. (1997) also confirmed that a strong relation between sensation seeking and speeding behavior where drivers did over speed when they were in angry mood, driving alone or with friends. Some drivers did speeding when width visual increased (M.P. Manser 2007). Moreover, Liu (2007) identified that extra conditions such as rush-hour status, traffic light condition, vehicle type and driver gender are also contributed to speeding behavior. The risk of speeding in the suburbs was six-fold higher than the urban areas while in the non-rush hours it was three times higher than that of the rush hours. However, some drivers were only driven with the speeding behavior in some cases, for instance, losing their driving license in which they attempted to loosely estimate how long does it take they could exceed the area where they thought the driving license was loosen (Finn Jørgensen 2005).

On the contrary, other drivers would reduce their speed when they realize they drive faster than the speed limit (Musselwhite 2006) or they awared their speeding is dangerous and under a surveillance of polices (Wendy Wrapsona 2006) or the decreasing width visual pattern (M.P. Manser 2007). However, many researchers have been trying to find out the way to eliminate the speeding behavior through examining relationships between the speeding controls and the risky driving behavior. The role of speedometer and restricted speed for the speeding behavior of drivers have been considered and reported by (Miguel Angel Recarte 2002). In the cases of non-speedometer, the drivers have chosen the over-speeding of 11 km/h compared to the free speed in the restricted speed condition. When speedometer was visualized, a difference between free and restricted speed was greater than speedometer is concealed. (Damian R. Poulter 2007) also indicated that speeding on residential roads was unacceptable and to be the greatest problem in local communities for all ages.

There are differences in speeding behavior in each group of people such as age (young/old), gender (female/male), driving skill (experience/inexperience), sensation seeker (high/low). Gabany, G. et al. (1997) had investigated an evaluation of speeding perception inventory of young and old people as well as gender through five factor loadings: (1) degree of ego-gratification item within male and female, (2) degree of risk-taking within younger and older people, (3) effects of time pressure onto older and younger people and/or male and female, (4) disdain of driving and (5) inattention within female and male. Moreover, (Arnett, Offers et al. 1997) reported that young people driving at high speed rather than the older people. High sensation seekers prefer driving at higher speed rather low sensation seekers (Charles Goldenbeld 2007). Finn Jørgensen (2005) showed that old drivers have less knowledge of the speeding threshold level and more knowledge of the detection rate in comparison with younger drivers. Also experienced drivers have knowledge of the threshold level for serious speeding rather than inexperienced drivers.

As mentioned above, there was a strong relation of speed and number of accidents, injuries, fatalities (Elvik 2005), therefore the speed limit is the most important parameter to be concerned.

6.3.5 Prior Use Of Behavioral Models

Because of a complicated behavior of human being, a number of road user behavior models were being studied to explore how and why people behave risk-taking like the way they do. In term of risk and threat concepts, (CAST 2009) reported three models of risk-taking behavior such as risk homeostasis theory, Zero-risk Theory and Threat Avoidance Model which focus on the way drivers manage risk. Moreover, other research groups have been developing road user behavior models to predict their reactions to risky traffic behavior as well as to identify the way for motivating and persuading to change their risky driving violation. Several theoretical models are recently mentioned as motivational models, TRA, TPB, HBM and Protection Motivation Theory (CAST 2009). However, an appropriated behavior model is eager to be figured out that can be used to predict a typical risky behavior from relevant individual motivations. Here, road user behavior is affected by many related motivational factors, for instances, personal characteristics, habits, attitudes, experiences, motivations, emotions, gender, age, income, life style, living environments. Particularly, the most important motivational factors were selected and considered instead of predicting road user behavior; e.g. social-psychological approach (Cheng-qiu Xie 2002), social cognitive variables (Norman, Abraham et al. 2006), social cultural characteristics (Melinder 2007), psychological variables (Mette Moller and Gregersen 2008). In fact, a combination of theoretical model and implementation intentions was considered to promote workplace health and safety (Sheeran and M 2003). In a particular case, motivation models/ integrated behavior models Kris (2012) were used to investigate or extend for a specific public transport type, i.e. car (TPB, Norm Activation Model), habit (Klöckner and Matthies 2009) and/or for switching intention from motorbike and car to public transport (TPB, Technology Acceptance Model) and Habit (Chen and Chao 2011). As mentions above, a series of study in the risky road user behavior, the integrated behavior model that was resulted from a combination of the TPB and HBM is applied for helmet wearing in a specific area, i.e. Cambodia (Brijs, 2012), it is also able to use as a predicting method for speeding behavior in a particular area, i.e. HCMC, Vietnam.

By applying behavioral models for examination or predicting speeding behavior, this work is mainly mentioned in social cognitive determinants that impact to risky driving behavior. The differences among behavioral models and socio-cognitive variables are detailed in the next section.

6.3.6 Theoretical Background

A. Health Belief Model (HBM)

HBM is an innovative model describing human behavior and assists for the design campaigns. This model was successfully developed by (Rosenstock 1966; Rosenstock 1974). The main purpose of this model is to avoid negative health consequences and motivate positive actions to preserve/promote health (CAST 2009).

The HBM focuses mainly on the benefit – cost analysis and perceive threat of performance of a health behavior (i.e. speeding). Perceived benefits, i.e. the advantage of speeding such as speeding makes saving time, a good impression on others, and perceived barriers, i.e. the disadvantage of speeding as increasing the risk of getting fined, that are shown to be useful for predictions of a change in human behavior. Perceived threat is described via perceived susceptibility (defined as the chance of getting a ticket) and perceived severity (defined as degree of danger) on a given behavior (i.e. speeding). Another factor is cues to action which is described via internal and external information that are related to support higher fines and information from campaign/education, respectively, this is to motivate readiness for behavior changing. However, the HBM has not been widely used and it is not a highly applicable model for characterization of behavior changing in a general road safety area, i.e. speeding particularly. There are differences of risky driving behavior models that are used for predicting of differences from limited HBM variables. Recently, (Fernandes, Hatfield et al. 2006; Fernandes and Neves 2010) was used the HBM to predict four risky driving related behaviors such as speeding, drinking-driving, driving while fatigued and un-wearing seat belts. Their results were shown that perceived susceptibility strongly effected to speeding and seat-belts wearing behavior. Drinking-driving behavior is predicted via perceived cost however 'driving while fatigued' has no significances with any HBM variables. Similarly, (Sissons-Joshi, Beckett et al. 1994; Quine, Rutter et al. 1998; Lajunen and Räsänen 2004; Quine 2006; Ambak 2010) have found that there is no significant effects in the case of the wearing helmet to all of HBM variables. Moreover, perceived benefit was also identified as the strongest predicting parameter into behavior of the wearing helmet (Quine 2006).

6.3.7 Theory of Planned Behavior

One of the success models which is popularly used in predicting speeding behavior, named as Theory of Planned Behavior, TPB (Vogel and Rothengatter 1984; Parker, Manstead et al. 1992; A° berg, Larsen et al. 1997; Forward 1997; Stradling and Parker 1997; Victoir, Eertmans et al. 2005; Martine Stead 2005 ; Warner and Åberg 2006; L. Åberg 2007; Olivier Desrichard 2007; Paris and Broucke 2008; Mark A. Elliott 2010). This model was extended from the theory of reasoned action (Fishbein and Ajzen 1975; Ajzen and Fishbein 1980). The model was used for predicting of volitional behavior and understanding of psychological determinants of human via intentions, those determinants are directly/ indirectly affected to significant impacts of attitude (belief), subjective norm (normative belief), perceived behavior control (control belief) (Ajzen, Iagolnitzer et al. 1985; Ajzen 1989; Ajzen 1991; Conner and Sparks 1996; Ajzen 2002; Armitage and Conner 2001).

Here, attitude means that the individual evaluation of a performance for a target behavior (like or dislike speeding), cognitive and affective components are included in attitude variable (Eagly and Chaiken 1993; De Pelsmacker and Janssens 2007). Even people know/may know that speeding is a dangerous/wrong action however at an excited period time they may try speeding to get an excited feeling. Subjective norm is defined as a personal perception in the social environment, i.e. family, friends, onto his/her performance/ non-performance, e.g. speeding/non-speeding. Perceived behavior control is measured by personal perception (e.g. difficult/easy) to perform a given behavior (e.g. speeding). Behavior intention refers personal decisions or motivation of people to perform a given behavior (respecting the speed limit).

In a number of studies on speeding behavior, results were showed that attitude, subjective norm and perceived behavioral control are dominant and in the range of 28 to 66 of the variances in drivers' intention to speed (weighted average of 39) (Parker and Manstead 1992; Elliott, Armitage et al. 2003; Newnam, Watson et al. 2004; Letirand and Delhomme 2005; Mark A. Elliott 2005; Conner, Lawton et al. 2007; Paris and Broucke 2008; Armitage and Conner 2001), and in the range of 27 to 67 of the variances in subsequent speeding behavior (Elliott, Armitage et al. 2003; Warner and Åberg 2006; Conner, Lawton et al. 2007; Elliott, Armitage et al. 2007). Also, cognitive and affective attitude are significant factors impact on behavior intention and behavior (Eagly and Chaiken 1993; De Pelsmacker and Janssens 2007). Most researches have been studying self-reported speeding or logged speeding of the drivers.

Even HBM covers a wide range of variables rather than that of the TPB model, while the TPB model has greater predictive power (e.g. with less redundancy) than the HBM (Section 6.2). An integrated model was proposed in this study for eliminating any weak points and increasing good points in the two behavior models (HBM and TPB), applied for speeding behavior.

6.3.8 Integrated Behavioral Model

The integrated behavior model (IBM) was established from the extended TPB and HBM models, this aims to develop, examine and predict speeding intention/ behavior of road drivers in HCMC. A simplified schematic of the integrated behavior model is shown in Figure 6.10. Here, we have five notices in the proposed IBM.

First, the proposed HBM predicts either the probability/likelihood of a certain prevention unsafe behavior and the behavioral intention in which the behavioral intention is a mediating variable between variables HBM and behavior (Conner, Lawto et al. ; Quine 2006). Second, the two variables are related to threat perception (i.e., perceived susceptibility and severity) and behavioral evaluation (i.e., perceived benefits and barriers), they act as separate factors (Quine 2006). Third, as already discussed in the previous paper (Kris, 2012), the HBM variables as "perceived benefits and barriers" as well as "perceived severity and susceptibility" are to be considered as identical to the TPB variables, "positive and negative behavioral beliefs". Fourth, attitude consist two individual cognitive (instrumental) and affective (emotional) attitude variables in the model. Finally, three other concepts from the extended TPB have been incorporated as descriptive norm, perceived behavior control in a specific situation and past behavior to improve the predictive power of the model.

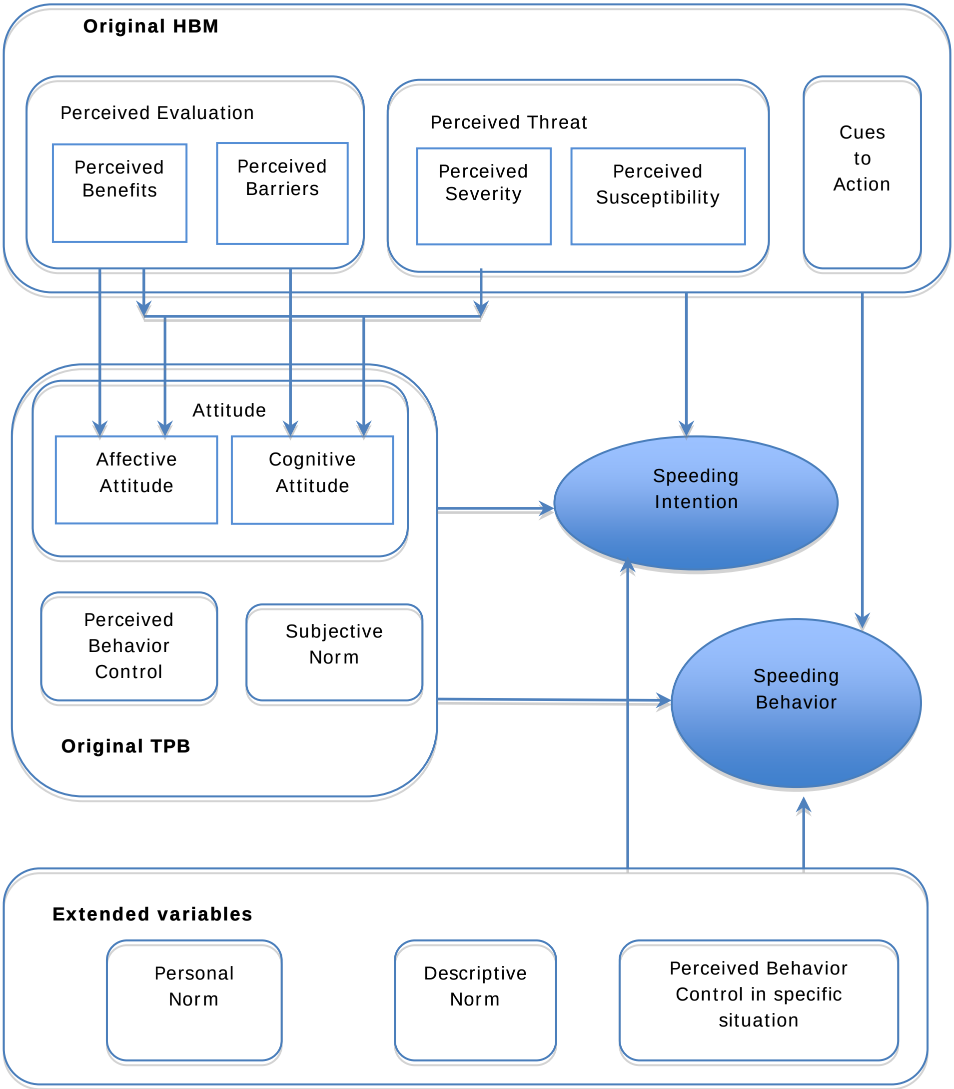

Figure 6.10 Proposed integrated behavior model structure

Descriptive norms are typical patterns of behavior, generally accompanied by the expectation that people will behave according to the pattern (Rothengatter 1991; Connolly and Aberg 1993; Groeger and Chapman 1997; Donald and Cooper 2001; Elliot 2001). In 14 studies, descriptive norm (B = .24, p < .001, (Rivis and Sheeran 2003) was a stronger independent predictor of intention to predict speeding behavior and it is in range of 10-30 (Aberg, Larsen et al. 1997). Descriptive norm and subjective norm are two components of perceived social pressure. Subjective norm has been reported as a weak predictor of intention (Mark A. Elliott 2010) and behavior in the TPB (6-10) (Å berg, Larsen et al. 1997). Perceived behavior control in a specific situation is a perceived ease or a difficulty of performing the behavior, i.e. speeding. Personal norm is a combination of moral values (degree of people's thinking, i.e. important) and anticipated regret (Manstead and Parker 1995; Connor and Abraham 2001; Newman and Di Pietro 2001), it has a significant effect on attitude towards speeding and on self-reported speeding (De Pelsmacker and Janssens 2007), its values in range of 10–15 of traffic behavior (Manstead and Parker 1995) and keep a high prominent role (Elliot 2001) of the predictive traffic behavior model.

6.3.9 Methods And Data Collection

As mentioned above, the IBM is integrated all original and extended variables of the HBM and TPB models. This aims to predict a specific driving violation, called speeding behavior. Here, speed limitations were setup for motorbikes, cars and trucks in the city and rural environment, respectively (MT 2009). Those chosen limited speeds are 40 km/h and 50km/h, 50km/h and 80km/h, 40km/h and 70km/h. The face to face method was also used to interview random responders in the vicinity of identified public transport terminals, households, companies, industry zones, gas stations, markets, colleges, universities in 24 districts of HCMC and this was done in the academic year 2011. The interviewers were carefully instructed for understandings of the questionnaire content, interviewing skills to get valid attitude of participants toward road safety and their determinant actions on speeding behavior. A pre-test survey of 10% samples was conducted before implementing the main survey, this aims to adjust a good questionnaire form and survey skills. Participation is voluntary and respondents and their data can be withdrawn at any time. Each interview takes approximately 30 minutes.

450 motor drivers were interviewed, 415 questionnaires were completed with valid answers (92%). The collected questionnaires are representative for HCMC residents with an almost equal in gender (54.6% of male). A wide range of ages was undertaken from 13 to 70 years old, the averaged-age is subsequently of 29.8 years old. The respondents are in different levels of education, i.e. 45%-bachelor degree, 20%-finished high school level, 19.4%-student from universities, 16.4%-government employee and 16.4%-workers (farmers/ casual laborers). Among those respondents, 37% of them were married, 30% of them having four members in their family. The majority of participants (77.2%) have an own motorbike at least.

To predict road user behavior, results of the study were firstly characterized background information of respondents and then measured 14 socio-cognitive factors in which the factors were chosen based on literatures and discussions with experts in this field. The general road user survey was focused on the importance role of road safety. This was then compared to other social problems, for instances, domestic violence, unemployment, drug use, HIV/AIDS and traffic congestion. The questions of the second part are developed to measure perceived benefits, perceived barriers, cognitive attitude, affective attitude, personal norm, descriptive norm, subjective norm, perceived behavior control, situation-specific perceived behavior control, cues to action, perceived severity, perceived susceptibility, past behavior, behavior intension and behavior of the drivers with respect to speeding.

The research uses a typical five-point Likert scale (Bertram) to measure the level of disagreement (=1) and agreement (= 5) and similar to never and very often of their attitude, determinant of driving violation behavior. In term of road safety, the higher score presents a positive view of road safety (5 is very good and 1 is very bad) and mean scores are used to represent reliable scales. So, those questions are on the opposite of road safety dimension, they have to be reversed the scale to get same direction with each other questions.

The Pearson correlation, mean, standard deviation are tested to identify potential predictors of behavioral intention and behavior. Besides, Cronbach's alpha is used to check the reliability of all items (questions) in each proposed variable and α-value of over 0.6 is considered acceptably (Nunnally 1978; Peterson 1994; Slater 1995) (as shown in Table 6.8). Variables in each subgroup (i.e. male and female, illiterate and university education, student and farmer/casual laborer/worker, single and married status...) were undertaken and compared in order to find significant differences by an independent sample t-test.

Original HBM and basic TPB models were applied to examine the contribution of each predictor in each model and also identify a better model for predicting the speeding intension and speeding behavior by multivariate regression model (Table 6.9, 6.10). In addition, this work also explored the power of behavior beliefs through perceived benefits and barriers as well as perceived severity and susceptibility on cognitive attitude and affective attitude by two separate regression analysis (Table 6.11).

Four steps were conducted to examine associations of the proposed socio-cognitive variables to speeding intention and speeding behavior through the IBM by using the linear stepwise regression model. The independent variables of the better original model were added in the first step, the variables of the weaker model were added in the second step (followed by section 6.27). Extended variables of TPB are added in turn in the three remain steps to predict the best speeding intention model (Table 6.12 and Table 6.13).

6.3.10 Results

A. General Analysis

Concerning to the road safety problem, 82.1% of respondents were calculated which is related to a high position compared to other social issues. The perceived important care of respondent to the road traffic safety is still lower than health care system (85.5%), food safeguard (85.5%) and air pollutant (83.5%). Among respondents, 84.8% of respondents were used motorbike and subsequently causing road accident while 77.1% of road accident is belongs to trucks. It is an remarkable finding that bus system (63.9%) is considered in the top of three causes contributing to the road accident. Moreover, the drivers can express their confidences to the government for handling road traffic safety, so the degree of confidences can be classified into the fourth position if compares to other social problems. Here, 48.7% is agree and strongly agree with mean score is of 3.38, it means they expect that the government can solve the problem faster and better than other social issues, i.e. fighting crime (e.g. mean

= 3.68 with 62.1% people agree and strongly agree), improving national economy (e.g. mean 3.6 with 59.3% people agree and strongly agree), reducing the threat of terrorist attack (e.g. mean 3.41 with 49% people agree and strongly agree).

In the case of speeding, speed is measured via speeding frequency at a specific period of time for the type of respondent occupation aiming to check which occupations are mostly contributed to the road safety accident. Among numerous objects, the speeding is often occurred on the student with the highest rate of 2.2%, the second occupation rate is occurred on famer/casual laborer/worker (2%) and the third in the occupation is occurred on government employment, whereas the people working in cargo transport companies are rarely exceeded the speed (0.2%).

Among these respondent, 14% and 11% of answers are “often” and “very often” undertaken speeding at the present (behavior), respectively. Moreover, 1.2% and 6.7% of answers are they did speeding at the past. Especially, driving violations were mostly done on urban roads (69.9%) and averaged ages of people who were undertaken the speeding are in range of 20-34 years (78.3%). Respondents were agreed supporting for any enforcement policies of the government and education programs to prevent speeding behavior (Mean = 4.03, 4.14, 3.78, 4.21).

Here, table 6.8 presents a correlation within 14 socio-cognitive variables: means, standard deviations and reliability (cronbach alpha test) of each variable. The different “directions” in which the variables have been measured that describe reality meaning. For instance, behavior intentions were positively oriented - meaning it was formulated in terms of complying with the speed limit - while behavior was negatively oriented – meaning it was formulated in terms of not complying with the speed limits. Exclusive of the correlations between “cues to action” and “perceived behavioral control”, “behavior”, the remaining correlation for all proposed variables are significant at the 0.01 level. These correlation values are acceptable and significant. The speeding behavior has a significant, positive and high correlation (0.64).

Most of drivers were agreed that they did speeding because of the speeding benefits, i.e. saving time, having a good feeling, having a strong impression on other people). Also they have highly agreed with speeding barriers which are increased a risk of getting fined during driving (perceived benefits: Mean = 2.15, SD = 0,79 vs. to perceived barriers: Mean = 3.97, SD = 0.76). In opposite, if people think that speeding is dangerous, then perceived severity will be received: Mean 4.16, SD = 0.92) or it is a big risk of getting a ticket/ damage/ hurt, then perceived susceptibility can be received: Mean = 3.94, SD = 0.78. Regarding cues to action, the respondents highly support for the policy measures such as higher fines, campaign, education programs to present excessing the speed limit (mean = 4.04, SD = 0.68).

Table 6.8 A description of 15 socio-cognitive variables which were analyzed by using the model in this work

Variables	1	2	3	4	5	6	7	8	9	1	11	12	13	14
1. PBe														
2. PBa	-0.71[b]													
3. C_ATT	-0.77[b]	0.74[b]												
4. A_ATT	0.74[b]	-0.66[b]	-0.69[b]											
5. PN	-0.68[b]	0.60[b]	0.71[b]	-0.71[b]										
6. DN	-0.38[b]	0.33[b]	0.35[b]	-0.35[b]	0.28[b]									
7. SN	0.39[b]	-0.27[b]	-0.38[b]	0.38[b]	-0.33[b]	-0.27[b]								
8. PBC	-0.65[b]	0.55[b]	0.70[b]	-0.59[b]	0.61[b]	0.25[b]	-0.24[b]							
9. PBC_ss	-0.51[b]	0.47[b]	0.53[b]	-0.49[b]	0.41[b]	0.25[b]	-0.14[b]	0.51[b]						
10. CA	-0.18[b]	0.15[b]	0.16[b]	-0.20[b]	0.20[b]	0.17[b]	-0.17[b]	0.08	0.13[b]					
11. Pse	-0.60[b]	0.61[b]	0.55[b]	-0.56[b]	0.51[b]	0.39[b]	-0.32[b]	0.43[b]	0.33[b]	0.13[b]				
12. Psu	-0.31[b]	0.40[b]	0.32[b]	-0.35[b]	0.32[b]	0.17[b]	-0.11[a]	0.28[b]	0.24[b]	0.14[b]	0.33[b]			
13. BI	-0.70[b]	0.66[b]	0.74[b]	-0.67[b]	0.69[b]	0.31[b]	-0.34[b]	0.67[b]	0.50[b]	0.16[b]	0.57[b]	0.32[b]		
14.B	0.63[b]	-0.48[b]	-0.63[b]	0.55[b]	-0.53[b]	-0.19[b]	0.31[b]	-0.54[b]	-0.39[b]	-0.36	-0.47[b]	-0.24[b]	-0.59[b]	
Mean[†]	2.15	3.97	3.74	2.12	3.69	3.68	2.02	3.75	3.47	4.04	4.16	3.94	3.85	2.49
SD	0.79	0.96	0.76	0.88	0.88	0.89	0.94	0.78	0.70	0.68	0.92	0.78	0.88	1.05
Cronbach alpha	0.81		0.8	0.86	0.83		0.87	0.81	0.63	0.78		0.95	0.89	

*p values are as follows: ap < 0.05; bp < 0.01; cp < 0.001

†Scores range between 1 and 5

In term of attitude that consists of cognitive and affective attitudes, results indicate that if respondents are positively agreed with speeding, then the speeding is bad/dislikeable/unacceptable (cognitive attitude: Mean = 3.74, SD = 0.76), whereas if respondents are negatively agreed with speeding, then the speeding is fun/exciting (affective attitude: Mean = 2.12, SD = 0.88). Besides, subjective norm shows that respondents are deeply reflected their important social referents that would not accept their speeding behavior (Mean = 2.02, SD = 0.94) and confirmed that speeding is irresponsible/ intolerable by a mean value of 3.69 (SD =0.88) of personal norm but they see the high speeding frequency from other road users through descriptive norm (Mean =3.68, SD = 0.89). Drivers are strongly confident themselves that if they want they can control the speed limit (perceived behavior control: Mean = 3.75, SD = 0.78) even they are in a hurry and/or other people around them are speeding (perceived behavior control in specific situation: Mean = 3.47, SD = 0.70). Finally, the respondents are willing to respect the speed limit toward the un-speeding behavior intention (Mean = 3.85, SD=0.88) and the speeding behavior (Mean = 2.49, SD=1.05). All the positive and negative directions of independent variables are significant to predict intention and behavior of road users, because behavior intention is described as degree of respect to the speed limit and behavior can be measured by speeding frequency.

B. Health Belief Model

Table 6.9 presents predicted results of original health belief model which were based on perceived benefits, perceived barriers, perceived severity, perceived susceptibility and cues to action variables. Perceived benefits, perceived barriers, perceived severity were estimated about 56% of the variance in speeding intentions ($p<0.001$). Here, the perceived benefit is considered as the most important factor (ß= -0.386, $p<0.001$), following the perceived benefit, perceived barriers (ß= 0.284, $p<0.001$) and perceived severity (ß = 0.155, $p<0.001$) are also significant. However, speeding intention was not predicted by using the two remain variables (perceived susceptibility and cues to action) in which they have insignificant statistics ($p>0.4$).

Table 6.9 HBM model in speeding

Regression of behavioral intentions on HBM-variables*

Variables entered	B	SE B	β	t	p	$sr^{2\dagger}$
PERCEIVED BENEFITS	-.429	.059	**-.386**	-7.284	**.000**	**.064**
PERCEIVED BARRIERS	.255	.049	**.284**	5.176	**.000**	**.032**
PERCEIVED SEVERITY`	.146	.044	**.155**	3.317	**.001**	**.013**
PERCEIVED SUSCEPTIBILITY	.035	.044	.030	.786	.432	.001
CUES TO ACTION	.010	.046	.008	.217	.828	.000

*N= 370, R^2= 0.56

$^\dagger sr^2$= the squared semi-partial correlation coefficient. This coefficient equals the R-square change value from the regression when a variable is added or removed.

Regression of behavior on HBM-variables*

Variables entered	B	SE B	β	t	p	sr^2
PERCEIVED BENEFITS	.600	.073	**.495**	8.183	**.000**	**.106**
PERCEIVED BARRIERS	-.067	.062	-.068	-1.096	.274	.002
PERCEIVED SEVERITY	-.164	.055	**-.158**	-2.982	**.003**	.014
PERCEIVED SUSCEPTIBILITY	-.019	.055	-.015	-.347	.729	.000
CUES TO ACTION	.129	.057	**.091**	2.260	**.024**	.008

*N= 370, R^2= 0.43

For the speeding behavior model, three variables were included such as perceived benefits ($p<0.001$), perceived severity ($p<0.003$) and cues to action ($p<0.05$), they are significant and independent predictors of behavior, taken 43% of the total variance. Results are consistent with the model where perceived benefits is a strongest predictor (ß = 0.495), following is perceived severity (ß=-0.158) and cues to action (ß=-0.024). The negative perceived severity is unexpected because of behavior direction.

C. Theory Of Planned Behavior

As shown in the table 6.10, the original proposed TPB variables account for 60% of the total variance in speeding intention, they are statistically significant and independent predictors. The cognitive attitude variable contributes as the strongest prediction (ß = 0.506, $p<0.001$), followed by perceived behavioral control (ß = -0.78, $p<0.01$) and subjective norm (ß = 0.292, $p<0.03$).

Table 6.10 TPB model for Speeding Intention and Speeding behavior

Regression of behavioral intentions on TPB-variables*

Variables entered	B	SE B	β	t	p	sr^2
COGNITIVE ATTITUDE	.579	.053	**.506**	10.929	**.000**	**.118**
SUBJECTIVE NORM	-.073	.032	**-.078**	-2.309	**.021**	**.005**
PERCEIVED BEHAVIORAL CONTROL IN GENERAL	.326	.049	**.292**	6.611	**.000**	**.043**
*N= 415, R^2= 0.60						

Regression of behavior on TPB-variables*

Variables entered	B	SE B	β	t	p	sr^2
BEHAVIORAL INTENTIONS	-.491	.062	**-.410**	-7.893	**.000**	**.093**
PERCEIVED BEHAVIORAL CONTROL IN GENERAL	-.355	.070	**-.265**	-5.094	**.000**	**.039**
*N= 415, R^2= 0.38						

The independent predictors of speeding behavior are behavioral intention and perceived behavioral control, which are statistically significant in the speeding behavior model and explaining 38% of the total variance. The most important predictor of the speeding behavior is behavior intention (ß=-0.410, $p<0.001$), followed by perceived behavior in general (ß =-0.265, $p<0.001$).

Besides, the separate regression results from the different variables were found that the perceived benefits and perceived barriers are affected and interacted with cognitive and affective attitudes (as seen in Table 6.11).

Moreover, “speeding increases the risk of getting fined” is the most important predictor of the cognitive attitude (ß = 0.389, $p<0.0001$), otherwise, “speeding produces a good impression” is strongly contributed to affective attitude as the strongest prediction (ß = 0.347, $p<0.0001$).

C. Integrated Behavioral Model

Speeding behavioral intention models were predicted by using TPB and HBM variables through four steps that present in Table 6.12 and Figure 6.11.

Table 6.11 Regression predictive model for attitude and cognitive attitude

Regression of cognitive attitude on perceived benefits and barriers*						
Variables entered	B	SE B	β	t	p	sr^2
Speeding makes you save time	-.143	.033	**-.172**	-4.356	**.000**	**.015**
Speeding gives you a feeling of control over the car	-.214	.032	**-.254**	-6.679	**.000**	**.036**
Speeding is making a good impression	-.125	.033	**-.157**	-3.817	**.000**	**.012**
Speeding increases the risk of getting fined	.309	.032	**.389**	9.663	**.000**	**.076**
*N= 415, R^2= 0.67						

Regression of affective attitude on perceived benefits and barriers*						
Variables entered	B	SE B	β	t	p	sr^2
Speeding makes you save time	.140	.042	**.146**	3.352	**.001**	**.011**
Speeding gives you a feeling of control over the car	.163	.041	**.167**	3.972	**.000**	**.016**
Speeding is making a good impression	.321	.042	**.347**	7.641	**.000**	**.058**
Speeding increases the risk of getting fined	-.233	.041	**-.253**	-5.690	**.000**	**.032**
*N= 415, R^2= 0.60						

Regression of cognitive attitude on perceived benefits and barriers + perceived severity and susceptibility*						
Variables entered	B	SE B	β	t	p	sr^2
Speeding makes you save time	-.138	.034	**-.169**	-4.057	**.000**	**.015**
Speeding gives you a feeling of control over the car	-.212	.034	**-.254**	-6.276	**.000**	**.035**
Speeding is making a good impression	-.099	.035	**-.126**	-2.815	**.005**	**.007**
Speeding increases the risk of getting fined	.305	.036	**.395**	8.432	**.000**	**.063**
Speeding is dangerous	.019	.033	.023	.574	.566	.000
The chance of getting a ticket when speeding is high	.008	.049	.008	.156	.876	.000
The chance of damaging my vehicle when speeding is high	.070	.068	.074	1.033	.302	.001
The chance of getting hurt in an accident when speeding is high	-.035	.069	-.039	-.506	.613	.000
The chance of hurting others in an accident when speeding is high	-.029	.067	-.031	-.426	.670	.000
*N= 374, R^2= 0.68						

Regression of affective attitude on perceived benefits and barriers + perceived severity and susceptibility*						
Variables entered	B	SE B	β	t	p	sr^2
Speeding makes you save time	.123	.044	**.129**	2.814	**.005**	**.008**
Speeding gives you a feeling of control over the car	.147	.043	**.150**	3.373	**.001**	**.012**
Speeding is making a good impression	.290	.045	**.314**	6.421	**.000**	**.044**
Speeding increases the risk of getting fined	-.197	.047	**-.218**	-4.233	**.000**	**.019**
Speeding is dangerous	-.081	.042	-.085	-1.917	.056	.004
The chance of getting a ticket when speeding is high	-.057	.063	-.054	-.901	.368	.001
The chance of damaging my vehicle when speeding is high	-.125	.087	-.113	-1.432	.153	.002
The chance of getting hurt in an accident when speeding is high	.161	.090	.152	1.803	.072	.003
The chance of hurting others in an accident when speeding is high	-.070	.086	-.066	-.816	.415	.001
*N= 374, R^2= 0.61						

The three predictors of cognitive attitude, subjective norm and perceived behavior control in the TPB are firstly provided as input variables at the step 1, because they are stronger predictors of intentions rather than that of the proposed HBM (see sections 6.2 and 6.3). All three variables were contributed to predict behavior intention with R^2 = 0.61, p<0.000. Cognitive attitude is the most important predictor with ß = 0.525, p<0.001; followed by perceived behavioral control (ß = 0.279, p<0.001) and subjective norm (ß = -0.073, p<0.05).

In the second step, affective attitude and perceived behavioral control variables in specific situations were added and they make a very small change of the R^2 (increase only 2, R^2 = 0.63, p<0.000). However, subjective norm and perceived behavior control variables in specific situations were not contributed in any degrees of the variance in the speeding intention model. Cognitive attitude is remained as the most important predictor of the speeding intention model (ß = 0.396, p<0.000), however the ß-value was reduced in comparison to the step 1, followed by perceived behavioral control (ß = 0.219, p<0.000), affective attitude (ß = -0.210, p<0.000).

Here, the variance is explained details in the step 3. By adding descriptive norm and personal norm variables into the speeding intention model, they are dominated over 65% of the variance. This level is slightly higher than that of 63 from the step 2, this is due to a small increment in predictive power (p<0.000). The other variables of cognitive attitude (ß = 0.314, p<0.000), perceived behavior control in general (ß = 0.184, p<0.000), affective attitude (ß = -0.124, p<0.05), perceived behavioral control in specific situations (ß = 0.080, p<0.05) and personal norm (ß = 0.217, p<0.000) are also contributed to explain the variances of the speeding intentions, whilst subjective and descriptive norms are statistically insignificant to predict the speeding intention.

HBM variables were used from the step 4, among those variables, twelve of them are used to explain for 67% of the variation in speeding intention with p<0.001. There is a small change which is affected by following variables. The most important predictor is cognitive attitude (ß = 0.228, p<0.000), followed by perceived behavioral control in general (ß = 0.182, p<0.000), personal norm (ß = 0.190, p<0.000), perceived severity (ß = 0.132, p<0.005), perceived barriers (ß = 0.105, p<0.005).

As the final step, all above TPB and HBM variables were included which aims to predict a complete speeding intention. It was found that 68% of the total variance, past behavior having the highest value through 5 steps. Six of other variables, such as cognitive attitude, perceived behavioral control, personal norm, perceived severity, and perceived barriers were also considered. The most important variable for predicting the integrated speeding intention model is still cognitive attitude (ß = 0.014, p<0.005), followed by perceived behavior control in general (ß = 0.183, p<0.000), personal norm (ß = 0.172, p<0.005), perceived severity (ß = 0.123, p<0.005) and perceived barriers (ß = 0.110, p<0.005).

Table 6.13 presents speeding behavior models by adding in turn HBM and TPB variables in five steps. All HBM variables are added to predict speeding behavior by stepwise regression model in the first step. However, the variables in the HBM are stronger than that in TPB model (section 6.2 and 6.3). Here, 43% of variance is explained in speeding behavior from the most important predictor as perceived benefits (ß = 0.495, p< 0.000), and the other predictors as perceived severity (ß = 0.158, p < 0.04) and cues to action (ß = 0.091, p < 0.04).

Table 6.12 IBM for predictive speeding intention

STEP 1	B	SE B	β	t	p	sr^2
COGNITIVE ATTITUDE	.612	.057	**.525**	10.784	**.000**	**.125**
SUBJECTIVE NORM	-.069	.034	**-.073**	-2.038	**.042**	**.004**
PERCEIVED BEHAVIORAL CONTROL IN GENERAL	.312	.052	**.279**	5.997	**.000**	**.039**
R^2= .61 R^2 change= .61 F change= 187.057 (p< .000)						
STEP 2	B	SE B	β	t	p	sr^2
COGNITIVE ATTITUDE	**.462**	.062	**.396**	7.445	**.000**	**.056**
SUBJECTIVE NORM	-.042	.033	-.044	-1.264	.207	.002
PERCEIVED BEHAVIORAL CONTROL IN GENERAL	**.246**	.052	**.219**	4.691	**.000**	**.022**
AFFECTIVE ATTITUDE	**-.208**	.046	**-.210**	-4.551	**.000**	**.021**
PERCEIVED BEHAVIORAL CONTROL IN SPECIFIC SITUATIONS	.083	.050	.067	1.673	.095	.003
R^2= .63 R^2 change= .03 F change= 13.646 (p< .000)						
STEP 3	B	SE B	β	t	p	sr^2
COGNITIVE ATTITUDE	.366	.065	**.314**	5.649	**.000**	**.031**
SUBJECTIVE NORM	-.033	.033	-.035	-.999	.319	.001
PERCEIVED BEHAVIORAL CONTROL IN GENERAL	.206	.052	**.184**	3.938	**.000**	**.015**
AFFECTIVE ATTITUDE	-.123	.049	**-.124**	-2.505	**.013**	.006
PERCEIVED BEHAVIORAL CONTROL IN SPECIFIC SITUATIONS	.099	.049	**.080**	2.019	**.044**	**.004**
DESCRIPTIVE NORM	.015	.034	.015	.448	.654	.000
PERSONAL NORM	.217	.051	**.217**	4.250	**.000**	**.017**
R^2= .65 R^2 change= .02 F change= 9.165 (p< .000)						
STEP 4	B	SE B	β	t	p	sr^2
COGNITIVE ATTITUDE	.265	.072	**.228**	3.705	**.000**	**.013**
SUBJECTIVE NORM	-.036	.033	-.038	-1.090	.276	.001
PERCEIVED BEHAVIORAL CONTROL IN GENERAL	.204	.052	**.182**	3.918	**.000**	**.014**
AFFECTIVE ATTITUDE	-.059	.052	-.060	-1.146	.253	.001
PERCEIVED BEHAVIORAL CONTROL IN SPECIFIC SITUATIONS	.088	.049	.071	1.809	.071	.003
DESCRIPTIVE NORM	-.016	.035	-.016	-.464	.643	.000
PERSONAL NORM	.190	.051	**.190**	3.727	**.000**	**.013**
PERCEIVED BENEFITS	-.024	.065	-.022	-.367	.714	.000
PERCEIVED BARRIERS	.094	.048	**.105**	1.958	**.051**	**.004**
PERCEIVED SEVERITY	.125	.040	**.132**	3.125	**.002**	**.009**
PERCEIVED SUSCEPTIBILITY	.003	.039	.002	.065	.949	.000
CUES TO ACTION	-.010	.041	-.007	-.232	.816	.000
R^2= .67 R^2 change= .02 F change= 4.230 (p< .001)						

Regarding the second step, behavioral intentions and perceived behavioral control in general are strongly affected to the HBM resulting 3% was increased in the total variance in this step (R^2 = 46%, p<0.000), besides perceived benefits is remained as the most important predictor (ß = 0.350, p<0.000), followed by behavior intentions (ß = -0.200, p<0.002), perceived severity (ß = -0.127, p < 0.02), perceived behavior control (ß = -0.130, p < 0.03) and cues to action (ß = 0.087, p < 0.04).

In the step 3, three more variables of perceived behavior control in specific situation, descriptive and personal norms were added and proved that they are statistically insignificant with the predictive speeding model. An increasing of 1% in the total variance (R^2 = 47%, p<0.5) where only four variables (perceived benefits (ß = 0.325, p < 0.000), behavior intention (ß = -0.174, p < 0.009), perceived severity (ß = -0.133, p < 0.02), cues to action (ß = 0.092, p < 0.04)) were significantly contributed to the speeding model.

Table 6.13 IBM for predictive speeding behavior

STEP 1	B	SE B	β	t	p	sr^2
PERCEIVED BENEFITS	.600	.073	**.495**	8.183	**.000**	**.106**
PERCEIVED BARRIERS	-.067	.062	-.068	-1.096	.274	.002
PERCEIVED SEVERITY	-.164	.055	**-.158**	-2.982	**.003**	**.014**
PERCEIVED SUSCEPTIBILITY	-.019	.055	-.015	-.347	.729	.000
CUES TO ACTION	.129	.057	**.091**	2.260	**.024**	**.008**
R^2= .43 R^2 change= .43	F change= 54.320 (p< .000)					
STEP 2	B	SE B	β	t	p	sr^2
PERCEIVED BENEFITS	.423	.080	**.350**	5.292	**.000**	**.042**
PERCEIVED BARRIERS	.008	.062	.009	.137	.891	.000
PERCEIVED SEVERITY	-.131	.054	**-.127**	-2.422	**.016**	**.009**
PERCEIVED SUSCEPTIBILITY	-.002	.053	-.002	-.046	.964	.000
CUES TO ACTION	.123	.056	**.087**	2.211	**.028**	**.007**
BEHAVIORAL INTENTIONS	-.219	.068	**-.200**	-3.206	**.001**	**.015**
PERCEIVED BEHAVIORAL CONTROL IN GENERAL	-.159	.068	**-.130**	-2.331	**.020**	**.008**
R^2= .46 R^2 change= .04	F change= 12.298 (p< .000)					
STEP 3	B	SE B	β	t	p	sr^2
PERCEIVED BENEFITS	.394	.084	**.325**	4.658	**.000**	**.032**
PERCEIVED BARRIERS	.021	.063	.021	.334	.739	.000
PERCEIVED SEVERITY	-.138	.056	**-.133**	-2.476	**.014**	**.009**
PERCEIVED SUSCEPTIBILITY	.003	.053	.002	.056	.955	.000
CUES TO ACTION	.131	.056	**.092**	2.315	**.021**	**.008**
BEHAVIORAL INTENTIONS	-.190	.071	**-.174**	-2.655	**.008**	**.010**
PERCEIVED BEHAVIORAL CONTROL IN GENERAL	-.128	.071	-.105	-1.806	.072	.005
PERCEIVED BEHAVIORAL CONTROL IN SPECIFIC SITUATIONS	-.071	.067	-.052	-1.060	.290	.002
DESCRIPTIVE NORM	.029	.048	.027	.614	.540	.001
PERSONAL NORM	-.077	.067	-.070	-1.139	.255	.002
R^2= .47 R^2 change= .00	F change= .831 (p= .478)					
STEP 4	B	SE B	β	t	p	sr^2
PERCEIVED BENEFITS	.304	.089	**.251**	3.426	**.001**	**.017**
PERCEIVED BARRIERS	.096	.066	.097	1.463	.144	.003
PERCEIVED SEVERITY	-.145	.055	**-.140**	-2.624	**.009**	**.010**
PERCEIVED SUSCEPTIBILITY	.001	.053	.001	.019	.985	.000
CUES TO ACTION	.133	.056	**.094**	2.391	**.017**	**.008**
BEHAVIORAL INTENTIONS	-.138	.072	-.126	-1.909	.057	.005
PERCEIVED BEHAVIORAL CONTROL IN GENERAL	-.072	.072	-.059	-.992	.322	.001
PERCEIVED BEHAVIORAL CONTROL IN SPECIFIC SITUATIONS	-.042	.066	-.031	-.634	.526	.001
DESCRIPTIVE NORM	.043	.047	.039	.902	.368	.001
PERSONAL NORM	-.005	.071	-.005	-.077	.939	.000
COGNITIVE ATTITUDE	-.308	.099	**-.242**	-3.122	**.002**	**.014**
AFFECTIVE ATTITUDE	.092	.071	.085	1.305	.193	.003
R^2= .48 R^2 change= .02	F change= 5.724 (p< .01)					

At the step 4, cognitive and affective attitudes were added and dominated over 48 of the variance (p<0.01). The strongest factor was significantly contributed to the speeding behavior is perceived benefits (ß = 0.251, p < 0.002), followed by cognitive attitude (ß = -0.242, p < 0.003), perceived severity (ß = -0140, p < 0.010), cues to action (ß = 0.094, p < 0.04).

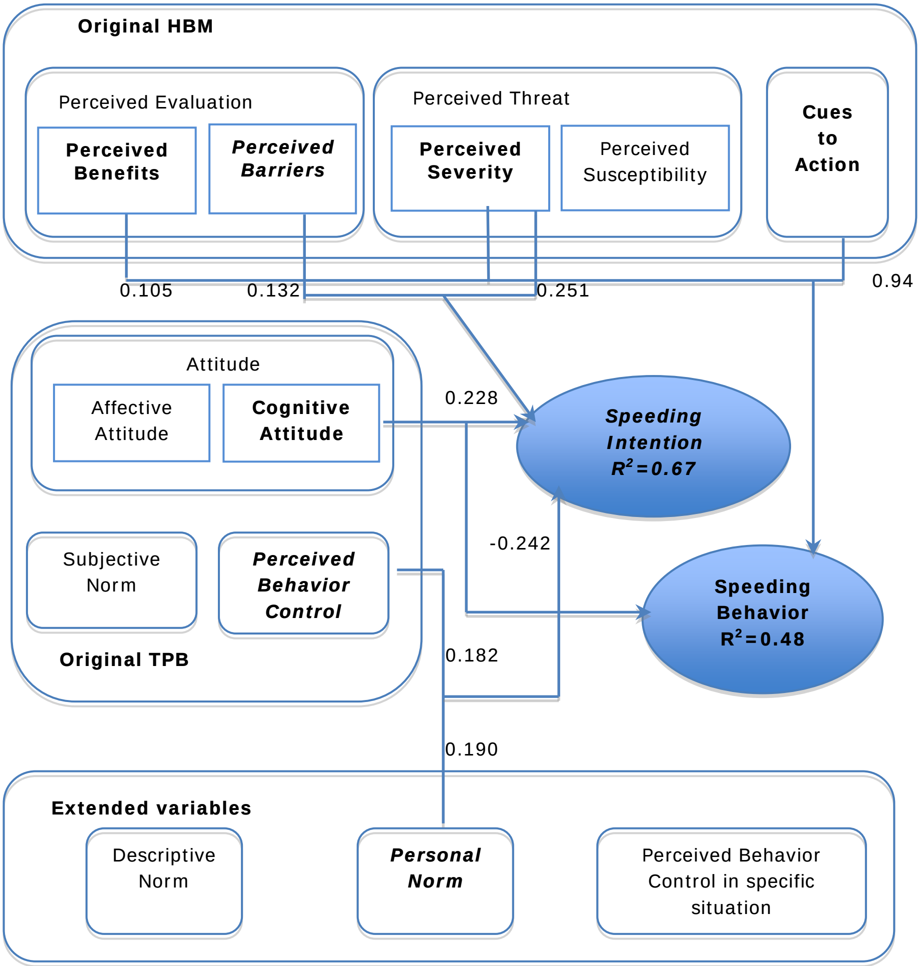

Figure 6.11 IBM for predicting speeding intention and behavior

6.3.11 Discussion

A. Descriptive Findings

The results of descriptive analysis were focused into the socio-cognitive concepts, this helps to get a better understanding of the speeding behavior for the road users in HCM city, Vietnam. Here, the road users concern much about the road safety problem and they strongly believe that the government can have a quick action on that. Even people have seen the positive efforts of the government in solving the existing social problems, especially road safety prevention however the progress seems to be rather slow as people expected. This study is to add deeply understanding in one of those problems and showing potential results for a specific area. Here, the respondents from Vietnamese drivers were analyzed. The results show that bus system is rated in top three contributions of the road accident and driving violation also occurs mainly on urban roads. The majority of road users preferred speeding was fallen into young adults with ages of 20 – 34 years. Especially, students were dominantly in the highest rate of exceeding the speed, followed by famer/casual laborer/ worker and government employment. The trend of speeding is willing to be increased. In fact, a person has an exceeding of the speed in the past he/she can be repeatable at the present. If people did “often” in the past, then they are able to do that “often” or “more often” in the future.

In most cases, drivers think and believe positively that exceeding the speed is bad or dangerous, but they behave in negative sides because of speeding will save their time and make a good impression/ feeling. In this study, the results from respondents are able to support for any government enforcement policies and education programs to prevent speeding behavior. This is useful results which also support for the traffic safety department and the education system, especially in primary and secondary schools.

B. Theoretical Findings

There are nine socio-psychological concepts which can be applied for examining speeding intention and speeding behavior. The speeding behavior when using HBM can be explained in three mechanisms: (1) behavioral evaluation (describing through perceived benefit and perceived barrier of speeding); (2) perceived threat (perceived susceptibility and severity towards speeding decision making); (3) cues to action (strategies to activate the readiness to speeding). Moreover, the TPB model presents three more important psychological factors, such as (4) attitude (including affective and cognitive attitude of road user about speeding); (5) subjective norm (the impact of social referents to speeding opinion); (6) perceived behavioral control (the personal confident to respect speed limit in specific situation). Three extended factors were explored to identify exceeding the speed limit are (7) personal norm (anticipated regret caused by speeding); (8) descriptive norm (risky behavior of social referents though the observation.

Behavioral Evaluation: Perceived benefits and perceived barriers are variables of behavioral evaluation concepts in HBM. Perceived benefits refers the positive self-feeling level while perceived barriers measure possible getting risky when focusing on unsafe behavior (speeding). Here, the result was shown that perceived barriers are weak significances of contribution to the behavior intentions in prediction model. Although perceived barrier has significant to predict behavioral intention in both separated HBM and IBM, the unique contributions are nevertheless small in both models (e.g. sr^2 =3.2% and 0.4% for HBM and IBM, respectively). And perceived barrier is not found to be a significant predictor in the prediction of speeding behavior neither in the separated HBM nor IBM. The result is not the same line with the previous studies (Harrison, Mullen et al. 1992; Champion and Skinner 2008).

However, perceived benefits factor is more powerful in predictions of behavior than the perceived barriers one. For perceived benefits, in term of speeding intention, it has the most significance in the HBM model and insignificant in the

IBM that is same the result of helmet study (section 6.2.10, 6.2.11). Moreover, perceived benefits was found as a high significant factor for both separate HBM or IBM which contributes as the most important impact to predict speeding behavior (see tables 6.9 and 6.12). That is not found high impact in the helmet behavior study (section 6.2.10, 6.2.11). Regarding squared semi-partial correlation coefficient, perceived benefits has a unique contribution of 10.6% in the prediction behavior estimating by individual HBM and it drops to 1.1% in the IBM model where TPB is in combination of the HBM and IBM.

In the fact, the young people tend to do speeding because of “saving time, giving their feeling of control over the car and making a good impression on others” than the older. It is also confirmed in this study because almost the speeders are student and the average respondents are young (section 6.3.10.A). Respondents did not agree “speeding increase the risk of getting fined” when they were asked. This is explained because of the serious corruption situation in Vietnam that mentions in the below explanation of “Cues to action” factor in this part, so the drivers do not afraid of getting fined.

Both perceived benefits and perceived barriers have significant effects to affective and cognitive attitudes that same as finding in the helmet study (section 6.2.10, 6.2.11). Perceived barrier is a better predictor to cognitive attitude (sr^2=7.6%) while perceived benefits is a better variable to predict affective attitude.

Thus, the above findings suggest that behavioral evaluation is an important psychological concept which can be considered in the speeding prediction study, particularly perceived benefits.

Perceived Threat: Perceived threat is described and mainly consisted of perceived severity and perceived susceptibility. The perceived severity is an important aspect for preventive health behavior and perceived susceptibility is the least powerful predictor for preventive action taking (section 6.2; (Champion and Skinner 2008). Results obtained in this study are not the line with these findings and the suggest is because of Saigonist characteristics. Perceived severity is an important predictor of both intention and behavior models rather than perceived susceptibility in this study. In fact, perceived severity only has significant values for the intention and behavior prediction of both HBM and IBM. In term of behavior intention, it has high significant contribution in the separate HBM (sr^2=1.3%) rather than IBM when adding TPB variables (sr^2=0.8). Regarding behavior, perceived severity is not important as perceived benefits in the separately HBM (sr^2=1.4%), and standing in the fourth of the predictive contributions in the IBM (sr^2=0.8%). Oppositely, perceived susceptibility neither contributes to HBM nor IBM in both behavior intention and behavior prediction model. The drivers were confident that speeding “is dangerous” than is “a chance to getting of ticket” or “damaging vehicle” or “getting hurt from the accident” due to the below “subjective norm and perceived behavior control” and “cues to action” discussions about Saigonist confident characteristic and the corruption situation in Vietnam in this part.

Perceived threat is insignificant effect to predict both cognitive and affective attitudes.

As shown in the results, the role of perceived severity in term of perceived threat in the explanation of speeding intention and behavior for both separate HBM and IBM.

Cues To Action: Cues to action was found as a little or non-significant impact to intention or behavior in previous studies (section 6.2). This study was also examined this parameter through increasing road safety enforcements, policies, education and awareness programs. It was found that this has insignificant effects into the speeding intention models, but it has a role in prediction of behavior for both HBM and IBM. Even so the unique contributions were not high enough (sr^2= 0.8%), however cues to action should be considered in term of changing behavior (speeding) of road users in HCMC. It is interesting that cues to action has the same squared semi-partial correlation coefficient (sr^2 = 0.008%, $p<0.03$) in separate HBM and all five steps of IBM in predicting speeding behavior. Besides, the results were indicated that this can be more supported for safety enforcements and campaigns in contribution of speeding. Through this factor, some respondents from road users are to be recorded, for instance, “I will keep the speed in the road or road sectors by installing speed cameras and police posts because I do not want to be fined. Out of this road I will exceed the speed again”. So, this situation will reflect an actual that they have respect for the speed limit because they do not want to get any trouble with the police, but it does not mean they think that speeding is un-safety. Otherwise, the road users also think polices just want to “make money”, if they give some money to polices when they are arrested it would be save their time and save their money rather than going to pay a fine in the government office/ department. A number of people do not care what kind of faults or mistakes that they did when they are arrested by polices, they just think firstly to give money for handling all. These thinking might come from a result of the survey in 1000 habitants of 5 big cities in Vietnam (Hanoi, HCMC, Danang, Hai Phong, Can Tho) where the majority urbanist (62%) thinks that the corruption was being increased in Vietnam, a part of them (36%) believe the corruption level is increasing very fast. Therein, the most corruption component contributed in the total corruption level is police (82%) and regarding their experience works with the police, there is 49% of people have to give a bribe (Global corruption parameter report, 2010). Because of those problems, some of drivers/road users have bad reactions/ behaves to the police, i.e. abusing, fighting or so.

Attitude: Attitude consists of affective and cognitive attitudes. The significant impacts of cognitive and affective attitudes toward intention and behavior were proved in the previous studies (Rothengatter 1993; Levelt and Swov 1998). In term of behavior intention, cognitive attitude is considered as the most important predictor in the separate HBM and IBM. Affective attitude has insignificant value when adding HBM variables to the IBM model. Besides, cognitive attitude does not contribute any value to the prediction of TPB model. However, it has significant effects while affective attitude has insignificant effects in the IBM. It is also proved by the results in a study undertaken by (De Pelsmacker and Janssens 2007) where cognitive attitude was contributed more impact to behavior than affective attitude.

Although Saigonist strongly confident in their driving skills while speeding but they do think speeding “bad” than “exciting” and “fun”. Hence, the policy maker should provide suitable campaigns to decrease the speeding times of drivers.

Subjective Norm and Perceived Behavior Control: In few previous studies which were mentioned that subjective norm has weak relationship with intention (Godin and Kok 1996; Forward 2006) and it is the weakest predictor of intention in the TPB (Armitage and Conner 2001). In this study, subjective norm is the weakest significant predictor of intention in the TPB (sr^2= 0.5%). Subjective norm is not a social pressure issue to decide excessing the speed limit or not, from Vietnamese road users. In the IBM, when adding affective attitude and perceived behavioral control in a specific situation, subjective norm turns to insignificant effect to intention.

Perceived behavior control in general is presented as the second important in predicting intention and behavior by TPB and behavior by IBM while perceived behavior control in a specific situation has insignificant to both intention and behavior in IBM. Drivers strongly believe themselves that if they want they can control and manage for respect the speed limit even they are in a hurry or other people are speeding that is confirmed by the independent character of Vietnamese in HCMC.

The unexpected of impact among other variables and behavior of Saigonist is a consequence of Saigonist personality, Saigonist culture and unbalancing in developments of economic and education (ethnic education). They understand that respecting speed limit is good and strongly believe on themselves to control of un-speeding. However, it does not mean that they will respect speed in their traveling, it depends on their feeling and their decision at a certain situation.

Personal Norm: Personal norm is a combination factor from moral value and anticipated regret in which it has a significant impact to intention and behavior (Elliot 2001; Mark A. Elliott 2010). In this study, personal norm has significant effect in the predictive speeding intention of IBM, however a unique contribution is small (sr^2= 1%) and it stands on the top three predictors of intention. Result is in line with the speeding awareness, knowledge findings on the road users in the study.

Descriptive Norm: Descriptive norm was found is a stronger predictor of intention rather than the subjective norm (Rivis and Sheeran 2003) and this was used to predict behavior (Mark A. Elliott 2010). Results in this work shows that the opposite, descriptive norm are insignificant effects for both intention and behavior in IBM. This is also confirmed by Vietnamese characteristics and culture. As the matter of fact, people with non-religion are popular in Vietnam, and thus the prominent character of Saigonist is independent and individual. This character is totally different from general Vietnamese characters of the people living in the north and the center of the country, i.e. if they like they will do and they will listen to somebody/rule but they will have their own decisions where their decisions are the most important, subsequently other opinions are referred (AC Nielson, 2009). Some respondents say “I drive for myself why do I have to follow the other people’ styles?”

Comparison findings: This work was measured socio-cognitive variables, that following TPB and HBM variables, to predict the speeding intention and behavior in two different mechanisms: (1) within original behavior models (separated original TPB and HBM) and (2) within integrated behavioral model (a combination of two original models and extended TPB variables). The best predictive speeding intention and speeding behavior models are considered as the highest R^2 value in the five steps.

Regarding behavior intention, the above analyses show that the predictive speeding behavior intentions on original TPB variables is better than that on original HBM variables (R^2 for HBM is equal to 56 while R^2 for TPB is equal to 60). The best IBM (R^2 = 68%) was predicted significantly from two original TPB variables (cognitive attitude and perceived behavioral control in general), two original HBM (perceived barriers and perceived severity) and an extended TPB variable (personal norm). It would be improved 12% and 8% into the total of variance rather than original models of TPB and HBM, respectively.

In term of behavior, the predictive speeding behavior on HBM variables is better than that on TPB variables due to the R value (R^2 for HBM is equal to 43% while R^2 for TPB is equal to 38%). The best IBM (R^2 = 52%) is over 9% of R^2 value to compare to separate original HBM and 14% to separate original HBM, that explained from three original HBM variables (perceived benefits, perceived severity, cues to action), one original TPB variable (cognitive attitude) and one extended TPB variable (past behavior). Behavior intention is the most important predictor to contribute in the TPB model that becomes unimportant, insignificant, non-contributing in the IBM. The cognitive attitude and perceived behavior control in general variables were calculated as the most important contribution on IBM, both of them are come from original TPB model.

Based on the above results, we might conclude that there is no unique model which describes for any particular situations and conditions. However, in a specific area or condition one can correct the model which is best fitted to the current problem. Normally, we argue that the best model is the model having a highest R^2, it means more variables need to be added/ adjusted for predicting. Section 6.2 reviewed from Lippke and Ziegelmann study (2008), said that "theories have to be comprehensive but also parsimonious, in other words, clear and simple". In this work, the IBM was needed thirteen variables to explain 52 of the variance while HBM have five variables to explain 43% of the variance to predict speeding behavior. In addition to that, the higher R^2 for the IBM is contributed mostly from perceived benefits and past behavior that belong to HBM and extended TPB variables, respectively.

6.3.12 Implementation

Applying socio-psychological theories does not only examine the practical problem or finding the main causes (impacts) of problem or helping usefully for proposing the implementation to eliminate the problem; but also helping in efficient planning and evaluating of the proposed intervention. The theories would help the intervention program targeting closer to the road user, and to select which measures, method for the implementation and future intervention programs (Glanz and Rimer 1995). Socio-psychological theories are developed to understand why HCMC' road users do exceeding the speed limit and to propose the efficient intervention program.

The important things of a success implementation program or intervention program for respecting speed limit are to understand clearly (1) "why people do speeding", they do not care themselves in healthy way; (2) "what things should need to know before developing and organizing an efficient program", (3) "how to do for getting an efficient program?" and (4) "what should be measured, evaluated, monitored in the program evaluation?" (Section 6.2). For planning and implementing efficiently, road users were asked their support of policy measures for reducing over speed.

In the fact, drivers think and believe positively that exceeding the speed is bad or dangerous, they strongly believe in their respecting speed limit, but they behave in negative sides in some specific situations (in a hurry up or making a good impression/ feeling). The research also present road user' positive intention and behavior of respecting speed.

Same as the Cambodia helmet study, the result of study proves HCMC road users gone through the earlier stages of the behavioral change process (6.2.12) and the policy maker would do the intervention program targeting re-orienting their speeding behavior.

According to the regression analysis results and Saigonist characteristics, five identified key-determinants should involve to consider for policy makers as well as intervention programs to reduce the speeding or to increase respecting the speed limit. The most important determinants of the respondents are the speeding frequency in the past (past behavior) and the positive self-feeling while speeding (perceived benefits), even more, negative perception (perceived severity), unsafe perception of speeding (cognitive attitude) and support safety enforcements and campaigns (cues to action).

For the question (1), "why people do speeding?", this was clarified and given a better understanding of past behavior frequency, the positive self-feeling, the unsafe perception and the negative perception of speeding.

To answer the question (2), "what thing should need to know before developing and organizing an efficient program?", one should consider more speeding frequency in the past that might influent to speeding behavior in the present; the more positive self-feeling contributes the more speeding; the more unsafe speeding perception impacts less speeding; the more negative speeding perception effects impacts less speeding; the more road safety enforcement, policy and awareness programs lead more speeding.

To answer the third question, "how to do for getting an efficient program?" (3), an appropriate intervention program should be proposed basing on the findings of the question (1) and (2), and the big supports of road users to road safety policy and enforcement, awareness and education programs (section 7.1, 7.2.3). This intervention program will be motivated readiness for behavior change of road users.

(4) The potential awareness, campaign, education programs should focus mainly into two aspects as the negative and the unsafe perceptions of speeding through images of speeding, consequently that lead to serious road accidents as well as bad health for speeder and other road users. People in HCMC believe in media, non-government and religion organizations, so these organizations will be helpful for deploying the road safety promotions to increase road safety perception. Besides, the road safety policy and enforcement should be considered more strictly, it is not only applied for road users but also for polices. (Global corruption parameter report, 2010) also showed that Vietnamese has positive thinking about the prevention of corruption than other neighbor countries. The ratio of people belief is governed by the political institutions (45%). A strict penalty should be investigated for speeding drivers. Also, a campaign of "say no to bribe transport police" should be investigated by media tools, public organizations, etc. Otherwise, another important thing is to increase HCMC people beliefs by applying new strict rules to punish police who are being opened for increasing of corruption. Thus, policies, approaches, people, time, cost for evaluating, monitoring, measuring are to be detailed for the intervention program in order to satisfy the final question.

6.3.13 Conclusions

Socio-cognitive determinants toward speeding in a sample of HCMC road users were investigated through behavioral models. Two original behavior models (TPB and HBM) and IBM with integrated original TPB, HBM and extended TPB variables such as personal norm, descriptive norm, perceived behavioral control in specific situation and past behavior were separately estimated in details to find an appropriate and better model for predicting speeding intention and behavior in Vietnam. The main results of this work can be addressed as the followings:

Firstly, cognitive and affective attitudes were measured from perceived benefits and barriers. Secondly, cues to action has the same squared semi-partial correlation coefficient (sr^2=0.008%, p<0.03) in separated HBM and all five steps of IBM for predicting speeding behavior. Besides, the result of cues to action indicates that the more support safety enforcements and campaigns the more contributing in speeding, because road users do not believe in the efficiency of these actions for reducing the speeding. Behavior intention does not contribute to any impacts to predict the speeding behavior. Thirdly, in term of predictive speeding intentions, original TPB variables are better than that of original HBM variables. However, the predictive speeding behavior on HBM variables is better than that on TPB variables. The best IBM for predicting intention is improved of 12% and 8% of the total variance rather than that on separated original TPB and HBM, respectively. The best IBM for predicting behavior is over 9% and 14% of the total variance rather than that in separated original HBM and TPB. Fourthly, the proposed IBM is a useful model to help/find out the most important impacts toward speeding behaviors of drivers that have not been mentioned in Vietnam. This will also help the governor authority understands clearly in speeding behavior of drivers to make a right decision for developing the public education and awareness programs to eliminate number of road accidents in Vietnam. Finally, the appropriate intervention program of road safety was proposed from the significant independent variables (perceived benefits, perceived severity, cues to action, cognitive attitude) by using IBM of speeding.

The study methodology should be applied popularly in the other provinces in Vietnam to propose more suitable campaign for each province to decrease road accidents. But it should not be applied automatically, it has to consider the different people characteristic of each provinces. Non-road user should be considered for further study. Another interesting issue would be to evaluate result after applying the proposed policies and campaigns from the modal findings for better road safety.

6.4 Case 3: An Investigation Of Illegal Direction Change Behavior Of Road Users Using Behavioral Models

6.4.1 Abstract

Illegal direction change is accounted the first position of road accident causes in Hochiminh city, Vietnam. Illegal direction change is examined through separate behavioral models as theory of planned behavior, health belief model and integrated behavior model. Integrated behavior model including health belief model, theory of planned behavior variables and extended socio-cognitive variables is identified to be a best model (with the highest percentage of total variance) that is not only for applying predictive illegal direction behavior in HCMC but also for other cities and provinces of Vietnam. The high significant variables of the integrated behavior model as behavioral intention, perceived benefits, subjective norm, perceived severity are selected to propose the appropriate community campaigns of road safety.

6.4.2 Introduction

Road accidents have caused a huge lost to the society in Vietnam. 880 million USD of economic lost due to road accident in Vietnam (accounting 2.45% of GDP) was estimated by (ADB 2003). This was higher than the average economic lost of Asian countries (2.1% of GDP). In 2007, it estimated about 2.89% of GDP in the Master Plan of Road Safety in Vietnam (MOT 2007).

Hochiminh city (HCMC) was considered as the place which have had the highest number of accidents, fatalities and injuries (accounting 9.14% of the country in period of 1999-2009. However, unfortunately the number of accidents, injuries, and fatalities has fluctuated uncertainly for the last many years.

According to (MOT 2007), almost road accidents and deaths have occurred on the highways and urban roads where the traffic is high in volume and highly mixed or the roads quality is better than others. Road users behavior has been identified as the main road safety risk (84%); the error of vehicle was very low taking 1% (2009) and the risk due to infrastructure accounted for 15%.

Averagely, the main causes of serious road accident were going on illegal direction change (28%), wrong way (21%), speeding (18%). This has proved that the illegal changing direction (IDC) behavior has been one of the highest root cause that has driven the increase of road accident in HCMC.

The differences of topography, weather, ethnic distribution, population and colony create different cultural regions of the North, The Central and The South of Vietnam with specific Regional characteristics. Being considered as a major hub for economic, commerce, finance, tourist, culture and science of Vietnam, Ho Chi Minh City (HCMC) has attracted many immigrants from the whole country (accounting for 1/3) to come to work and live. Therefore the different people characteristics of HCM people have created the diversified road user' perception.

Studying and research of IDC behaviors will surely be helpful us better understand the socio-cognitive variables of road users from which we can predict behavioral intention and behavior and to propose the road safety campaigns for increasing the road user perceptions in term of road safety

With all above reasons, IDC behavior in HCMC is chosen by the author to predict behavior intention as well as behavior through the methods of individual theory of planned behavior (TPB), health belief model (HBM) and integrated behavior models (IBM).

6.4.3 Objectives

Essentially, the first objective of this research is to investigate what factors among separated behavior models (TPB, HBM) and integrated behavioral model (IBM) and any predictive variables (perceived benefits, perceived barriers, cognitive attitude, affective attitude, personal norm, descriptive norm, subjective norm, perceived behavioral control in general, perceived behavioral control in specific situations, cues to action, perceived severity, perceived susceptibility) would help predict the illegal direction change intention and behavior of road users in Vietnam. In addition, all social - environment variables such as age, gender, occupation, household type, leisure activities of the drivers are included in the model to examine. The predictive variables of IDC behavioral intension and behavior models are used to find common and different social cognitive impacts for risky behavior prediction in HCMC. The Vietnamese habit, characters are examined by the behavioral model to propose suit road safety campaigns, education program or awareness program for increasing road safety perception of people in HCMC.

6.4.4 Theoretical Approach

Road traffic safety is caused mainly by driver' behaviors rather than technical failures or environment conditions (Lajunen, Parker et al. 2002; NTSC 2005). Risky driving behavior or traffic violent behavior basically includes self-assertive driving, speeding, rule violations (M. Anthony Machin 2007), dangerous overtaking (Miguel Angel Recarte 2002), not checking mirror, overtaking a right turner, going for the wrong switch, racing away from traffic lights… (Lajunen, Parker et al. 2002), dangerous violent, skill errors (Winter and Dodou 2010), drunk driving (Beullens and Bulck 2008).

It has been mandated by the Government regulation of No:34/2010/NĐ-CP signed by (Nguyen_Tan_Dung 2010) that the Illegal direction change behaviors (IDC) includes turning left, turning right, turning around which are explained specifically as following are not permitted:

- ✓ Do not respect priority rights for pedestrian, handicapped, handicapped wheelchair, un-motorized vehicle on their lanes and vehicles on opposite lane;
- ✓ Without turning on signal, light of vehicle;
- ✓ In the pedestrian lane, bridge, under bypass, narrow road, limited seeing of curve, prohibited turn sign;
- ✓ At the intersection between road and railway

In reality, the IDC behaviors has not been found in any researches or studies yet however some topic which have covered dangerous overtaking (Miguel Angel Recarte 2002), wrong lane at roundabout/ junction, taking wrong exit from roundabout, failing to notice a cyclist were found as the relation with IDC behaviors (Lajunen, Parker et al. 2002).

With the purpose of understanding what drivers do risky driving behaviors and how they have done those activities, many studies, researches have concentrated studying on drivers behaviors through different behavioral models with the aim of increasing their perception to reduce road accident loss (Rothengatter 2002; Josep Castellà a 2004; Eric R. Dahlen 2005; Victoir, Eertmans et al. 2005; De Pelsmacker and Janssens 2007; Mette Moller and Gregersen 2008; Mark A. Elliott 2010). Some of popular behavioral models which were discussed, applied to examine road user behavior are HBM (Rosenstock 1974), TPB model (Ajzen 1991), social-cognitive model (Melinder 2007), psychosocial function (Mette Moller and Gregersen 2008).

The extended socio-cognitive variables in the original models were applying widely to predict violation driving intension and behavior (Warner ; Letirand and Delhomme 2005; Mark A. Elliott 2005; Forward 2006; Warner and Aberg 2006; De Pelsmacker and Janssens 2007; L. Åberg 2007; Paris and Broucke 2008; Mark A. Elliott 2010). IBM were proved its powerful in predictive road user behavior toward helmet wearing behavior (section 6.2) and speeding behavior (section 6.3).

A. Health Belief Model (HBM)

Health belief model was proved the helpful road safety model of motivation for taking a positive action to prevent the negative action (speeding, wearing helmet) (CAST 2009). Three main variables were concerned in the model as perceived evaluation, perceived threat and cues to action (CAST 2009).

Perceived evaluation consists perceived benefits and perceived barriers. Perceived benefits is described the advantage when road user do IDC behavior, as “saving time”, “giving a feeling of control over vehicles”, “making a good impression on others”. Perceived barriers is presented the disadvantage (increasing the risk of getting fined) when road user do IDC.

Perceived threat includes perceived susceptibility and perceived severity. Perceived susceptibility is mentioned the chance of getting bad consequences (getting a ticket, damaging vehicle, getting hurt, hurting others) while doing IDC. Perceived severity is clarified the dangerous level of doing IDC.

The last variable of the model is cues to action. This variable mentions the internal information such as supporting higher fine, automatic ticket and external information such as supporting the campaign, education programs to motivate readiness for behavior change (legal direction change).

HBM was applied widely in road safety area to predict different risky driving behaviors (Fernandes, Hatfield et al. 2006; Fernandes and Neves 2010). HBM variables had not found significant much in predictive the risky behaviors. (Sissons-Joshi, Beckett et al. 1994; Quine, Rutter et al. 1998; Lajunen and

Räsänen 2004; Quine 2006; Ambak 2010). Perceived benefits was found significant impact to predict intention and behavior of wearing helmet (Quine 2006; section 6.2), speeding (Section 6.3) Perceived susceptibility was identified significant predictor in the wearing helmet behavioral model (Section 6.2).

B. Theory of Planned Behavior

TPB was extended from the theory of reasoned action and that included 5 variables in the model as attitude, subjective norm, perceived behavior control, intention and behavior (CAST 2009; Armitage and Conner 2001).

Attitude indicates the cognitive attitude and affective attitude (Eagly and Chaiken 1993; De Pelsmacker and Janssens 2007). Road users understand IDC is bad/ dislikable/inacceptable but doing this behavior made them feel exciting/ fun.

Subjective norm is described road user perception from the social pressure (their mother, farther, sister, boy/girl friend…) in the doing IDC.

Perceived behavior control is measured their control level (easy or hard) toward the IDC behavior.

IDC behavioral intention is their personal decision of doing legal direction changing in the next 3 months.

Affective attitude and cognitive attitude, subjective norm and perceived behavioral control were found significantly in lots of the predictive risk traffic models (Parker, Reason et al. 1995; Forward 2006).

Original HBM are found greater predictive power than original HBM in term of predictive behavioral intention (section 6.2, 6.3). In the predictive road user behavior model researches, original HBM is showed efficient predictive power than original TPB in wearing helmet behavior (Kris, 2012) on the contrary speeding behavior (Section 6.3). IBM was applied in the 2 other models (section 6.2, 6.3) are proved their predictive power for eliminating disadvantage points and increasing advantage points of original HBM and TPB models.

C. Integrated Behavioral Model

IBM is a combination among original HBM variables, original TPB variables and extended socio-cognitive variables to examine and to predict IDC intention and behavior of Vietnamese. A simplified schematic of IBM is presented in the figure 6.12.

Similar approach method of the proposed IBM in the previous researches (section 6.2, 6.3); original TPB (cognitive attitude, perceived behavioral control in general, subjective norm, behavioral intention), original HBM variables (perceived evaluation, perceived threat, cues to action) and four more socio-cognitive variables (affective attitude, perceived behavioral control in specific, descriptive norm, personal norm) are inputted in turn to the model.

Perceived behavioral control in specific situations describes the level control (easy/ hard) of road user to do legal direction change in specific situations (in a hurry, all other do IDC).

Descriptive norm was proved as a strong predictor of the behavioral intention models and the behavior models (Rivis and Sheeran 2003). Descriptive norm shows the frequency of road user in HCMC do the typical behavior (IDC).

Personal norm is a combination of moral value (IDC is irresponsible) and anticipated regret (IDC is intolerable). Personal norm is significant impact to traffic behavior model (De Pelsmacker and Janssens 2007, Elliot 2001).

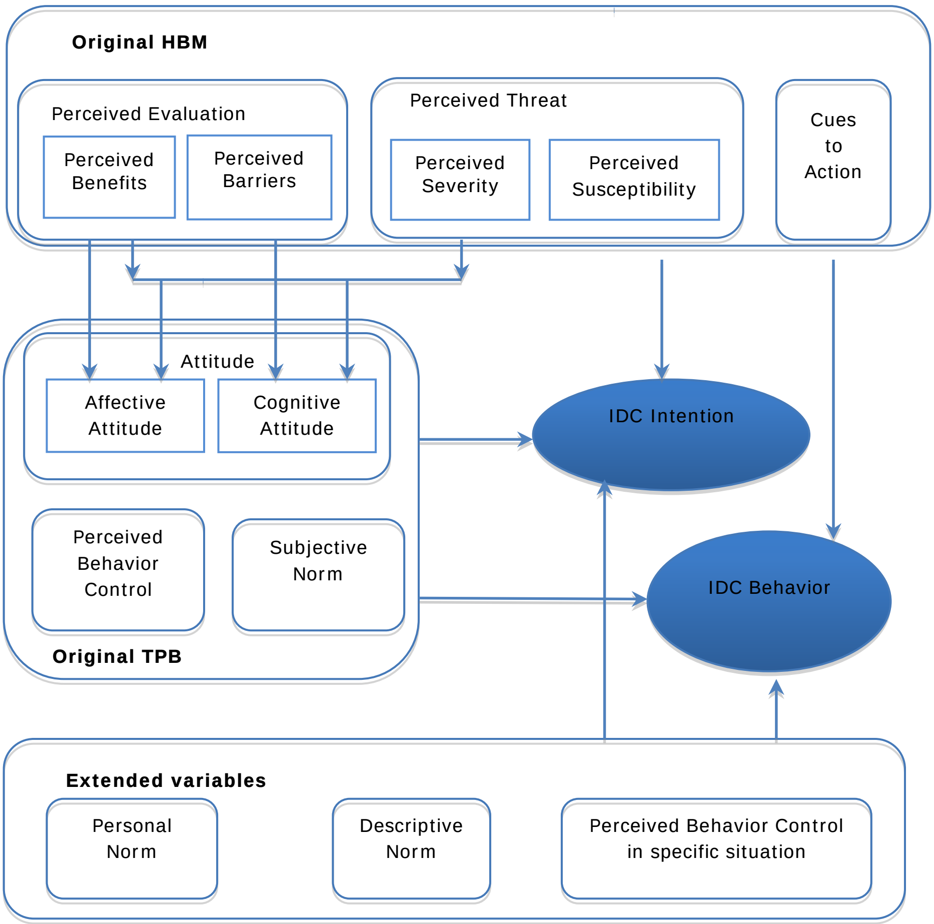

Figure 6.12 Proposed Integrated behavior model for IDC

6.4.5 Methods And Data Collection

A questionnaire is designed to measure IDC behavior of road users by the face to face method at the public transport terminals, households, companies, industry zones, gas stations, markets, colleges, universities in 24 districts and sub-districts of HCMC in spring 2011. The interviewers are provided a careful training of the questionnaire content, interviewing skill, locations, samples to know how collect valid attitude of participant's determinant in term of the IDC behavior. To get the good and value result form the main survey, 10% of samples is conducted for the pretest survey to adjust a completed and perfect questionnaire form and survey skills before. Participation is voluntary and respondents can withdraw at any time and their data would be withdrawn. 415 valid questionnaires show a respond rate of 92%. The sample includes 55% (n=226) of male and 45% of female with a mean age of 30 years (range from 13 - 70 years). 20.5% of participants is student and 48% of them has university level degree. The majority of respondents has at least one motorbike with the rate is 85.6%.

14 standard items (variables), commonly used in the previous research (section 6.3), are used to measure the socio-cognitive constructs of the integrated illegal direction changing behavior. All items are measured using 5-point scales (1: disagreement/ never to 5: agreement/ very often)

The participants' responses on the provisional questionnaire are entered into an SPSS data file and aggregated all questions to be a variable. The Pearson correlation, mean, standard deviation and Cronbach's alpha are tested to identify potential predictors of behavioral intention and behavior as well as to check the reliability of all items (questions) in each proposed (Table 3).

Separate original HBM and TPB variables are entered to examine the contribution of the predictors and to identify better predictive models of IDC intension behavior and behavior by the regression model (Table 2, Table 3). Cognitive attitude and affective attitude are explored on the threat perceived (perceived benefits and barriers) and both the threat perceived and the perceived evaluation (perceived severity and susceptibility) by regression models.

IBM variables are input in turn in four steps by the stepwise linear regression model. The original variables of the better predictive model (HBM or TPB) are added in the first step (same as section 6.2.7, 6.3.9). The remaining steps are done by adding the variables of the weaker model and extended variables (Table 6.19, 6.20).

6.4.6 Results

There are 30.1% and 38.8% of respondents answer that they "occasionally" and "rarely" do IDC. They "occasionally" do this violation behavior on the urban roads (23.1). The result shows famer is occupied the highest ratio (1%) of "very often" doing IDC while private employer get the highest ratio of often doing its (3.1%) among other occupations. Young people (20-30 years) do IDC "occasionally" (30.7%) and "often" (5.7%) than other age levels.

Table 6.14 shows all questions of road users trend positive of risky behavior (mean range from 3-4 point).

Table 6.15 presents the means, the standard deviations, the reliability (cronbach alpha test) of each variable and the correlations for each measure. These correlation values are acceptable and significant. The cronbach' alpha checks for reliability of all concepts are higher than 0.71 with the exception of perceived behavior control in general (0.58) and perceived behavior control in specific situation (0.47).

Table 6.14 Descriptive of 14 socio-cognitive variables

(1): 1=disagree: 5=agree
(2): 1=never: 5=very often
(3): 1=very hard: 5=very easy

Concepts	Items	Scoring	M	S.D.	N
PBe	IDC makes you save time	(1)	2.33	0.89	415
(α= .80)	IDC gives you a feeling of control over the car	(1)	2.41	0.90	415
	IDC makes a good impression on others	(1)	1.99	0.87	415
PBa	IDC increases the risk of getting fined	(1)	3.85	0.7	415
C_ATT	IDC is bad	(1)	3.85	0.88	415
(α= .75)	IDC is dislikeable	(1)	3.83	0.90	415
	IDC is acceptable (reverse coded)	(1)	3.58	0.96	415
A_ATT	IDC is exciting	(1)	2.07	0.90	415
(α= .87: r= .77)	IDC is fun	(1)	2.07	0.92	415
PN	IDC is irresponsible	(1)	3.81	0.85	415
(α= .83: r= .71)	IDC is intolerable	(1)	3.78	0.89	415
DN	How often do other drivers in HCMC IDC?	(2)	3.47	0.91	415
SN	Important social referent 1 would accept I IDC	(1)	2.02	0.95	415
(α= .89)	Important social referent 2 would accept I IDC	(1)	2.07	0.98	415
	Most people who are important to me think I should never IDC (reverse coded)	(1)	2.23	0.83	415
PBC	I am able to prevent myself from IDC	(1)	3.72	0.93	415
(α= .74: r= .58)	It is easy for me to legal direction change	(1)	3.61	0.91	415
PBC_SS (α= .64: r= .47)	Preventing myself from IDC when I am in a hurry	(3)	3.45	0.75	415
	Preventing myself from I IDC when most others do	(3)	3,42	0,86	415
CA (α= .79)	I fully support cameras to automatically ticket IDC on highways	(1)	4.03	0.85	413
	I fully support more public road safety awareness campaigns	(1)	4.14	0.83	413
	I fully support higher fines	(1)	3.78	1.02	411
	I fully support more traffic safety education in primary & secondary schools	(1)	3.99	0.87	412
PSe	IDC is dangerous	(1)	3.90	0.90	415
PSu	The chance of getting a ticket when IDC is high	(1)	4.04	0.86	413
(α= .79)	The chance of damaging my vehicle when IDC is high	(1)	3.88	0.86	400
	The chance of getting hurt in an accident when IDC is high	(1)	3.88	0.82	400
	The chance of hurting others in an accident when is high	(1)	3.93	0.86	400
BI (α= .90: r= .82)	I have the intention to legal direction change in the next 3 months	(1)	3.83	0.88	415
	I am willing to legal direction change in the next 3 months	(1)	3.94	0.92	415
B	How often do you IDC?	(2)	2.41	1.00	415

Table 6.15 Statistic of 14 socio-cognitive variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. PBe														
2. PBa	-.69^{b}													
3. C_ATT	-.62^{b}	.56^{b}												
4. A_ATT	.53^{b}	-.48^{b}	-.55^{b}											
5. PN	-.61^{b}	.57^{b}	.66^{b}	-.61^{b}										
6. DN	-.44^{b}	.38^{b}	.38^{b}	-.41^{b}	.40^{b}									
7. SN	.67^{b}	-.60^{b}	-.62^{b}	.60^{b}	-.64^{b}	-.47^{b}								
8. PBC	-.50^{b}	.47^{b}	.57^{b}	-.44^{b}	.54^{b}	.40^{b}	-.52^{b}							
9. PBC_SS	-.45^{b}	.44^{b}	.44^{b}	-.45^{b}	.43^{b}	.31^{b}	-.45^{b}	.40^{b}						
10. CA	-.18^{b}	.19^{b}	.19^{b}	-.15^{b}	.25^{b}	.17^{b}	-.23^{b}	.19^{b}	.18^{b}					
11. PSe	-.69^{b}	.69^{b}	.53^{b}	-.49^{b}	.52^{b}	.41^{b}	-.58^{b}	.47^{b}	.39^{b}	.14^{b}				
12. PSu	-.21^{b}	.27^{b}	.26^{b}	-.25^{b}	.32^{b}	.23^{b}	-.29^{b}	.23^{b}	.15^{b}	.30^{b}	.21^{b}			
13. BI	-.60^{b}	.57^{b}	.57^{b}	-.47^{b}	.60^{b}	.46^{b}	-.64^{b}	.47^{b}	.43^{b}	.19^{b}	.56^{b}	.26^{b}		
14. B	.60^{b}	-.54^{b}	-.58^{b}	.51^{b}	-.54^{b}	-.41^{b}	.62^{b}	-.45^{b}	-.41^{b}	-.14^{b}	-.56^{b}	-.19^{b}	-.61^{b}	
Mean†	2.25	3.85	3.75	2.07	3.80	3.47	2.11	3.67	3.43	3.98	3.90	3.92	3.88	2.41
SD	0.75	0.97	0.75	0.86	0.80	0.91	0.83	0.82	0.69	0.70	0.99	0.66	0.86	1.00

*p values are as follows: $^{a}p < 0.05$; $^{b}p < 0.01$; $^{c}p < 0.001$

†Scores range between 1 and 5

A. Health Belief Model

All original variables of HBM including perceived benefits, perceived barriers, perceived severity, perceived susceptibility and cues to action are predicted the IDC intention and behavior. Perceived benefits, perceived barriers, perceived severity and perceived susceptibility account for 41% of the variance in IDC intentions ($p<0.001$). The perceived benefit is considered as the most important factor (ß= -0.238, $p<0.000$), followed by perceived barriers (ß= 0.223, $p<0.000$), perceived severity (ß = 0.214, $p<0.000$) and perceived susceptibility (ß= 0.084, $p<0.05$) (Table 6.16).

Table 6.16 HBM model in speeding

Regression of behavioral intentions on HBM-variables*						
Variables entered	B	SE B	β	t	p	$sr^{2\dagger}$
PERCEIVED BENEFITS	-.270	.067	-.238	-4.010	.000	.025
PERCEIVED BARRIERS	.195	.053	.223	3.674	.000	.021
PERCEIVED SEVERITY	.184	.051	.214	3.613	.000	.020
PERCEIVED SUSCEPTIBILITY	.109	.055	.084	1.991	.047	.006
CUES TO ACTION	.044	.051	.036	.870	.385	.001
*N= 395, R^2= 0.41						
Regression of behavior on HBM-variables*						
Variables entered	B	SE B	β	t	p	sr^2
PERCEIVED BENEFITS	.480	.076	.369	6.278	.000	.059
PERCEIVED BARRIERS	-.135	.060	-.135	-2.250	.025	.008
PERCEIVED SEVERITY	-.198	.058	-.202	-3.449	.001	.018
PERCEIVED SUSCEPTIBILITY	-.060	.062	-.041	-.970	.333	.001
CUES TO ACTION	.024	.057	.017	.417	.677	.000
*N= 395, R^2= 0.42						

$^{\dagger}sr^2$= the squared semi-partial correlation coefficient. This coefficient equals the R-square change value from the regression when a variable is added or removed.

Regarding the predictive IDC behavior model, perceived benefits, perceived barriers and perceived severity variables are significant with 42% of the total variance. The strongest predictor is contributed from perceived benefits (ß = 0.369, p<000), followed by perceived barriers (ß = -0.135, $p<0.03$) and perceived severity (ß=-0.202, $p<0.002$) (Table 6.16).

B. Theory Of Planned Behavior

In the case of adding separately the original TPB variables in to the predictive model, it is presented statistically significant predictors with accounting for 60 of the total variance in IDC intention (Table 6.17). The subjective norm variable is considered as the strongest predictor (ß = -0.431, $p<0.000$), followed by cognitive attitude (ß = 0.243, $p<0.000$), perceived behavioral control in general (ß = 0.048, $p<0.03$).

Behavior intentions and perceived behavioral control in general are predicted statistically significant toward the IDC behavior and explaining 41% of the total variance. Behavior intention is identified as the most important predictor (ß = -0.516, $p<0.000$), followed by perceived behavior in general (ß =-0.206, $p<0.000$).

Table 6.17 TPB model for Speeding Intention and Speeding behavior

Regression of behavioral intentions on TPB-variables*						
Variables entered	B	SE B	β	t	p	sr^2
COGNITIVE ATTITUDE	.280	.057	.243	4.931	.000	.032
SUBJECTIVE NORM	-.446	.049	-.431	-9.037	.000	.107
PERCEIVED BEHAVIORAL CONTROL IN GENERAL	.111	.048	.106	2.318	.021	.007
*N= 415, R^2= 0.46						
Regression of behavior on TPB-variables*						
Variables entered	B	SE B	β	t	p	sr^2
BEHAVIORAL INTENTIONS	-.600	.050	-.516	-12.006	.000	.207
PERCEIVED BEHAVIORAL CONTROL IN GENERAL	-.251	.053	-.206	-4.786	.000	.033
*N= 415, R^2= 0.41						

Cognitive attitude is predicted on all of questions that are representative for perceived benefits and barriers with 42% of the total variance. Affective attitude is contributed from one question of perceived benefits and perceived barriers accounting 31% of the variance. “IDC increases the risk of getting fined” is presented the strongest predictor of the cognitive attitude regression model (ß = 0.257, p<0.000) and being the weaker predictor of the affective attitude regression model (ß = -0.222, p<0.000). “IDC is making a good impression” is considered as the most important predictor (ß = 0.246, p<0.000).

Considering more perceived severity and perceived susceptibility in the predictive cognitive and affective attitude models, the total variance is a bit higher (42% and 31% respectively). The predictors of the cognitive attitude model are less than the previous models (Table 6.18). “IDC is making a good impression” is contributed as the strongest predictor in both cognitive and affective attitude models (ß = -0.224, p<0.000; ß = 0.212, p<0.000).

Table 6.18 Regression predictive model for attitude and cognitive attitude

Regression of cognitive attitude on perceived benefits and barriers*						
Variables entered	B	SE B	β	t	p	sr^2
IDC makes you save time	-.137	.049	-.163	-2.820	.005	.011
IDC gives you a feeling of control over the vehicle	-.105	.044	-.127	-2.388	.017	.008
IDC is making a good impression	-.202	.041	-.235	-.4880	.000	.033
IDC increases the risk of getting fined	.197	.041	.257	4.834	.000	.033
*N= 415, R^2= 0.42						
Regression of affective attitude on perceived benefits and barriers*						
Variables entered	B	SE B	β	t	p	sr^2
IDC makes you save time	.119	.061	.123	1.951	.052	.006
IDC gives you a feeling of control over the vehicle	.075	.056	.078	1.353	.177	.003
IDC is making a good impression	.245	.052	.246	4.704	.000	.037
IDC increases the risk of getting fined	-.196	.051	-.222	-3.826	.000	.025
*N= 415, R^2= 0.31						
Regression of cognitive attitude on perceived benefits and barriers + perceived severity and susceptibility*						
Variables entered	B	SE B	β	t	p	sr^2
IDC makes you save time	-.121	.050	-.146	-2.397	.017	.008
IDC gives you a feeling of control over the vehicle	-.077	.045	-.094	-1.701	.090	.004
IDC is making a good impression	-.191	.043	-.224	-4.416	.000	.029
IDC increases the risk of getting fined	.149	.046	.196	3.222	.001	.015
IDC is dangerous	.067	.044	.090	1.529	.127	.003
The chance of getting a ticket when IDC is high	.041	.034	.048	1.214	.225	.002
The chance of damaging my vehicle when IDC is high	.020	.061	.023	.320	.749	.000
The chance of getting hurt in an accident when IDC is high	.132	.080	.146	1.644	.101	.004
The chance of hurting others in an accident when IDC is high	-.066	.074	-.076	-.890	.374	.001
*N= 398, R^2= 0.44						
Regression of affective attitude on perceived benefits and barriers + perceived severity and susceptibility*						
Variables entered	B	SE B	β	t	p	sr^2
IDC makes you save time	.102	.064	.105	1.598	.111	.004
IDC gives you a feeling of control over the vehicle	.034	.057	.036	.600	.549	.001
IDC is making a good impression	.211	.054	.212	3.869	.000	.026
IDC increases the risk of getting fined	-.101	.058	-.114	-1.736	.083	.005
IDC is dangerous	-.154	.055	-.178	-2.805	.005	.013
The chance of getting a ticket when IDC is high	-.065	.043	-.065	-1.532	.126	.004
The chance of damaging my vehicle when IDC is high	-.137	.077	-.136	-1.780	.076	.005
The chance of getting hurt in an accident when IDC is high	.063	.101	.060	.624	.533	.001
The chance of hurting others in an accident when IDC is high	-.022	.093	-.022	-.237	.813	.000
*N= 398, R^2= 0.34						

C. Integrated Behavioral Model

IDC behavioral intention models are predicted from proposed socio-cognitive variables in four steps that present in Table 6.19 and Figure 6.13

Table 6.19 IBM for predictive IDC intention

STEP 1	B	SEB	β	t	p	sr^2
COGNITIVE ATTITUDE	.264	.059	**.228**	4.477	**.000**	**.028**
SUBJECTIVE NORM	-.449	.051	**-.435**	-8.802	**.000**	**.109**
PERCEIVED BEHAVIORAL CONTROL IN GENERAL	.113	.049	**.109**	2.309	**.021**	**.007**
R^2= .45 R^2 change= .45 F change= 107.447 (p< .000)						
STEP 2	B	SE B	β	t	p	sr^2
COGNITIVE ATTITUDE	.228	.060	**.197**	3.777	**.000**	**.020**
SUBJECTIVE NORM	-.407	.055	**-.394**	-7.408	**.000**	**.076**
PERCEIVED BEHAVIORAL CONTROL IN GENERAL	.089	.049	.085	1.804	.072	.004
AFFECTIVE ATTITUDE	-.032	.049	-.032	-.651	.515	.001
PERCEIVED BEHAVIORAL CONTROL IN SPECIFIC SITUATIONS	.145	.055	**.117**	2.635	**.009**	**.010**
R^2= .46 R^2 change= .01 F change= 4.154 (p= 0.16)						
STEP 3	B	SE B	β	t	p	sr^2
COGNITIVE ATTITUDE	.135	.062	**.116**	2.189	**.029**	**.006**
SUBJECTIVE NORM	-.324	.056	**-.314**	-5.838	**.000**	**.044**
PERCEIVED BEHAVIORAL CONTROL IN GENERAL	.038	.049	.037	.782	.435	.001
AFFECTIVE ATTITUDE	.036	.049	.036	.728	.467	.001
PERCEIVED BEHAVIORAL CONTROL IN SPECIFIC SITUATIONS	.131	.053	**.105**	2.453	**.015**	**.008**
DESCRIPTIVE NORM	.131	.040	**.138**	3.282	**.001**	**.014**
PERSONAL NORM	.231	.058	**.217**	4.001	**.000**	**.021**
R^2= .50 R^2 change= .04 F change= 13.482 (p< .000)						
STEP 4	B	SE B	β	t	p	sr^2
COGNITIVE ATTITUDE	.096	.062	.083	1.552	.122	.003
SUBJECTIVE NORM	-.263	.058	**-.254**	-4.524	**.000**	**.026**
PERCEIVED BEHAVIORAL CONTROL IN GENERAL	.017	.048	.016	.347	.729	.000
AFFECTIVE ATTITUDE	.053	.049	.053	1.080	.281	.001
PERCEIVED BEHAVIORAL CONTROL IN SPECIFIC SITUATIONS	.106	.053	**.085**	1.985	**.048**	**.005**
DESCRIPTIVE NORM	.112	.040	**.119**	2.821	**.005**	**.010**
PERSONAL NORM	.200	.058	**.188**	3.431	**.001**	**.015**
PERCEIVED BENEFITS	.007	.068	.006	.100	.920	.000
PERCEIVED BARRIERS	.092	.050	.106	1.859	.064	.004
PERCEIVED SEVERITY	.112	.047	**.130**	2.380	**.018**	**.007**
PERCEIVED SUSCEPTIBILITY	.022	.051	.017	.439	.661	.000
CUES TO ACTION	-.016	.047	-.013	-.352	.725	.000
R^2= .52 R^2 change= .02 F change= 3.634 (p= .003)						
*N= 395						

TPB variables are more powerful predictions than the HBM variables in term of the predictive IDC behavioral intention (same findings as section 6.2 and 6.3). So original TPB variables and other socio-cognitive variables are entered before HBM variables in four steps by stepwise regression model.

In the first step, all three original TPB variables are identified contributing to the model with 45% of total variance. Subjective norm is the most important predictor (ß = -0.435, p<0.000) followed by cognitive attitude (ß = 0.228, p<0.000) and perceived behavior control in general (ß = 0.109, p<0.05).

The second step including more affective attitude and perceived behavioral control in specific situations are added to explain 46% of the total variance. The strongest predictor is contributed from subjective norm (ß = -0.394, $p<0.000$), followed by cognitive attitude (ß = 0.197, $p<0.000$) and perceived behavior control in specific situation (ß = 0.117, $p<0.01$).

Descriptive norm and personal norm are added in the third step accounting 50% of total variance. Subjective norm is contributed as the most important variable in the predictive model (ß = -0.314, $p<0.000$). The other significant predictors are personal norm, descriptive norm, cognitive attitude and perceived behavioral control in specific situation (ß = 0.217, ß = 0.138, ß = 0.116, ß = 0.105, $p<0.01$).

All original HBM variables are entered in the predictive model explaining 52% of total variance. Subjective norm is identified as the strongest predictor with ß = -0.254, $p<0.000$. Perceived severity of the HBM model is considered at the second important predictor, followed by personal norm, descriptive norm and perceived behavioral control in specific (ß = 0.130, 0.188, 0.119, 0.085, $p<0.05$, respectively).

Regarding the predictive IDC behavior, HBM variables are added first because of their power predictions that are examined in the separate HBM and TPB (same previous research in section 6.2 and 6.3).

At the first step, HBM variables explain 42% of the variance in IDC, with perceived benefits (ß = -0.369, $p<0.03$) is considered as the strongest contribution, followed by perceived severity (ß = -0.202, $p<0.02$) and perceived barriers (ß = -0.135, $p<0.03$).

Behavioral intention, perceived behavioral control in general are added accounting 49% of total variance. Behavioral intention becomes the most important predictor of the IBM model in the second step with ß = -0.316, $p<0.000$. Perceived benefits and perceived severity are significant predictors with ß = 0.273, -0.121, $p<0.04$, respectively.

In the step 3, no significant prediction is found from adding more descriptive norm and personal norm but perceived behavioral control in specific situation is significant predictor for the IDC model (ß = -0.091 $p<0.000$). All variables explain 50% of the variance with the strongest predictor as behavior intention (ß = -0.266 $p<0.000$) followed by perceived benefits (ß = 0.230, $p<0.000$), perceived severity (ß = -0.115, $p<0.05$).

Regarding the last step, 13 socio-cognitive variables (adding more cognitive and affective attitude) explain an additional 2 of the variance comparing to the third step (R^2 = 50). Behavioral intention is considered as the most important variable of the predictive model (ß = -0.115, $p<0.000$), followed by perceived benefits (ß = 0.196, $p<0.002$), cognitive attitude (ß = -0.139, $p<0.05$) and affective attitude (ß = -0.109, $p<0.05$).

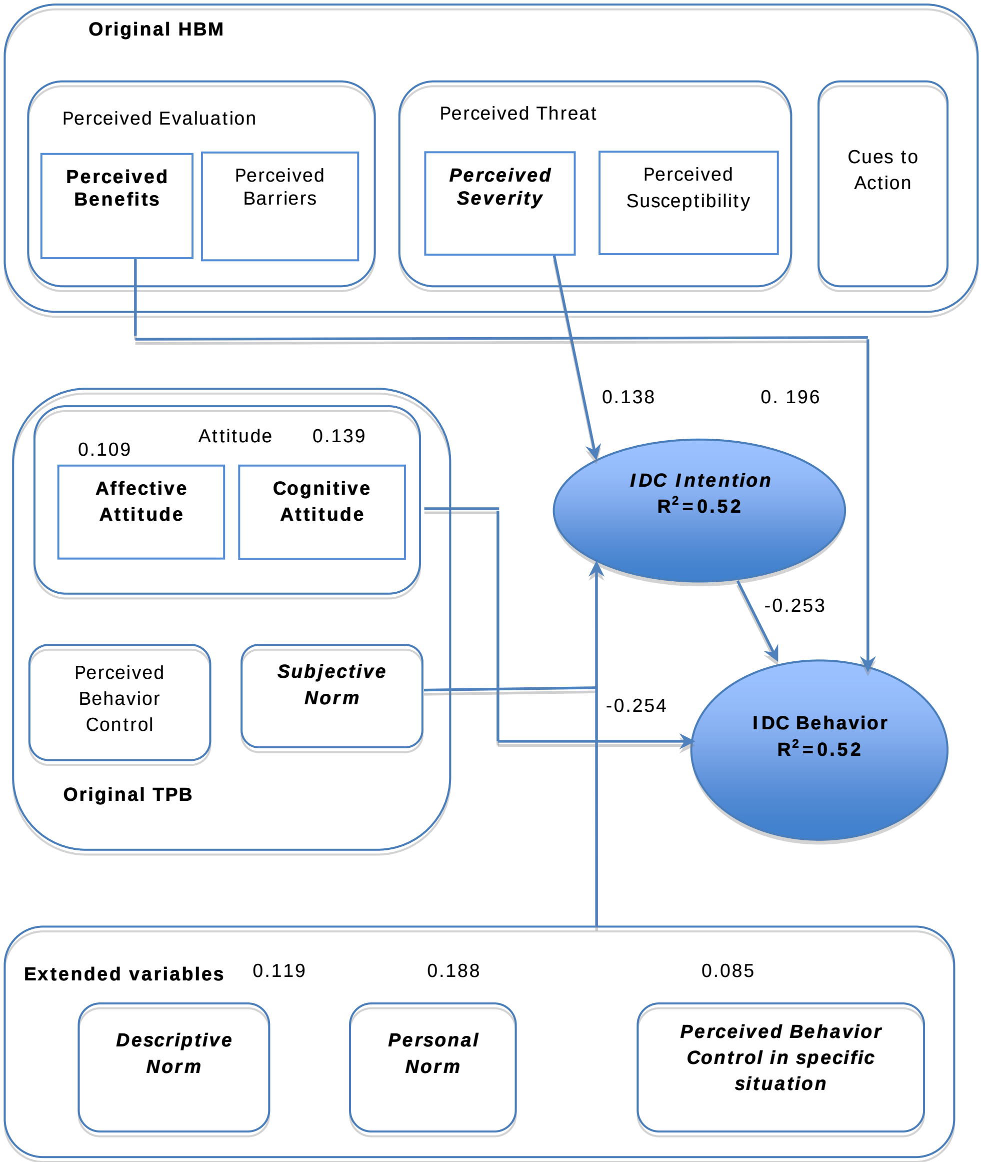

Figure 6.13 IBM for IDC intention and behavior.

Table 6.20 IBM for predictive IDC behavior

STEP 1	B	SE B	β	t	p	sr^2
PERCEIVED BENEFITS	.480	.076	**.369**	6.278	**.000**	**.059**
PERCEIVED BARRIERS	-.135	.060	**-.135**	-2.250	**.025**	**.008**
PERCEIVED SEVERITY	-.198	.058	**-.202**	-3.449	**.001**	**.018**
PERCEIVED SUSCEPTIBILITY	-.060	.062	-.041	-.970	.333	.001
CUES TO ACTION	.024	.057	.017	.417	.677	.000
R^2= .42 R^2 change= .42	F change= 55.364 (p< .000)					
STEP 2	B	SE B	β	t	p	sr^2
PERCEIVED BENEFITS	.355	.074	**.273**	4.781	**.000**	**.030**
PERCEIVED BARRIERS	-.052	.058	-.052	-.906	.365	.001
PERCEIVED SEVERITY	-.119	.055	**-.121**	-2.155	**.032**	**.006**
PERCEIVED SUSCEPTIBILITY	-.012	.059	-.008	-.198	.843	.000
CUES TO ACTION	.047	.054	.034	.874	.382	.001
BEHAVIORAL INTENTIONS	-.361	.055	**-.316**	-6.579	**.000**	**.058**
PERCEIVED BEHAVIORAL CONTROL IN GENERAL	-.098	.053	-.082	-1.852	.065	.004
R^2= .49 R^2 change= .07	F change= 26.383 (p< .000)					
STEP 3	B	SE B	β	t	p	sr^2
PERCEIVED BENEFITS	.299	.076	**.230**	3.918	**.000**	**.020**
PERCEIVED BARRIERS	-.028	.058	-.028	-.491	.624	.000
PERCEIVED SEVERITY	-.113	.055	**-.115**	-2.060	**.040**	**.006**
PERCEIVED SUSCEPTIBILITY	.002	.059	.002	.042	.966	.000
CUES TO ACTION	.069	.054	.049	1.267	.206	.002
BEHAVIORAL INTENTIONS	-.304	.058	**-.266**	-5.263	**.000**	**.036**
PERCEIVED BEHAVIORAL CONTROL IN GENERAL	-.047	.055	-.040	-.864	.388	.001
PERCEIVED BEHAVIORAL CONTROL IN SPECIFIC SITUATIONS	-.130	.061	**-.091**	-2.117	**.035**	**.006**
DESCRIPTIVE NORM	-.070	.046	-.065	-1.524	.128	.003
PERSONAL NORM	-.097	.064	-.080	-1.525	.128	.003
R^2= .50 R^2 change= .01	F change= 3.323 (p= .020)					
STEP 4	B	SE B	β	t	p	sr^2
PERCEIVED BENEFITS	.255	.076	**.196**	3.343	**.001**	**.014**
PERCEIVED BARRIERS	-.019	.057	-.019	-.336	.737	.000
PERCEIVED SEVERITY	-.098	.054	-.100	-1.805	.072	.004
PERCEIVED SUSCEPTIBILITY	.016	.058	.011	.276	.783	.000
CUES TO ACTION	.055	.054	.039	1.020	.308	.001
BEHAVIORAL INTENTIONS	-.289	.057	**-.253**	-5.037	**.000**	**.032**
PERCEIVED BEHAVIORAL CONTROL IN GENERAL	-.012	.055	-.010	-.212	.832	.000
PERCEIVED BEHAVIORAL CONTROL IN SPECIFIC SITUATIONS	-.088	.062	-.062	-1.432	.153	.003
DESCRIPTIVE NORM	-.048	.046	-.044	-1.037	.300	.001
PERSONAL NORM	-.003	.068	-.003	-.047	.962	.000
COGNITIVE ATTITUDE	-.185	.071	**-.139**	-2.597	**.010**	**.008**
AFFECTIVE ATTITUDE	.123	.055	**.109**	2.238	**.026**	**.006**
R^2= .52 R^2 change= .02	F change= 6.543 (p= .002)					
*N= 395						

6.4.7 Discussion

In general, the respondents are found “occasionally” and “rarely” doing IDC and mainly doing in urban roads. Most of road users doing IDC “often” are identified as famer, private employer and young respondents.

A. Theoretical Findings

Nine variables of three different models (HBM, TPB, extended socio-cognitive variables) are found and estimated significantly the IDC model. In term of the original HBM, (1) perceived severity, (2) perceived benefit are contributed the significant impact to predict IDC. Original TPB variables are predicted toward IDC model such as (3) subjective norm, (4) cognitive attitude, (5) and behavioral intention. The remaining four extended socio-cognitive variables are identified significant contribution toward the predictive IDC model included (6) affective attitude, (7) perceived behavior control in specific situation, (8) descriptive norm, and (9) personal norm.

Perceived Threat: Perceived severity and perceived susceptibility are two main aspects to evaluate the perceived threat concept.

Perceived severity is proved a weak power while perceived susceptibility is more important power in the predictive model (Becker 1974; Janz and Becker 1984; Harrison, Mullen et al. 1992; Champion and Skinner 2008)). But it is different in this study and speeding study (section 6.2), perceived severity is identified more important that perceived susceptibility and it is the second important predictors of the predictive IDC intention model by IBM and the third position impact to the predictive model by HBM. In term of predictive behavior by HBM, perceived severity is kept the second important. For IBM, perceived severity could not contribute as the strongest predictor toward IDC behavior but still has impact until cognitive and affective attitude variables are entered in the model.

Perceived severity has not been found with any significant contribution to both predictive affective and cognitive attitude in this research.

Perceived benefits: Perceived evaluation are measured from perceived benefits and perceived barriers.

From prior researches, perceived benefits measures to have stronger effects when focusing on unsafe behavior and perceived barriers would be the most powerful predictor within the HBM (Becker, 1974; Champion and Skinner, 2008; Harrison et al., 1992; Janz and Becker, 1984). The results of this research are not same line with those above findings, but both of variables are significant contribution to predict unsafe intention and behavior (IDC) and same with the previous studies of the thesis (section 3.1, 3.2). Perceived benefits is identified the significant important variable to predict IDC intention and behavior than perceived barrier. In term of HBM, perceived benefit is contributed the most important toward IDC intention and behavior. For IBM, perceived benefits is found the significant impact toward the predictive IDC behavior only. It is became the most important predictor when applying only HBM variables, and it is turned to the second important predictor when applying TPB and extended socio-cognitive variables. Perceived barriers contribute a small significant to the predictive model by HBM but it is an insignificant predictor by IBM.

Attitude: Affective and cognitive attitudes are combined to evaluate the attitude of road users regarding IDC. These variables were identified significantly to predictive intention and behavior in the previous studies (Rothengatter 1993; Levelt and Swov 1998).

Cognitive attitude is found with the significant impact toward IDC intention by TPB model and IBM model before adding HBM variables (same as speeding study). In this study, affective attitude is presented the significant contribution in the predictive IDC behavior by the IBM when these variables are added into the model while it found insignificantly in the two previous studies (helmet wearing and speeding).

Subjective Norm And Perceived Behavior Control in specific situation: Subjective norm was proved as the weak relationship with intention (Godin and Kok 1996; Forward 2006) (Armitage and Conner 2001). Subjective norm is same as the above conclusion, it found insignificant contribution with intention and behavior of the previous studies (helmet wearing and speeding) and IDC behavior.

The interesting finding in this research is the most important role of subjective norm toward predictive IDC intention by both TPB and IBM. The behavior mechanism is hypothesized that subjective norm → Intention → Behavior. The perceived social pressure (the important person of the road users) to engage in unsafe behavior (IDC) has a strongest significant impact to behavior intention of road users in the near future (next 3 month). And behavior intention is the most important contribution to predict unsafe behavior (IDC). Social pressure should be considered in the campaign for convincing road users to respect direction changing.

Perceived behavior control in specific situation is proved its predictive power of IDC intention model. Although perceived behavior control in specific situation can not contributed a high impact to predict IDC intention but it is contribute the impact to all of models of IBM. In term of IDC behavior, perceived behavior control in specific situation is become insignificant when cognitive and affective attitude are entered to the model.

Personal Norm and Descriptive Norm: Personal norm was identified significantly to predict intention and behavior (Elliot 2001; Mark A. Elliott 2010). And descriptive norm was found a stronger contribution to predict the intention than subjective norm (Rivis and Sheeran 2003) and to predict behavior (Mark A. Elliott 2010).

In this research, personal norm and descriptive norm are found significant predictors toward IDC intention after they are added in the models. Personal norm is ranked at the top three predictors of intention and have a bigger impact to IDC behavior than descriptive norm.

Behavioral Intention: Behavior intention is found as the most powerful predictor of IDC behavior by both TPB or IBM, that same conclusion with other researches (Conner, Lawto et al.)

B. Comparison Findings

Separate original HBM, TPB and IBM are applied to estimate IDC intention and behavior of road user in HCMC, Vietnam. The results find that (1) within original behavior models (TPB and HBM): in term of IDC intention, original TPB variables are predicted more powerful than original HBM variables but HBM variables are predicted well than original TPB variables. (2) within integrated model (IBM):

the original TPB variables (step 1) are explained the lowest of variance (R^2 = 45%). Adding 2 more socio-cognitive variables (step 2), 3 socio-cognitive variables (step 3) and 5 original HBM variables (step 4) are made a small increasing of the total variance in each step (R^2= 0.46, 0.50 and 0.52, respectively) to predict the IDC behavioral intention. In term of the predictive IDC behavior, 5 original HBM variables are contributed the lowest of variance (R^2=42%). Adding original TPB variables (step 2) is made 7 increasing of total variance than the first step. 3 socio-cognitive variables (step 3) and 2 socio-cognitive variables (step 4) are contributed more 1 and 2 of variance than the previous step. Original TPB variables and extended socio-cognitive variables are predicted IDC intention and behavior better than original HBM variables.

In theoretical aspect, best model is considered as the highest R^2 value but in the practical aspect, best model should be considered "clean and clear" (Lippke and Ziegelmann, 2008). The results show adding more variables (total of 12 variables in step 4) to be made higher R^2 for predictive IDC intention and behavior so the final step is selected as the best model of IDC for both IDC intention and behavior

6.4.8 Implementation

The advantages of applying socio-psychological theories to predict road user intention and behavior and to help proposing suit, good future campaigns interventions are mentioned in lost of researches (Glanz and Rimer 1995) and the two previous studies (helmet wearing and speeding in section 6.2, 6.3). Through the findings and results of the predictive IDC road user models, there are some significant social-psychological variables are found differentially, then the local authorities should consider more carefully in their decision making for the proposed intervention.

To reduce the IDC behavior of road users, the proposed implementation should consider four main factors that mentioned in the helmet wearing and speeding studies (6.2, 6.3) following the same (1) "Why people do IDC"; (2) "What kind of implementation should be considered?"; (3) "What thing should involve in the proposed implementation"; (4) "How to implement efficiently".

Following the proposed model mention in section 6.2.7, the key determinants should be considered for policy makers in order as behavior intention, perceived severity, subjective norm and perceived benefits. Perceived benefits of IDC is caused a big from "making a good impression on the others" idea of road user than "saving time" or "giving them a feeling of control vehicles".

Answering the (1) question, road users in this research are found that they do IDC mainly because of their intention and their willing to do IDC in the next three months (behavioral intention), the dangerous level to do this behavior (perceived severity), and their idea to do IDC would make a good impression on the others (perceived benefits). The road user intentions of doing IDC in the next 3 months are indicated mainly from the important social person accept their IDC behavior and think them should never do IDC behavior (subjective norm), and the dangerous level of doing IDC behavior (perceived severity).

All causes of doing IDC intention and behavior are proved that an appropriate community campaign to increasing the road user perception and awareness is necessary (2).

The proposed campaign should designed following social marketing theory (CAST 2009). (3) So, the key success of the potential campaign is identifying the target audiences and designing the appropriate education, awareness programs through creation of messages and selection of media channels to motivate readiness for behavior change. The messages in the awareness and education programs should concentrated to the "dangerous level of IDC behavior" and "the other people boycott the IDC behavior". The public media should be considered as television, radio, panel, poster, education in the school. A strict enforcement from the government combination with the proposed campaign can raise audience awareness about campaign theme.

(4) The detail plan of work, approach, people, time, cost for evaluating, monitoring, measuring the intervention program should be established to satisfy the final question.

6.4.9 Conclusion

Behavioral models including TPB, HBM and IBM are applied separately to examine the road users toward IDC behavior and to select the best model to apply further in Vietnam; the case study is in HCMC.

Behavioral intention variable is the strongest predictor of behavior models while subjective norm variable is the most important predictor of behavioral intention models. Perceived severity is quite important predictor because of contributing to all type of models (HBM, IBM of both predictive IDC intention and behavior). For the application of IDC intention model, the original TPB model has proved to be more efficient than the original HBM model. While predicting the IDC behavior model, original HBM is identified more efficient than original TPB model. IBM including original HBM and TPB variables is selected as the best model of theory as well as practice for Vietnamese road user behavior.

The most important effective result of this research is to identify an efficient and scientific model of road user behavior in Viet Nam. This model could be consider as research successfully for the first time in Vietnam and it can obviously be able to explain the current situation and suitable in term of IDC behavior. With only 9 applied simple Variables and without complexity this model will potentially help the governor authority understand IDC behavior and efficiently design, implement as well as effectively evaluate road safety communication campaigns.

6.5 Conclusions

Wearing helmet behavior in Cambodia, speeding behavior and illegal direction change behavior in HCMC were established through 14 socio-cognitive variables to predict and to select the best model for each studied behavior and to propose appropriate community campaigns toward road safety for increasing people' awareness in each paper (section 6.2, 6.3, 6.4). Separate HBM, TPB, IBM are applied in three mentioned behaviors. Speeding and illegal direction change variables are same structures. 9 socio-cognitive variables are described same among three behavior models as subjective norm, descriptive norm, personal norm, perceived behavior control, perceived severity, perceived susceptibility, cues to action, behavior intention and behavior. Helmet model has some different structures to Speeding and Illegal direction change as normative belief, behavior belief (+, -). Otherwise, control belief variable of helmet wearing model is same definition with perceived behavior control in specific situation of speeding and illegal direction change, attitude of helmet study is described same as cognitive attitude of the remaining models.

Target studied behaviors are focused on the hot problems of road safety in their area such as helmet wearing is the big cause of road accident in Cambodia, speeding is the serious problem of Vietnam while illegal direction change accounts a highest ratio of road accident in HCMC, Vietnam. All selected areas are city and central of cultural, economic of the countries. The people characteristic, weather conditions of these areas are quite similar. The survey method is same "face to face" method; average age of respondent is mostly between 23 and 30 years in Phnom Penh and HCMC, respectively.

In term of predicting road user behavior model on HBM variables, the total variances of behavioral intention model are identified big differences from the different models (helmet wearing, speeding, illegal direction change) but the variance of behavior models are quite same. Speeding behavioral intention model has the highest total variance (R^2= 0.56), followed by illegal direction change (R^2= 0.41) and helmet wearing behavioral intention (R^2= 0.39) models; while helmet wearing, speeding, illegal direction change behavior model has R^2 as 0.41, 0.43, 0.42 respectively. Perceived benefits and perceived severity are the most important variables in predicting both behavioral intention and behavior of three behaviors because of their big and significant contribution in all models. In general, cues to action, perceived barriers, perceived susceptibility are not contributed strongly and equally to predict different behaviors, they contribute differently in the different model (intention and behavior) and different violence behaviors (wearing helmet, speeding, illegal direction change). Perceived benefits is the most predictive power of the speeding and illegal direction changing behavioral intention and behavior and it is the third and fourth important position of the wearing helmet behavioral intention and behavior respectively. Perceived severity is the most important variable to predict helmet wearing behavioral intention while it is the second and third important variable for the remaining models. The interesting finding is a significant cues to action in predictive helmet wearing behavioral intention (Cambodia) and speeding behavior model (Vietnam). Perceived susceptibility has a strongest predictive power in the wearing helmet behavior but has a weak significant contribution in the helmet behavioral intention and speeding behavior. Perceived barriers is significant variable in the helmet wearing behavior, speeding behavioral intention, illegal direction change behavioral intention and behavior.

Regarding basic TPB model, the TPB variables are estimated a high percentage of variance in speeding behavioral intention, helmet wearing behavioral intention and behavior (R^2>60%), and a low percentage of total variance in speeding behavior and illegal direction change behavioral intention and behavior (R^2 = 0.38, 0.46 and 0.41, respectively). Perceived behavior control, attitude (cognitive attitude) are the most important predictors of all models. They are in turn to be the most important variable in each model. Behavioral intention is the important significant variable for predictive helmet wearing, speeding and illegal direction change, and subjective norm is contributed a small impact to the models in general. Perceived behavior control is presented in all models although it is the most important variable in the predicting both wearing helmet behavioral intention and behavior. Subjective norm is strong significant to predict speeding and illegal direction change behavioral intention only.

In comparing the two models, basic TPB variable are predicted wearing helmet behavioral intention and behavior better than basic HBM variables. Basic HBM is proved more powerful prediction than TPB in the speeding and illegal direction change behavior models, otherwise, basic TPB is stronger prediction than HBM in the speeding and illegal direction change behavioral intention models.

Using integrated behavior model, it is presented a best powerful prediction model with the highest R^2 values for all models (wearing helmet, speeding, illegal direction change behavioral intention and behavior models) than when applying TPB and HBM models. TPB variables and extended socio-cognitive variables are proved as stronger powerful predictors (through the large number of their variable contributing in the predictive models) than HBM variables. Perceived behavior control (in general) is proved the most important predictor in the wearing helmet, speeding and illegal direction change behavioral intention and wearing helmet behavior models. Attitude (cognitive) are significant variables in predictive wearing helmet behavioral intention, speeding behavioral intention and behavior and illegal direction changing behavior models. Personal norm is predicted in the wearing helmet behavior model, the speeding and illegal direction change behavioral intention models. Behavioral intention are predicted the wearing helmet and illegal direction change behavior. Non-HBM variables are significant in the predictive wearing helmet behavioral intention. Perceived severity is significant predictor in the speeding and illegal direction change behavioral intention and perceived susceptibility is significant impact in the wearing helmet behavior model while perceive benefits are significant contribution to the speeding and illegal direction change behavior. Cues to action is contributed to the predict model only in the speeding behavior.

Chapter 7. Conclusions, Implementation And Future Research

7.1 General Conclusions

Road safety has become a serious problem in Vietnam and has constantly caused a huge people and social loss yearly. It has been increasingly costing Government's efforts and finance to find efficient methods to eliminate its negative impact as well as to eliminate their exposures and severity. Considered as the first time developed in Vietnam this thesis has significantly built a set of models which could be able to apply into reality and significantly help resolve the road safety problems. In addition to this set of road safety models, a road safety database was also developed, and solutions have been proposed.

With its diversity of people, economics and culture, HCMC is selected purposefully as the representative city case study for the whole Vietnam. Three model groups have been carried out in 24 districts and in each divided groups of this city includes:

- ✓ The statistic models
- ✓ DEA models
- ✓ Road user behaviors models

The statistic model has been built and tested with the collected database in order to predict the number of accidents, number of fatalities, number of injury and to identify the variables which impact to these critical numbers.

It is important that the DEA models group which consists of basic DEA model, DEA-MI model, composite index model have been carried out and substantially helped identify which one among 24 districts are the best and the worst road safety performer particularly.

Road user behaviors models which covers helmet wearing (in Cambodia), road user speeding and illegal direction change have consisted of IBM models, HBM model and TPB model and their analysed result has proved that IBM Model is the best model to apply into the reality.

With built models which consists of 8 variables for DEA Model, 11 variables for statistic models and 14 variables for road user behaviors models, It is proven that statistic model, data envelopment analysis (DEA) models and road user behavior models can be potentially applied broadly for the whole country to analyse, to predict road accident and road user behavior from which can help propose programs of road safety.

7.1.1 Statistic Model

Generalized linear regression model are built to predict the accident consequences (number of accidents, injuries and fatalities). Generalized linear regression model is showed significantly to predict road accident consequences. Applying GLM to predict road accident and to examine the impact of road accident causes is simple so it is suitable for the limited resources in Vietnam nowadays.

The number of accidents, fatalities and injuries of 24 districts in HCMC has not followed the standard normal distribution nor Poisson distribution rule. They have followed negative binomial distribution.

The proposed variables are valid and useful in predicting number of accident, fatality and injury in the whole HCMC. Half proposed variables are predicted significantly in ACC and FAT models, especially almost variables are estimated significantly in INJ model for the whole country by GLM. But they are insignificant to predict by the different areas (district groups). The proposed dataset estimates only road accident models in the new downtown area (Group 2).

The derived data has different role and important contributing to predict different road accident models of HCMC. BT is the most important predictor of all road accident models (ACC, FAT, INJ) and DT is the second important variable to estimate FAT and INJ model. SA has positive impact to FAT, while PC increase number of ACC and INJ. AI is a significant factor to predict INJ model while significant effect of SP in predicting INJ models.

7.1.2 DEA Model

The applied DEA models which includes basic DEA, DEA-MI productivity and composite index are built to focus mainly on reducing number of fatalities.

Built basic DEA model for the whole city and for each area is to identify the districts whose the best and the worst road safety performance, benchmarking district and the death target that needs to reduce in each district. The basic DEA model for the whole country has found big road safety performance gaps between the worst and the best or the benchmark districts. These big gaps will create difficulties for proposing ways to reduce number of fatalities, especially for the limited budget and resources in Vietnam nowadays. Some worse districts in the whole country model is turned to better or best or benchmark districts of the area. The percentage of death target needs to reduce in some districts are not high as in the whole country model.

DEA-MI is evaluated through the technical efficiency change, technology efficiency change, and total productivity change in the whole district and in each area for time period from 2004 to 2009. In general, technical efficiency change is identified as lower than 1 because of unsatisfying travel demand. The technology efficiency change and the total productivity change in all districts are found larger than 1 or equal 1. The trend and result of DEA-MI reflect the actual situation in each district and in each year. The typical districts including the best, the worst road safety performances, and the central district are selected to analyse deeply under the combination of the theory and practice.

Composite index is applied to identify the share of each variable (inputs) to number of fatalities (output). The result will critically help to understand road safety efficiency in each district and each district groups.

7.1.3 Road User Behavior Model

One of the causes that strongly impacts to road safety in Vietnam that is road user behavior. The target of behaviors studies are focused on the hot problems of road safety in specific areas such as unwearing helmet that is a big cause of serious head injuries when happening road accident in Cambodia, speeding which is the most serious problem of Vietnam while illegal direction change accounts a highest ratio of road accident in HCMC, Vietnam.

The separate application of the theory of planned behavior and the health belief model are proved that the powerful prediction model is different in various behaviors and different places. Basic TPB variables are predicted wearing helmet behavioral intention and behavior better than basic HBM variables. Basic HBM is proved more powerful prediction than TPB in the speeding and illegal direction change behavior models, otherwise, basic TPB is stronger prediction than HBM in the speeding and illegal direction change behavioral intention models.

Integrated behavior model are built by the combination of theory of planned behavior, health behavior belief and extended socio-cognitive variables. To verify the important of campaigns in relation to the knowledge achieved in HCMC is considered in the near future. Beside that, building and examining integrated behavior model is demonstrated to be a best behavior model for applying broadly in Vietnam. The proposed integrated behavior model has high science (acceptable R^2) and high practical application (not too complicated).

The significant contribution of variables in the predictive behavioral intention and behavior models are proved to be difference with various traffic violent (wearing helmet, speeding, illegal direction change) at various places (Phnom Penh and HCMC).

To conclude, all the main and specific objectives of the thesis are solved through building successfully road user behavior models, building database for applying probabilistic model, DEA model to analyse road safety consequences and proposing the solutions, community campaigns to improve road safety in HCMC. The combination of different methods and models to analysis road safety are useful to the typical transportation environment.

7.1.4 Database Development

A strongly helpful database is built not only for the proposed models in this thesis but also for other purpose of complicated models. The thesis has used different methods including linear regression model, weighted method, and traffic forecast method to build the completed database, which not only depend on the conducting raw data.

The previously used data was too simple and too insufficient to ensure the quality of road safety analysis which mainly focuses on simple statistical analysis as description and frequency of number of accident, fatalities, injuries, recorded summarized number of accident by causes. Therefore the newly developed database will totally address this problem.

The certain derived variables from the database are identified suitably with Vietnam road safety features that based on the past researches, the project, and the national experts. The typical character of road safety (in Vietnam in general and in HCMC in particularly) including low road infrastructure, poor road facilities, mixed vehicles in a traffic lane, a popular of motor bike, road user perceptions and awareness are described by variables in the database. Total eleven derived variables of the database are proved the strong relationship with road accident consequences including number of accident, number of injuries and fatalities. The database is built in 9 years in 24 districts of Hochiminh city for the period of 2001 to 2009.

7.2 Implementation

The thesis found suitable road safety models to analyse, to evaluate and to predict in actual HCMC transportation environment. For these models are useful practical applications and to improve road safety situation in Vietnam, it is necessary to propose an efficient implementation.

Road user behavior is found as the serious cause of road accident compaired to other causes as infrastructure, vehicle, and environment in the different models of this thesis. The implementation proposes to concentrate on road user behavior. In term of road safety, minimizing risk is better than maximizing road safety (Shinnar, 2007). Swiss Cheese Model helps to propose measures for decreasing the risk of accident from all impacts (mentioned in section 6.1.2). The implementation is following Swiss Cheese Model, decreasing successfully road accident risk is needed to combinate between training issues on human factors (including road infrastructure and road environment, legal and technical influence) and road safety communication campaigns for addressing behavior changes. The training issused on human factors are mentioned in the section 7.2.5 below.

The proposing, organizing and monitoring of road safety community campaigns are important impacts to contribute to the efficiency of the implementation. The wearing helmet legislation success in 2007 was a prove of the good implementation (combination between print media and other supports like political, legislative program, enforcement issues…) (Peter S. Hill, Anh D. Ngo et al. 2009) helping much while it was fall down in 2001.

The separate implementations are proposed from the findings of different building road safety models, analysis, and evaluation in the end of chapter 4, chapter 5, and chapter 6. The implementation in the thesis is proposed following Swiss Cheese model to road way system (mentioned in section 6.1.2), road safety community campaigns and social marketing theory (CAST 2009) and combining of all individual implementation in each chapter and to reduce the negative impacts of the road safety.

7.2.1 Target Audiences (Road Users As Audiences)

(1) Young people (20-35 years) are selected as key targeted audience of the implementation because most of the violent road traffic mainly occurred on these young ages in the studies of the thesis (chapter 6).

The other audiences need to provide some simple programs to increasing their perception in road safety. They are (2) the teen people whom will turn to "target audience" soon and (3) people aged from 45 to 60 years whom are parents of "target audience" and has to be selected as the most important person (over 52) of target respondent, they have to impact positively for changing the "target audience" (chapter 6).

7.2.2 Target Behaviors (Products)

Speeding and illegal direction changing are selected as the target behaviors of the implementation for the target audiences. The target behaviors concentrate only to the benefits of the safe behaviors to reduce number of accidents, fatalities, injuries causes (core product).

7.2.3 Place

The thesis is found almost dangerous behaviors including speeding and illegal direction change behaviors on urban roads, followed by highways, rural and other roads (chapter 6). So the message, campaigns, education programs have to concentrate to urban roads and highways for reducing unsafe behaviors.

The proposed road safety campaigns and education programs are offered to be concentrated more in the suburban and the rural areas than the old and new down town areas (finding at chapter 4, 5).

7.2.4 Promotion

Creation the message is important for promoting to change people awareness. The message content has to focus on "dangerous level (consequences) of traffic violent behaviors" and "the other people boycott the dangerous behaviors" (findings at chapter 6).

Viral marketing is proposed to send the message to the target audience. Selection of media channels includes the choosing of the place (where), time (when) and whom to perform the proposed message. Choosing of the place is considered as choice of media channels and the media vehicle. Choice of media channels is selected as advertising, printed materials (panel, poster). The media vehicle is considered for teen and young people as the internet (facebook, zingme, twitter, blog, youtube, kenh 14.vn, vnexpress, vietnamnet, tuoitre), television (yan tivi, yeah1, vtv6) radio programs (zone FM, VOH transport), print media (Thanh nien, Saigon giai phong, Lao dong, Sinh vien). Internet is a powerful and save media tool in Vietnam nowadays. The huge increasing of the internet user is 30.8 million accounting 38.5% of Vietnamese population (Dien 2012). Facebook is considered as the most important website for transfer the campaign message. Vietnam is the country has the highest increasing facebooker in the Asian area (ranked at the eleventh), approximately 5.5 million until 30 June 2012, that 55.6% of the increasing than 1 April 2012 (Ha 2012).

7.2.5 Possible Supportive Activities

Enforcement is one of the methods supporting to the campaign message. A strict enforcement from the government includes higher fines, cameras to automatically tickets speeding, illegal direction change on highways (chapter 6) will help to reduce dangerous behaviors.

Education is proposed to communicate information and raise awareness of specific behavior (speeding and illegal direction change) to the target audience (2) (teenager). The education programs could be organized in primary and secondary schools (chapter 6).

Engineering improvements are concentrated in the suburban and rural areas that include improving old roads, building new roads, enhancing traffic control. The universities, big companies have been expecting to move out of the downtown areas, the big residential parks and big offices have to stop building in the down town areas.

The combination of the proposed campaign and the possible supportive activities can raise target audience awareness about the campaign theme. The control, monitoring of the road safety community campaign and supportive activities are considered detail before, during and after the implementation to receive the proposed benefits.

7.3 Future Research

As mentioned in the problems statement, road safety has existed many big challenging problems which needs a long term strategy and execution plan to address with a very deep and continuous researches. For Vietnam, an emerging country these road safety problems are more complicated and it has been not easy to address soon therefore this thesis has mainly focused on the key problems which are building three road safety models to approach Vietnam road safety problems by limited data. Regarding to the road safety aspect, the future researches will be interested in and focus the study on (1) to optimize the database such as finding more impacted variables to road consequences, (2) to apply broadly these models to all cities and provinces in Vietnam and (3) to expand the application of this study methodology in other areas of transportation.

(1) Continuously to optimize the database: The collecting data of road accident consequences as number of accident, fatalities, injuries in each district, provinces and derived data are kept doing for the long time. More data of road accident consequences in specific locations (highways, main urban roads, cause) should be considered to conduct. Some impacting variables of road accident consequences should be considered as young age level that is the high ratio in Vietnam population, different vehicle type special as motorbike, heavy truck, other construction vehicle cause lot of serious

accidents, road user occupation that related to perception and awareness in road safety and traveling.

(2) Applying broadly these models in all cities and provinces in Vietnam will help generate lots of idea and solution for improving road safety. The differences of geography and climate areas of cities and provinces in Vietnam should be considered to research in the future models. Vietnam's topography is diverse and complex with many differently divided areas such as mountain region in the northwest (up to 2,000m), the central highland (less than 1,000m), the land transition between mountain/ highland and the flat and the delta areas account respectively for 1, 50, 24, 25 of the country (VNE 2007). Beyond the delta areas, roads and bridge constructions are very difficult. Narrow, dangerous connecting roads and bridges across different provinces are highly potential threats of serious road accidents. Although Vietnam has a tropical monsoon climate but the climate and weather in the north, the central and the south are quite different. The southern of Vietnam has only rainy and dry season, the rainy season starts from May to September. Rainfall is abundant, with annual rainfall exceeding 1,000mm almost everywhere. Annual rainfall is even higher in the hills, especially those facing the sea, in the range of 2,000-2,500mm. The coastal areas and the parts of the central highlands facing to the northeast receive lots of rainfalls, typhoons, and flood from the summer. The northern of Vietnam has four seasons obviously with light rainy and cloudy days on the winter from November to January while the southern Vietnam tends to be dry and sunny (VNE 2007). The different weathers in various regions of Vietnam have many negative impacts to the safe traveling of road users so it is a cause of lots road accident. Hence, considering climate and geography factors is very necessary to the further models. It will help provide drivers with ahead warning and help propose the government authority with road policies to eliminate road accident consequences.

Drinking and driving are also found as urgent problems to serious road accidents, the further study will concentrate on those road user behaviors to help eliminate road accidents.

(3) Furthermore, the data envelopment management (DEA) could be applied not only for the road safety problems but also for traffic congestion, which is the very serious problem in urban transportation of Vietnam nowadays. The future researches can apply the thesis methodology into transportation areas such as transportation planning, urban transportation and transportation management in Vietnam.

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APPENDIXES

APPENDIX I: GLM Model Results

ACC model (except SA variable). Goodness of Fit[a]

	Value	df	Value/df
Deviance	69.237	208	.333
Scaled Deviance	69.237	208	
Pearson Chi-Square	41.274	208	.198
Scaled Pearson Chi-Square	41.274	208	
Log Likelihood[b]	-1091.696		
Akaike's Information Criterion (AIC)	2199.391		
Finite Sample Corrected AIC (AICC)	2200.087		
Bayesian Information Criterion (BIC)	2226.394		
Consistent AIC (CAIC)	2234.394		

Dependent Variable: ACC
Model: (Intercept), PD, AI, DT, PC, EB, BT, SP

Omnibus Test[c]

Likelihood Ratio Chi-Square	df	Sig.
75.588	7	.000

Dependent Variable: ACC
Model: (Intercept), PD, AI, DT, PC, EB, BT, SP

ACC model (except PD variable) - Goodness of Fit[a]

	Value	df	Value/df
Deviance	66.452	208	.319
Scaled Deviance	66.452	208	
Pearson Chi-Square	34.625	208	.166
Scaled Pearson Chi-Square	34.625	208	
Log Likelihood[b]	-1090.303		
Akaike's Information Criterion (AIC)	2196.606		
Finite Sample Corrected AIC (AICC)	2197.302		
Bayesian Information Criterion (BIC)	2223.608		
Consistent AIC (CAIC)	2231.608		

Dependent Variable: ACC
Model: (Intercept), AI, DT, PC, EB, BT, SP, SA

Omnibus Test[c]

Likelihood Ratio Chi-Square	df	Sig.
78.374	7	.000

Dependent Variable: ACC
Model: (Intercept), AI, DT, PC, EB, BT, SP, SA

FAT Model (except – SA) Goodness of Fit[a]

	Value	df	Value/df
Deviance	63.688	208	.306
Scaled Deviance	63.688	208	
Pearson Chi-Square	42.114	208	.202
Scaled Pearson Chi-Square	42.114	208	
Log Likelihood[b]	-996.770		
Akaike's Information Criterion (AIC)	2009.539		
Finite Sample Corrected AIC (AICC)	2010.235		
Bayesian Information Criterion (BIC)	2036.542		
Consistent AIC (CAIC)	2044.542		

Dependent Variable: Fatal
Model: (Intercept), AI, DT, PC, EB, BT, SP, PD

Omnibus Test[c]

Likelihood Ratio Chi-Square	df	Sig.
85.102	7	.000

Dependent Variable: Fatal
Model: (Intercept), AI, DT, PC, EB, BT, SP, PD

FAT Model (except PD) Goodness of Fit[a]

	Value	df	Value/df
Deviance	59.676	208	.287
Scaled Deviance	59.676	208	
Pearson Chi-Square	35.970	208	.173
Scaled Pearson Chi-Square	35.970	208	
Log Likelihood[b]	-994.764		
Akaike's Information Criterion (AIC)	2005.528		
Finite Sample Corrected AIC (AICC)	2006.223		
Bayesian Information Criterion (BIC)	2032.530		
Consistent AIC (CAIC)	2040.530		

Dependent Variable: Fatal
Model: (Intercept), AI, DT, PC, EB, BT, SP, SA

Omnibus Test[c]

Likelihood Ratio Chi-Square	df	Sig.
89.114	7	.000

Dependent Variable: Fatal
Model: (Intercept), AI, DT, PC, EB, BT, SP, SA

INJ Model (except PD) Goodness of Fit[a]

	Value	df	Value/df
Deviance	59.676	208	.287
Scaled Deviance	59.676	208	
Pearson Chi-Square	35.970	208	.173
Scaled Pearson Chi-Square	35.970	208	
Log Likelihood[b]	-994.764		
Akaike's Information Criterion (AIC)	2005.528		
Finite Sample Corrected AIC (AICC)	2006.223		
Bayesian Information Criterion (BIC)	2032.530		
Consistent AIC (CAIC)	2040.530		

Dependent Variable: Fatal
Model: (Intercept), AI, DT, PC, EB, BT, SP, SA

Omnibus Test[c]

Likelihood Ratio Chi-Square	df	Sig.
89.114	7	.000

Dependent Variable: Fatal
Model: (Intercept), AI, DT, PC, EB, BT, SP, SA

INJ Model (except SA) Goodness of Fit[a]

	Value	df	Value/df
Deviance	130.498	208	.627
Scaled Deviance	130.498	208	
Pearson Chi-Square	90.861	208	.437
Scaled Pearson Chi-Square	90.861	208	
Log Likelihood[b]	-1042.163		
Akaike's Information Criterion (AIC)	2100.327		
Finite Sample Corrected AIC (AICC)	2101.022		
Bayesian Information Criterion (BIC)	2127.329		
Consistent AIC (CAIC)	2135.329		

Dependent Variable: Injury
Model: (Intercept), AI, DT, PC, EB, BT, SP, PD

Omnibus Test[c]

Likelihood Ratio Chi-Square	df	Sig.
110.282	7	.000

Dependent Variable: Injury
Model: (Intercept), AI, DT, PC, EB, BT, SP, PD

ACC model (except PD, SP) Goodness of Fit[a]

	Value	df	Value/df
Deviance	66.967	209	.320
Scaled Deviance	66.967	209	
Pearson Chi-Square	35.408	209	.169
Scaled Pearson Chi-Square	35.408	209	
Log Likelihood[b]	-1090.560		
Akaike's Information Criterion (AIC)	2195.121		
Finite Sample Corrected AIC (AICC)	2195.659		
Bayesian Information Criterion (BIC)	2218.748		
Consistent AIC (CAIC)	2225.748		

Dependent Variable: ACC
Model: (Intercept), AI, DT, PC, EB, BT, SA

Omnibus Test[c]

Likelihood Ratio Chi-Square	df	Sig.
77.859	6	.000

Dependent Variable: ACC
Model: (Intercept), AI, DT, PC, EB, BT, SA

FAT model (except PD, SP) Goodness of Fit[a]

	Value	df	Value/df
Deviance	59.736	209	.286
Scaled Deviance	59.736	209	
Pearson Chi-Square	36.009	209	.172
Scaled Pearson Chi-Square	36.009	209	
Log Likelihood[b]	-994.794		
Akaike's Information Criterion (AIC)	2003.588		
Finite Sample Corrected AIC (AICC)	2004.126		
Bayesian Information Criterion (BIC)	2027.215		
Consistent AIC (CAIC)	2034.215		

Dependent Variable: Fatal
Model: (Intercept), DT, PC, EB, BT, SA, SP

Omnibus Test[c]

Likelihood Ratio Chi-Square	df	Sig.
89.054	6	.000

Dependent Variable: Fatal
Model: (Intercept), DT, PC, EB, BT, SA, SP

INJ Model (-SA, -DT) Goodness of Fit[a]

	Value	df	Value/df
Deviance	130.498	209	.624
Scaled Deviance	130.498	209	
Pearson Chi-Square	90.849	209	.435
Scaled Pearson Chi-Square	90.849	209	
Log Likelihood[b]	-1042.163		
Akaike's Information Criterion (AIC)	2098.327		
Finite Sample Corrected AIC (AICC)	2098.865		
Bayesian Information Criterion (BIC)	2121.954		
Consistent AIC (CAIC)	2128.954		

Dependent Variable: Injury
Model: (Intercept), PC, EB, BT, SP, AI, PD

Omnibus Test[c]

Likelihood Ratio Chi-Square	df	Sig.
110.282	6	.000

Dependent Variable: Injury
Model: (Intercept), PC, EB, BT, SP, AI, PD

Group 1: ACC Model (except PD) Goodness of Fit[a]

	Value	df	Value/df
Deviance	2.703	64	.042
Scaled Deviance	2.703	64	
Pearson Chi-Square	2.625	64	.041
Scaled Pearson Chi-Square	2.625	64	
Log Likelihood[b]	-337.365		
Akaike's Information Criterion (AIC)	690.729		
Finite Sample Corrected AIC (AICC)	693.015		
Bayesian Information Criterion (BIC)	708.943		
Consistent AIC (CAIC)	716.943		

Dependent Variable: ACC
Model: (Intercept), AI, SA, DT, PC, EB, BT, SP

Omnibus Test[c]

Likelihood Ratio Chi-Square	df	Sig.
22.149	7	.002

Dependent Variable: ACC
Model: (Intercept), AI, SA, DT, PC, EB, BT, SP

Group 1: FAT Model (except PD) Goodness of Fit[a]

	Value	df	Value/df
Deviance	3.945	64	.062
Scaled Deviance	3.945	64	
Pearson Chi-Square	3.990	64	.062
Scaled Pearson Chi-Square	3.990	64	
Log Likelihood[b]	-293.126		
Akaike's Information Criterion (AIC)	602.252		
Finite Sample Corrected AIC (AICC)	604.538		
Bayesian Information Criterion (BIC)	620.465		
Consistent AIC (CAIC)	628.465		

Dependent Variable: Fatal
Model: (Intercept), AI, SA, DT, PC, EB, BT, SP

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
9.509	7	.218

Dependent Variable: Fatal
Model: (Intercept), AI, SA, DT, PC, EB, BT, SP

Group 1: INJ Model (except SA, DT) Model Goodness of Fit[a]

	Value	df	Value/df
Deviance	11.386	65	.175
Scaled Deviance	11.386	65	
Pearson Chi-Square	11.241	65	.173
Scaled Pearson Chi-Square	11.241	65	
Log Likelihood[b]	-321.740		
Akaike's Information Criterion (AIC)	657.480		
Finite Sample Corrected AIC (AICC)	659.230		
Bayesian Information Criterion (BIC)	673.416		
Consistent AIC (CAIC)	680.416		

Dependent Variable: Injury
Model: (Intercept), AI, PC, EB, BT, SP, PD

Group 2: ACC Model (except PD) Goodness of Fit[a]

	Value	df	Value/df
Deviance	16.733	46	.364
Scaled Deviance	16.733	46	
Pearson Chi-Square	17.635	46	.383
Scaled Pearson Chi-Square	17.635	46	
Log Likelihood[b]	-260.550		
Akaike's Information Criterion (AIC)	537.100		
Finite Sample Corrected AIC (AICC)	540.300		
Bayesian Information Criterion (BIC)	553.012		
Consistent AIC (CAIC)	561.012		

Dependent Variable: ACC
Model: (Intercept), AI, SA, DT, PC, EB, BT, SP

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
42.311	7	.000

Dependent Variable: ACC
Model: (Intercept), AI, SA, DT, PC, EB, BT, SP

Group 2: FAT Model (except PD) Goodness of Fit[a]

	Value	df	Value/df
Deviance	14.014	46	.305
Scaled Deviance	14.014	46	
Pearson Chi-Square	16.422	46	.357
Scaled Pearson Chi-Square	16.422	46	
Log Likelihood[b]	-242.855		
Akaike's Information Criterion (AIC)	501.710		
Finite Sample Corrected AIC (AICC)	504.910		
Bayesian Information Criterion (BIC)	517.622		
Consistent AIC (CAIC)	525.622		

Dependent Variable: Fatal
Model: (Intercept), AI, SA, DT, PC, EB, BT, SP

Omnibus Test[c]

Likelihood Ratio Chi-Square	df	Sig.
37.678	7	.000

Dependent Variable: Fatal

Model: (Intercept), AI, SA, DT, PC, EB, BT, SP

INJ Model (except SA, DT) Goodness of Fit[a]

	Value	df	Value/df
Deviance	18.280	47	.389
Scaled Deviance	18.280	47	
Pearson Chi-Square	14.538	47	.309
Scaled Pearson Chi-Square	14.538	47	
Log Likelihood[b]	-261.324		
Akaike's Information Criterion (AIC)	536.647		
Finite Sample Corrected AIC (AICC)	539.082		
Bayesian Information Criterion (BIC)	550.570		
Consistent AIC (CAIC)	557.570		

Dependent Variable: ACC
Model: (Intercept), AI, PC, EB, BT, SP, PD

Omnibus Test[c]

Likelihood Ratio Chi-Square	df	Sig.
40.764	6	.000

Dependent Variable: ACC
Model: (Intercept), AI, PC, EB, BT, SP, PD

Group 3: ACC (except PD) Goodness of Fit[a]

	Value	df	Value/df
Deviance	2.333	46	.051
Scaled Deviance	2.333	46	
Pearson Chi-Square	2.282	46	.050
Scaled Pearson Chi-Square	2.282	46	
Log Likelihood[b]	-296.173		
Akaike's Information Criterion (AIC)	608.345		
Finite Sample Corrected AIC (AICC)	611.545		
Bayesian Information Criterion (BIC)	624.257		
Consistent AIC (CAIC)	632.257		

Dependent Variable: ACC
Model: (Intercept), AI, SA, DT, PC, EB, BT, SP

Omnibus Test[c]

Likelihood Ratio Chi-Square	df	Sig.
15.757	7	.027

Dependent Variable: ACC
Model: (Intercept), AI, SA, DT, PC, EB, BT, SP

Group 3: FAT Model (except PD) Goodness of Fit[a]

	Value	df	Value/df
Deviance	1.883	46	.041
Scaled Deviance	1.883	46	
Pearson Chi-Square	1.845	46	.040
Scaled Pearson Chi-Square	1.845	46	
Log Likelihood[b]	-280.267		
Akaike's Information Criterion (AIC)	576.534		
Finite Sample Corrected AIC (AICC)	579.734		
Bayesian Information Criterion (BIC)	592.446		
Consistent AIC (CAIC)	600.446		

Dependent Variable: Fatal
Model: (Intercept), AI, SA, DT, PC, EB, BT, SP

Omnibus Test[c]

Likelihood Ratio Chi-Square	df	Sig.
10.780	7	.148

Dependent Variable: Fatal
Model: (Intercept), AI, SA, DT, PC, EB, BT, SP

Group 3: INJ Model (except SA, DT) Goodness of Fit[a]

	Value	df	Value/df
Deviance	14.626	47	.311
Scaled Deviance	14.626	47	
Pearson Chi-Square	13.761	47	.293
Scaled Pearson Chi-Square	13.761	47	
Log Likelihood[b]	-277.182		
Akaike's Information Criterion (AIC)	568.365		
Finite Sample Corrected AIC (AICC)	570.799		
Bayesian Information Criterion (BIC)	582.288		
Consistent AIC (CAIC)	589.288		

Dependent Variable: Injury
Model: (Intercept), AI, PC, EB, BT, SP, PD

Omnibus Test[c]

Likelihood Ratio Chi-Square	df	Sig.
30.966	6	.000

Dependent Variable: Injury
Model: (Intercept), AI, PC, EB, BT, SP, PD

Group 4: ACC Model (except PD) Goodness of Fit[a]

	Value	df	Value/df
Deviance	3.639	28	.130
Scaled Deviance	3.639	28	
Pearson Chi-Square	3.576	28	.128
Scaled Pearson Chi-Square	3.576	28	
Log Likelihood[b]	-175.694		
Akaike's Information Criterion (AIC)	367.388		
Finite Sample Corrected AIC (AICC)	372.721		
Bayesian Information Criterion (BIC)	380.056		
Consistent AIC (CAIC)	388.056		

Dependent Variable: ACC
Model: (Intercept), AI, SA, DT, PC, EB, BT, SP

Omnibus Test[c]

Likelihood Ratio Chi-Square	df	Sig.
19.329	7	.007

Dependent Variable: ACC
Model: (Intercept), AI, SA, DT, PC, EB, BT, SP

Group 4: FAT Model (except PD) Goodness of Fit[a]

	Value	df	Value/df
Deviance	4.266	28	.152
Scaled Deviance	4.266	28	
Pearson Chi-Square	3.799	28	.136
Scaled Pearson Chi-Square	3.799	28	
Log Likelihood[b]	-160.732		
Akaike's Information Criterion (AIC)	337.464		
Finite Sample Corrected AIC (AICC)	342.797		
Bayesian Information Criterion (BIC)	350.132		
Consistent AIC (CAIC)	358.132		

Dependent Variable: Fatal
Model: (Intercept), AI, SA, DT, PC, EB, BT, SP

Omnibus Test[c]

Likelihood Ratio Chi-Square	df	Sig.
25.586	7	.001

Dependent Variable: Fatal
Model: (Intercept), AI, SA, DT, PC, EB, BT, SP

Group 4: INJ Model (SA, DT) except Goodness of Fit[a]

	Value	df	Value/df
Deviance	7.414	29	.256
Scaled Deviance	7.414	29	
Pearson Chi-Square	7.061	29	.243
Scaled Pearson Chi-Square	7.061	29	
Log Likelihood[b]	-175.766		
Akaike's Information Criterion (AIC)	365.532		
Finite Sample Corrected AIC (AICC)	369.532		
Bayesian Information Criterion (BIC)	376.617		
Consistent AIC (CAIC)	383.617		

Dependent Variable: Injury
Model: (Intercept), AI, PC, EB, BT, SP, PD

Omnibus Test[c]

Likelihood Ratio Chi-Square	df	Sig.
24.036	6	.001

Dependent Variable: Injury
Model: (Intercept), AI, PC, EB, BT, SP, PD

a. Information criteria are in small-is-better form
b. The full log likelihood function is displayed and used in computing information criteria.
c: Compares the fitted model against the intercept-only model

APPENDIX II: The result of DEA models

Table AII.1 Technical Efficiency change (EFch) of 24 districts in HCMC

No	District	2005	2006	2007	2008	2009	Mean[1]
1	1	0.9930	0.9040	0.9840	1.0620	0.6240	0.8984
2	2	1.1230	0.7050	0.7910	0.7500	1.1480	0.8838
3	3	1.0140	0.5670	1.6630	1.1620	1.0000	1.0213
4	4	1.3750	0.4670	1.3780	1.7880	0.6040	0.9910
5	5	1.0000	0.6540	1.5290	0.8430	0.9580	0.9582
6	6	1.1850	0.6210	0.8470	1.1760	0.8620	0.9123
7	7	1.4390	0.3310	1.4180	0.8480	0.9090	0.8776
8	8	1.0000	0.8020	1.2460	1.0000	0.5360	0.8826
9	9	0.7040	0.9160	0.9350	0.6980	1.5120	0.9136
10	10	1.0000	0.7150	1.3980	0.8460	1.1390	0.9925
11	11	1.3230	0.6460	1.3620	0.7120	0.9570	0.9547
12	12	1.2530	0.6590	1.0090	1.1250	1.1970	1.0233
13	Binh Tan	1.0540	0.6180	0.7710	1.0310	0.8900	0.8565
14	Binh Thanh	0.9290	0.9170	0.7760	0.8210	1.1940	0.9169
15	Go Vap	1.0090	0.9850	1.1280	0.8560	1.1530	1.0204
16	Phu Nhuan	0.9500	1.2500	1.0000	1.0000	1.0000	1.0350
17	Tan Binh	1.4620	1.0000	0.9870	1.0130	0.8200	1.0369
18	Tan Phu	0.7310	0.9640	0.6500	1.7170	0.5450	0.8441
19	Thu Duc	1.3020	0.7550	0.7570	1.0350	1.3060	1.0012
20	Binh Chanh	0.6340	1.2000	0.6850	0.7910	1.1350	0.8591
21	Can Gio	2.3030	0.7470	1.2950	0.2780	1.1120	0.9281
22	Cu Chi	1.0250	0.9350	0.7210	0.6270	0.8220	0.8134
23	Hoc Mon	1.1430	1.0710	1.1520	0.2930	0.7560	0.7924
24	Nha Be	0.8220	0.9870	0.7850	1.0660	0.5010	0.8060
Mean[2]	EFchC	1.0751	0.7761	1.0138	0.8716	0.9072	

Mean[1]: The yearly geometric mean of EFch for 5 years of each district
Mean[2]: The geometric mean of the all districts on EFFch over years from 2005 to 2009)

Table AII.2 Technology change (TECHch) of 24 districts in HCMC

No	District	2005	2006	2007	2008	2009	Mean[1]
1	1	1.0050	1.2240	1.0560	1.3380	1.4930	1.2101
2	2	0.9930	1.4130	1.0350	1.3900	1.2810	1.2093
3	3	0.8690	1.4050	0.9220	1.5990	1.5280	1.2243
4	4	0.9490	1.8440	0.7270	1.4350	1.2910	1.1870
5	5	0.9390	1.2120	1.2810	1.0730	1.4910	1.1846
6	6	0.9580	1.2790	1.1910	1.1790	1.2820	1.1714
7	7	0.9360	2.7550	0.7240	1.8150	1.2980	1.3448
8	8	1.1340	1.3360	1.2300	1.3250	0.9660	1.1899
9	9	1.1340	1.4210	1.1550	1.3720	1.0010	1.2065
10	10	0.8730	1.4780	0.8920	1.5400	1.3880	1.1973
11	11	0.9490	1.8090	0.7410	1.5430	1.3230	1.2103
12	12	1.1580	1.4390	1.2320	1.3950	0.9800	1.2292
13	Binh Tan	1.1550	1.4480	1.1980	1.4170	0.9910	1.2298
14	Binh Thanh	1.1190	1.3060	1.2230	1.3320	0.9640	1.1807
15	Go Vap	1.1590	1.4350	1.2470	1.3770	0.9780	1.2280
16	Phu Nhuan	0.9280	2.6260	0.7090	1.7990	1.3920	1.3404
17	Tan Binh	1.2140	1.0350	1.1690	1.1410	1.4400	1.1927
18	Tan Phu	1.1740	1.0420	1.1730	1.1280	1.4590	1.1875
19	Thu Duc	1.1500	1.4230	1.2120	1.4050	0.9830	1.2233
20	Binh Chanh	1.1580	1.0980	1.1790	1.1670	1.2990	1.1784
21	Can Gio	1.1460	1.4840	1.0360	1.5840	1.3570	1.3052
22	Cu Chi	1.1580	1.4340	1.2470	1.2480	1.4510	1.3026
23	Hoc Mon	1.1580	1.4340	1.2470	1.2920	1.2730	1.2777
24	Nha Be	1.1290	1.4890	1.1040	1.4420	1.4980	1.3201
Mean[2]	TECHchC	1.0585	1.4513	1.0619	1.3766	1.2504	

Table AII.3 Total factor productivity change (TFPch) of 24 districts in HCMC

No	District	2005	2006	2007	2008	2009	Mean[1]
1	1	0.9970	1.1060	1.0390	1.4220	0.9320	1.0871
2	2	1.1150	0.9970	0.8190	1.0420	1.4700	1.0688
3	3	0.8820	0.7970	1.5330	1.8580	1.5280	1.2506
4	4	1.3050	0.8610	1.0020	2.5660	0.7800	1.1764
5	5	0.9390	0.7930	1.9580	0.9050	1.4280	1.1351
6	6	1.1360	0.7950	1.0080	1.3870	1.1040	1.0687
7	7	1.3470	0.9120	1.0270	1.5380	1.1800	1.1802
8	8	1.1340	1.0720	1.5330	1.3250	0.5170	1.0501
9	9	0.7980	1.3020	1.0810	0.9580	1.5140	1.1025
10	10	0.8730	1.0570	1.2460	1.3030	1.5810	1.1882
11	11	1.2560	1.1690	1.0100	1.0980	1.2650	1.1555
12	12	1.4510	0.9490	1.2430	1.5690	1.1740	1.2582
13	Binh Tan	1.2180	0.8950	0.9240	1.4600	0.8820	1.0534
14	Binh Thanh	1.0400	1.1970	0.9490	1.0930	1.1510	1.0825
15	Go Vap	1.1690	1.4140	1.4070	1.1780	1.1280	1.2531
16	Phu Nhuan	0.8810	3.2820	0.7090	1.7990	1.3920	1.3870
17	Tan Binh	1.7750	1.0350	1.1530	1.1560	1.1810	1.2366
18	Tan Phu	0.8580	1.0050	0.7620	1.9360	0.7950	1.0023
19	Thu Duc	1.4970	1.0740	0.9180	1.4550	1.2830	1.2247
20	Binh Chanh	0.7350	1.3180	0.8070	0.9230	1.4740	1.0124
21	Can Gio	2.6390	1.1090	1.3410	0.4400	1.5090	1.2111
22	Cu Chi	1.1870	1.3410	0.8990	0.7830	1.1930	1.0598
23	Hoc Mon	1.3240	1.5360	1.4360	0.3790	0.9630	1.0128
24	Nha Be	0.9280	1.4690	0.8670	1.5370	0.7500	1.0638
Mean[2]		1.1380	1.1266	1.0765	1.1999	1.1342	

Table AII.4 Mean of Malmquist Productivity Indexes in each district following group

Group	Dis	EFch	TECHch	TFPch	Group	Dis	EFch	TECHch	TFPch
G1	1	0.9	1.2	1.08	G3	2	1	1.05	1.05
	3	1.02	1.22	1.25		7	1	1.13	1.13
	4	0.99	1.19	1.18		9	1	1.08	1.08
	5	0.96	1.19	1.14		12	1.08	1.15	1.24
	6	0.91	1.19	1.09		Thu Duc	1.06	1.1	1.16
	10	0.99	1.2	1.19		Binh Chanh	1	1	1
	11	0.96	1.23	1.17					
	Phu Nhuan	1.04	1.34	1.39					
G2	8	0.98	1.08	1.06	G4	Can Gio	1	1.22	1.22
	Binh Tan	0.84	1.25	1.05		Cu Chi	0.91	1.15	1.04
	Binh Thanh	0.98	1.14	1.12		Hoc Mon	1	1.04	1.04
	Go Vap	1.1	1.14	1.26		Nha Be	0.97	1.05	1.02
	Tan Binh	1.05	1.23	1.29					
	Tan Phu	0.91	1.14	1.04					

Table AII.5 Annual means of Malmquist Productivity Indexes in groups

Group	Dis	EFch	TECHch	TFPch	Group	Dis	EFch	TECHch	TFPch
	2005	1.127	0.904	1.019	G3	2005	1.059	1.028	1.088
G1	2006	0.728	1.492	1.086		2006	1.027	1.049	1.077
	2007	1.204	0.948	1.142		2007	0.988	0.955	0.944
	2008	1.02	1.461	1.491		2008	1.018	1.162	1.183
	2009	0.849	1.439	1.222		2009	1.018	1.247	1.269
Average		0.986	1.249	1.192	Average		1.022	1.088	1.112
G2	2005	0.911	1.326	1.208	G4	2005	0.781	1.727	1.348
	2006	1.015	1.056	1.072		2006	1.064	1.178	1.254
	2007	0.786	1.462	1.148		2007	0.792	1.299	1.029
	2008	1.02	1.379	1.407		2008	1.4	0.53	0.742
	2009	1.183	0.75	0.887		2009	0.925	1.199	1.109
Average		0.983	1.195	1.144	Average		0.9924	1.187	1.096

Table AII.6 Correlation of number of fatalities and input variables

District	PD	AI	SA	DT	PC	EB	BT	SP
1	0.47	-.754*	-.792*	-.817**	-.791*	0.44	-0.61	.842**
2	0.55	0.63	0.58	0.58	0.57	0.55	.722*	-0.58
3	.730*	-.776*	-.754*	-.745*	-.730*	.731*	-0.1	.739*
4	0.15	-0.59	-0.47	0.41	-0.47	0.13	.847**	0.41
5	0.19	-.779*	-.769*	-.769*	-.670*	0.17	-0.65	.730*
6	-0.27	-0.03	0.07	-0.14	0.05	-0.23	0.03	-0.13
7	-0.53	-0.56	-0.59	-0.60	-0.54	-0.53	-0.36	0.59
8	-0.39	-0.55	-0.54	-0.58	-0.50	-0.38	-0.05	0.57
9	-0.37	-0.17	-0.25	-0.26	-0.29	-0.36	0.03	0.32
10	.735*	-.831**	-.830**	-.832**	-.783*	.713*	.708*	.842**
11	0.11	-0.36	-0.37	0.34	-0.37	0.12	0.28	0.33
12	-0.66	-.713*	-.703*	-.700*	-.696*	-0.66	-0.41	0.65
Binh Tan	.870**	.894**	.883**	.854**	.917**	.771*	.926**	0.65
Binh Thanh	-0.66	-.720*	-.788*	.825**	-.766*	0.06	0.30	.869**
Go Vap	-.980**	-.898**	-.939**	-.954**	-.957**	0.38	-0.57	.970**
Phu Nhuan	-0.09	-.752*	-.756*	.725*	-.759*	-.671*	.757*	0.41
Tan Binh	.865**	-.782*	-.839**	-.867**	0.15	0.02	.938**	.883**
Tan Phu	.774*	.776*	.810**	.775*	.807**	0.59	.917**	.691*
Thu Duc	-.764*	-.734*	-.772*	-.775*	-.772*	0.14	0.29	.781*
Binh Chanh	.770*	-0.49	-0.56	-0.58	0.07	0.25	0.25	0.19
Cu Chi	-.733*	-0.64	-.691*	-.714*	-0.42	-0.62	0.48	-.678*
Can Gio	-0.51	-0.47	-0.54	-0.54	-0.48	0.44	-0.25	-0.54
Hoc Mon	-0.28	-0.48	-0.55	-0.58	-0.65	0.49	-0.44	-0.59
Nha Be	0.16	0.20	0.25	0.25	.741*	.753*	.687*	0.26

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

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

Table AII.9 Composite index

Averager CI	2004	2005	2006	2007	2008	2009	A_CI
1	0.9	0.9	0.9	0.9	0.8	0.8	0.8
2	0.7	0.8	0.7	0.7	0.6	0.6	0.7
3	1.0	0.9	0.9	0.9	0.8	0.8	0.9
4	0.8	0.8	0.7	0.7	0.7	0.7	0.7
5	0.9	0.9	0.9	0.9	0.8	0.8	0.9
6	0.8	0.8	0.8	0.8	0.7	0.7	0.8
7	0.8	0.8	0.8	0.8	0.7	0.7	0.8
8	0.9	0.9	0.9	0.9	0.7	0.7	0.8
9	0.7	0.8	0.7	0.7	0.6	0.6	0.7
10	0.9	1.0	0.9	0.9	0.8	0.8	0.9
11	0.9	0.9	0.8	0.8	0.7	0.7	0.8
12	0.6	0.6	0.6	0.6	0.5	0.5	0.6
Binh Tan	0.8	0.8	0.8	0.8	0.6	0.6	0.7
Binh Thanh	0.9	0.9	0.9	0.9	0.6	0.7	0.8
Go Vap	1.0	1.0	1.0	0.9	0.6	0.6	0.8
Phu Nhuan	0.9	0.9	0.8	0.8	1.0	1.0	0.9
Tan Binh	0.9	1.0	0.9	0.9	0.7	0.7	0.9
Tan Phu	0.7	0.7	0.6	0.6	0.5	0.5	0.6
Thu Duc	0.7	0.7	0.7	0.8	0.4	0.5	0.6
Binh Chanh	0.6	0.7	0.3	0.3	0.3	0.3	0.4
Can Gio	1.0	1.0	0.9	0.9	0.9	0.9	0.9
Cu Chi	0.7	0.7	0.5	0.5	0.5	0.5	0.6
Hoc Mon	0.7	0.8	0.4	0.4	0.4	0.4	0.5
Nha Be	0.8	0.7	0.6	0.6	0.7	0.6	0.7
Correlation w FAT	-0.6	-0.7	-0.5	-0.5	-0.8	-0.7	-0.6

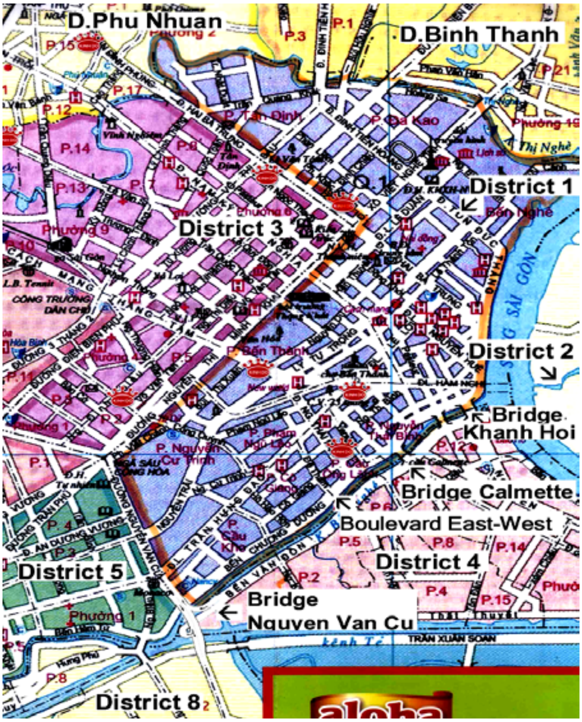

Figure AII.1 Map of district No1

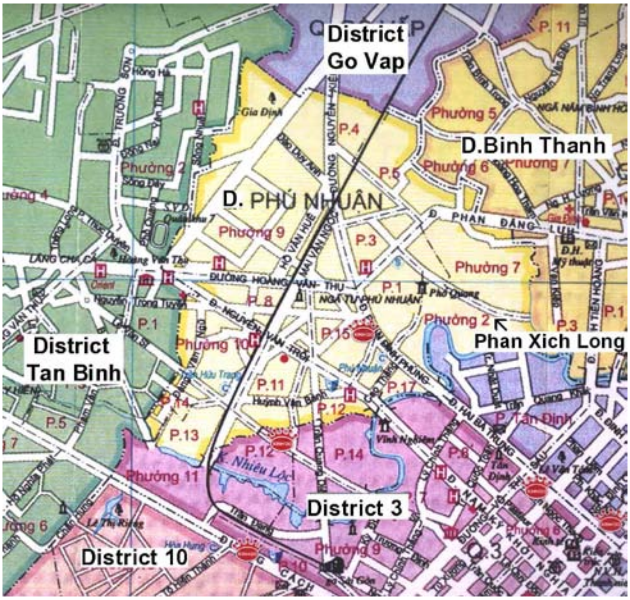

Figure AII.2 Map of Phu Nhuan district

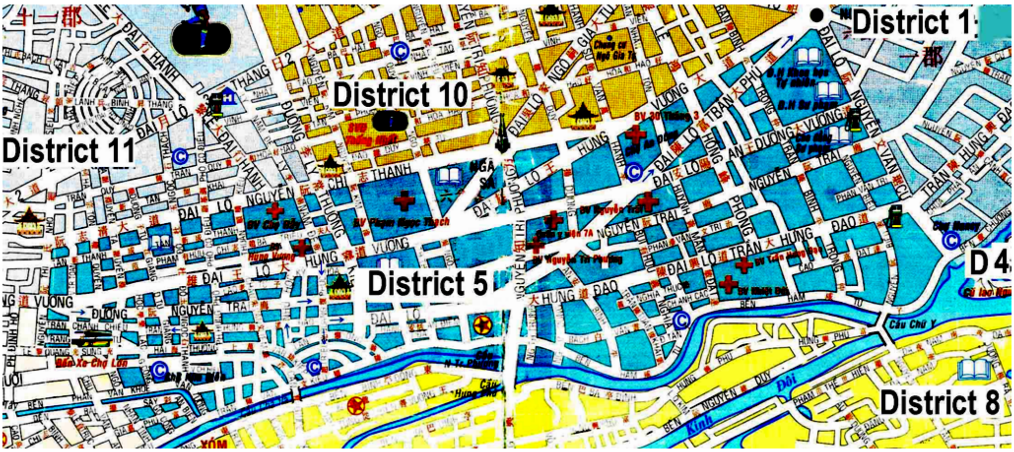

Figure AII.3 Map of district 5

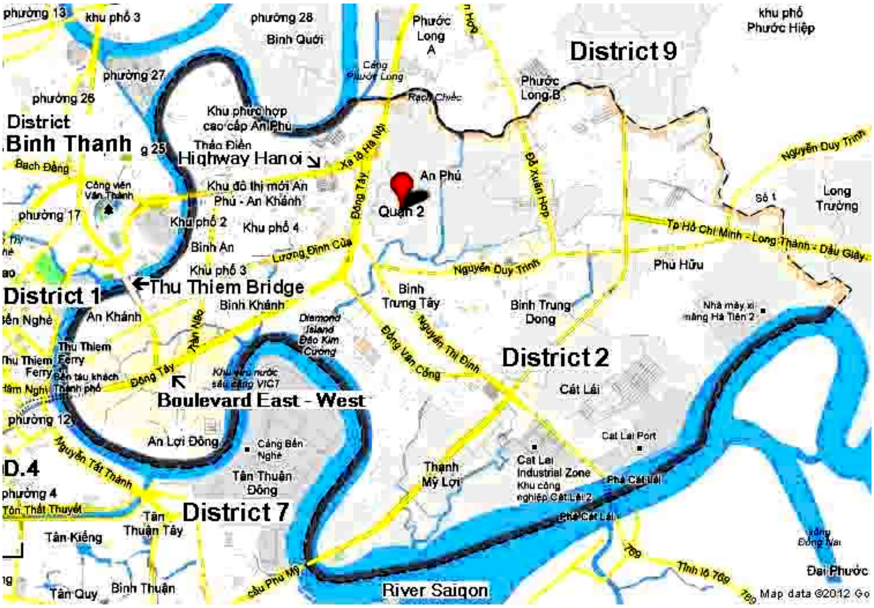

Figure AII.4 Map of district 2

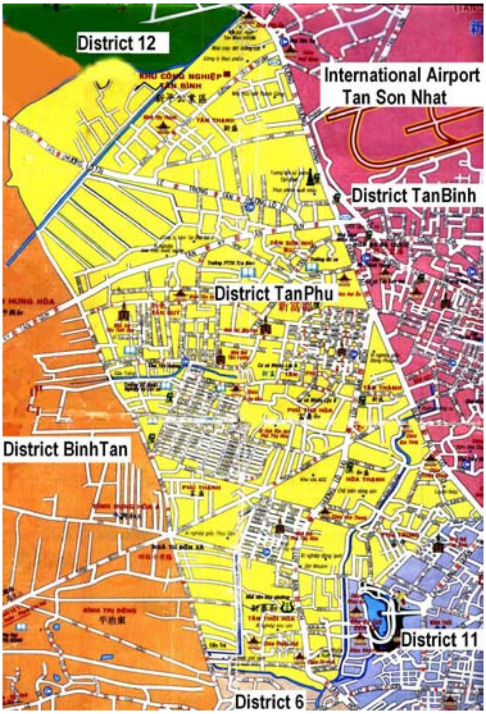

Figure AII.5 Map of Tan Phu district

APPENDIX III: Road User's Questionnaire for unsafe behavior

ROAD SAFETY QUESTIONNAIRE

This questionnaire is part of a Phd thesis on traffic safety and road user behavior in Hochiminh city. It does not serve any business or law purposes. Please feel free to answer (or not) the questions below. It is very important to get your honest answers in order to obtain a valid estimate of the road safety situation in HCMC.

Target respondents: people driving a motor vehicle.
Date of interview: No of questionnaire:

Part 1: Personal concern with traffic safety

Q11. How much do you agree or disagree that the government can handle the issues listed below?

Issues	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
Improve health care system	1.❒	2.❒	3.❒	4.❒	5. ❒
Reduce pollution	1.❒	2.❒	3.❒	4.❒	5. ❒
Increase food safeguard	1.❒	2.❒	3.❒	4.❒	5. ❒
Reduce the threat of a terrorist attack	1.❒	2.❒	3.❒	4.❒	5. ❒
Fight crime	1.❒	2.❒	3.❒	4.❒	5. ❒
Improve road traffic safety	1.❒	2.❒	3.❒	4.❒	5. ❒
Improve the economy	1.❒	2.❒	3.❒	4.❒	5. ❒
Fight global warming	1.❒	2.❒	3.❒	4.❒	5. ❒
Reduce traffic congestion	1.❒	2.❒	3.❒	4.❒	5. ❒

Q12. How often do you think the different road users listed below cause a main accident in HCMC?

Road users	Never	Rarely	Occasionally	Often	Very often
Pedestrians	1.❒	2.❒	3.❒	4.❒	5. ❒
Cyclists	1.❒	2.❒	3.❒	4.❒	5. ❒
Motorbike drivers	1.❒	2.❒	3.❒	4.❒	5. ❒
Car drivers	1.❒	2.❒	3.❒	4.❒	5. ❒
Truck drivers	1.❒	2.❒	3.❒	4.❒	5. ❒
Bus drivers	1.❒	2.❒	3.❒	4.❒	5. ❒
Taxi drivers	1.❒	2.❒	3.❒	4.❒	5. ❒
Other, specify	1.❒	2.❒	3.❒	4.❒	5. ❒

Part 2: Attitude toward road safety (road user)

BQ13. How often do you do the behaviors listed up below? **R**

Behaviors	Never	Rarely	Occasionally	Often	Very Often
Excessive speeding	1.❐	2.❐	3.❐	4.❐	5. ❐
Illegally changing direction	1.❐	2.❐	3.❐	4.❐	5. ❐

DNQ14. How often have you seen **other** drivers in HCMC do the behaviors listed up below? REVERSE

Behaviors	Never	Rarely	Occasionally	Often	Very Often
Excessive speeding	1.❐	2.❐	3.❐	4.❐	5. ❐
Illegally changing direction	1.❐	2.❐	3.❐	4.❐	5. ❐

PSQ16. How much do you agree or disagree the behaviors listed up below is dangerous?

Behaviors	Totally disagree	Disagree	Neither agree nor disagree	Agree	Totally agree
Excessive speeding	1.❐	2.❐	3.❐	4.❐	5. ❐
Illegally changing direction	1.❐	2.❐	3.❐	4.❐	5. ❐

BB(+) Q17. How much do you agree or disagree the behaviors listed below make you save time or arrive at your destination more quickly? R

Behaviors	Totally disagree	Disagree	Neither agree nor disagree	Disagree	Totally agree
Driving fast	1.❐	2.❐	3.❐	4.❐	5. ❐
Illegally changing direction	1.❐	2.❐	3.❐	4.❐	5. ❐

BB(+) Q18. How much do you agree or disagree the behaviors listed below give you a feeling of control over your vehicle? R

Behaviors	Totally disagree	Disagree	Neither agree nor disagree	Agree	Totally agree
Driving fast	1.❐	2.❐	3.❐	4.❐	5. ❐
Illegally changing direction	1.❐	2.❐	3.❐	4.❐	5. ❐

BB(-) Q19. How much do you agree or disagree the behaviors listed below increase the risk of you getting fined?

Behaviors	Totally disagree	Disagree	Neither agree nor disagree	Agree	Totally agree
Driving fast	1.❐	2.❐	3.❐	4.❐	5. ❐
Illegally changing direction	1.❐	2.❐	3.❐	4.❐	5. ❐

BB(+) Q21. How much do you agree or disagree when you did mentioned behaviors, it means “you are showing a stylish example for other drivers”? REVERSE CODE

Behaviors	Total Disagree	Disagree	Neither agree nor disagree	Agree	Totally agree
Exceeding the speed limit	1.❒	2.❒	3.❒	4.❒	5. ❒
Illegal changing direction	1.❒	2.❒	3.❒	4.❒	5. ❒

C_ATTQ22. How much do you agree or disagree that doing the behaviors listed up below is bad

Behaviors	Totally disagree	Disagree	Neither agree nor disagree	Agree	Totally agree
Driving faster than the speed limit	1.❒	2.❒	3.❒	4.❒	5. ❒
Illegally changing direction	1.❒	2.❒	3.❒	4.❒	5. ❒

C_ATTQ23. How much do you agree or disagree that doing the behaviors listed up below is dislikeable?

Behaviors	Totally disagree	Disagree	Neither agree nor disagree	Agree	Totally agree
Driving faster than the speed limit	1.❒	2.❒	3.❒	4.❒	5. ❒
Illegally changing direction	1.❒	2.❒	3.❒	4.❒	5. ❒

C_ATTQ24. How much do you agree or disagree that occasionally doing the behaviors listed up below is acceptable? RESVERVE CODE

Behaviors	Totally disagree	Disagree	Neither agree nor disagree	Agree	Totally agree
Driving faster than the speed limit	1.❒	2.❒	3.❒	4.❒	5. ❒
Illegally changing direction	1.❒	2.❒	3.❒	4.❒	5. ❒

PBCQ25. How much do you agree or disagree that most of the time, you are able to prevent yourself from doing the behaviors listed up below?

Behaviors	Totally disagree	Disagree	Neither agree nor disagree	Agree	Totally agree
Driving faster than the speed limit	1.❒	2.❒	3.❒	4.❒	5. ❒
Illegally changing direction	1.❒	2.❒	3.❒	4.❒	5. ❒

PBCQ26. How much do you agree or disagree that most of the time, it is easy for you to do the behaviors listed up below?

Behaviors	Totally disagree	Disagree	Neither agree nor disagree	Agree	Totally agree
Respecting the speed limit	1.❐	2.❐	3.❐	4.❐	5. ❐
Legally changing direction	1.❐	2.❐	3.❐	4.❐	5. ❐

BIQ27. How much do you agree or disagree your personal intention is to do the behaviors listed up below **during the next 3 months**?

Behaviors	Totally disagree	Disagree	Neither agree nor disagree	Disagree	Totally agree
Keeping within the speed limit	1.❐	2.❐	3.❐	4.❐	5. ❐
Legally changing direction	1.❐	2.❐	3.❐	4.❐	5. ❐

BIQ28. How much do you agree or disagree that you are willing to do the behaviors listed up below the next three months?

Behaviors	Totally disagree	Disagree	Neither agree nor disagree	Agree	Totally agree
Respecting the speed limit	1.❐	2.❐	3.❐	4.❐	5. ❐
Legally changing direction	1.❐	2.❐	3.❐	4.❐	5. ❐

PNQ29. How much do you agree or disagree that the behaviors listed up below are irresponsible?

Behaviors	Totally disagree	Disagree	Neither agree nor disagree	Agree	Totally agree
Exceeding the speed limit	1.❐	2.❐	3.❐	4.❐	5. ❐
Illegally changing direction	1.❐	2.❐	3.❐	4.❐	5. ❐

PN Q30. How much do you agree or disagree that the behaviors listed up below is intolerable?

Behaviors	Totally disagree	Disagree	Neither agree nor disagree	Agree	Totally agree
Exceeding the speed limit	1.❐	2.❐	3.❐	4.❐	5. ❐
Illegally changing direction	1.❐	2.❐	3.❐	4.❐	5. ❐

A_ATTQ31. How much do you agree or disagree that the behaviors listed up below is exciting? REVERSE

Behaviors	Totally disagree	Disagr ee	Neither agree nor disagree	Agree	Totally agree
Exceeding the speed limit	1.❒	2.❒	3.❒	4.❒	5. ❒
Illegally changing direction	1.❒	2.❒	3.❒	4.❒	5. ❒

A_ATTQ32. How much do you agree or disagree that the behaviors listed up below is fun ? REVERSE

Behaviors	Totally disagree	Disagr ee	Neither agree nor disagree	Agree	Totally agree
Exceeding the speed limit	1.❒	2.❒	3.❒	4.❒	5. ❒
Illegally changing direction	1.❒	2.❒	3.❒	4.❒	5. ❒

Q33. Could you select the 2 most important people for you? These should be persons whose opinion you consider as most influential in your life.

1.❒ Your partner
2.❒ Your children
3.❒ Your father
4.❒ Your mother
5.❒ Your boss
6.❒Your brother/Your sister
7.❒ Your close friend
8.❒ Other, *please clarify*

SNQ34. How much do you agree or disagree these important persons would accept you doing the behaviors listed up below? REVERSE

The first important person

Behaviors	Totally disagree	Disagr ee	Neither agree nor disagree	Agree	Totally agree
Exceeding the speed limit	1.❒	2.❒	3.❒	4.❒	5. ❒
Illegally changing direction	1.❒	2.❒	3.❒	4.❒	5. ❒

SNThe second important person REVERSE

Behaviors	Totally disagree	Disagr ee	Neither agree nor disagree	Disagre	Totally disagr ee
Exceeding the speed limit	1.❒	2.❒	3.❒	4.❒	5. ❒
Illegally changing direction	1.❒	2.❒	3.❒	4.❒	5. ❒

SS_PBCQ36. How hard or easy is it for you to do the behaviors listed up below **when you are in a hurry**?

Behaviors	Very Hard	Hard	Neither easy nor hard	Easy	Very easy
Respecting the speed limit	1.❒	2.❒	3.❒	4.❒	5. ❒
Legally changing direction	1.❒	2.❒	3.❒	4.❒	5. ❒

SS_PBCQ37. How hard or easy is it for you to do the behaviors listed up below **when most other drivers do not behave like that**?

Behaviors	Very Hard	Hard	Neither easy nor hard	Easy	Very Easy
Respecting the speed limit	1.❒	2.❒	3.❒	4.❒	5. ❒
Legally changing direction	1.❒	2.❒	3.❒	4.❒	5. ❒

REQ38. How much do you agree or disagree that speed cameras or traffic police posts can prevent you from doing the behaviors listed up below?

Behaviors	Totally disagree	Disagree	Neither agree nor disagree	Agree	Totally agree
Exceeding the speed limit	1.❒	2.❒	3.❒	4.❒	5. ❒
Illegally changing direction	1.❒	2.❒	3.❒	4.❒	5. ❒

PBQ40. How often did you do the behaviors listed up below **over the last year**? If your answer is "never" for all the behaviors → skip to Q.42 **R**

Behaviors	Never	Rarely	Occasionally	Often	Very Often
Exceeding the speed limit	1.❒	2.❒	3.❒	4.❒	5. ❒
Illegal changing direction	1.❒	2.❒	3.❒	4.❒	5. ❒

Q41. On what type of road did you do the behaviors you indicated as "often" or "very often"? (you can select more than 1 option)

1.❒Urban road 2.❒ Highway 3.❒ Rural road 4.❒ Other, specify

PV Q42. How much do you agree or disagree the chance of risk mentioned behaviors is high when you did? (select the behaviors that you did above only)

Behaviors	Total Disagree	Disagree	Neither agree nor disagree	Agree	Totally agree
Getting a ticket	1.❒	2.❒	3.❒	4.❒	5. ❒
Damaging your vehicle in an accident	1.❒	2.❒	3.❒	4.❒	5. ❒
Getting hurt in an accident	1.❒	2.❒	3.❒	4.❒	5. ❒
Hurting others in an accident	1.❒	2.❒	3.❒	4.❒	5. ❒

CA Q43. How much do you agree or disagree the policy measures listed up below will receive your full support? **R**

Policy measures	Totally disagree	Disagree	Neither agree nor disagree	Agree	Totally agree
Cameras to automatically ticket speeding on highways	1.❒	2.❒	3.❒	4.❒	5. ❒
More public road safety awareness campaigns	1.❒	2.❒	3.❒	4.❒	5. ❒
Higher fines	1.❒	2.❒	3.❒	4.❒	5. ❒
More traffic safety education in primary and secondary schools	1.❒	2.❒	3.❒	4.❒	5. ❒

Part 3: Respondent Background

Q1. Gender 1.❒ Male 2.❒ Female	Q2. Age	Q3. Number of members in your home:	Q4. Current Living Area District:
Q5. Marriage Status 1.❒ Single 2.❒ Married 3.❒ Divorced 4.❒ Other			
Q6. Occupation 1. ❒ Government Employee 2. ❒ Private Employer 3. ❒ Pupil 4. ❒ Student 5. ❒ Farmer/ casual laborer/Worker 6. ❒ Non-occupation 7. ❒ Driver 8. ❒ Housework 9. ❒ Other *(describe detail)*			
Q7. Education 1. ❒ Illiterate 2. ❒ Primary school 3. ❒ Secondary school 4. ❒ High school 5. ❒ Technical school 6.❒ University 7.❒ Post graduate			
Q8. Ownership of Vehicles 1.❒ Car 2.❒ Motor Bike 3.❒ Bike 4.❒ Truck 5. ❒ None 6. Other*(describe detail)*			
Q9. Leisure time (it is possible to select 2 categories) Doing sport 1.❒ Never 2.❒ Rarely 3.❒ Occasionally 4.❒ Often 5. ❒ Very Often Consuming alcohol 1.❒ Never 2.❒ Rarely 3.❒ Occasionally 4.❒ Often 5. ❒ Very Often Shopping 1.❒ Never 2.❒ Rarely 3.❒ Occasionally 4.❒ Often 5. ❒ Very Often Going out with friends 1.❒ Never 2.❒ Rarely 3.❒ Occasionally 4.❒ Often 5. ❒ Very Often Staying at home (reading books, watching movies, listening music, cooking….) 1.❒ Never 2.❒ Rarely 3.❒ Occasionally 4.❒ Often 5. ❒ Very Often Other, specify: 1.❒ Never 2.❒ Rarely 3.❒ Occasionally 4.❒ Often 5. ❒ Very Often			

THANK YOU VERY MUCH FOR YOUR VALUABLE CONTRIBUTION.

Trịnh Tú Anh