DEVELOPMENT OF A PREDICTIVE MODEL FOR FACTORS INFLUENCING RISKY BEHAVIOR AND SEVERITY OF ROAD ACCIDENTS IN INDUSTRIAL AREAS OF THAILAND

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A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of
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การพัฒนาแบบจำลองทำนายปัจจัยที่มีอิทธิพลต่อพฤติกรรมเสี่ยงและความรุนแรงของอุบัติเหตุทางถนนในเขตอุตสาหกรรมของประเทศไทย

นางสาวมัลลิกา สีฟอง

วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาปรัชญาดุษฎีบัณฑิต
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มัลลิกา สีฟอง: การพัฒนาแบบจำลองทำนายปัจจัยที่มีอิทธิพลต่อพฤติกรรมเสี่ยงและความรุนแรงของอุบัติเหตุทางถนนในเขตอุตสาหกรรมของประเทศไทย (DEVELOPMENT OF A PREDICTIVE MODEL FOR FACTORS INFLUENCING RISKY BEHAVIOR AND SEVERITY OF ROAD ACCIDENTS IN INDUSTRIAL AREAS OF THAILAND) อาจารย์ที่ปรึกษา: ผู้ช่วยศาสตราจารย์ ดร. รัตนาภรณ์ เกษมศรี, 144 หน้า.

คำสำคัญ: การวิเคราะห์ข้อมูลขนาดใหญ่/ความรุนแรงของอุบัติเหตุ/การวิเคราะห์การถดถอยเชิงปรับตัวหลายตัวแปร/แบบจำลองสมการเชิงโครงสร้าง/แบบจำลองความเชื่อด้านสุขภาพ/ทฤษฎีแรงจูงใจในการป้องกัน/ทฤษฎีพฤติกรรมที่วางแผนไว้/3Es+Es/ พฤติกรรมการขับรถเร็วเกินกำหนด/ผู้ขับขี่รถบรรทุก/ผู้ขับขี่รถจักรยานยนต์/เขตอุตสาหกรรม

ปัจจุบันการใช้แบบจำลองทางสถิติและเทคนิคการเรียนรู้ของเครื่องมีบทบาทสำคัญในการทำนายพฤติกรรมเสี่ยงและความรุนแรงของอุบัติเหตุเพื่อระบุปัจจัยสำคัญที่เกี่ยวข้องกับความเสี่ยงที่เพิ่มขึ้นของการบาดเจ็บและการเสียชีวิต ด้วยคุณสมบัติในการทำนายได้อย่างแม่นยำและมีประสิทธิภาพกลายเป็นเครื่องมือสำคัญที่ช่วยในการปรับปรุงมาตรการและการจัดการความปลอดภัยทางถนนในปัจจุบัน สำหรับประเทศไทยยังคงเป็นประเทศชั้นนำที่เผชิญกับความท้าทายเกี่ยวกับอุบัติเหตุทางถนนมาอย่างต่อเนื่อง โดยความท้าทายเหล่านี้มีความรุนแรงอย่างมากในพื้นที่เขตอุตสาหกรรม เนื่องจากสภาพการขับขี่ที่ซับซ้อนโดยเฉพาะอย่างยิ่งในพื้นที่ที่มีประชากรหนาแน่นและปริมาณจราจรคับคั่งสิ่งเหล่านี้เป็นกลไกเพิ่มความเสี่ยงของการเกิดอุบัติเหตุเป็นอย่างมาก โดยเฉพาะการชนที่เกี่ยวกับจักรยานยนต์และรถบรรทุกส่งผลให้มีอัตราการเสียชีวิตเป็นอันดับต้น ๆ ในพื้นที่เขตอุตสาหกรรม จากสถานการณ์ดังกล่าวเป็นข้อกังวลอย่างมากต่อความปลอดภัยทางถนนในประเทศไทย ดังนั้นตรวจสอบปัจจัยที่มีอิทธิพลต่อพฤติกรรมเสี่ยงและความรุนแรงของอุบัติเหตุพร้อมการกำหนดนโยบายและมาตรการด้านความปลอดภัยทางถนนที่มีประสิทธิภาพจะนำไปสู่การลดอัตราการบาดเจ็บและเสียชีวิตบนท้องถนนโดยรวม จากความสำคัญดังกล่าวการศึกษานี้มุ่งเน้นการพัฒนาแบบจำลองทางสถิติและการเรียนรู้ของเครื่องในการทำนายปัจจัยที่มีอิทธิพลต่อพฤติกรรมเสี่ยงและความรุนแรงของอุบัติเหตุทางถนน ซึ่งมีวัตถุประสงค์หลัก 3 ประการ ประกอบไปด้วย 1) เพื่อพัฒนาแบบจำลองในการทำนายปัจจัยที่ส่งผลต่อความรุนแรงของการชนที่เกี่ยวข้องกับรถบรรทุกและการชนที่ไม่เกี่ยวข้องกับรถบรรทุก 2) เพื่อพัฒนาแบบจำลองในการทำนายปัจจัยที่ส่งผลต่อพฤติกรรมเสี่ยงของผู้ขับขี่รถบรรทุก และ 3) เพื่อพัฒนาแบบจำลองในการทำนายปัจจัยที่ส่งผลต่อพฤติกรรมการใช้ความเร็วของผู้ขับขี่รถจักรยานยนต์ โดยมุ่งเน้นศึกษาในพื้นที่ที่มีความท้าทายเกี่ยวกับอุบัติเหตุทางถนนอย่างเขตอุตสาหกรรมในประเทศไทย จากผลลัพธ์ของการศึกษานี้เผยให้เห็นถึงข้อมูลเชิงลึกและ

มุมมองใหม่ที่สำคัญหลายประการเกี่ยวกับปัจจัยสำคัญที่มีอิทธิพลต่อพฤติกรรมเสี่ยงและความรุนแรงของอุบัติเหตุ นอกจากนี้ได้มีการเสนอแนวทางที่เป็นประโยชน์ต่อผู้ตัดสินใจรวมไปถึงหน่วยงานด้านความปลอดภัย ทั้งทางภาครัฐ และเอกชนที่เกี่ยวข้องในการกำหนดนโยบายและมาตรการเชิงประจักษ์ที่เหมาะสมกับบริบทเชิงพื้นที่เพื่อรับมือกับความท้าทายของอุบัติเหตุทางถนนท้ายที่สุดนำไปสู่การลดอัตราการบาดเจ็บและเสียชีวิตบนท้องถนนโดยรวมอย่างมีประสิทธิภาพ

สาขาวิชา <u>วิศวกรรมขนส่ง</u>
ปีการศึกษา <u>2567</u>

ลายมือชื่อนักศึกษา.......................................
ลายมือชื่ออาจารย์ที่ปรึกษา..............................

MANLIKA SEEFONG: DEVELOPMENT OF A PREDICTIVE MODEL FOR FACTORS INFLUENCING RISKY BEHAVIOR AND SEVERITY OF ROAD ACCIDENTS IN INDUSTRIAL AREAS OF THAILAND THESIS ADVISOR: ASST. PROF. DR. RATTANAPORN KASEMSRI, Ph.D., 144 PP.

Keyword: Big Data Analysis/Severity of Accidents/Multivariate Adaptive Regression Splines/Structural Equation Modeling/Health Belief Model/Protection Motivation Theory/Theory of Planned Behavior/3Es+Es/ Speeding Behavior/Truck Drivers/Motorcycle Rider/Industrial zones

Currently, the use of statistical models and machine learning methods are essential in predicting risky behaviors and assessing the severity of crashes, aiming to identify critical factors linked to the heightened risk of injury and fatality. Due to their capacity for accurate and efficient predictions, these tools have become essential in improving road safety measures and management in the present day. Thailand continues to be a leading country facing ongoing challenges related to road crashes, with these challenges being particularly severe in industrial areas. This is due to the complex driving conditions, especially in areas with dense populations and heavy traffic volumes. These factors substantially elevate the likelihood of accidents occurring, particularly crashes involving motorcycles and trucks, which result in some of the highest fatality rates in industrial areas. This issue poses serious concerns regarding road safety in Thailand. Hence, examining the factors influencing risky driving behaviors and the severity of collisions is essential, along with the formulation of effective road safety policies and measures, understanding these factors is essential for minimizing accidents and improving overall traffic safety. Recognizing this significance, this study concentrates on developing statistical models and applying machine learning techniques to predict key factors. The study has three main objectives: 1) to develop a model for predicting factors that affect the severity of truck-involved and non-truck-involved crashes, 2) to develop a model for predicting factors that affect the risky behavior of truck drivers, and 3) to develop a model for predicting factors that affect the speeding behavior of motorcycle riders. This study focuses on

areas with significant challenges regarding road crashes, specifically industrial areas in Thailand. The findings provide valuable insights and new perspectives on the key factors influencing risky behavior and crash severity. Additionally, practical recommendations are offered for decision-makers, including both public and private safety agencies, to establish evidence-based policies and measures tailored to the local context in order to address the challenges of road crashes. Ultimately, these strategies are designed to effectively lower the overall rates of injuries and fatalities on the roads.

School of Transportation Engineering

Academic Year 2024

Student's Signature ....

Advisor's Signature ....

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I would also like to express my gratitude to Suranaree University of Technology, the Ministry of Transport, and road safety organizations for their generous support in providing data, knowledge, and research facilities throughout the course of this study.

In addition, I am deeply grateful to my close family and friends for their support, encouragement, and for being by my side throughout this journey. Their support has been invaluable in helping me overcome challenges and successfully complete this research.

I sincerely hope that the findings of this study will prove valuable to those interested in the factors influencing risky behaviors and the severity of road crashes. Additionally, I hope that the knowledge gained from this study can be further utilized and developed for future research and practical applications.

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LIST OF ABBREVIATIONS

$\hat{y}$	=	Predicted response variable
β_n	=	Represents the vector of estimated parameters
X_{in}	=	Denotes the vector of explanatory variables
ε_n	=	Signifies the error term
μ_I	=	Estimated parameter (or threshold)
Φ	=	Cumulative standard normal distribution
β_{in}	=	Vector of estimated parameters
β	=	Denotes the constant term for random parameters
Z_n	=	Represents the vector of explanatory variables capturing differences in the mean of random parameters.
H	=	Vector of estimated parameters aligned with Z_n
ηZ_n	=	Denotes terms to describe undetected differences resulting from interactions (intercepting explanatory variables) causing variations in the parametric function of random parameters
ω_n	=	K×1 vector that cannot be observed
Γ	=	Symmetric Cholesky matrix used to compute the standard deviations of random parameters.
$LL(\beta)$	=	Log-likelihood at convergence
X^2, R^2	=	Chi-square distributed statistics
GCV	=	Generalized Cross-Validation

LIST OF ABBREVIATIONS (Continued)

ACC	=	Accuracy
SNS	=	Sensitivity
SP	=	Specificity
PRC	=	Precision
AUC	=	Area Under the Receiver Operating Characteristic Curve
KMO	=	Kaiser–Meyer–Olkin
CR	=	Composite reliability
X^2/df	=	Ratio of the chi-square to degrees of freedom
CFI	=	Comparative fit index
TLI	=	Tucker–Lewis index
RMSEA	=	Root mean square error of approximation
SRMR	=	Standardized root mean square residual
WHO	=	World Health Organization
3Es+Es	=	Road safety concept

CHAPTER I

INTRODUCTION

1.1 Rationale of the research

Road traffic crashes continue to be a critical global issue, presenting a major challenge for countries around the world. The devastating impact of such crashes has resulted in approximately 1.19 million fatalities annually, resulting in a global mortality rate of approximately 15 deaths per 100,000 individuals. (World Health Organization, 2023). Addressing this issue has become a major challenge for nations worldwide, particularly for developing countries, which continue to struggle with managing and mitigating road traffic crashes (Wisutwattanasak, Jomnonkwao, Se, Champahom, & Ratanavaraha, 2023). Given that 92% of road traffic fatalities occur in developing countries (World Health Organization, 2023), Thailand, as a nation in the midst of social, economic, and industrial development, continues to encounter significant challenges related to road traffic crashes.

Based on the most recent report from the World Health Organization (2023), Thailand's road traffic fatality rate stands at approximately 25.4 deaths per 100,000 individuals. (World Health Organization, 2023). Although some progress has been made in improving road safety, the country remains far from achieving its target of reducing road traffic fatalities and continues to be one of the leading nations in Asia struggling with severe road traffic crash issues. Researchers have made significant efforts to identify appropriate and effective measures for mitigating road traffic crashes. However, managing this issue remains a persistent challenge, as the rates of injuries and fatalities in developing countries remain considerably higher compared to those in developed nations. (Jadaan, Al-Braizat, Al-Rafayah, Gammoh, & Abukahlil, 2018).

Over the past year, road traffic crashes in Thailand have been predominantly concentrated in provinces designated as industrial areas. These areas encompass industrial estates, industrial parks, and industrial zones. Analyzing crash data in industrial areas from 2020 to 2023 reveals that the average injury and fatality rate was significantly high at 30.30% (Ministry of Transport, 2024). This statistical disclosure underscores the challenges posed by complex driving conditions, particularly in densely populated areas with heavy traffic congestion, which serve as critical factors increasing the risk of road crashes. Additionally, an analysis of crash data by vehicle type in 2023 indicates that motorcycle- and truck-involved crashes accounted for 10.00% and 47.23% of total crashes, respectively. Collectively, these two vehicle types were involved in more than 50% of all reported crashes (Ministry of Transport, 2024).

Considering the nature of truck-involved collisions, they pose a greater threat than non-truck- involved crashes. Due to their substantial size and weight, trucks require longer braking distances, making it difficult to stop quickly in emergency situations (M. Chen, Zhou, Choo, & Lee, 2022). As a result, in 2023, the injury and fatality rate from truck-related crashes in Thailand's industrial areas was the highest among all vehicle types (Ministry of Transport, 2024). Considering the importance of this issue, A thorough examination of the key factors influencing the severity of injuries and fatalities in crashes can help predict potential future crashes. (Fernando, Yoshii, & Tsubota, 2023). Moreover, this understanding enables policymakers and practitioners to develop effective and context-specific crash prevention measures.

Recently, many studies have concentrated on identifying the factors that influence the severity of collisions, aiming to enhance understanding and improve safety measures. Most of these studies emphasize the analysis of large-scale data using advanced platforms or high-performance techniques to gain deeper insights into the causes and contributing factors of crashes (Ait-Mlouk, Gharnati, & Agouti, 2017; Fan, He, & Brézillon, 2017; Feng, Zheng, Ren, & Liu, 2020; L. Huang, Wu, Wang, & Ouyang, 2018). Most studies investigating factors influencing crash severity typically consider variables such as driver characteristics, road characteristics, vehicle characteristics, crash characteristics, environmental characteristics and driving time. (M. Chen et al., 2022; J. Hong, Park, Lee, & Park, 2019).

Additionally, techniques without predefined parameters, such as Multivariate Adaptive Regression Splines (MARS), have gained attention as a machine learning algorithm for predicting crash severity (Champahom et al., 2022) and transportation-related issues. These include studies on behaviors such as lane changing (Das & Khan, 2020), rear-end collisions (Haleem, Abdel-Aty, & Santos, 2010; Y. Zhang, Jiang, Haghani, & Huang, 2015), as well as the safety benefits of shoulder width on rural highways with multiple lanes. (J. Park & Abdel-Aty, 2016). MARS' exceptional capability to identify complex nonlinear relationships and interactions between variables provides a significant advantage in managing intricate data patterns. However, no previous studies have specifically examined the factors influencing the severity and injuries of truck-involved and non-truck-involved collisions in industrial areas. To avoid missing key findings, the current study focuses on examining the key factors influencing collisions, addressing two key issues: truck-involved collisions and non-truck-involved collisions. This is especially important in areas with a high concentration of crashes, such as industrial areas.

Although there are many factors influencing road traffic crashes, the most significant factors often stem from unsafe driving behaviors (Dadipoor, Ranaei, Ghaffari, Rakhshanderou, & Safari-Moradabadi, 2020; Niu, Li, & Fan, 2021; Rashmi & Marisamynathan, 2023). This is supported by previous evidence indicating that over 90% of crashes are primarily caused by risky or unsafe driving behaviors (Niu et al., 2021; B. Zhang, Huang, Rau, Roetting, & Liu, 2006). Neglecting safety can lead to dangerous behaviors among road users, particularly drivers, resulting in an increased risk of crashes and injuries. (Fitrianti & Yanuvianti, 2013). This is especially true for truck drivers, who face dense traffic conditions and spend much of their time on the road due to the high volume of assigned tasks. Additionally, it has been found that truck drivers are generally older than other drivers (Hege, Lemke, Apostolopoulos, & Sönmez, 2018; Sullman, Meadows, & Pajo, 2002), which creates conditions conducive to unsafe driving behaviors that may result in road crashes. As a consequence, the injury and fatality rates from road crashes are among the highest for truck drivers compared to others (Wei, Lee, Luo, & Lu, 2021).

Furthermore, the injury and fatality rate from truck-involved collisions remains the highest in industrial areas in Thailand, with motorcycle-involved crashes ranking second in terms of injuries and fatalities, mainly due to speeding behaviors (Ministry of

Transport, 2024). Motorcycle riders are often exposed to congested traffic conditions that encourage speeding during rush hours. These factors contribute to hazardous driving behaviors and greatly enhance the likelihood of crashes occurring (V. Hong et al., 2020; H. Huang et al., 2016; Seefong et al., 2023). Vehicle speed has a direct impact on the risk of rear-end collisions (F. Chen, Song, & Ma, 2019; V. Hong et al., 2020; Qaid et al., 2022). In addition, high-speed changes in velocity before an crash increase the likelihood of a collision occurring (F. Chen & Chen, 2011; V. Hong et al., 2020; Qaid et al., 2022; World Health Organization, 2023; R. Yu & Abdel-Aty, 2014).

Given the importance of these factors, reviewing and gaining insights into the elements that influence the driving behavior of truck and motorcycle drivers is a crucial approach in reducing road crashes and improving overall traffic safety. Therefore, selecting a model with high accuracy in prediction is crucial to obtaining results and insights that reflect the real-world driving behaviors. The models that are widely trusted and commonly used today for predicting driving behavior include the Theory of Planned Behavior (Chorlton, Conner, & Jamson, 2012; Elliott, Armitage, & Baughan, 2005; Parker, Manstead, Stradling, & Reason, 1992; Rowe et al., 2016; Shruthi, Meundi, & Sushma, 2019), the Health Belief Model (Dadipoor et al., 2020; Razmara, Aghamolaei, Madani, Hosseini, & Zare, 2018; Tavafian, Aghamolaei, Gregory, & Madani, 2011), and the Protection Motivation Theory (Amaral et al., 2017; Qi, Zhu, & Long, 2023). Additionally, several countries facing road traffic crashes have collaboratively developed a safety framework to address road traffic situations in the long term. This framework departs from the traditional approach, which stated that humans are responsible for road crashes, and instead adopts the idea that all stakeholders in society should be accountable for road safety and crashes (Morimoto, Wang, & Kitano, 2022). This collaboration has led to the development of the safety framework, which encompasses the fundamental 3Es: Education, Engineering, and Enforcement along with an additional E: Emergency Response. However, there has been no prior study that has applied and thoroughly examined the safety framework. Therefore, applying the 3Es+Es safety framework to investigate the key factors influencing driving behavior could lead to important new findings and valuable insights for safety agencies in formulating effective, evidence-based policies and measures.

An analysis of previous studies on the factors that influence driver behavior, aimed at identifying strategies to mitigate road traffic crashes, predominantly presents empirical findings using Structural Equation Modeling (SEM) (Javid & Al-Hashimi, 2020; Javid & Al-Roushdi, 2019; Javid, Ali, Abdullah, & Shah, 2021; Qaid et al., 2022; Warner & Åberg, 2006). This approach is advantageous for evaluating multiple relationships between variables simultaneously and for rigorously comparing similarities and differences between two or more groups, enabling a precise analysis of the relationships between variables. (Dilalla, 2000). In addition, the Random Parameter technique has gained attention as another method for examining the factors influencing driver behavior. This approach provides a way to explain models that can accurately capture variability and complexity, allowing the model to reflect real-world predictions effectively (Champahom et al., 2023; Šarić, Xu, Xiao, & Vrkljan, 2021; W. Wang, Yuan, Liu, Yang, & Yang, 2019; Ye, Cheng, Wang, Liu, & Bai, 2021). However, current studies still lack exploration of these potential relationships, and such research gaps could lead to missing key findings and insights in examining the factors influencing driver behavior to find ways to mitigate road traffic crashes.

Based on the aforementioned importance, this study aims to focus on identifying key factors influencing risky behaviors and the severity of crashes using statistical modeling and machine learning for industrial areas in Thailand. The study emphasizes identifying factors that affect the severity of both truck-involved and non-truck-involved collisions, as well as examining the factors that affect the risky behaviors of truck drivers and speed-related behaviors of motorcycle riders. These groups are particularly vulnerable to injury and fatality from crashes in industrial areas. Furthermore, the key findings from this study will be beneficial to safety organizations in formulating evidence-based policies and measures that are effective and contextually appropriate for specific areas. Ultimately, this will contribute to the reduction of injury and death rates on the roads overall.

1.2 Purpose of the research

I. To develop a model for predicting the factors influencing the severity of truck-involved and non-truck-involved collisions in industrial areas in Thailand using machine learning

II. To develop a model for predicting the factors influencing the risky behaviors of truck drivers in industrial areas in Thailand using a Random Parameters Model.

III. To develop a model for predicting the factors influencing the speed-involved behaviors of motorcycle riders in industrial areas in Thailand using Structural Equation Models.

1.3 Scopes of the research

I. The study area of this research focuses on the industrial areas in 18 provinces of Thailand.

II. The study utilizes crash data from 2020 to 2023, provided by the Ministry of Transport.

III. The research surveys the attitudes of truck and motorcycle drivers, with a particular focus on drivers aged 18 years and older.

1.4 Research questions

I. What are the factors influencing the severity of truck-involved collisions

II. What are the factors influencing the severity of non-truck-involved collisions

III. What are the factors influencing risky driving behaviors of truck drivers

IV. What are the factors influencing the speed behavior of motorcycle riders

1.5 Research contribution

I. Determining the factors affecting both truck-involved and non-truck-involved collisions assists policymakers and relevant safety agencies in developing effective strategies to address future road crash challenges. This enables the formulation of effective and appropriate measures, covering both truck-involved and general vehicle-involved policies.

II. Determining the factors that contribute to the risky behavior of truck drivers helps decision-makers understand the feelings, attitudes, and behaviors that contribute to traffic rule violations. The insights gained from this study allow policymakers to establish effective and appropriate measures, focusing on improving safety for truck drivers.

III. Determining the factors that contribute to the risky behavior of motorcycle riders helps decision-makers understand the feelings, attitudes, and behaviors that contribute to traffic rule violations, particularly in relation to speeding. The insights gained from this study enable policymakers to develop and select effective and appropriate measures, focusing on improving the speeding behavior of motorcycle riders.

1.6 Organization of the research

This research is organized into five main chapters as follows:

Chapter I: Introduction, this chapter presents the rationale and significance of the study, the research purpose, scope, research questions, and the contribution of the research.

Chapter II: Big data analytics with the multivariate adaptive regression splines to analyze key factors influencing crash severity in industrial areas of Thailand: a study on truck and non-truck collisions.

Chapter III: Exploring heterogeneity in risk-taking propensity of truck drivers in industrial areas in Thailand with empirical policy recommendations.

Chapter IV: A study of motorcycle riders related to speeding behavior in Thailand's Industrial areas.

Chapter V: Conclusion and Recommendations, this chapter summarizes the findings from Chapters 2 to 4, along with practical approaches and provides additional suggestions for future research.

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CHAPTER II

BIG DATA ANALYTICS WITH THE MULTIVARIATE ADAPTIVE REGRESSION SPLINES TO ANALYZE KEY FACTORS INFLUENCING ACCIDENT SEVERITY IN INDUSTRIAL ZONES OF THAILAND: A STUDY ON TRUCK AND NON-TRUCK COLLISIONS

2.1 Abstract

Machine learning currently holds a vital position in predicting collision severity. Identifying factors associated with heightened risks of injury and fatalities aids in enhancing road safety measures and management. Presently, Thailand faces considerable challenges with respect to road traffic crashes. These challenges are particularly acute in industrial zones, where they contribute to a rise in injuries and fatalities. The mixture of heavy traffic, comprising both trucks and non-trucks, significantly amplifies the risk of crashes. This situation, hence, generates profound concerns for road safety in Thailand. Consequently, discerning the factors that influence the severity of injuries and fatalities becomes pivotal for formulating effective road safety policies and measures. This study is specifically aimed at predicting the factors contributing to the severity of crashes involving truck and non-truck collisions in industrial zones. It considers a variety of aspects, including roadway characteristics, underlying assumptions of cause, crash characteristics, and weather conditions. Due to the fact that crash data is big data with specific characteristics and complexity, with the employment of machine learning In tandem with the Multi-variate Adaptive Regression Splines technique, we can make precise predictions to identify the factors influencing the severity of collision outcomes. The analysis demonstrates that various factors augment the severity of crashes involving trucks. These include darting in front of a vehicle, head-on collisions, and pedestrian collisions. Conversely, for non-truck related collisions, the significant factors that heighten severity are tailgating, running signs/signals, angle collisions, head-on collisions, overtaking collisions, pedestrian

collisions, obstruction collisions, and collisions during overcast conditions. These findings illuminate the significant factors influencing the severity of crashes involving trucks and non-trucks. Such insights provide invaluable information for developing targeted road safety measures and policies, thereby contributing to the mitigation of injuries and fatalities.

2.2 Introduction

Road safety remains a critical global concern (Fernando et al., 2023). As per the Road Safety Situation Report by Road Safety for All, road crashes annually result in approximately 1.35 million deaths and 50 million injuries (Vivas Pacheco, Rodríguez-Mariaca, Jaramillo, Fandiño-Losada, & Gutiérrez-Martínez, 2023). Disturbingly, 93% of these fatalities occur in low to middle-income countries. In this context, middle-income developing nations like Thailand face serious issues concerning road crashes (Road Safety for All | UNECE, 2019). World Health Organization (WHO) data reveal Thailand as having the ninth highest number of road crash fatalities globally, making it the leading country in Asia and the ASEAN regions. The mortality rate stands at approximately 32.7 deaths per 100,000 population, amounting to an average of 22,491 deaths annually or roughly 60 deaths per day (Global status report on road safety, 2018).

Throughout the preceding year, the prevalence of road crashes in Thailand has been notably concentrated within provinces classified as industrial zones, as visually depicted in Figure 2.1. These zones encompass a diverse range of spatial categories, encompassing industrial zones, industrial estate parks, and comprehensive industrial zones. Delving further into the crash data for the industrial province regions during the period spanning 2020 to 2022, a striking finding emerges, indicating that injuries and fatalities collectively averaged a substantial 22.11% (Ministry of Transport, 2023). This statistical revelation underscores the inherent challenges of navigating through complex driving conditions in densely populated areas, which inherently magnify the inherent risk of crashes. Complex driving conditions in densely populated areas significantly escalate the risk of crashes. Notably, collisions involving trucks pose a higher threat than those not involving trucks, largely due to the trucks' size and weight impeding swift braking in emergencies (M. Chen et al., 2022). In 2021, data categorized by vehicle type indicated that truck-involved crashes constituted 12.41% of all crashes (Department of Land Transport, 2022). When assessing the proportion of injuries and fatalities from truck-involved collisions in industrial zones, the figures are markedly higher compared to collisions not involving trucks Figure 2.2. Consequently, the rate of injuries and fatalities from truck crashes ranks second in comparison to other vehicle types (Ministry of Transport, 2023). Given this significance, a detailed study of factors contributing to the severity of truck crash injuries and fatalities is essential for enhancing road safety.

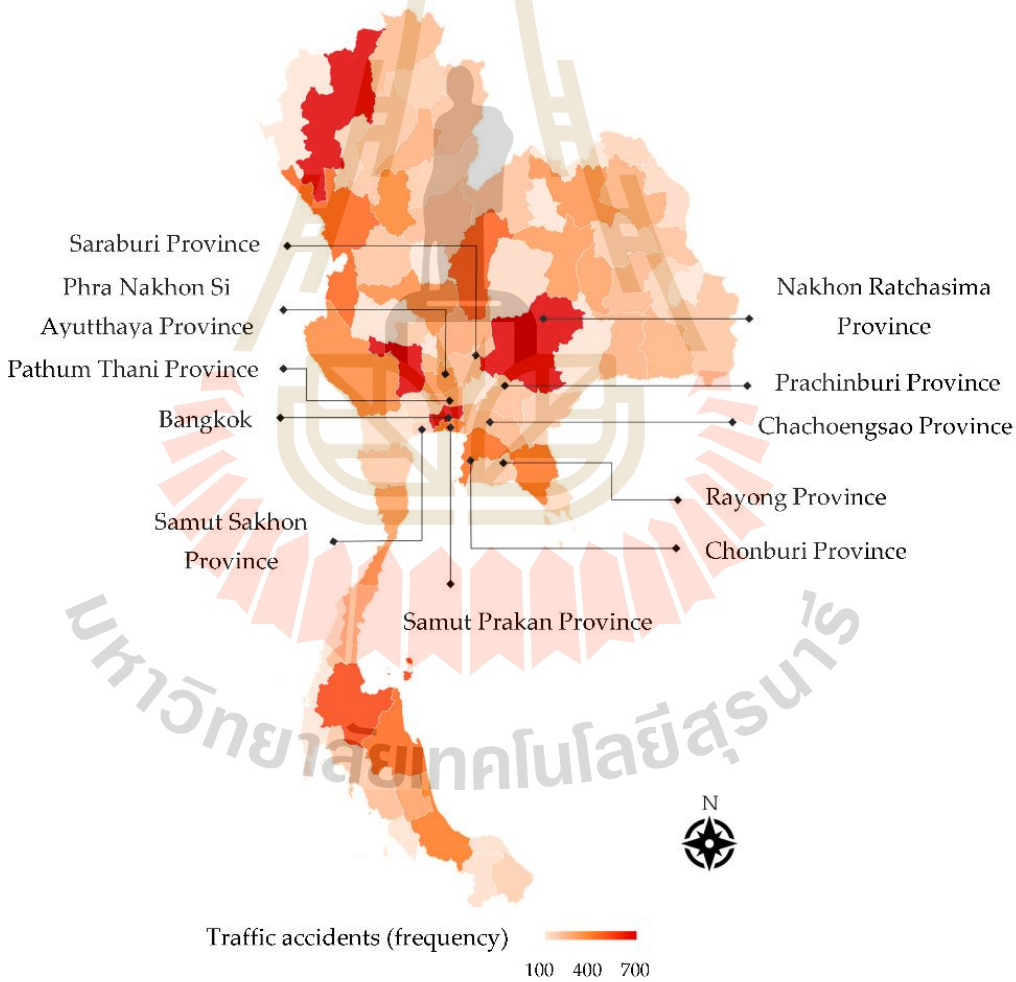

Figure 2.1 Road Traffic crashes frequency in Thailand by Provinces from 2020 to 2022

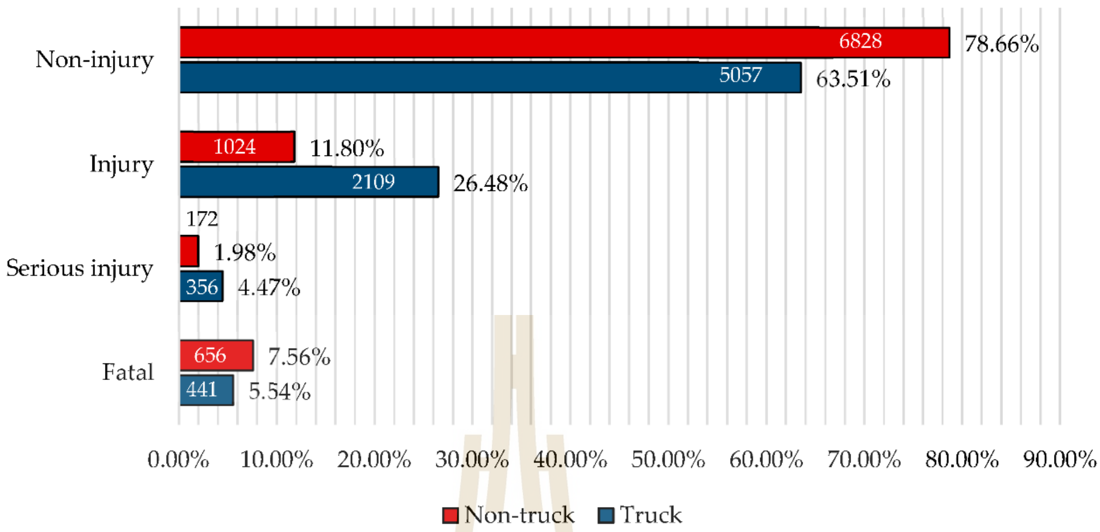

Figure 2.2 Injury severity distribution of non-truck and truck-involved crashes in the industrial zones of Thailand from 2020 to 2022 (Ministry of Transport, 2023)

To effectively mitigate road crashes, a comprehensive understanding of their causes and a capability to predict potential crashes are necessary (Fernando et al., 2023). This understanding enables the implementation of effective preventive strategies and measures. In recent years, substantial attention has been paid to studying factors that contribute to road crash severity. Examples include predictions related to crash severity on expressways (Kunt, Aghayan, & Noii, 2011), urban roads (Astarita, Haghshenas, Guido, & Vitale, 2023), and signalized intersections (Abdelwahab & Abdel-Aty, 2001), factors influencing injury severity in car crashes (Delen, Tomak, Topuz, & Eryarsoy, 2017) as well as studies on truck collisions (Behnood & Mannering, 2019; Kim, Ulfarsson, Shankar, & Kim, 2008; Uddin & Huynh, 2018; Zheng, Lu, & Lantz, 2018; Zhu & Srinivasan, 2011; Zou, Wang, & Zhang, 2017). In several studies, the focus has been on analyzing big data through high-efficiency platforms to analyze crashes, which enables the discovery of new insights and a deeper understanding of the problem (Ait-Mlouk et al., 2017; Fan et al., 2017; Feng et al., 2020; L. Huang et al., 2018). Parameter-free techniques, such as Multivariate Adaptive Regression Splines (MARS), are gaining traction for their efficacy in discerning factors contributing to crash severity (Champahom et al., 2022) and in the field of transportation (Das & Khan, 2020). The Multivariate Adaptive Regression Spline (MARS) model presents a blend of distinct advantages and disadvantages. On the positive side, its remarkable capability to unravel intricate nonlinear relationships and detect interactions among variables makes it an invaluable asset in tackling intricate data patterns that defy traditional linear regression approaches. MARS sets itself apart from other well-known parametric linear regression techniques by offering a heightened degree of flexibility in investigating nonlinear relationships between input and response variables (Y. Zhang et al., 2015). MARS operates autonomously in selecting pertinent features and offers insights into the pivotal variables, thereby enhancing its interpretability. Notably, MARS rigorously explores all potential levels of interaction, effectively unveiling a comprehensive spectrum of interactions among variables. By thoroughly considering all interactions and functional shapes inherent in input variables, the approach excels at unveiling latent connections within high-dimensional datasets and capturing intricate structures apparent within data points (Naser, Badr, Henedy, Ostrowski, & Imran, 2022). However, there is a slight risk of limited adaptability in feature partitioning due to the model's weakness a potential lack of continuity and difficulty in capturing straightforward relationships like linear, additive or interactions with lower orders (Friedman, 1991). The inherent complexity of MARS poses challenges, particularly the risk of overfitting, which looms large when dealing with expansive datasets or an extensive array of variables. Furthermore, MARS models are notably sensitive to noise in the data, potentially incorporating irrelevant patterns that can compromise predictive accuracy when applied to previously unseen data instances (unobserved heterogeneity). While MARS retains a higher level of interpretability compared to some intricate models, comprehending its behavior becomes progressively intricate as the model's complexity grows. The application of Multivariate Adaptive Regression Splines (MARS) has been predominantly used in existing studies for investigating driver behavior, notably lane changing acceptance behavior (Das & Khan, 2020), and developing crash modification factors for freeway interchange areas in urban environments (Haleem, Gan, & Lu, 2013). It has also been used in predicting rear-end collisions (Haleem et al., 2010; Y. Zhang et al., 2015) and studying the safety impacts of wider shoulders on rural multilane highways (J. Park &

Abdel-Aty, 2016). However, it is crucial to recognize that there is a notable gap in research specifically examining the factors influencing the severity of crashes involving trucks in industrial zones, particularly using this machine learning technique. Omitting areas prone to truck crashes from such study parameters may result in significant challenges when aiming to effectively reduce the number of severe injuries and fatalities stemming from these crashes. Therefore, it is vital to expand the application of MARS to such specific and high-risk contexts. This approach would facilitate a more comprehensive understanding of road safety, particularly in areas dominated by industrial traffic.

This research is novel as it prioritizes collisions involving trucks and non-trucks in industrial zones, utilizing a promising new approach in safety research—the Multivariate Adaptive Regression Splines (MARS) methodology. The primary objective is to identify significant factors contributing to injury and fatality severity. The findings will provide valuable reference data for policymaking and safety measures aimed at effectively reducing injuries and fatalities. Utilizing crash data from Thailand, a country grappling with unique road safety challenges, serves as the basis for this investigation.

2.3 Materials and Methods

2.3.1 Method

The superiority of parameter-free techniques over parameter-based models stems from their capability in making accurate predictions and the absence of predefined assumptions. These techniques are capable of modeling complex relationships, including nonlinearity, and can simultaneously manage a substantial number of explanatory variables (Das & Khan, 2020). Considering these strengths, this study has selected to utilize Multivariate Adaptive Regression Splines (MARS), a parameter-free technique proposed by Friedman (Friedman, 1991). This model serves to identify key factors influencing the severity of crashes involving both trucks and non-trucks. MARS offers critical advantages in accurately capturing and predicting such data. Moreover, it provides flexibility in exploring nonlinear relationships between independent and dependent variables (L.-y. Chang, Chu, Lin, & Lui, 2012). Therefore, it can construct a model that effectively captures the complex Interrelationships among various variables. This approach delivers in-depth insights into the critical factors influencing the severity of crashes involving trucks and non-trucks with high precision. The fundamental form of the MARS model is represented by Equation (2.1) (J. Park & Abdel-Aty, 2016):

$$\hat{y} = \exp\left(b_0 + \sum_{m=1}^{M} b_m B_m(x)\right) \tag{2.1}$$

where

$\hat{y}$ = predicted response variable,

b_0 = coefficient of the constant basis function,

b_m = coefficient of the mth basis function,

M = number of nonconstant basis functions, and

$B_m(x)$ = mth basis functions.

The process of curve fitting using the Multivariate Adaptive Regression Splines (MARS) model encompasses three primary steps (Put, Xu, Massart, & Vander Heyden, 2004). The initial step involves constructing the model by integrating predictor and response variables and assigning weights to these variables to derive the MARS model. Subsequently, the pruning phase takes place, addressing overfitting issues within the MARS curve fitting model. The final step involves selecting the most suitable MARS model, which can then be assessed for predictive performance using the MARS curve fitting technique.

In the first phase of constructing a curve-fitting model with the MARS method, continuous basic functions are added to the MARS base model. These basic functions could comprise single splines or multiple splines, each yielding different predictive outcomes. A “two-at-a-time” strategy is implemented during this addition, whereby the optimal pair of spline functions is chosen to enhance the model. Each pair consists of one left function and one right function, divided by knots as illustrated in Equations (2.2) and (2.3) respectively. Following this, the positions of the knots are iteratively optimized until the location that maximizes the model’s efficiency is selected. Additionally, after each iteration, the model is continuously examined and adjusted as necessary. Equations (2) and (3) can be defined as follows:

$$[-(x-t)^q]=\begin{cases}(t-x)^q \text{ ; } x<t \\ 0 \text{ ;otherwise}\end{cases} \tag{2.2}$$

$$[+(x-t)^q]=\begin{cases}(x-t)^q \text{ ; } x>t \\ 0 \text{ ;otherwise}\end{cases} \tag{2.3}$$

where

x = independent variable

t = constant denoting knot

q = the order of the spline and the subscript indicates the positive part of the argument.

The second stage in this process is the pruning step, which employs a “one-at-a-time” approach to eliminate basic functions contributing minimally to the model. The pruning process adheres to the Generalized Cross-Validation (GCV) criterion, in which a lower GCV value tends to result in a more parsimonious model. Equation (2.4) below showcases the GCV criterion:

$$GVC(M)=\frac{1}{N}\frac{\sum_{i=1}^{N}(y_i-\hat{y})^2}{(1-C(M)/N)^2} \tag{2.4}$$

where

N = number of observations

y_I = observation i

y = predicted response for observation i

C(M) = complexity penalty function

The final stage involves choosing the best fitting spline-based model utilizing the Multivariate Adaptive Regression Splines (MARS) method. This decision is based on the evaluation of the predictive performances of the various spline-based models developed using the MARS method. Figure 2.3 illustrates the process of the Multivariate Adaptive Regression Splines (MARS) model.

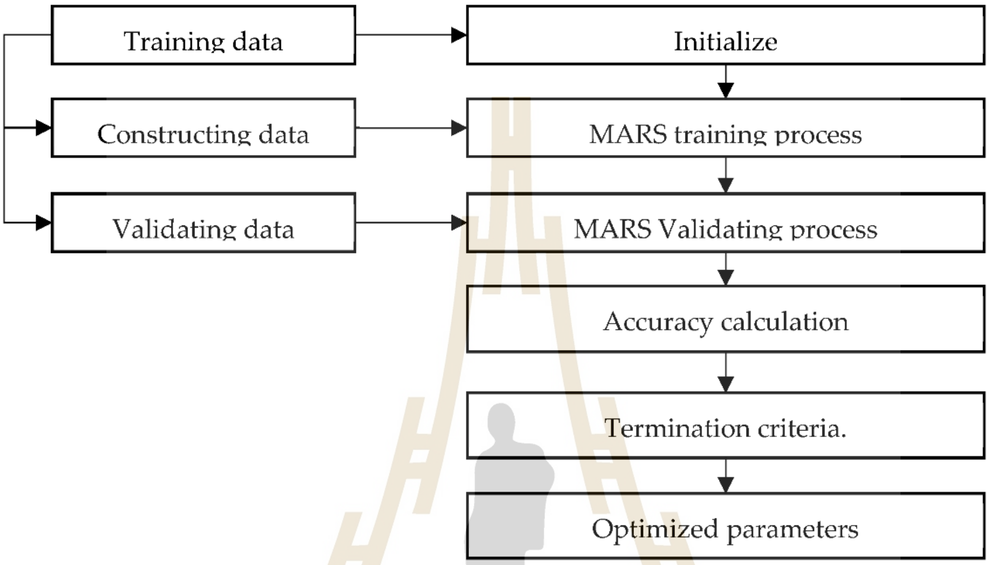

Figure 2.3 The process of Multivariate Adaptive Regression Splines (MARS) model (Put et al., 2004)

2.3.2 Measures for Performance Evaluation

In this study, the accuracy (ACC), sensitivity (SNS), specificity (SP), precision (PRC), F1-score, and AUC were used as performance metrics for the prediction model of MARS. These metrics can be calculated from the confusion matrix, as shown in Figure 2.4 The confusion matrix consists of four components, the count of true positives (TP), count of true negatives (TN), count of false positives (FP) and count of false negatives (FN) (Yao, Yang, & Zhan, 2013).

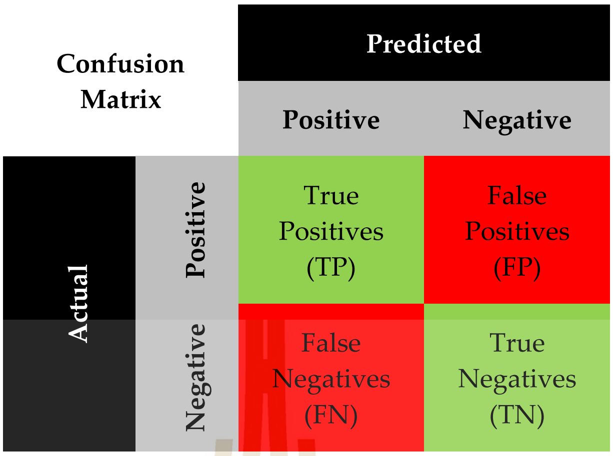

Figure 2.4 Confusion Matrix

When the confusion matrices were obtained, the four classifier performance metrics can be calculated as (Mokhtarimousavi, Anderson, Azizinamini, & Hadi, 2020; Sokolova & Lapalme, 2009):

$$\mathrm{ACC}=\frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{TN}+\mathrm{FP}+\mathrm{FN}}\times 100 \tag{2.5}$$

$$\mathrm{SNS}=\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \tag{2.6}$$

$$\mathrm{SP}=\frac{\mathrm{TN}}{\mathrm{TN}+\mathrm{FP}} \tag{2.7}$$

$$\mathrm{PRC}=\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}} \tag{2.8}$$

$$F_1=2\times\frac{\mathrm{SNS}\times\mathrm{PRC}}{\mathrm{SNS}+\mathrm{PRC}} \tag{2.9}$$

$$\mathrm{AUC}=\frac{1}{2}(\mathrm{SNS}+\mathrm{SP}) \tag{2.10}$$

Among the previously mentioned evaluation criteria, “Accuracy” stands as a comprehensive measure of a classifier’s overall effectiveness. “Sensitivity” assesses the classifier’s ability to correctly identify positive labels, while “Specificity” measures its capacity to accurately recognize negative labels. The “F-score” provides insight into the relationship between the actual positive labels in the dataset and those identified by the classifier. To further enhance the evaluation process, the “AUC” metric, which represents the area under the receiver operating characteristic curve, sheds light on the classifier’s capability to minimize erroneous classifications.

2.3.3 Data Collection

This research used the most recent crash data from the 2020–2022 period, obtained from the Ministry of Transport, with a specific focus on crashes occurring within industrial zones in Thailand. The study used the accumulated data to generate two models aimed at identifying the critical factors influencing the severity of collisions involving trucks and non-trucks. The collected data revealed 7963 truck-involved collision cases, resulting in 797 Severe/Fatal cases. Conversely, there were 8680 non-truck involved collision cases, leading to 828 Severe/Fatal cases. Influential factors were categorized into four main groups: (1) Roadway Characteristics, (2) Cause of Assumption, (3) Crash Characteristics, and (4) Weather Conditions. The total extracted risk factors for each case were 38 explanatories. Each variable was coded 1 = “Yes”, 0 = “Otherwise”. Table B1 summarizes all the influencing factors, categorized according to the severity levels of injuries, for both trucks and non-truck vehicles, using two levels of injury severities, namely, PDO/minor injury and severe/fatal injury (Se, Champahom, Jomnonkwao, Karoonsoontawong, & Ratanavaraha, 2021).

2.3.4 Model Evaluation

From the results of the analysis of the performance metrics of the MARS prediction model in Table 2.1, it was found that the non-truck involved crashes model and the truck-involved crashes model exhibit high prediction accuracies of 91.05% and 90.32%, respectively, which is relatively higher as compared to previous studies that utilized the big data analysis approach (Mokhtarimousavi et al., 2020; H. Yu, Li, Zhang, Liu, & Ma, 2021). The F1-Scores of 0.242 and 0.133 suggest that there is a trade-off between precision and sensitivity, indicating that the model might not be performing well in both aspects simultaneously. This phenomenon is likely attributable to a substantial disparity in the number of instances across classes, causing the model to exhibit a preference for the majority class (i.e., PDO/minor injury, in this case). This preference subsequently results in reduced sensitivity and, consequently, a lower F1 score. However, when measures the model's ability to distinguish between positive and negative classes across different probability thresholds, the AUC values of 0.773 and 0.774 suggest that the model has a relatively higher capabilities to distinguish between the two classes, as compared to the findings of the previous studies (Banerjee & Khadem, 2019; Jamal & Umer, 2020; Mokhtarimousavi et al., 2020). Hence, the outcomes derived from the MARS models could be deemed acceptable for the purpose of valid model interpretation.

Table 2.1 Goodness of fit for the truck and non-truck crash severity model

	Accuracy	Sensitivity	Specificity	Precision	F1-Score	AUC
Non-truck involved crashes	91.05%	0.629	0.917	0.150	0.242	0.773
Truck-involved crashes	90.32%	0.641	0.906	0.074	0.133	0.774

2.4 Result and Discussion

2.4.1 Roadway Characteristics Factor

Table 2.2 presents an in-depth analysis of roadway characteristics concerning truck-involved collisions. The study found that attributes such as Interchange Roads/Ramps and Expressways significantly contribute to reducing injuries. Interchange Roads/Ramps, designed to minimize traffic conflicts and enhance junction safety, naturally decrease injury occurrences. Similarly, Expressways, due to their facilitation of consistent speeds and uninterrupted traffic flow, mitigate the potential for crashes and subsequent injuries. Straight roads also contribute to injury reduction, given their flat surface and increased visibility, which allows for swift driver responses to unforeseen circumstances (Ye et al., 2021). These findings underscore the role of road attributes, including Interchange Roads/Ramps, Expressways, and Straight Roads, in injury reduction within truck-involved crashes. Additionally, there is a surprising finding suggesting that the characteristic of a wide curved road leads to decreased injury occurrences. This contradicts the findings of previous studies that indicated collisions on curved road segments resulted in increased injuries (M. B. Islam & S. Hernandez, 2013). Nevertheless, this variable might be contingent on the width of the lanes, The statement aligns with the findings of previous studies indicating that an increased lane width could potentially help reduce the risks of collisions and injuries. This is because a wider lane provides drivers with a greater separation from traffic, promoting a heightened sense of safety (Li, Liu, Liu, & Qi, 2020; Zegeer, Deen, & Mayes, 1980).

Table 2.2 Estimation results for the truck crash severity model

Model	Variable	Coefficients
Truck	Intercept	0.290
	Roadway Characteristics Factor	
	Interchange road/Ramps	−0.159
	Wide curved road	−0.162
	Expressway	−0.138
	Straight road	−0.045
	Cause of Assumption Factor	
	Darting in front of a vehicle	0.058
	Malfunctioning equipment	−0.074
	Crash Characteristics Factor	
	Head-on collision	0.227
	Pedestrian collision	0.529
	Sideswipe collision	−0.120
	Rear-end collision	−0.135
	Curved-road rollover	−0.233
	Straight-road rollover	−0.188
	Weather Conditions Factor	
	Rain	−0.031

For collisions not involving trucks, as displayed in Table 2.3, the study discerned that Straight Roads, due to their extended visibility, were associated with a reduction in injuries. Previous research has identified road characteristics significantly influencing crash severity as typically being intersections with conflicting points and shortened visibility (Mussone, Ferrari, & Oneta, 1999; Rezaie Moghaddam, Afandizadeh, & Ziyadi, 2011). Furthermore, road sections with curves and steep slopes, which inherently have reduced visibility, were found to elevate injury rates (F. Chang et al., 2016; Se, Champahom, Jomnonkwao, & Ratanavaraha, 2020).

Table 2.3 Estimation results for the non-truck crash severity model

Model	Variable	Coefficients
Non-Truck	Intercept	0.135
	Roadway Characteristics Factor	
	Straight road	−0.060
	Cause of Assumption Factor	
	Tailgating.	0.369
	Running signs/signals	0.310
	Obstruction	−0.172
	Crash Characteristics Factor	
	Angle collision	0.246
	Head-on collision	0.386
	Overtaking collision	0.358
	Pedestrian collision	0.598
	Obstruction Collision	0.126
	Weather Conditions Factor	
	Rain	−0.031
	Overcast	0.414

2.4.2 Cause of Assumption Factor

Table 2.2 displays a comprehensive analysis of factors contributing to truck-involved collisions. The study found that attribute malfunctioning equipment, which traditionally exacerbates injury rates, had a decreasing effect on injuries within this specific context. High traffic congestion, impeding high-speed driving, combined with defective vehicle equipment, could lead to more cautious driving and prompt vehicle management, thus reducing the likelihood of injuries. Conversely, collisions involving vehicles darting in front of trucks, which allow for short braking distances, were found to increase injury rates. This finding aligns with earlier studies showing that sudden lane changes often result in more severe injuries and fatalities in truck-involved collisions (Knipling, 1993; Shawky, 2020).

In crashes unrelated to trucks (Table 2.3), the presence of road obstacles or barriers helps reduce the impact of injuries, consistent with previous research. Obstructions or roadblocks, which typically serve as safety measures for traffic regulation, play a role in decreasing injury consequences (Prenzler, 2006; World Road Association, 2020). However, tailgating as a cause of collisions and running signs and signals both increased injury rates. Previous studies have identified the violation of traffic signals and signs as significant contributors to crashes (Moffis, Martinez, & Choi, 2022; Penmetsa & Pulugurtha, 2017; Shawky, 2020). Moreover, closely following another vehicle with a short braking distance was found to be a critical factor impacting injuries (Begg & Langley, 2004).

2.4.3 Crash Characteristics Factor

Table 2.2 presents an analysis of crash characteristics in truck-involved collisions. Rear-end collisions were found to reduce injury rates, presumably because these crashes often occur in areas where the speed differential between vehicles is minimal (Champahom et al., 2021). The characteristics of rollover collisions, whether on straight or curved roads also had a decreasing effect on injuries. The nature of rollovers generally leads to avoidance behavior or less forceful impacts with other vehicles, thus reducing the number of injuries. Moreover, sideswipe collisions also result in reduced injuries. This aligns with the findings of a previous study which revealed that collisions within the same direction tend to involve less severe impacts, particularly for large trucks colliding with each other (M. Islam & S. Hernandez, 2013). It is possible that the skill of truck drivers in controlling the steering wheel in the same direction contributes to mitigating the severity of injuries in lateral collision scenarios. Conversely, head-on collisions amplified the impact on injuries, a finding consistent with studies on truck collision characteristics (A. J. Khattak & Targa, 2004; Xu, Wali, Li, & Yang, 2019). The substantial force generated when trucks collide head-on or at an angle with other vehicles escalates injury severity. Likewise, collisions with pedestrians were found to increase the impact on injuries (M. Chen et al., 2022; Verzosa & Miles, 2016). Developed countries often have safer pedestrian infrastructure, while developing countries like Thailand grapple with safety issues, such as poorly maintained pedestrian paths and the lack of protective equipment. This lack of protection, combined with the direct collision between trucks and pedestrians, markedly raises injury severity.

For collisions not involving trucks (Table 2.3), angle collisions resulted in an increased impact on injuries. These crashes occur when vehicles collide at a perpendicular angle, as observed in sideswipe or T-bone collisions. This finding is congruent with various studies that found sideswipe collisions, particularly in the same direction, tended to cause severe injuries (Champahom et al., 2021). Head-on collisions also had a more substantial impact on injuries compared to collisions in the same direction, corroborating previous research findings (Jonsson, Ivan, & Zhang, 2007; Nafis, Alluri, Wu, & Kibria, 2022). Furthermore, overtaking maneuvers were linked to increased injury impact. High acceleration rates during these maneuvers can lead to poor situational awareness and an increased probability of erroneous driver decisions, thereby increasing the likelihood of injuries (Richter, Ruhl, Ortlepp, & Bakaba, 2016, 2017). Pedestrian collisions lead to an increase in injuries. This finding is consistent with previous research that found pedestrians without protective equipment in pedestrian areas had a high tendency to suffer severe injuries and fatalities when directly hit by vehicles (Prato, Kaplan, Patrier, & Rasmussen, 2018; Selmoune et al., 2023). Important studies have also revealed that pedestrian crashes primarily occur in areas near schools and industrial zones (S.-H. Park & Bae, 2020). Furthermore, obstruction collisions on roads result in an increased likelihood of injuries, especially when colliding with concrete barriers. This is supported by multiple prior studies. Obstructions have a higher structural rigidity compared to vehicles, resulting in less energy absorption during the collision. As a result, vehicles sustain greater damage from the impact (W. Hu & Donnell, 2010; Russo & Savolainen, 2018; Rzepczyk, Majer, & Obst, 2022). Therefore, direct collisions with obstructions have an elevated propensity for increased injuries (Ye et al., 2021).

2.4.4 Weather Conditions Factor

Table 2.2 presents an analysis of weather factors in truck-involved collisions revealing that rainy conditions have a diminishing effect on injury rates, aligning with the study conducted by Li et al. (2020). Nevertheless, this result contradicts several previous studies that found an increased risk of injuries under adverse weather conditions, especially during rainfall (Li et al., 2020). It is hypothesized that decreased visibility and slippery road conditions during rainy weather contribute to decreased situational awareness and a need for increased driving caution and a decrease in driving speed resulting in reduced collision severity.

The analysis of weather factors influencing non-truck collisions revealed that rainy conditions have a diminishing effect on injury rates (Table 2.3). This can be attributed to the reduced visibility and slippery road conditions during rainfall, which tend to induce more cautious driving and lower vehicle speeds. Therefore, rainy weather indirectly contributes to a decrease in collision severity. In contrast, collisions occurring under overcast conditions were found to escalate the severity of collisions. This aligns with existing literature which suggests that the decreased visibility associated with overcast conditions can exacerbate the severity of collisions (Behnood & Mannering, 2015; Champahom et al., 2021; Lenguerrand, Martin, & Laumon, 2006; Z. Wang et al., 2017; Ye et al., 2021).

2.5 Conclusions

Given the high fatality rate of truck-involved crashes in Thailand’s industrial zones, where they rank second when compared to other vehicles, it is essential to identify the factors contributing to the severity of injuries and fatalities in both truck and non-truck involved crashes. This understanding is crucial for developing effective road safety policies and measures.

Our current study uses crash data from Thailand between 2020 and 2022, comprising large and complex datasets. We applied machine learning in conjunction with the Multivariate Adaptive Regression Splines (MARS) technique. This method identifies influential factors affecting the severity of injuries and fatalities in both truck and non-truck involved crashes without relying on predefined parameters. These factors encompass roadway characteristics, cause of assumption, crash characteristics, and weather conditions.

The analysis considers two levels of injury severity namely, PDO/minor injury and severe/fatal injury. Upon examining truck-involved crashes within Thailand's industrial zones, we discovered that darting in front of a vehicle, head-on collisions, and pedestrian collisions all enhance the severity of injuries. Conversely, non-truck related crashes in these industrial zones revealed that tailgating, running signs/signals, angle collisions, head-on collisions, overtaking collisions, pedestrian collisions, obstruction collisions, and collisions during overcast conditions also increase injury severity.

A comparison of the two models highlighted that head-on collisions and pedestrian collisions significantly increase injury severity in both truck and non-truck crashes. However, the influencing factors differ between crashes involving trucks and those not involving trucks. Hence, it is vital that road safety policies and measures are appropriately tailored without neglecting any specific factor to improve road safety in Thailand effectively.

Following our statistical analysis, we proposed several road safety policies and measures aimed at reducing the severity of injuries and fatalities in both truck and non-truck related crashes. Our recommendations are informed by crucial variables identified within our models (Table 2.4), and the key guidelines are as follows:

Policies and safety measures for trucks: First, road design should focus on enhancing traffic safety. This could involve designing intersections or upgrading them into interchange roads/ramps to minimize conflict points at junctions. Especially at T-junctions, which are commonly implicated in severe injury or fatality-involved crashes with trucks (Haq, Zlatkovic, & Ksaibati, 2022; Islam, Hosseini, & Jalayer, 2022; A. Khattak, Schneider, & Targa, 2002; Lemp, Kockelman, & Unnikrishnan, 2011). Because of the reasons mentioned, it is critical to design intersections with a minimal number of conflict points and align these with typical driver behavior to mitigate crash risks. Furthermore, this approach includes designing an expressway-like road layout to shorten travel distances and reduce the risk of crashes, designing a straight road layout to increase visibility and reduce points of risk that lead to crashes and increasing the number of lanes for curved sections of the road where there is a higher risk. Such measures coincide with this study's findings that these road characteristics can influence a reduction in injury severity.

Enforcing speed limits for trucks is an approach intended to reduce the risk of crashes caused by darting in front of a vehicle and pedestrian collisions, all of which heighten the likelihood of injuries. This includes installing advanced V2V (Vehicle to Vehicle) devices within vehicles to provide rear-end collision warnings, ensuring a safe following distance.

Promoting educational policies for truck drivers to minimize collision risk should encompass training on diverse collision types, such as angle collision, rear-end, single-vehicle, and head-on collisions (Champahom et al., 2021). Special emphasis should be placed on head-on collisions, given their significant contribution to the severity of crashes. Furthermore, this approach includes promoting skill training for truck drivers to effectively control the steering wheel in the same direction during emergency situations and can significantly reduce the severity of injuries. The study suggests that the Department of Land Transport integrate topics on collision types into driver's license training. By gaining a comprehensive understanding of the causes and consequences of different collision types, truck drivers can cultivate increased awareness and promote safer driving practices.

Installing safety devices for both drivers and road users should encompass provisions for pedestrians, such as Pedestrian Crosswalks, Raised Crosswalks, and pedestrian-specific traffic signals. The aim is to stimulate driver awareness, mitigate injuries resulting from unforeseen crashes, and bolster overall road safety.

Lastly, promoting consistent safe driving behavior in emergency situations is crucial (Malfunctioning equipment), as it can significantly reduce the severity of injuries. Encouraging drivers to remain composed, activate hazard lights, and safely navigate their vehicles to the side of the road or a suitable stopping point is essential.

Policy and safety measures for general vehicles: Specifically, designing roads with a focus on traffic safety should give priority to creating straight road sections. These sections offer extended visibility and have been linked to a decrease in the occurrence of injuries. This includes designing roads to reduce the severity of overtaking collisions, another crucial consideration. Overtaking collisions primarily occur on roads where overtaking is permitted, particularly in areas without designated passing zones (Richter et al., 2016). Therefore, integrating knowledge of safe passing zones into road design is an important strategy for improving overall roadway safety and effectiveness.

Installing safety devices for both drivers and road users is important. This includes installing safety devices for pedestrians. Implementing impact-absorbing barriers designed to mitigate crash severity without inflicting significant vehicular damage, including barriers crafted from polyethylene plastic, is also key. Additionally, the installation of red-light cameras at all intersections is an approach that should be strongly considered to reduce the risk of collisions resulting from red light running and traffic signal violations. These violations are notable contributors to increased injury risks. Red-light cameras, as a crucial component of the transportation infrastructure, facilitate more effortless enforcement of traffic laws. This approach aligns with studies conducted in the United States, which found that the implementation of red-light cameras can reduce injuries resulting from signal violations by up to 29% (R. A. Retting & Kyrychenko, 2002). Installing advanced V2V (Vehicle to Vehicle) devices within vehicles to provide rear-end collision warnings from tailgating is another crucial approach. This includes installing road markings to guide drivers and help them maintain a safe following distance is equally important. Furthermore, installing obstruction devices at high-risk points, such as curved or sharp-angle sections, has been shown by the study’s findings to effectively reduce injuries. As a final guideline for installing safety devices for both drivers and road users, focusing on reducing the risk of collisions during dark and low-light conditions should entail conducting assessments of areas at high risk for crashes. Following these assessments, the installation of enhanced visibility devices for drivers, such as streetlights, should be prioritized. However, this initiative must be executed within the constraints of the available budget and timeframe. The study recommends prioritizing the installation of streetlights in areas with low-light conditions, especially at high risk for crashes, as these factors significantly increase the likelihood of injuries and fatalities.

Promoting educational policies for drivers to minimize collision risk should encompass training in various collision types, including angle collisions, rear-end collisions, single-vehicle collisions, and head-on collisions (Champahom et al., 2021). For general vehicle drivers, special emphasis should be placed on preventing head-on collisions and angle collisions, as they have a significant impact on the severity of crashes. Lastly, promoting responsible driving behavior in continuous rainy weather conditions is essential; such proactive measures not only decrease the likelihood of crashes but also play a crucial role in minimizing the severity of injuries.

Table 2.4 Appropriate strategies based on such findings

Variables	Truck	Non-Truck	Guidelines
Roadway Characteristics Factor			
Interchange road/Ramps	(–)		Designing the characteristics of an interchange road/ramp for intersections with conflicts and high crash rates
Wide curved road	(–)		Increasing the number of lanes for curved sections of the road where there is a higher risk
Expressway	(–)		Designing an expressway-like road layout to shorten travel distances and reduce the risk of crashes
Straight road	(–)	(–)	Designing a straight road layout to increase visibility and reduce points of risk that lead to crashes
Darting in front of a vehicle	(+)		1) Install advanced V2V (Vehicle to Vehicle) devices within vehicles to provide rear-end collision warnings, ensuring a safe following distance.

Table 2.4 Appropriate strategies based on such findings (Continued)

Variables	Truck	Non-Truck	Guidelines
Cause of Assumption Factor			
			2) Configure lower speed limits to reduce the severity of injuries in emergency situations.
Tailgating.		(+)	1) Install advanced V2V (Vehicle to Vehicle) devices within vehicles to provide rear-end collision warnings, ensuring a safe following distance. 2) Install road markings to guide drivers and help them maintain a safe following distance.
Malfunctioning equipment	(–)		Promoting consistent safe driving behavior in emergency situations.
Running signs/signals		(+)	Installing cameras to monitor red-light signals at all intersections to mitigate unsafe driving behavior.
Obstruction		(–)	Installing obstruction devices at high-risk points, such as curved or sharp-angle sections.
Crash Characteristics Factor			
Angle collision		(+)	1) Promote awareness among drivers about risky scenarios that can lead to increased injuries, such as angled collisions and head-on collisions.
Head-on collision	(+)	(+)	2) Advocate for the use of seatbelts for both drivers and passengers to minimize the severity of injuries. 3) Install Automatic Emergency Braking (AEB) systems to reduce the severity of injuries by automatically applying brakes in emergency situations. 4) Install airbag systems within vehicles to mitigate the severity of injuries.

Table 2.4 Appropriate strategies based on such findings (Continued)

Variables	Truck	Non-Truck	Guidelines
Overtaking collision		(+)	Design roads to enhance safety during overtaking maneuvers and mitigate the risk of collisions during passing.
Pedestrian collision	(+)	(+)	1) Install safety devices for pedestrians. 2) Configure lower speed limits in situations involving pedestrians.
Obstruction Collision		(+)	Install impact-absorbing barriers designed to reduce the severity of crashes without causing significant damage to vehicles, such as barriers made from Polyethylene plastic.
Curved-road rollover	(–)		Promoting skill training for truck drivers to effectively control the steering wheel in the same direction during emergency situations can significantly reduce the severity of injuries resulting from crashes.
Straight-road rollover	(–)		
Weather Conditions Factor			
Rain	(–)	(–)	Promoting responsible driving behavior in continuous rainy weather conditions.
Overcast		(+)	Install roadside conveniences or additional lighting systems to enhance road safety.

+: Indicates an increase in the estimated likelihood for severe injuries. –: Indicates a decrease in the estimated likelihood for severe injuries.

2.6 Limitations and Further Research

This study, while providing valuable insights, is not devoid of limitations. As it primarily concentrates on industrial zones, the enforcement and implementation of the proposed safety policies and measures must be carefully executed, particularly when extrapolating them to regions outside of the industrial zone. Additionally, due to data constraints, the study might not encompass all pertinent factors. Thus, further considerations are needed to account for other potentially influential variables. These may include driver demographics such as gender and age, roadway attributes like the number of lanes, and traffic characteristics, such as volume, etc.

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CHAPTER III
EXPLORING HETEROGENEITY IN RISK-TAKING PROPENSITY OF TRUCK DRIVERS IN INDUSTRIAL ZONES IN THAILAND WITH EMPIRICAL POLICY RECOMMENDATIONS

3.1 Abstract

In the present day, truck drivers have assumed a key role in promoting industrial development, yet they face higher risks of injury and death from road crashes compared to other drivers. This increased risk is due to chaotic traffic conditions and risky behaviors, especially in industrial zones crowded with trucks. This article analyzes the factors influencing truck drivers' risky behaviors in Thailand's main industrial zones using a model based on randomly sampled parameters related to average differences. The study combines concepts from the Health Belief Model and Protection Motivation Theory to examine driving behaviors from various perspectives. Key factors influencing risky behaviors include perceived susceptibility (When drivers perceive the risk of crashes while driving), perceived severity (When drivers feel that crashes will impact their work), perceived barriers (when truck drivers perceive that fastening seat belts causes discomfort, and when they perceive safety equipment for vehicles as expensive and unaffordable), cues to action (When truck drivers encounter safe driving campaigns), and health motivation (When truck drivers prioritize adequate rest and relaxation). These factors significantly impact truck drivers' risky behaviors and offer valuable insights for policymakers. The findings suggest policy recommendations that could enhance road safety, providing essential guidance for stakeholders to reduce injuries and fatalities among truck drivers.

3.2 Introduction

Road traffic crashes remain a significant global traffic disaster that persists today. The loss from crashes claims approximately 1.19 million lives worldwide, with a fatality rate of 15 per 100,000 population (World Health Organization, 2023). This poses a challenge for countries worldwide striving to manage the traffic disaster, especially developing nations (Wisutwattanasak, Jomnonkwao, et al., 2023). According to estimates by the World Health Organization, the economic cost of road traffic injuries globally is high, reaching up to 1.8 to 2 trillion US dollars, equivalent to about 10-12% of the Gross Domestic Product (GDP) worldwide. It's deeply concerning that 92% of fatalities occur in low and middle-income developing countries (World Health Organization, 2023). Researchers have diligently attempted to study influential factors and behaviors of drivers to find ways to mitigate traffic disasters. However, it seems traffic disasters remain a continuous challenge as the number of fatalities and injuries in developing countries remains higher than those in developed countries (Jadaan et al., 2018).

In the current context, Thailand's narrative has shifted to that of a country in social, economic, and industrial development, yet it is plagued by the curse of road traffic disasters. According to statistics recorded by the World Health Organization, road crashes claim a high number of lives in Thailand, ranking 9th globally and making it a leading country in Asia and the ASEAN region (Global status report on road safety, 2018). In 2022, there were 17,000 fatalities and 15,000 disabilities due to road injuries, resulting in significant human and economic losses estimated at around 500,000 million baht (approximately 12.5 billion USD) (World Health Organization, 2023). When considering statistics from recent years, Thailand's crash figures concentrate heavily in provinces situated within industrial zones. Due to the environment in areas designated specifically for industrial activities, particularly manufacturing, these areas are densely packed with buildings, factories, and residential housing. This results in heavy traffic congestion filled with trucks and numerous other vehicles, making it highly prone to crashes. A cumulative 22.11% of fatalities and injuries occurred between 2020 to 2022 (Ministry of Transport, 2023). Particularly alarming is the fact that collisions involving trucks result in far greater losses than those not involving trucks. Figure. 3.1 illustrates the traffic conditions in industrial zones, showing the abundance of trucks and other vehicles, such as personal cars and motorcycles, on the roads, which clearly leads to congestion and challenging driving conditions. Furthermore, significant disclosures from the statistics reveal that the mortality rate from truck crashes in industrial zones is the highest compared to other vehicles (Seefong et al., 2023), as shown in Figure 3.2.

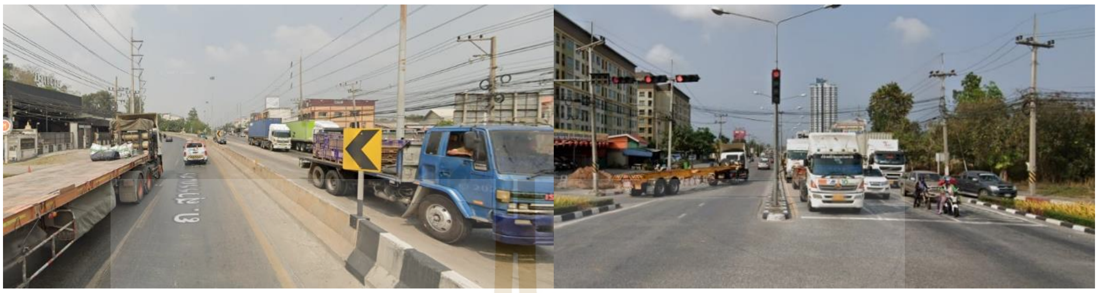

Figure 3.1 Physical characteristics of traffic conditions in industrial zones

Even though there are numerous factors contributing to road crashes, the major factors often stem from abnormal driving behaviors (Dadipoor et al., 2020; Niu et al., 2021; Rashmi & Marisamynathan, 2023). This is because driver behavior plays a significant role in controlling vehicle movements in road situations (Rashmi & Marisamynathan, 2023). This aligns with crucial evidence indicating that 95% of crashes result from human factors, with over 90% attributed to unsafe driving behaviors (Niu et al., 2021; B. Zhang et al., 2006). Despite truck drivers playing a vital role in promoting industrial development, they also face a higher risk of unforeseen road events resulting in fatalities and injuries compared to drivers in other groups (Wei et al., 2021). This is due to truck drivers encountering chaotic traffic conditions, spending longer periods on the road, and having demanding schedules. Additionally, truck drivers are generally older than other drivers due to the nature of their work (Hege et al., 2018; Sullman et al., 2002), which relies on long-term driving expertise and experience, leading to certain personal traits and risky behaviors that contribute to road crashes. Therefore, systematically reviewing abnormal driving behaviors of truck drivers is crucial for implementing preventive measures to promote safe and effective driving among this group.

Previously, studies have examined factors influencing driver behavior to find ways to mitigate road crashes s, often utilizing results from conventional statistical models (Dadipoor et al., 2020; Harbeck, Glendon, & Hine, 2018; Razmara et al., 2018).

However, it appears that these studies still lack robustness in explaining the parameters using random effects models, which are widely employed nowadays due to their ability to capture variability and complexity accurately (Champahom et al., 2023; Šarić et al., 2021; W. Wang et al., 2019; Ye et al., 2021). Furthermore, the current trend includes utilizing the concept of unobserved heterogeneity (in means) to study traffic safety (Wisutwattanasak, Jomnonkwao, et al., 2023). Unobserved heterogeneity refers to characteristics that may not directly influence the outcome but may have indirect effects. Moreover, it can be applied to random parameter models, where the hidden influence in the unobserved heterogeneity method may affect the direction of model parameters and increase the model's complexity (Champahom et al., 2023). This is an interesting aspect to consider in studying factors influencing driver behavior because most studies have not explored these potential relationships, which could lead to missing significant results. Additionally, significant evidence suggests that models with unobserved diversity have greater explanatory and predictive power than conventional models (Fountas, Anastasopoulos, & Abdel-Aty, 2018; Se, Champahom, Jomnonkwao, Chaimuang, & Ratanavaraha, 2021; Wisutwattanasak, Jomnonkwao, et al., 2023).

To further fill the gap in previous research, this study aims to investigate factors influencing the risky behavior of truck drivers in Thailand's industrial zones. Given the unique traffic conditions in these areas, which may reflect certain risky behaviors among truck drivers, the study utilizes a method of explaining parameters using random effects models known for their precision in capturing variability and model complexity accurately, along with the concept of unobserved heterogeneity (in means). These potential relationships have been overlooked in previous studies, possibly resulting in missed significant findings. Ultimately, the study's findings will provide valuable insights for relevant organizations in policymaking to mitigate road crashes and promote safe and effective driving among truck drivers.

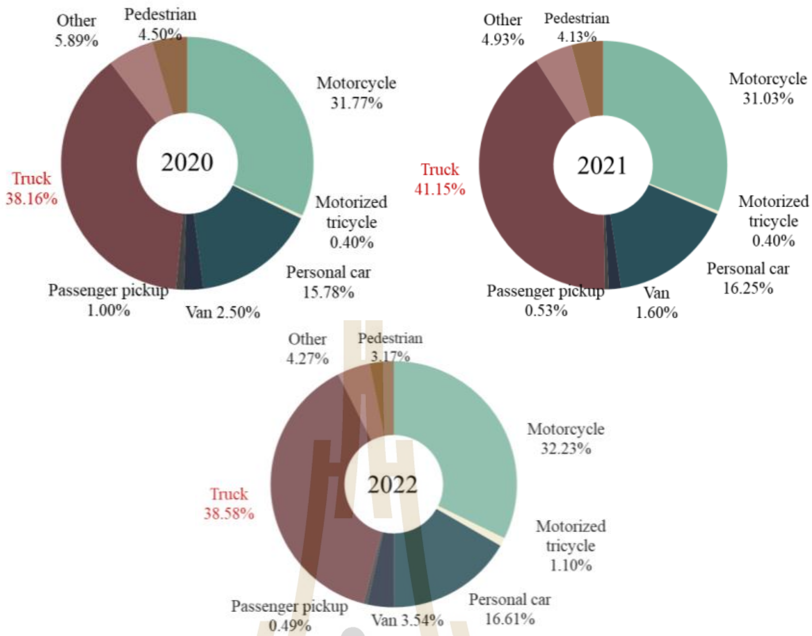

Figure 3.2 The mortality rates in industrial zones categorized by vehicle type from 2020 to 2022

3.3 Methodological approach

3.3.1 Model development

To consider the unnoticed differences and the nature of ranking risky driving behaviors among truck drivers, this study employs an ordered probit model that allows for parameter variability. In theoretical terms, it is necessary to define the latent utility function Y^*_{in} that specifies the likelihood of the outcome of driving behavior I for driver (i.e., respondent) n. This is outlined as follows (Sarwar, Anastasopoulos, Ukkusuri, Murray-Tuite, & Mannering, 2018; Se, Champahom, Jomnonkwao, et al., 2023; Se, Champahom, Wisutwattanasak, Jomnonkwao, & Ratanavaraha, 2023; Washington, Karlaftis, Mannering, & Anastasopoulos, 2020) :

$$Y^*_{in} = \beta_n X_{in} + \varepsilon_n \tag{3.1}$$

Where β_n represents the vector of estimated parameters, X_{in} denotes the vector of explanatory variables, and ε_n signifies the error term, assumed to follow a normal distribution with a mean of 0 and a variance of 1 for driving scenario n. Here, n denotes driver (i.e., respondent). This can be specified as follows (Ahmed, Cohen, & Anastasopoulos, 2021; Se, Champahom, Wisutwattanasak, et al., 2023; Washington et al., 2020) :

$$Y^{*}_{in}=\mathrm{I},\ \text{if}\ \mu_{i-1,n}<Y^{*}_{n}\leq\mu_{\mathrm{I},n} \tag{3.2}$$

Where I (with I = 1,2,3) represents "Sometimes," "often," and "Regularly," respectively, and μ_{I} is the estimated parameter (or threshold) for defining Y^{*}_{n} in accordance with the ordered levels of driving behavior such that $\mu_{i-1}<\mu_{i}$. The probability of each level $P(y=\mathrm{I})$ of risky driving behavior of truck drivers for each observed crashes can be specified as follows (Se, Champahom, Wisutwattanasak, et al., 2023; Washington et al., 2020) :

$$P(y=i)=\Phi(\mu_{i}-\beta_{n}X_{n})-\Phi(\mu_{i+1}-\beta_{n}X_{n}) \tag{3.3}$$

Where Φ represents the cumulative standard normal distribution, influencing the mean and variance of the explanatory variables, and β_{in} is the vector of estimated parameters, which vary according to the specified constraints (Ahmed et al., 2021; Fountas et al., 2018; Hou, Huo, & Leng, 2020; Se, Champahom, Jomnonkwao, Chaimuang, et al., 2021).

$$B_{in}=\beta+\eta Z_{n}+\omega_{n,} \tag{3.4}$$

In which β denotes the constant term for random parameters (Hou, Huo, Tarko, & Leng, *2021*; Se, Champahom, Jomnonkwao, Chaimuang, et al., *2021*). Z_n represents the vector of explanatory variables capturing differences in the mean of random parameters. H is the vector of estimated parameters aligned with Z_n, ηZ_n denotes terms to describe undetected differences resulting from interactions (intercepting explanatory variables) causing variations in the parametric function of random parameters (Hou et al., 2020; Hou et al., 2021; Se, Champahom, Jomnonkwao, Chaimuang, et al., 2021). Ω_n is a $K\times1$ vector that cannot be observed, where K is the number of random parameters. Embedded random terms with zero mean affect the mean and covariance-variance matrix of random parameters, which become $E\left(\left(\beta_n|\omega_n\right)=\beta+\eta Z_n\right)$ and $Var\left(\beta_n|\omega_n\right)=\Gamma\Gamma^T$, respectively (Hou et al., 2020; Hou et al., 2021; Se, Champahom, Jomnonkwao, Karoonsoontawong, et al., 2021). Γ is a symmetric Cholesky matrix used to compute the standard deviations of random parameters. This study estimates the model using maximum likelihood estimation with 200 Halton draws to simplify the interpretation of the results and calculates marginal effects to analyze the impact of explanatory variables on the probability of each risky driving behavior level. The direction of the impact cannot be indicated by parameter values *(*Fountas & Anastasopoulos, *2017)*. Additional marginal effects were calculated by changes in the probability of each outcome for each level. These additional marginal effects were computed by averaging the observed values as follows (*Fountas & Anastasopoulos,* 2017*; Se, Champahom, Wisutwattanasak, et al.,* 2023) :

$$\frac{P(y=i)}{\partial X}=\left[\Phi\left(\mu_{i-1}-\beta X\right)-\Phi\left(\mu_i-\beta X\right)\right]\beta \qquad (3.5)$$

3.3.2 Model evaluation and comparison

In analyzing the factors influencing risky driving behavior among truck drivers in Thailand's industrial zones, a comprehensive assessment of the model's goodness-of-fit, confirming that the model is effective in predicting outcomes as specified (Se, Champahom, Jomnonkwao, Chaimuang, et al., 2021; Washington et al., 2020).

$$X^2= -2\left[LL(\beta_A)-LL(\beta_B)\right] \qquad (3.6)$$

Where $LL(\beta)$ is the log-likelihood at convergence, and $LL(\beta_A)$ and $LL(\beta_B)$ represent the likelihoods of the converged records for Models A and B, respectively. The X^2 statistic is a chi-square distributed statistic with degrees of freedom equal to the difference in the number of parameters between Model A and Model B. The overall goodness-of-fit assessment of the estimated model is shown in Table 3.4.

3.4 Data collection

3.4.1 Questionnaire structure

For the questionnaire structure is divided into three sections. The first section gathers general information about the socio-economic characteristics of truck drivers, such as gender, age, marital status, education level, income, and occupation. These data are categorical and can describe the baseline and differences among drivers. The second section collects data on truck drivers' attitudes towards crashes based on the Health Belief Model and Protection Motivation Theory. These theories are widely used to explore drivers' attitudes (Amaral et al., 2017; Dadipoor et al., 2020; Qi et al., 2023; Razmara et al., 2018; Tavafian et al., 2011). Nine factors are considered: 1) Perceived Susceptibility, 2) Perceived Severity, 3) Perceived Benefits, 4) Perceived Barriers, 5) Cues to Action, 6) Health Motivation, 7) Response Efficacy, 8) Self-efficacy, and 9) Behavioral Intention. Likert scales with 5 levels were used for measurement (1=Strongly Disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly Agree). These data reflect the diverse attitudes, perceptions, awareness, and expectations of truck drivers regarding the risks of road crashes involving trucks. The final section collects data on the behaviors of truck drivers, which can explain the different driving experiences of drivers. Seven main factors are considered: 1) Violations, 2) Errors in driving, 3) Lapses, 4) Use of safety equipment, 5) Control errors, 6) Use of distracting devices such as social media, and 7) Alcohol consumption and drug use. Likert scales with 3 levels were used for measurement (1=Sometimes, 2=Often, 3=Regularly).

3.4.2 Data collection and sample statistics

In this study, data was collected from truck drivers covering the main industrial zones in Thailand. These drivers were aged 18 and above and operated trucks within the main industrial zones in 11 provinces of Thailand. To ensure that the survey respondents represent the largest possible population of truck drivers in the industrial zone, the goal was to gather responses from 600 respondents. The survey was conducted from June 13th, 2023, to July 13th, 2023. Participants were briefed on the purpose of the survey, the concepts of the Health Belief Model and the Protection Motivation Theory (PMT), and some key information before answering the questions. This was done to ensure that they fully understood the objectives of the survey and the underlying concepts to provide accurate data. The study adhered to important ethical considerations, including obtaining approval from the Ethics Committee of Suranaree University of Technology. The survey questionnaire received approval and was deemed to have low risk (COE No.94/2565, November 8, 2022). The demographic characteristics of the survey respondents are presented in Table 3.1.

Table 3.1 Participants' demographic characteristics

Category	Frequency	Percentage
Age		
18 – 25 years old	26	4.33
26 – 35 years old	159	26.50
36 – 45 years old	260	43.33
46 – 55 years old	127	21.17
56 – 65years old	28	4.67
Gender		
Male	562	93.67
Female	38	6.33
Marital status		
Single	144	24.00
Married	401	66.83
Divorced	55	9.17
Education		
Primary school	159	26.50
Lower secondary school	222	37.00
Higher secondary school/Vocational certificate	186	31.00
Diploma/high vocational certificate	20	3.33
Bachelor's degree	5	0.83
Master's degree	-	-
Doctor of philosophy	-	-
Others	8	1.33

Table 3.1 Participants' demographic characteristics (Continued)

Category	Frequency	Percentage
Personal income (Baht per month)		
Less than 10,000	27	4.50
10,000-20,000	436	72.67
20,001-30,000	113	18.83
30,001-40,000	22	3.67
40,000 or higher	2	0.33
Driver's license ownership		
No	27	4.50
Yes	573	95.50
Crash experience		
Never	536	89.33
Ever	64	10.67
Driving time		
0:00-6:00 AM (Late night)	83	13.83
6:00-12:00 PM (Morning)	316	52.67
12:00-6:00 PM (Afternoon)	129	21.50
6:00-12:00 AM (Night)	72	12.00

3.4.3 Model Specification and Descriptive Statistics.

This study utilized questionnaire data obtained from a survey of truck drivers, focusing on truck drivers in the main industrial zones in Thailand, with a sample size of 600 respondents. The data collected from the survey was used to construct a model aimed at analyzing factors influencing the risky behaviors of truck drivers. The model considered a total of 33 influencing factors and indicators. Tables 3.2 and 3.3 present details of the variables and descriptive statistics.

Table 3.2 Definition and Descriptive Statistics of Dependent Variables

Variables	Code	Sometimes		Often		Regularly	
		Frequency	Percent	Frequency	Percent	Frequency	Percent
1) You drive above the legally prescribed speed limit.	BH1	51	8.50	166	27.70	383	63.80
2) You take curves at high speeds to the extent that you feel you may lose control of the vehicle.	BH2	23	3.80	60	10.00	517	86.20
3) You disregard speed limits, especially during late-night and early-morning hours.	BH3	28	4.70	82	13.70	490	81.70
4) You exceed speed limits in community or village zones.	BH4	26	4.30	83	13.80	491	81.80
5) You overtake in no-passing zones (solid line indicating restricted passing area).	BH5	43	7.20	75	12.50	482	80.30
6) You exceed the legally permitted load weight.	BH6	45	7.50	61	10.20	494	82.30
7) You frequently drive beyond the 4-hour limit.	BH7	155	25.80	134	22.30	311	51.80
8) You tend to drive while fatigued.	BH8	102	17.00	134	22.30	364	60.70
9) You do not wear a seatbelt while driving.	BH9	129	21.50	1	0.20	470	78.30
10) You do not use traffic cones or a red flag as a precaution to prevent crashes caused by other vehicles.	BH10	88	14.70	90	15.00	422	70.30

Table 3.2 Definition and Descriptive Statistics of Dependent Variables (Continued)

Variables	Code	Sometimes		Often		Regularly	
		Frequency	Percent	Frequency	Percent	Frequency	Percent
11) You drive without turning on headlights during the daytime.	BH11	319	53.20	116	19.30	165	27.50
12) You lose control of the vehicle when driving at high speeds.	BH12	41	6.80	57	9.50	502	83.70
13) You use a phone or headset while driving.	BH13	99	16.50	160	26.70	341	56.80
14) You engage in social media (Facebook, Twitter, Instagram, Line) while driving.	BH14	38	6.30	56	9.30	506	84.30
15) You drive after consuming alcohol or while actively drinking alcohol.	BH15	16	2.70	31	5.20	553	92.20
16) During major festive periods such as New Year, Songkran, or social gatherings, you commonly drink and drive.	BH16	17	2.80	41	6.80	542	90.30

Table 3.3 Definition and Descriptive Statistics of Independent Variables

Variables	Code	Min	Max	Mean	Std. Deviation
Perceived Susceptibility					
1) I am aware that when driving, I may be at risk of having a crash.	PS1	1	5	4.120	1.036
2) I know that familiarity with the route due to regular driving can help me avoid crashes.	PS2	1	5	4.082	0.959
3) I am aware that lack of experience in driving increases the risk of crashes.	PS3	1	5	4.192	0.929

Table 3.3 Definition and Descriptive Statistics of Independent Variables (Continued)

Variables	Code	Min	Max	Mean	Std. Deviation
4) I know that drinking alcoholic beverages and then driving can lead to crashes.	PS4	1	5	4.597	0.780
5) I know that using a mobile phone/social media while driving may cause crashes.	PS5	1	5	4.473	0.809
6) I am aware that carrying a heavy load can increase the risk of crashes.	PS6	1	5	4.093	1.089
Perceived Severity					
7) If not wearing a seatbelt, I may face a higher risk of injury or death in a crash.	PV1	1	5	4.440	0.872
8) Crashes from driving may result in long-term injuries or disabilities.	PV2	1	5	4.510	0.758
9) Crashes can significantly impact my work.	PV3	1	5	4.510	0.839
10) Crashes can affect the lives of people I know, such as family and friends.	PV4	1	5	4.485	0.827
11) Each crash may cause damage to my property and consume time.	PV5	1	5	4.515	0.766
Perceived Benefits					
12) I believe that wearing a seatbelt reduces the severity of injuries in case of a crash.	PB1	1	5	4.417	0.805
13) I feel unsafe when driving without wearing a seatbelt.	PB2	1	5	4.428	0.879
14) I feel safe when driving cautiously and within the speed limits.	PB3	1	5	4.502	0.767
15) I think following traffic rules enhances safety.	PB4	1	5	4.443	0.803
Perceived Barriers					
16) Wearing a seatbelt makes me feel secure.	PR1	1	5	2.473	1.444
17) I think safety equipment for cars is expensive and impractical to purchase.	PR2	1	5	2.515	1.426
Cues to Action					
18) I often receive compliments on my safe driving from people close to me.	CA1	1	5	3.812	1.141

Table 3.3 Definition and Descriptive Statistics of Independent Variables (Continued)

Variables	Code	Min	Max	Mean	Std. Deviation
19) Public awareness campaigns on safe driving make me constantly aware of the importance of safe driving.	CA2	1	5	4.075	1.068
20) Strict traffic enforcement by police motivates me to drive safely.	CA3	1	5	4.040	1.137
Health Motivation					
21) I believe that crashes involving vehicles are the most dangerous.	HM1	1	5	4.293	1.023
22) I think health and physical condition are crucial for safe driving.	HM2	1	5	4.410	0.998
23) Adequate rest is important for safe driving.	HM3	1	5	4.495	0.949
24) I prioritize safety when driving.	HM4	1	5	4.367	1.020
Response Efficacy					
25) Driving within speed limits reduces the risk of crashes.	RE1	1	5	4.303	0.974
26) Using safety equipment can lessen the severity of crashes.	RE2	1	5	4.203	0.993
27) Strict penalties for traffic violations can decrease the likelihood of crashes.	RE3	1	5	3.940	1.120
Self-efficacy					
28) I can drive within speed limits.	SE1	1	5	4.168	1.092
29) I can drive in strict adherence to traffic rules.	SE2	1	5	4.237	1.056
30) I can use safety equipment every time I drive.	SE3	1	5	4.213	1.057
Behavioral intention					
31) I will use safety equipment to make driving safer.	BI1	1	5	4.233	1.033
32) I will strictly follow traffic rules to reduce the risk of crashes.	BI2	1	5	4.292	1.046
33) I will recommend friends to use safety equipment to reduce the risk of crashes.	BI3	1	5	4.130	1.104

3.5 Result and Discussion

3.5.1 Model evaluation result

Table 3.4 presents the results of estimating the Random Parameters Model for truck driving behavior. The estimated values from the model reveal a noticeable improvement in model fit, as evidenced by the evaluation metrics. The 95% confidence interval of the model indicates a confident statistic of 97.2%, and the R^2 value is 0.222, which is considered acceptable compared to existing studies (Alnawmasi & Mannering, 2019; Alogaili & Mannering, 2022; Se, Champahom, Jomnonkwao, Chaimuang, et al., 2021; Se, Champahom, Laphrom, Jomnonkwao, & Ratanavaraha, 2023). Additionally, an analysis was conducted with a Random Parameters Model with heterogeneity in means and found no significant implications. The following section provides a detailed discussion of the results obtained from the Random Parameters Model. A positive coefficient indicates that the likelihood of risky behavior increases with an increase in the associated variable, while a negative coefficient suggests a decrease in the likelihood of risky behavior as the variable increases.

Table 3.4 Results of the random parameters model for truck driving behavior

Variables		Fixed-Probit Model			Random parameters Model		
		Coefficient	t-Stat		Coefficient	t-Stat	
	Threshold μ	1.336	11.903	***	2.044	3.651	***
	constant	-1.185	-2.382	*	-1.517	-2.070	*
Random parameters							
I know that familiarity with the route due to regular driving can help me avoid crashes.	PS2	-0.207	-2.433	*	-0.496	-2.159	*
	sd.PS2	-	-		0.295	2.104	*
Fixed parameters							
Perceived Susceptibility							
1) I am aware that when driving, I may be at risk of having a crash.	PS1	0.167	1.947	.	0.271	1.785	.
2) I am aware that lack of experience in driving increases the risk of crashes.	PS3	-0.132	-1.379		-0.195	-1.343	

Table 3.4 Results of the random parameters model for truck driving behavior (Continued)

Variables		Fixed-Probit Model			Random parameters Model		
		Coefficient	t-Stat		Coefficient	t-Stat	
3) I know that drinking alcoholic beverages and then driving can lead to crashes.	PS4	-0.142	-1.159		-0.153	-0.887	
4) I know that using a mobile phone/social media while driving may cause crashes.	PS5	0.117	0.860		0.122	0.613	
5) I am aware that carrying a heavy load can increase the risk of crashes.	PS6	-0.064	-0.860		-0.121	-1.008	
Perceived Severity							
6) If not wearing a seatbelt, I may face a higher risk of injury or death in a crash.	PV1	0.140	1.317		0.274	1.531	
7) Crashes from driving may result in long-term injuries or disabilities.	PV2	0.112	0.774		0.103	0.510	
8) Crashes can significantly impact my work.	PV3	0.280	2.118	*	0.496	1.943	.
9) Crashes can affect the lives of people I know, such as family and friends.	PV4	-0.133	-1.209		-0.179	-1.066	
10) Each crash may cause damage to my property and consume time.	PV5	-0.330	-2.281	*	-0.570	-2.058	*
Perceived Benefits							
11) I believe that wearing a seatbelt reduces the severity of injuries in case of a crash.	PB1	-0.141	-1.094		-0.292	-1.295	
13) I feel safe when driving cautiously and within the speed limits.	PB3	-0.002	-0.015		0.054	0.253	
14) I think following traffic rules enhances safety.	PB4	-0.336	-2.867	**	-0.585	-2.298	*

Table 3.4 Results of the random parameters model for truck driving behavior (Continued)

Variables		Fixed-Probit Model			Random parameters Model		
		Coefficient	t-Stat		Coefficient	t-Stat	
Perceived Barriers							
15) Wearing a seatbelt makes me feel secure.	PR1	0.331	6.651	***	0.538	3.218	**
16) I think safety equipment for trucks is expensive and impractical to purchase.	PR2	0.223	4.265	***	0.361	2.898	**
Cues to Action							
17) I often receive compliments on my safe driving from people close to me.	CA1	-0.126	-1.302		-0.166	-1.151	
18) Public awareness campaigns on safe driving make me constantly aware of the importance of safe driving.	CA2	0.238	1.866	.	0.407	1.818	.
19) Strict traffic enforcement by police motivates me to drive safely.	CA3	0.112	1.112		0.133	0.915	
Health Motivation							
20) I believe that crashes involving vehicles are the most dangerous.	HM1	0.145	1.233		0.243	1.266	
21) I think health and physical condition are crucial for safe driving.	HM2	-0.085	-0.638		-0.204	-0.928	
22) Adequate rest is important for safe driving.	HM3	0.550	3.459	***	0.877	2.604	**
23) I prioritize safety when driving.	HM4	0.038	0.271		0.058	0.275	
Response Efficacy							
24) Driving within speed limits reduces the risk of crashes.	RE1	-0.232	-1.947	.	-0.398	-1.862	.
25) Using safety equipment can lessen the severity of crashes.	RE2	-0.042	-0.373		-0.034	-0.203	

Table 3.4 Results of the random parameters model for truck driving behavior (Continued)

Variables		Fixed-Probit Model			Random parameters Model		
		Coefficient	t-Stat		Coefficient	t-Stat	
26) Strict penalties for traffic violations can decrease the likelihood of crashes.	RE3	0.010	0.107		0.057	0.385	
Self-Efficacy							
27) I can drive within speed limits.	SE1	0.087	0.717		0.143	0.769	
28) I can drive in strict adherence to traffic rules.	SE2	-0.160	-1.294		-0.200	-1.103	
29) I can use safety equipment every time I drive.	SE3	-0.003	-0.020		0.025	0.121	
Behavioral Intention							
30) I will use safety equipment to make driving safer.	BI1	0.030	0.240		0.006	0.030	
31) I will strictly follow traffic rules to reduce the risk of crashes.	BI2	-0.287	-2.244	*	-0.459	-2.011	*
32) I will recommend friends to use safety equipment to reduce the risk of crashes.	BI3	-0.026	-0.248		-0.038	-0.235	

	Model statistic	Random Vs. Fixed
Parameters (K)	35	36
LL(B)	-314.7	-312.3
R^2	0.216	0.222
X^2		4.8
Degree of freedom		1
Confident		97.2%

3.5.2 Health Belief Model and Protection motivation theory Factor

I. Perceived Susceptibility

Table 3.4 The research findings indicate that perceived susceptibility has certain factors that influence the increase and decrease of risky behaviors among truck drivers. According to the study results, (PS1) when drivers perceive the risk of crashes while driving, it leads to an increase in risky behavior. Previous research has found that perceived susceptibility is not a variable in improving safe driving behavior among drivers (Dadipoor et al., 2020; Razmara et al., 2018). It is possible to infer that within the group of truck drivers, there is confidence in their well-received training and extensive driving expertise. Therefore, they may not perceive driving trucks as personally threatening in terms of road crashes, which consequently leads to an increase in risky behavior. On the contrary, (PS2) when drivers are familiar with the route, it leads to a decrease in risky driving behavior. This contradicts previous studies which found that drivers on familiar routes tend to exhibit more dangerous driving behavior due to their feeling of understanding the road conditions well and having less chance of encountering unexpected obstacles. These feelings lead to negligence and lack of attention while driving, resulting in increased risky behavior (Colonna, Berloco, Intini, & Ranieri, 2015; Harms & Brookhuis, 2016; L. Hu, Guo, Huang, Wu, & Chen, 2022; Intini, Berloco, Colonna, Ranieri, & Ryeng, 2018; Martens, 2018; Seeherman & Skabardonis, 2013; Wen & Xue, 2020; Yanko & Spalek, 2013). However, in the context of truck drivers, familiarity with the route may lead to the assumption that the benefits of their familiarity, understanding road conditions, and traffic situations well, can help reduce stress and anxiety, leading to increased attentiveness to the road ahead. This familiarity also enhances accuracy in remembering situations and quick responses in unexpected circumstances (Harms, Burdett, & Charlton, 2021). These findings are intriguing and suggest that effective road crash prevention measures must promote a good awareness of perceived susceptibility among drivers to ultimately lead to safer driving behavior among truck drivers.

II. Perceived Severity

Table 3.4 Shows that perceived severity influences both increases and decreases in risky behaviors among truck drivers. According to the study, (PV3) suggests that when truck drivers perceive that crashes impact their work, it significantly increases risky behavior. This confirms previous research findings indicating that perceived severity does not predict safe driving behavior (Ali, Haidar, Ali, & Maryam, 2011; Razmara et al., 2018). It is possible that perceiving risk regarding severity does not always lead to consistently safe driving behavior because drivers may not feel compelled to exhibit certain behaviors unless they feel they are in danger (Razmara et al., 2018). On the other hand, another perspective emerges where truck drivers believe that their high level of experience and expertise leads to lower risk perception, resulting in increased risky behavior. In contrast, (PV5) indicates that when truck drivers perceive that crashes result in both time and property damage, it leads to a decrease in risky behavior. This aligns with previous research findings suggesting that perceived severity, which directly impacts drivers, results in safer behavior. When drivers perceive negative severity that they feel puts them in dangerous situations regarding time and property, it leads to more cautious and safer driving behavior (Razmara et al., 2018; Şimşekoğlu et al., 2013).

III. Perceived Benefits

Table 3.4 The research findings indicate that perceived benefits influence reduced risk behavior. According to the study results, (PB4) when truck drivers perceive that following traffic rules leads to safety, it results in reduced risk behavior. This is supported by evidence from previous research that disobedient behavior may lead to severe traffic crashes caused by traffic rule violations (Himawan & No, 2023). Conversely, consistently following traffic rules is significant in helping road users drive safely and effectively reducing the number of traffic crashes (Åberg, 1998).

IV. Perceived Barriers

Table 3.4 The research findings indicate that perceived barriers influence increased risky behaviors. Previous studies have confirmed that perceived barriers are the best predictors of behavior among all variables in the HBM (Health Belief Model) (Okyere et al., 2021). According to the findings of this study (PR1), when truck drivers perceive that fastening seat belts causes discomfort, it affects increased risky behaviors. It is hypothesized that truck drivers experience discomfort and distress when fastening seat belts while driving. However, drivers engage in seat belt fastening when the route involves traffic congestion or hazardous conditions. Consequently, truck drivers tend to resist seat belt fastening, resulting in increased risky behaviors. Similarly to the findings of (PR2), when truck drivers perceive that safety equipment in vehicles is expensive and unaffordable, it influences increased risky behaviors. It is possible that drivers prioritize cost over the safety benefits of the equipment, as the barrier of affordability may make it difficult for drivers to access and afford these safety features. Consequently, the level of safety while driving may be compromised if such equipment is lacking (Dadipoor et al., 2020). However, these findings suggest that supporting awareness of barriers emphasizing the severe consequences may be sufficient to stimulate acceptance of safe behaviors, along with governmental support for access to basic safety equipment for truck drivers, which is crucial. Additionally, effective promotion of safety behaviors should aim to eliminate and minimize barriers as much as possible.

V. Cues to Action

Table 3.4 The research findings indicate that cues to action significantly influence increased risky behaviors. According to the findings of this study (CA2), when truck drivers encounter safe driving campaigns, it leads to increased risky behaviors. This contradicts previous studies that found continuous safe driving campaigns lead to increased safe driving behaviors by addressing aggressive driving issues, raising awareness of fatigue-related driving risks, and implementing effective coping strategies (Adamos, Nathanail, & Kapetanopoulou, 2013; Berg, 2006; Lee, Saxena, Lin, Gonzalez-Velez, & Rouse, 2010). These findings suggest that for truck drivers, safe driving campaigns that focus solely on promoting safe driving behaviors without emphasizing the severe negative consequences of non-compliance may not be sufficient to stimulate safe behaviors. However, continuous safe driving campaigns still play a crucial role in enhancing road safety. Moreover, according to previous studies, distributing flyers as a communication channel is the most effective method, with more than 70% effectiveness (Adamos et al., 2013). Given the importance mentioned above, increasing safe driving behaviors among truck drivers may require communication efforts that emphasize the negative consequences associated with non-compliance with traffic rules. Distributing flyers to advocate safe driving behaviors with a strong emphasis on the severe negative consequences of non-compliance may be one way to stimulate safe driving behaviors among truck drivers.

VI. Health Motivation

Table 3.4 The research findings reveal that health motivation significantly influences increased risky behaviors. According to the findings of this study (HM3), when truck drivers feel that sufficient rest is important, it affects increased risky behaviors. This contradicts previous studies that clearly indicate that health motivation influences safe driving behaviors among drivers (Vanlaar, Simpson, Mayhew, & Robertson, 2008). Because drivers are concerned about the problem of driving while fatigued due to insufficient rest, which is a significant factor in serious crashes. However, it is possible that truck drivers are well aware that sufficient rest and coping with fatigue are crucial for driving. Yet, due to heavy work schedules and increased workload, they tend to resist and lack awareness of the serious consequences of driving while fatigued to achieve work goals (J. Hong et al., 2019; Machin & De Souza, 2004; Rashmi & Marisamynathan, 2023). Given the aforementioned importance, health motivation for truck drivers should be a primary focus in raising awareness to promote safe driving behaviors on the roads. Sufficient rest also helps improve vehicle control abilities and decision-making skills in emergency situations efficiently to reduce the risk of crashes.

VII. Response Efficacy

Table 3.4The research findings suggest that response efficacy influences decreased risky behaviors. According to the findings of this study (RE1), when truck drivers feel that driving under speed limits reduces crashes, it aligns with previous research indicating that response efficacy influences safe behaviors in the context of seat belt use (Tavafian et al., 2011). However, in the context of driving under speed limits, further investigation is needed. It is possible that exceeding speed limits not only leads to crashes and injuries but also increases the severity of crashes (de Vries, De Koster, Rijsdijk, & Roy, 2017). This could be one reason why truck drivers recognize that driving under speed limits can reduce the likelihood of injuries from crashes.

VIII. Behavioral Intention

Table 3.4 The research findings indicate that behavioral intention influences reduced risk behavior. According to the findings from the study (BI2), truck drivers' intention to strictly adhere to traffic regulations to reduce the risk of crashes aligns with previous research that highlights the importance of experience or consistent adherence to traffic rules in promoting road safety and effectively reducing the number of traffic crashes (Åberg, 1998). These findings also suggest that campaigns focusing on encouraging truck drivers to adhere strictly to traffic regulations remain a crucial strategy for road safety, as they can significantly reduce risky behaviors among truck drivers.

3.5.3 Distribution of random parameters

According to Table 3.4, for the random sample characteristic of the model, this study tested all possible variables as random parameters obtained from truck drivers in industrial zones in Thailand. By exposing the significant mean and standard deviation of the random parameters in the model, it was found that familiarity with the route is a random variable for truck drivers.

The negative coefficient of the random parameter reports that 95.37% of the variance of PS2, when truck drivers are aware that familiarity with the route from regular driving can help prevent crashes, is associated with the decreased likelihood of risky behavior. Meanwhile, 4.63% of the related variance indicates high-risk behavior. This is illustrated in Fig. 3.3. This report aligns with findings from experimental psychology, social psychology, and sports psychology studies related to familiarity and expertise, showing that repetition significantly impacts the way human perceptual data processing works (Harms et al., 2021; TURING, 1950). Through repetition until humans become familiar and skilled, they are less overwhelmed (Fitts & Posner, 1967), and the advantage of individuals familiar with specific situations is their ability to remember situations accurately and respond much faster in these specific situations (Chase & Simon, 1973; De Groot, 1946; Harms et al., 2021). These findings effectively confirm and explain the aforementioned discoveries.

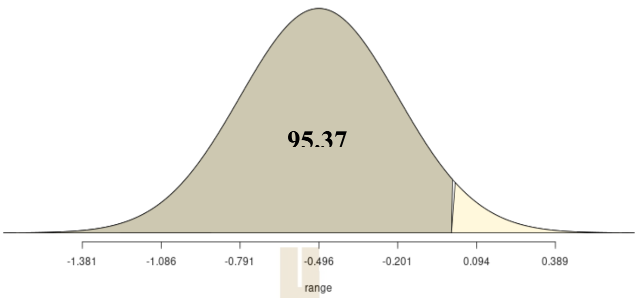

Figure 3.3 The distribution of random parameter model coefficients for truck driving behavior: When drivers are familiar with the route

3.6 Conclusion and implementations

This study developed a model to identify factors influencing risky driving behaviors among truck drivers in Thailand's main industrial zones, prompted by the high rate of fatalities from truck crashes, which rank second. Identifying key factors influencing truck drivers' risky behaviors is crucial for implementing road safety measures to reduce injuries and fatalities from crashes. The study surveyed 600 truck drivers in Thailand's main industrial zones, utilizing subtle characteristics not readily observable in the model, recording interrelated random parameters. Drawing from the Health Belief Model and the Protection Motivation Theory, the current findings reveal several previously overlooked but significant variables. It was found that perceived susceptibility, perceived severity, perceived benefits, perceived barriers, cues to action, health motivation, and response efficacy significantly influence truck drivers' risky behaviors.

From the statistical analysis, this study offers useful guidelines for road safety policy-making to reduce risky behaviors among truck drivers and consequently lower road injuries and fatalities. The recommendations are based on key variables identified key variables identified from the model findings Table 5. The major guidelines include:

The first policy and measure to promote Perceived Susceptibility can be carried out through raising awareness about the risks involved while driving. This aims to create awareness and reduce overconfidence in unsafe driving, which is a significant variable in truck driver crashes. Additionally, incorporating lessons about perceived susceptibility to driving risks and appropriate crisis management strategies into driver training curriculum is a crucial strategy widely recognized by previous studies (Alonso, Faus, Fernández, & Useche, 2021; Nathanail & Adamos, 2013). Furthermore, it has also been found that promoting the selection of familiar routes for driving is another important approach, as these variables can significantly reduce risky driving behaviors among truck drivers.

The second measure to promote Perceived Severity can be implemented by raising awareness about the severity of crashes and their serious impact on the drivers' life and work. By creating awareness about the severity of undesirable outcomes, it can lead to higher acceptance of safe driving behaviors (Dadipoor et al., 2020). Another important approach is to promote awareness of the severity of crashes that consistently cause damage to time and property. Since these variables can significantly reduce risky behaviors among truck drivers, they can continually promote safe driving attitudes and behaviors among them.

The third measure to promote Perceived Benefits can be implemented by emphasizing the advantages of following traffic rules while driving, which remains a fundamental strategy in consistently promoting safe attitudes and driving practices among truck drivers. This awareness serves as a vital guideline that can significantly diminish risky behaviors among truck drivers.

The fourth measure to promote perceived barriers can be implemented by advocating awareness of the importance of wearing seat belts and the severe consequences of not wearing them while driving, as well as promoting awareness of the serious consequences of not using additional safety equipment inside vehicles. Additionally, enhancing enforcement measures by authorities can focus on thorough inspections of basic safety equipment inside trucks (Kasmaei et al., 2014). This should be coupled with collaboration between government policies and drivers to access basic safety tools or equipment within trucks for better cooperation in a positive direction in the future. Furthermore, another crucial approach is to promote workforce involvement related to the design of safety equipment, particularly seat belt. This should earnestly consider the variables in using these tools during the equipment design process to make them more user-friendly, reducing barriers to wearing seat belts. These guidelines serve as aids in improving attitudes and raising awareness of the importance of using additional safety equipment within trucks.

The fifth measures aimed at promoting cues to action can be implemented by increasing advocacy for "safe driving" communication. This study suggests that for certain groups of truck drivers, encountering messages that support safe driving may not be sufficient to stimulate acceptance and adherence. However, the study recommends that advocacy should focus on highlighting the severe negative impacts of unsafe driving through the distribution of flyers, as they are a more effective communication channel, reaching more than 70% of the target audience (Adamos et al., 2013). This is aimed at stimulating greater acceptance of such behaviors among truck drivers.

The six measures to promote health motivation can be implemented by raising awareness of the risks of road crashes due to inadequate rest. Another effective approach is to include lessons on the importance of sufficient rest hours and coping strategies for appropriate crisis situations in driver training content. Fatigue resulting from insufficient rest is a significant factor contributing to risky behaviors and reduced driving efficiency (Fort, Chiron, Davezies, Bergeret, & Charbotel, 2013; Gastaldi, Rossi, & Gecchele, 2014; Philip et al., 2003; Yennu, Urbauer, & Bruera, 2012). However, drivers must also be equipped with the ability to handle crisis situations appropriately (Pourabdian, Lotfi, Yazdanirad, Golshiri, & Hassanzadeh, 2020) to reduce the likelihood of serious crashes, coupled with improving attitudes and behaviors towards safer truck driving.

The seven measures to promote response efficacy can be implemented by promoting attitudes and behaviors of driving within speed limits consistently to reduce the risk of crashes. Since these variables can significantly reduce risky driving behaviors among truck drivers, monitoring the impact of campaigns is considered crucial in the long run (Blackwell, Zanker, & Davidson, 2017) to continuously influence attitudes and promote safe driving practices among truck drivers.

Table 3.5 Appropriate Guidelines Based on Model Findings

Variables	Indicate	Guidelines
I am aware that when driving, I may be at risk of having a crash. (PS1)	(+)	1) Campaigning for awareness of the risks associated with driving trucks. 2) Incorporating lessons about the risks associated with driving trucks along with guidelines for handling appropriate crisis situations into the curriculum of driver training courses in particular.
I know that familiarity with the route due to regular driving can help me avoid crashes. (PS2)	(-)	Promoting the selection of familiar routes for driving to reduce the risk of crashes.
Crashes can significantly impact my work. (PV3)	(+)	A campaign to raise awareness of the severe impacts of crashes on drivers' job performance.
Each crash may cause damage to my property and consume time. (PV5)	(-)	Promoting awareness of the severity of crashes in terms of their time and property damage consistently.
I think following traffic rules enhances safety. (PB4)	(-)	Promoting awareness of the benefits of consistently adhering to traffic rules while driving.
Wearing a seatbelt makes me feel discomfort. (PR1)	(+)	1) Promoting awareness of the importance of wearing seat belts and the severe consequences of not wearing them while driving. 2) Promoting the involvement of safety equipment designers to make safety belt more convenient to use, aiming to reduce barriers to wearing seat belts.
I think safety equipment for trucks is expensive and impractical to purchase. (PR2)	(+)	1) Promoting awareness of the severe consequences of not using safety equipment inside vehicles. 2) Increasing enforcement measures by authorities to inspect basic safety equipment inside trucks. 3) Policy collaboration between governments and drivers to access fundamental safety tools or equipment inside trucks.
Public awareness campaigns on safe driving make me constantly aware of the importance of safe driving. (CA2)	(+)	Increasing the promotion of "safe driving" communication should focus on highlighting the severe negative consequences of unsafe driving. Distributing flyers is an effective media channel to achieve this.
Adequate rest is important for safe driving. (HM3)	(+)	1) Promoting awareness of the risk of road crashes due to inadequate rest.

Table 3.5 Appropriate Guidelines Based on Model Findings (Continued)

Variables	Indicate	Guidelines
		2) Including lessons on sufficient rest hours and coping strategies for appropriate crisis situations in driver training content.
Driving within speed limits reduces the risk of crashes. (RE1)	(-)	Promoting attitudes and behaviors of driving within speed limits to reduce the risk of crashes continuously and monitoring the impact of campaigns to continuously influence attitudes in the long run.
I will strictly follow traffic rules to reduce the risk of crashes. (BI2)	(-)	Encouraging truck drivers to consistently adhere to traffic regulations

(+) Indicates high possibility of risky behavior.

(-) Indicates high possibility of safe behavior.

3.7 Limitations and Further Research

While this study has provided valuable insights, there are still limitations to be addressed in future research. The survey of driving behavior focused on truck drivers in the main industrial zones of Thailand, so implementing safety policies and measures must be done cautiously, especially in areas different from industrial zones.

3.8 Acknowledgement

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CHAPTER IV
A STUDY OF MOTORCYCLE RIDERS RELATED TO SPEEDING BEHAVIOR IN THAILAND'S INDUSTRIAL ZONES

4.1 Abstract

Despite the considerable efforts to address traffic crashes, overspeeding in industrial zones remains a primary cause in Thailand. In order to effectively against this challenge (overspeeding), the deep-rooted factors influencing speeding behaviors, particularly drivers' risky behaviors, must be understood. Thus, this study employs the theory of planned behavior (TPB) and the framework comprising three basic Es (Education, Engineering, and Enforcement) and additional Es (Emergency response), i.e., the 3Es + Es framework, to examine these deep-rooted factors while considering the riders' sociodemographic data. Additionally, we performed structural equation modeling to investigate the factors influencing speeding behaviors, with key findings revealing that Engineering factors significantly account for overspeeding. Conversely, we revealed that attitude, subjective norm, and perceived behavioral control (which are essential TPB components) significantly influence riders' intentions to exhibit safe behavior, resulting in reduced speeding. Additionally, our examination of latent factors based on riders' sociodemographic data revealed that age, marital status, income, riding experience, crash history, and traffic tickets are significant factors that determine speeding habits. Specifically, we observed that single riders and those with less than five years of riding experience were less likely to exhibit safe riding behaviors. Overall, our findings would benefit Thailand's road-safety authorities, as we specifically proposed appropriate policies and empirical guidelines for Thailand's industrial zones, which are prone to high crash rates. This could effectively reduce speeding among motorcycle riders and mitigate traffic crashes.

4.2 Introduction

Injuries and fatalities due to overspeeding represent significant traffic hazards globally. It is concerning that approximately 50% of severe traffic crashes are attributable to overspeeding.(Distefano & Leonardi, 2019) Similar to many countries, Thailand is also plagued by severe traffic challenges. The latest report of the World Health Organization (WHO) in 2023 revealed that Thailand has a road-accident-death rate of approximately 25.4 per 100,000 population.(World Health Organization, 2023) Although the situation has improved slightly, Thailand still falls far short of its road-accident–fatality-reduction targets and may still be a leading Asian country in terms of traffic crashes.(Se, Champahom, Wisutwattanasak, et al., 2023) Moreover, owing to Thailand's deeply worrying statistics, WHO has ranked the country as number 1 globally for motorcycle-related road-accident-attributable deaths, with an estimated rate of 24.3 per 100,000 population in 2018. (World Health Organization, 2023) This poses a significant concern for road-safety agencies striving to mitigate traffic crashes.

The overall statistic (22.11%) encompasses the injury and fatality rates among road users in Thailand's industrial zones. (Ministry of Transport, 2023) Emphasizing statistical disclosure underscores the prevalence of traffic crashes as well as the driving risks in these zones, characterized by complex driving conditions in dense traffic, which favor speeding and significantly increase crashes.(Seefong et al., 2023) It is well-established that vehicle speed directly influences the risk of rear-end collisions with other vehicles, (Qaid et al., 2022) as high speeds preceding crashes could escalate the likelihood of crash (Qaid et al., 2022) and injury severities as well as fatality rates. (V. Hong et al., 2020; World Health Organization, 2023) These facts pose significant concerns, particularly for motorcycle riders, who are among the primary casualties in industrial-zone traffic crashes. (Department of Land Transport, 2022) In turn, these concerns warrant detailed scrutiny to uncover the deep-seated truths about the factors influencing speeding behaviors, particularly risky-riding behaviors, to effectively proffer control and prevention methods for mitigating the traffic crashes.

Several studies have revealed that human driving behavior is primarily a significant factor that contributes to traffic crashes. (Rashmi & Marisamynathan, 2023) Fundamentally, aberrant driving behaviors refer to risky behaviors that do not intentionally harm the driver or other drivers. (Yanuvianti, Coralia, & Qodariah, 2020) However, negligence and disregard for safety result in risky behaviors that may endanger drivers, passengers, pedestrians, and other road users. (Fitrianti & Yanuvianti, 2013) Although most accidents stem from unsafe behaviors, they can be addressed and prevented. (Dadipoor et al., 2020; Richard A Retting, Ferguson, & McCartt, 2003) Thus, we acknowledge that a comprehensive review and understanding of data on factors influencing speeding behaviors is one strategy for mitigating traffic crashes. Moreover, the selection of an appropriate model for accurately predicting driving/riding behavior is crucial, and one such model is the theory of planned behavior (TPB). TPB is a widely deployed psychological model for examining behavioral beliefs and intentions based on attitudes (positive/negative-behavior assessment), subjective norms (perceived social pressure regarding behavior), and perceived behavioral control (perception of ease/difficulty in controlling behavior) in each component. The model leverages these parameters to comprehensively study human behavior based on the consequences of such behavior. (Shruthi et al., 2019)

Notably, there is currently a collaborative learning effort to address long-term safety concerns. The development of a framework that emphasizes collective responsibility toward road safety and traffic-crash mitigation has resulted in the discard of the conventional approach, which emphasizes holding individuals responsible for traffic crashes. The new framework proposes that everyone in society is responsible for the safety system and traffic-crash mitigation in such a society. (Morimoto et al., 2022) This safety-concept framework comprises the three basic Es (Education, Engineering, and Enforcement) and additional Es (Emergency response), known as 3Es + Es. However, the framework has neither been explored nor thoroughly examined. Particularly, the studies on the behaviors of motorcycle riders have mainly explored TPB (Muntafi, 2022) and socio-demographic factors (V. Hong et al., 2020) to clarify the research gaps. To resolve this limitation, this study was aimed at investigating the synergistic effect of the conventional model (TPB) and the new frameworks (3Es + Es) as well as exploring the socio-demographic data of motorcycle riders to underscore the criticality of elucidating the factors influencing motorcycle riders' speed behavior in attempting to mitigate traffic crashes.

Therefore, to ensure that crucial deep insights and discoveries are not neglected, we investigated factors influencing motorcycle riders' speeding behaviors in areas with high accident rates in Thailand, e.g., the industrial zones, using the three key models: 1) the 3Es + Es safety framework, 2) the TPB model, and 3) socio-demographic data. Additionally, employing a statistically robust structural equation modeling (SEM) approach for accurate prediction, we gathered valuable and useful deep data for road-safety organizations. Our effort will facilitate policy-making as well as the establishment of appropriate standards for the effective mitigation of traffic crashes.

4.3 Literature review

Table 4.1 presents a review of the extant studies (spanning 2005–2023) on the factors influencing speeding behaviors. Thus, 27 studies were reviewed; these studies predominantly examined these factors using data obtained from general drivers. The data were obtained through questionnaire surveys based on various conceptual frameworks. These frameworks included the following: TPB, socio-demographic, PRECEDE, driver behavior questionnaire (DBQ), IF-THEN, Homel's, norm-activation model (NAM), social learning theory (SLT), and prototype/willingness model (PWM), as well as social, cultural, road environment, attitude, personality traits, and risky-driving behaviors. The review revealed that the TPB framework is the most frequently used owing to its accuracy, as a psychological model, to effectively predict behavior. However, no study has examined the synergistic effect of the TPB and 3Es + Es frameworks on investigating the factors influencing speeding behaviors while also incorporating the sociodemographic data. As most studies mainly integrated the road safety concept of the 3Es framework with the evaluation of road policies to examine similar standards across countries, this approach facilitates the gathering and refinement of effective road-safety programs. (Abbas, 2017; Effah, Umaru, Densua, George, & Kweku, 2023; Morimoto et al., 2022; Mwebesa, Chou, Yoh, & Doi, 2021; Mwebesa, Yoh, Inoi, & Doi, 2018) Over the past decade, various methodologies, including exploratory factor analysis (EFA), regression analysis, hierarchical multiple regression analysis, hierarchical regression analysis, linear network autocorrelation models (LNAM), principal component analysis (PCA), descriptive and inferential statistics, SEM, analysis of variance (ANOVA), ordered probit model, multiple regression analysis, and binary logistic regression, have been employed. Among them, SEM has attracted the most attention owing to its advantages, such as its capability of simultaneously assessing various types of relationships between variables and rigorously examining and comparing similarities and differences between two or more groups. (Dilalla, 2000)

Notably, only five accessible studies have specifically reviewed the studies on motorcycle riders' behaviors in Southeast Asia. The extant studies mainly examined riders' behaviors using TPB, PRECEDE, and Homel's models as well as other factors, such as attitude, behavior, road characteristics, motorcycle characteristics, speed, throttle, brake usage, distance, riding experience, and age. These studies applied statistical models, such as SEM, logistic regression, binary logistic regression, LNAM, and hierarchical multiple regression to analyze these factors, effectively predicting motorcycle-riding behaviors across various parameters.(Manan, Ho, Arif, Ghani, & Várhelyi, 2017; Muntafi, 2022; SUKOR & Fujii, 2011; Yuen, Karim, & Saifizul, 2014) However, these studies did not comprehensively capture the basic road-safety concept of the 3Es+Es framework, and this oversight might have resulted in the negligence of certain key insights.

Regarding the existing research gap, Table 4.1 reveals that the extant studies on the factors influencing speeding behavior mostly surveyed general drivers using the TPB framework as their primary survey method, with SEM being the most popular technique. However, no study has examined the factors influencing motorcycle riders' speeding behaviors by analyzing the interaction between the TPB and 3Es + Es frameworks using SEM statistical methods. Based on the foregoing, this study is among the first to consider the interaction between the TPB theoretical framework and 3Es + Es in investigating the factors affecting motorcycle riders' speeding behaviors.

Based on the literature review, we explored the factors influencing speeding behavior using the TPB (attitude, subjective norm, and perceived behavioral control) and 3Es + Es frameworks (education, engineering, enforcement, and emergency response). Additionally, we examined latent factors based on demographic data. Our findings will enhance the understanding of key in-depth factors influencing speeding behavior and provide valuable information and measures for policymakers aiming to effectively and contextually reduce speed-related traffic crashes. To achieve our goals, we proposed the following hypotheses for the TPB framework:

I. Hypothesis 1 (H1): Positive safety attitudes increase the intention of practicing safe behaviors, facilitating reduced-speeding behaviors.

II. Hypothesis 2 (H2): Reference groups exhibiting safe riding behavior increase the intention of practicing safe-riding behaviors, facilitating reduced-speeding behavior.

III. Hypothesis 3 (H3): Low perceived behavioral control over risky behaviors increases the intention of practicing safe-riding behaviors, facilitating reduced-speeding behavior.

Similarly, we proposed the following hypotheses for the 3Es + Es framework:

IV. Hypothesis 4 (H4): Education results in reduced speeding behavior.

V. Hypothesis 5 (H5): Safe road design (Engineering) facilitates reduced-speeding behavior.

VI. Hypothesis 6 (H6): Law enforcement leads to a reduction in speeding behavior.

VII. Hypothesis 7 (H7): Effective emergency response facilitates reduced-speeding behavior.

Table 4.1 Reviewing studies on factors influencing speeding behavior from previous studies

Paper	Country	Year	Factor					Method
			Target group	TPB	Socio demography	3Es + Es	Others	
Elliott et al. (Elliott et al., 2005)	England	2005	General Drivers	•				Hierarchical multiple regression analysis
Warner & Åberg(Warner & Åberg, 2006)	Sweden	2006	General Drivers	•				SEM
Mehmood(Mehmood, 2009)	United Arab Emirates	2009	General Drivers	•				Multiple regression analysis
Forward(Forward, 2010)	Sweden	2010	General Drivers	•				Hierarchical regression analysis
Cestac et al.**(**Cestac, Paran, & Delhomme, **2011)**	France	2011	Yung Drivers	•	•			Hierarchical regression analysis
SUKOR et al.(SUKOR & Fujii, 2011)	Malaysia	2011	Motorcycle Riders	•				SEM
Chorlton et al.(Chorlton et al., 2012)	United Kingdom	2012	Motorcycle Riders	•				Regression analysis
Cristea et al.(Cristea, Paran, & Delhomme, 2013)	France	2013	General Drivers	•	•			Hierarchical regression analysis
Dinh et al.(Dinh & Kubota, 2013)	Japan	2013	General Drivers	•	•			Hierarchical regression analysis

Table 4.1 Reviewing studies on factors influencing speeding behavior from previous studies (Continued)

Paper	Country	Year	Factor					Method
			Target group	TPB	Socio demography	3Es + Es	Others	
Scott-Parker et al.(Scott-Parker, Hyde, Watson, & King, 2013)	Australia	2013	Young Drivers				SLT and PWM	Hierarchical multiple regressions
Choon et al.(Yuen et al., 2014)	Malaysia	2014	Motorcycle Riders				Speed, Throttle, Brake, Weekly Travel Mileage, Distance, Riding Experience, and Age	SEM
Chumpawadee et al.(Chumpawadee, Homchampa, Thongkrajai, Suwanimitr, & Chadbunchachai, 2015)	Thailand	2015	Young Motorcycle Riders	•			PRECEDE Model	Descriptive and inferential statistics
Brewster et al.(Brewster, Elliott, & Kelly, 2015)	Scotland	2015	General Drivers	•			IF-THEN	ANOVAs
Rowe et al.(Rowe et al., 2016)	United Kingdom	2016	Motorcycle Riders	•				EFA
Atombo et al.(Atombo, Wu, Zhong, & Zhang, 2016)	Ghana	2016	General Drivers	•			DBQ	Regression analysis
Jovanović et al.(Jovanović, Šraml, Matović, & Mićić, 2017)	United States	2017	Motorcycle Riders	•				PCA

Table 4.1 Reviewing studies on factors influencing speeding behavior from previous studies (Continued)

Paper	Country	Year	Factor					Method
			Target group	TPB	Socio demography	3Es + Es	Others	
Manan et al.(Manan et al., 2017)	Malaysia	2017	Motorcycle Riders				Road Characteristics, Motorcyclist Riding Behavior, Motorcycle Characteristics, and Motorcyclist Characteristics	Logistic regression
Javid et al.(Javid & Al-Roushdi, 2019)	Oman	2019	General Drivers		•		NAM	SEM
Mohamad et al.(Mohamad, Abdullah, & Mohamad, 2019)	Malaysia	2019	General Drivers	•			Attitude	Binary logistic regression
Hong et al.(V. Hong et al., 2020)	Thailand	2020	Motorcycle Riders		•			LNAM
Javid & Al-Hashimi(Javid & Al-Hashimi, 2020)	Oman	2020	General Drivers	•				SEM
Javid et al.(Javid et al., 2021)	Pakistan	2021	General Drivers				NAM, Social, Cultural, and Road Environment	EFA and SEM
Muntafi(Muntafi, 2022)	Indonesia	2022	Young Motorcycle Riders	•				Hierarchical multiple regression analysis
Qaid et al.(Qaid et al., 2022)	Indonesia	2022	General Drivers	•			Homel's Model	SEM
Javid et al.(Javid et al., 2022)	Pakistan	2022	General Drivers		•			Ordered probit model

Table 4.1 Reviewing studies on factors influencing speeding behavior from previous studies (Continued)

Paper	Country	Year	Factor					Method
			Target group	TPB	Socio demography	3Es + Es	Others	
Tanglai et al.(Tanglai, Chen, Rattanapan, & Laosee, 2022)	Thailand	2022	Van Drivers		•		Personality Traits, Attitude Toward Traffic Safety, and Risky-Driving Behaviors	Hierarchical regression analysis
Alizadeh et al.(Alizadeh, Davoodi, & Shaaban, 2023)	Iran	2023	General Drivers	•				SEM

Note: •, factors considered; TPB, theory of planned behavior; EFA, exploratory factor analysis: LNAM, linear network autocorrelation models; PCA, principal component analysis; DBQ, driver behavior questionnaire; SEM, structural equation modeling, SLT, social learning theory; PWM, prototype/willingness model; NAM, norm-activated model

4.4 Methods

4.4.1 Questionnaire structure

The survey questionnaire comprised three sections. The first section examines the social and demographic information of the respondents, such as their gender, age, marital status, education level, income, occupation, riding experience, crash history, and traffic tickets. These pieces of information effectively highlight the individual differences among the respondents. The second section assesses the respondents' behavioral beliefs and intentions based on TPB comprising attitudes, subjective norms, and perceived behavioral control as well as the 3Es + Es framework comprising education, engineering, enforcement, and emergency response. The questions in this section were evaluated on a seven-point Likert scale (1 = strongly disagree, 2 = disagree, 3 = somewhat disagree, 4 = neutral, 5 = somewhat agree, 6 = agree, 7 = strongly agree). The final section evaluates the respondents' speeding behaviors. The questions were evaluated on a six-point Likert scale (1 = never, 2 = almost never, 3 = sometimes, 4 = fairly often, 5 = often, 6 = always). This section can effectively explain the individual differences among the speeding experiences of the riders.

4.4.2 Respondents

In this study, we interviewed motorcycle riders with riding experience around industrial zones in Thailand. The target participants were aged 18–60 years, as riders within this age range are characterized by enhanced physical capabilities, cognitive skills, perception, motor coordination, and readiness to respond to various situations. (Oxley, Fildes, Ihsen, Charlton, & Day, 1999; Wieschen, Makani, Radev, Voss, & Spaniol, 2023) Further, 2,000 samples were obtained, corresponding to the guideline of using more than five times the number of variables in the model, as reported in the literature. (Hair & Black, 2010; Kline, 2023) To ensure the reliability and accuracy of SEM and the results, respectively, we used a sample size that was 40 times the number of variables in the model, which included 48 variables. Therefore, the utilized sample size was 1,920 samples, with a reserve of 80 samples to account for potential loss. During the survey, 2,000 participants cooperated and responded to all the questions. This number of participants was employed to ensure that the sample represented the motorcycle riders' population as accurately as possible. Notably, we used the data from all the 2,000 participants for the model analysis. During the survey, we explained the objectives and fundamental concepts to the participants to ensure they completely understood the details of the study and provided accurate and complete information. Significant ethical considerations were submitted and approved by the Ethics Committee of Suranaree University of Technology, Thailand. The committee considered the survey and deemed it low risk, as the data do not pose greater risks to the participants than what they face in their daily lives. Moreover, the questions did not include personal or identifiable information, thus canceling out the possibility of subjecting the participants to physical or psychological stress. Additionally, Our field data collectors invited participants to join the project through verbal invitations and provided them with information sheets. All participants were fully informed about the study and provided their consent by signing the informed consent form. (COE No.5/2567; January 30, 2024).

4.4.3 Data analysis

The analyses of the social and demographic data of the respondents are presented in Supplementary Table C1 online, alongside the analyses of the dependent and independent variables, which are displayed as descriptive information. The survey recorded a complete response rate; the data from the 2,000 respondents were available for analysis, as detailed in Supplementary Tables C2 and C3 online. In this study, EFA was used to evaluate the district variables to identify or categorize variables with similar relationships and accurately determine the components that explain the main factors. The analysis included verifying the Kaiser–Meyer–Olkin (KMO) measure of the sampling adequacy and the ability of the components to explain variance. Additionally, confirmatory factor analysis was used to verify the quality of the latent-construct measurement. The analysis involved examining the composite reliability (CR) as well as the average variance extracted (AVE) before analyzing the factors influencing speeding behaviors by SEM. The model-fit was tested using the following statistics: X^2/df, ratio of the chi-square to degrees of freedom; CFI, comparative fit index; TLI, Tucker–Lewis index; RMSEA, root mean square error of approximation; and SRMR, standardized root mean square residual. The statistics were calculated to ensure accurate results and reliable conclusions. (Wisutwattanasak, Champahom, et al., 2023) All the analyses were conducted using the statistical software, Mplus version 7.0.

4.5 Results

4.5.1 Exploratory factor analysis of district variables

We performed EFA of the 3Es + Es framework and TPB models to reduce the latent factors and consolidate them into main factors reflecting different components. Table C4 online presents the results of EFA of the TPB model comprising 14 items. The KMO-test value was 0.805, explaining up to 79.494% of the variance. These factors were classified into four groups: 1) Attitude (SA1–SA3), 2) Subjective Norm (SS4–SS6), 3) Perceived Behavioral Control (SP7–SP11), and 4) Intention (SB12–SB14). Regarding the 3Es + Es framework also comprising 14 items, with a KMO-test value of 0.899, explaining up to 79.968% of the variance, these factors generated Cronbach's alpha values of 0.733–0.944. These factors were classified into four groups: 1) Education (SE15–SE17), 2) Engineering (SG18–SG21), 3) Enforcement (SF22–SF24), and 4) Emergency response (SM25–SM28). These factors generated Cronbach's alpha values of 0.863–0.921. All the statistics fell within acceptable ranges, as per the literature. (Fornell & Larcker, 1981; Theerathitichaipa et al., 2024; Wisutwattanasak, Jomnonkwao, Khampirat, Raungratanaamporn, & Ratanavaraha, 2024)

4.5.2 Confirmatory factor analysis

In this section, the importance of each item was examined and explained to confirm the possibility of using the indicators as components in each factor (Table C5 online). All the loading values exceeded 0.05, with each item being statistically significant at a 99% confidence level, thus indicating that the model achieved accuracy and consistency. (Satiennam et al., 2023) Furthermore, all the factors exhibited composite reliability (CR) values of over 0.7, and the AVE values of all the factors exceeded 0.05, falling within an acceptable range. Studies have recommended that CR and AVE values must be ≥0.7 and 0.05, respectively, to ensure statistical reliability. These statistics confirmed that SEM could be used to appropriately analyze all the factors. (Satiennam et al., 2023)

4.5.3 Factors in the theory of planned behavior model

The Attitude factor was measured using indicators SA1–SA3. The analyses of the three variables revealed that they were components of the Attitude Toward the Behavior factor with a p-value of <0.000. The loading values ranged from 0.692 to 0.818. Notably, SA2 exhibited the highest loading factor regarding Attitude, indicating the following: "I believe that speeding may result in running pedestrians/animals over" (γ = 0.818, t = 40.648).

The Subjective Norm factor was measured using indicators SS4–SS6. The analyses of these three variables revealed that they were components of the Subjective Norm factor with a p-value <0.000. The loading values ranged from 0.637 to 0.746. Notably, SS6 exhibited the highest Subjective Norm loading factor, indicating the following: "The people around me advise me not to drive faster than the legal speed limit" (γ = 0.746, t = 59.780).

The Perceived Behavioral Control factor was measured using indicators SP7–SP11. The analyses of these five variables revealed that they were components of the Perceived Behavioral Control with a p-value of <0.000. The loading values ranged from 0.729 to 0.949. Notably, SP9 displayed the highest loading factor regarding Perceived Behavioral Control, indicating the following: "I can drive faster than the legal speed limit even under unfavorable weather conditions, such as rain, fog, or heat" (γ = 0.949, t = 175.501).

Behavioral Intentions were measured using indicators SB12–SB14. The analyses of these five variables revealed that they were components of Behavioral Intentions with a p-value of <0.000. The loading values ranged from 0.708 to 0.887. Notably, SB14 exhibited the highest Behavioral Intentions loading factor, indicating the following: "I will advise my family and those around me to not exceed the legal speed limit" (γ = 0.887, t = 63.603).

4.5.4 3Es + Es Factor

The Education factor was measured using indicators SE15–SE16. The analyses of the three variables revealed that they were components of the Education factor with a p-value of <0.000. Their loading values ranged from 0.649 to 0.889. Notably, SE17 exhibited the highest Education loading factor, indicating the following:

"I believe that raising awareness in the community about the risks of speeding would help reduce speeding" (γ = 0.889, t = 83.571).

The Engineering factor was measured using indicators SG18–SG21. The analyses of the four variables revealed that they were components of the Engineering factor with a p-value of <0.000. The loading values ranged from 0.596 to 0.904. Notably, SG19 exhibited the highest Engineering loading factor, indicating the following: "I believe that installing warning and speed-limit signs would help reduce speeding" (γ = 0.904, t = 99.351).

The Enforcement factor was measured using indicators SF22–SF24. The analyses of the three variables revealed that they were components of the Enforcement factor with a p-value of <0.000. Their loading values ranged from 0.822 to 0.883. Notably, SF23 exhibited the highest Enforcement loading factor, indicating the following: "I believe that strict traffic discipline enforced by police would help reduce speeding" (γ = 0.883, t = 101.909).

The Emergency-Response factor was measured using indicators SM25–SM28. The analyses of the four variables revealed that they were components of the Emergency-Response factor with a p-value of <0.000. Their loading values range from 0.772 to 0.869. Notably, SM26 exhibited the highest loading Emergency-Response factor, indicating the following: "I believe that quick access to crash scenes by organizations when crashes occur due to speeding would reduce injuries and fatalities" (γ = 0.869, t = 92.213).

4.5.5 Structural equation modeling

The results of the model-fit test and SEM obtained by exploratory analysis are shown in Figure 4.1 and Table 4.2. The results revealed that the model appropriately fit the data, with the following statistics: $\chi 2/df$ = 2.04, CFI = 0.964, TLI = 0.961, RMSEA = 0.027, and SRMR = 0.047. A comparison of these statistics with those of previous studies revealed that they fell within acceptable ranges.(*Wisutwattanasak et al.,* 2024)

Table 4.2 Goodness-of-fit of SEM

Index	X^2/df	CFI	TLI	RMSEA	SRMR
values	2.04	0.964	0.961	0.027	0.047
Critical values	<3 (Kline, 2023; Tavakol & DENNĠCK, 2011)	>0.95 (Theerathitichaipa et al., 2024; Wisutwattanasak, Jomnonkwao, Se, & Ratanavaraha, 2022)	>0.95 (Joreskog & Sorbom, 1993)	<0.05 (Deb & Ahmed, 2018)	<0.08 (Schreiber, Nora, Stage, Barlow, & King, 2006; Theerathitichaipa et al., 2024)

* X^2/df, ratio of the chi-square to the degrees of freedom; CFI, comparative fit index; TLI, Tucker–Lewis index, RMSEA, root mean square error of approximation; SRMR, standardized root mean square residual

Table 4.3 Parameter estimation for the structural model

Variable	Coefficient	S.E.	t-Stat	*p*-Value
TPB Factor				
Attitude → Behavioral intentions	0.287	0.039	7.442	0.000
Subjective Norm → Behavioral intentions	0.183	0.038	4.747	0.000
Perceived Behavioral Control → Behavioral intentions	−0.136	0.024	−5.618	0.000
3Es + Es Factor				
Education → Speed	−0.145	0.007	−21.385	0.000
Engineering → Speed	0.399	0.029	13.647	0.000
Enforcement → Speed	−0.165	0.006	−26.577	0.000
Emergency response → Speed	−0.162	0.006	−26.158	0.000
Behavioral intentions → Speed	−0.173	0.008	−22.311	0.000
Demography				
Age2 → Attitude	0.083	0.035	2.374	0.018
Status (Single) → Attitude	−0.055	0.025	−2.187	0.029
Income → Behavioral intentions	0.094	0.024	3.836	0.000
Experience (<5 Y) → Behavioral intentions	−0.065	0.023	−2.775	0.006
Accident_Y → Emergency response	0.069	0.023	3.047	0.002
Accident _Firend_Y → Subjective Norm	0.116	0.026	4.376	0.000
Ticket_Y → Perceived Behavioral Control	−0.054	0.025	−2.184	0.029

The parameter-estimation results of the structural model revealed the factors influencing risky-riding behaviors that result in overspeeding, as presented in Table 4.3 and Figure 4.1. We observed that both sets of components effectively clarified speeding behaviors during riding. The first set was related to the TPB factors, where the results indicated that Attitude (γ = 0.28, t = 7.442), Subjective Norm (γ = 0.116, t = 4.747), and Perceived Behavioral Control (γ = −0.136, t = −5.618) influenced the riders' intention to engage in safer riding behaviors, resulting in a significant reduction in their speeding behaviors. The second set comprised the 3Es + Es factors, where the results indicated that Education (γ = −0.145, t = −21.385), Enforcement (γ = −0.165, t = −26.577), and Emergency Response (γ = −0.162, t = −26.158) significantly contributed to reduced-speeding behaviors. Conversely, Engineering (γ = 0.399, t = 13.647) significantly increased the riders' speeding behavior. Additionally, the deep dive resulted in the evaluation of the social and demographic factors of the riders, which acted as latent variables, The results revealed that the riders aged between 26 and 35 years exhibited increased attitude to practice safer riding behaviors (AGE2: γ = 0.083, t = 2.374). Moreover, the single riders exhibited decreased attitude toward safer riding behaviors (Single: γ = −0.055, t = −2.187), those with an income of 20,001–30,000 baht demonstrated increased intentions to engage in safer behaviors (Income: γ = 0.094, t = 3.836). The riders with less than five years of experience displayed decreased intention to engage in safer riding behaviors (Ex < 5: γ = −0.065, t = −2.775), whereas those with crash histories believed that efficient emergency-response agencies could contribute to increased safety (Accident_Y: γ = 0.069, t = 3.047). The riders whose relatives or acquaintances have crash histories believed that adhering to safe riding behavior increases safety (Accident_Firend_Y: γ = 0.116, t = 4.376). Finally, the riders who have received tickets exhibited significantly reduced risky-riding behaviors (Ticket_Y: γ = 0.116, t = 4.376). The results of the model parameter evaluation reveal several key factors that influence speeding behavior, which in turn lead to targeted interventions aimed at avoiding and reducing risky behaviors to promote a road safety culture.

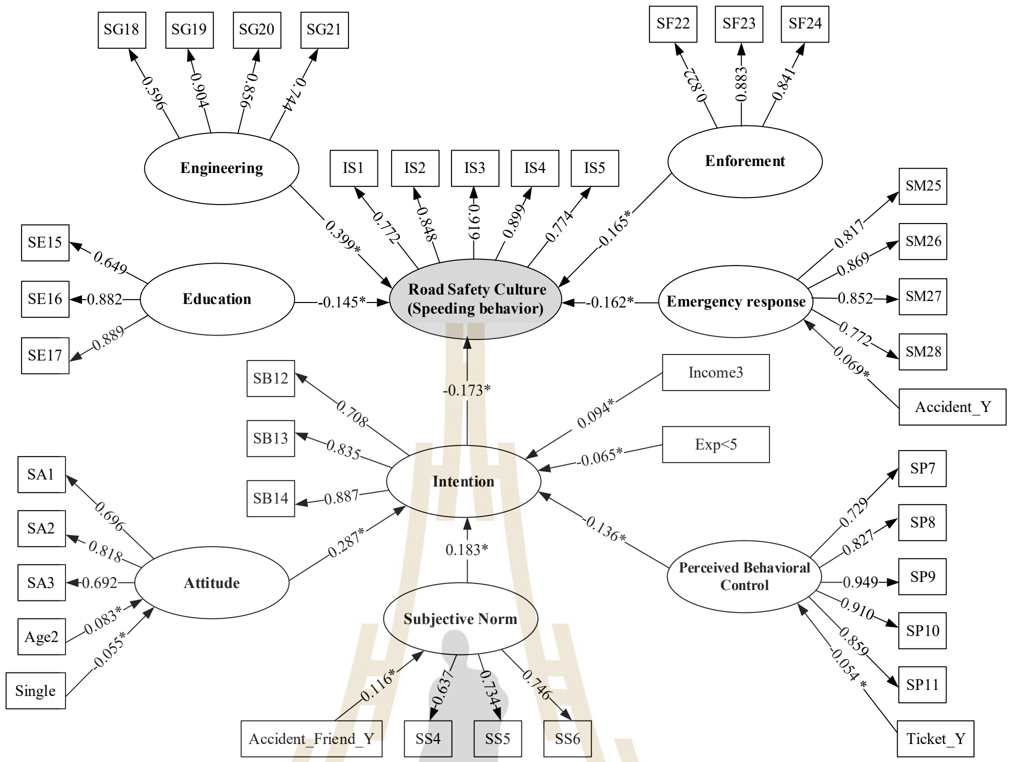

Figure 4.1 Structural Model of the Factors Influencing Risky Speeding Behavior

4.6 Discussion

4.6.1 Theory of planned behavior factors

A positive attitude toward safety increases riders' intentions to engage in safe riding, resulting in a decrease in riding speed and supporting H1. Several studies have indicated that attitude could significantly predict traffic-rule-violation and speeding behaviors. (Forward, 2009; Satiennam et al., 2023) Riders with a positive attitude toward safety might more likely exhibit good intentions toward safe riding behavior. (Yanuvianti et al., 2020). Conversely, riders with a negative attitude toward safety might engage in unsafe riding. These findings align with previous findings that riders with positive attitudes toward speeding tend to exhibit high-speeding behaviors (Shandhana Rashmi & Marisamynathan, 2024). Concurrently, riders to engage in risky-riding behaviors are more likely to do so when others agree to and accept their behaviors. (Özkan, Lajunen, Doğruyol, Yıldırım, & Çoymak, 2012)

Individuals who belong to reference groups with safe-riding behavior patterns are more likely to exhibit an increased intention to engage in safe-riding behaviors, resulting in decreased riding speed and supporting H2. This is consistent with the findings of previous studies, indicating that observing the safe-riding behaviors of other riders could significantly reduce the risky-riding intentions of a rider. (Newnam, Watson, & Murray, 2004) Regarding risky-riding behaviors, the attitudes and behaviors of others primarily account for riders' traffic violations (Yanuvianti et al., 2020). It is plausible that individuals who believe that most people around them would accept certain behaviors are motivated and feel the social pressure to exhibit such behaviors. Conversely, those who believe that most people around them would not accept certain behaviors lack the motivation to conform to such behaviors, thus creating a self-regulatory mechanism that steers them away from those behaviors. (Ajzen, 2005) Furthermore, a comparison with previous similar studies in Southeast Asia suggests that subjective norms significantly influence intentions and can effectively predict traffic violation behaviors. (Deng, Shi, & Jin, 2023; Muntafi, 2022; Satiennam et al., 2023; Tan et al., 2022) This observation may indicate that cultures with similar contexts tend to exhibit comparable driving behaviors, and such findings may reflect broader regional trends.

Perceived behavioral control influences the intention to engage in safe-riding behaviors, resulting in a decrease in the riding speed and supporting H3. This finding contradicts those of other studies that observed that individuals who perceived themselves as having control over low-risk behaviors are more confident in frequently overspeeding. (Muntafi, 2022) Additionally, if such individuals are influenced by situational facilitators for risk (e.g., driving on less congested roads, at night, alone, in a hurry, on roads with distant police checkpoints, or roads with fewer surveillance cameras), they tend to exhibit increased risky speeding behaviors. (Satiennam et al., 2023) Despite conflicting with the findings of the extant studies, our findings are supported by a notion that riders are less inclined to exhibit risky-riding behaviors when they perceive that they can control low-risk behaviors and perceive a lack of resources or opportunities to engage in risky behavior. (Ajzen, 2005) Additionally, perceived behavioral control can also reflect broader regional trends, as previous studies in

Southeast Asia have indicated that this factor is a significant predictor of behavior. (Jie-Ling & Yuan-Chang, 2021; Muntafi, 2022; Satiennam et al., 2023; Tan et al., 2022)

4.6.2 3Es + Es Factors

Education results in decreased riding-speed intentions, thus supporting H4. This finding is consistent with those of the extant studies that providing safety knowledge to riders can significantly reduce their risky behaviors and injury rates (Swaddiwudhipong, Boonmak, Nguntra, & Mahasakpan, 1998) Specifically, providing knowledge through web-based instructions (WBI) can significantly reduce risky speed-related behaviors (braking and cornering) by up to 73.93%. (Camden, Soccolich, Hickman, & Hanowski, 2019) Providing appropriate education can change riders' attitudes toward speeding, helping them to prioritize safety and adhere more to speed limits.

Engineering increases riders' intentions to engage in high riding speed, and this contradicts H5 as well as the findings of the extant studies that indicated that safe engineering designs play a role in reducing riding speeds. (Lin, Ozkul, Guo, & Chen, 2018; Satiennam et al., 2023) For instance, measures, such as road narrowing could reduce riding speeds by up to 35%, (Distefano & Leonardi, 2019) along with the creation of dedicated lanes for motorcycles, (Satiennam et al., 2023) among other engineering interventions. The findings can be explained by a psychological phenomenon known as Risk Compensation. (Levym & Miller, 2000) This phenomenon suggests that drivers tend to adjust their behavior to offset perceived risks when roads appear to be safer. Drivers may feel more confident in their ability to handle higher speeds, leading to risk-taking behaviors such as driving at excessive speeds. Moreover, road designs that unintentionally encourage higher speeds (such as highways with wide lanes, dedicated acceleration lanes, smooth curves, and clear signage) might inadvertently promote higher overspeeding. Although these designs are aimed at mitigating the risk of high-speed traffic crashes, they can also induce the misperception of the danger of overspeeding among riders, thereby increasing their risky-riding behaviors.

Enforcement results in decreased riding speed, thus supporting H6. This finding aligns with those of several studies that revealed that law enforcement measures could significantly influence speed reduction among riders. (De Pauw, Daniels, Brijs, Hermans, & Wets, 2014; Perzyński & Lewiński, 2018) Specifically, the presence and enforcement of laws over time have been shown to modify rider behavior and can significantly increase spatial effectiveness. (Karimpour, Kluger, Liu, & Wu, 2021; Yannis, Papadimitriou, & Antoniou, 2007) Thus, law enforcement coupled with strict penalties for speeding can deter speeding behaviors. Moreover, the presence of visible law enforcement officers can effectively deter overspeeding.

Emergency Response decreases driving speeds, and this supports H7. This finding is consistent with those of previous studies that revealed how emergency-response systems facilitate speed reduction and increase overall road safety. (Liu & Wang, 2019; Newnam et al., 2024) Prompt medical assistance and the application of traffic strategies in emergency responses, such as using speed-detection equipment, (Graham, Naik, McCoy, & Li, 2019; Jamil Alsayaydeh, bin Yusof, Mohan, Zakir Hossain, & Leoshchenko, 2023) monitoring high-risk areas, (Simpson, McCutcheon, & Lal, 2020; Wu, Lum, & Koper, 2021) and campaigns to raise awareness about the risks of speeding, (Desjardins & Lavallière, 2023) play significant roles in preventing overspeeding. Therefore, their roles are crucial to creating a safe driving environment that can reduce traffic crashes and mitigate the impact of unforeseen events.

4.6.3 Riders' demographic factors

Riders aged 26–35 years exhibited increased attitudes toward safety. This finding is consistent with those of previous studies that found younger riders (under 26 years old) tended to exhibit more adventurous-riding attitudes resulting in risky behaviors resulting in lower injuries and fatalities compared with their older counterparts. (Se, Champahom, Wisutwattanasak, et al., 2023) As riders aged 26–35 years are predominantly in the workforce to generate income, they might be significantly affected by crashes. This age group tends to prioritize safe riding and reduced risks. (Wisutwattanasak et al., 2024) Riders in this group prioritize safety to mitigate the impact of crashes on their lives.

Single riders exhibit decreased attitudes toward safety. This finding confirms previous findings, where unmarried riders tended to exceed the speed limits and engage in riskier behaviors compared with their married counterparts. (Javid et al., 2022; Shandhana Rashmi & Marisamynathan, 2024) Married riders might feel more responsibility and consider their family members, and these might force them to prioritize safety and avoid risks on the road to protect their well-being and livelihood. (Balakrishnan & Karuppanagounder, 2020)

Riders with monthly incomes of 20,001–30,000 baht exhibit increased intentions to engage in safe-riding behaviors. This aligns with the findings of the extant studies, indicating that riders with lower incomes (14,000–19,000 baht or less) tend to use motorcycles more often. (Iamtrakul, Chayphong, Makó, & Phetoudom, 2023) This group often faces higher financial stress, thus displaying increased stress levels, and loss of attention while riding, and these might result in riskier riding behaviors. However, we confirmed that riders with moderate to high incomes exhibited increased intentions to engage in safe-riding behaviors. These individuals experience lower financial stress compared with those with lower incomes, and financial problems do not force them into stress-induced risky behaviors. This is further supported by an extant study revealing that riders with lower incomes often experience higher financial stress, which significantly influences their risky-riding behaviors. (Okodudu, 2024)

Riders with less than five years of riding experience tended to ride faster or have a higher intention to engage in risky behaviors compared with those with more years of experience. This finding is consistent with those of the extant studies, indicating that riders with less experience have fewer coping mechanisms for stress-induced risky behaviors and unexpected events. (Okodudu, 2024) These findings indicated that less experienced riders often exhibit a decreased intention to engage in safe-riding behaviors.

Riders with crash histories believed that efficient emergency response enhances safety. This new finding from this study indicated that riders who have directly encountered severe incidents might become more aware of the risks associated with their behaviors, and this would reduce risky-riding intentions. (O'Brien, Bible, Liu, & Simons-Morton, 2017) Moreover, witnessing effective emergency responses to crashes might highlight the consequences of unsafe riding, thereby promoting safer riding behaviors.

Relatives and bystanders involved in crashes often believe that adopting safe-riding behaviors referenced by role models would increase safety. This finding is a discovery from this study. Perceiving crashes involving close individuals can exert intense emotional impacts related to pain or even the loss of loved ones. These perceptions can motivate riders to show respect or concern, especially toward supportive and exemplary riders. Such an environment might support their commitment to safer riding practices to avoid such losses. This finding is supported by those previously reported, indicating that riders would engage in certain behaviors if they perceived positive behaviors along with pressure and motivation from social environments to display such behaviors and if they believe that they can do so successfully. (Ajzen, 2005)

Riders who have received traffic tickets generally believe they need to reduce their risky-riding behaviors. This finding is supported by those previously reported, that speeding tickets are the most widely deployed tool for deterring overspeeding among riders. (Lawpoolsri, Li, & Braver, 2007) Receiving citations can reduce riders' overconfidence in their ability to control their risky behaviors, and receiving tickets serves as a stimulus for riders to reassess their riding behaviors and face the unnecessary expenses associated with traffic violations. This may lead them to become more mindful and attentive to safer riding behaviors.

4.7 Conclusions

In this study, we combined the TPB and 3Es + Es frameworks analyzed by EFA to examine the factors influencing motorcycle riders' speeding behaviors in Thailand's industrial zones. We identified several crucial factors that can determine riders' intentions to engage in speeding. Interestingly, we confirmed that Engineering factors significantly influenced speeding behaviors. Additionally, Attitude, Subjective Norm, and Perceived Behavioral Control emerged as crucial TPB factors that influence riders' intentions to exhibit safer riding behaviors, resulting in reduced-speeding behaviors. However, to obtain deeper insights, we investigated latent factors based on the socio-demographic data of the riders. The significant influential factors included age, marital status, income, riding experience, crash history, and traffic tickets. Notably, the single riders exhibited reduced safety attitudes, and those with less than five years of riding experience tended to ride faster or displayed intentions to engage in less safe-riding behaviors. To maximize the benefits of the study, important policies and guidelines for managing and addressing risky-riding behaviors leading to overspeeding among motorcycle riders in industrial zones were proposed (Table 4.4).

4.7.1 Practical applications

I. Education and awareness

General promotion: promoting the organization of educational programs and training within the community, integrating content related to 1) continuous awareness of the risks and consequences of consistently exceeding the legal speed limits can significantly reduce speeding behaviors. 2) An awareness of the risks and consequences of exceeding the legal speed limits under adverse weather conditions (rain, fog, or heat) can significantly reduce speeding behavior. 3) An awareness of technologies, such as warning signs and speed limiters can help reduce speeding behaviors. 4) Promoting good riding role models and encouraging positive attitudes toward speed usage among peers can significantly reduce speeding behavior. 5) Sharing experiences from individuals who have encountered unexpected events related to the direct and indirect impacts of crashes can significantly reduce speeding behaviors. These initiatives may focus on providing knowledge through online teaching, as WBI can significantly reduce speeding behavior by up to 73.93%. (Camden et al., 2019)

Targeted promotion: Promoting the organization of educational programs and training within specific groups of riders, including those under and over 26 and 35 years, respectively; single riders; riders with incomes of less than 20,001 baht, and riders with less than five years of experience is crucial. This process must incorporate content aimed at promoting attitudes and awareness regarding the risks and severe consequences of overspeeding. These groups are identified as having increased tendencies to exceed speed limits, thus making them the primary target for specialized safety-promotion efforts by safety organizations.

II. Engineering and infrastructural improvements: Promoting the design of safer roads by considering speed-reduction measures alongside the consequences of speeding is crucial. Furthermore, promoting the installation of speed-camera devices in high-risk areas is another strategy for reducing the likelihood of speeding by riders.(Rowe et al., 2016) Regular maintenance and upkeep are also crucial to preventing errors in road infrastructure and reducing risky behaviors among riders on the roads.

III. Legislation and enforcement: promoting strict law enforcement via severe penalties that align with speeding offenses can significantly deter speeding behaviors. For instance, measures could include increasing penalties for repeat offenders by temporarily suspending their riding licenses and establishing speed enforcement checkpoints in high-risk areas. Law enforcement must focus on the visible presence of officers where riders can see them, as this effectively deters overspeeding. (Karimpour et al., 2021)

IV. Emergency response and post-crash care: Efforts to continuously enhance efficient emergency-response capabilities are crucial, as such mechanisms play a role in preventing speeding and improving overall road safety. Additionally, providing timely medical assistance and implementing strategies for post-crash emergency response are vital to effectively reducing casualties and property damages. (Damaševičius, Bacanin, & Misra, 2023) For instance, training emergency medical services (EMS) personnel in both basic and advanced life-saving skills is vital. Equipping medical vehicles with comprehensive tools and life-saving devices ensures that injured individuals receive prompt assistance. Additionally, the development of advanced back-end systems, such as a unified communication platform, allows all relevant personnel to communicate through a single channel. This system enhances rapid inter-agency collaboration and improves decision-making accuracy in emergency situations. Moreover, the establishment of emergency service stations in high-risk areas or locations frequently associated with speed-related crashes plays a crucial role in providing timely assistance to injured individuals. Such localized support bridges critical response gaps, ensuring that emergency medical systems operate efficiently. However, listening to feedback from those who have directly experienced unforeseen events regarding the operational practices of emergency responders is another strategy for enhancing and improving emergency-response capabilities. This feedback mechanism is key to elevating the effectiveness of the emergency-response capabilities of safety organizations.

Table 4.4 Appropriate policies and guidelines proposed based on the findings using the model

Policy	Variable	Indicator	Guidelines	Planning S	Planning I	Planning L	Responsible department
1) Education and Awareness (General promotion)	Education → Speed	(+)	Promoting community awareness regarding the risks and consequences of exceeding the legal speed limits.	✓			1) Government Public Relations Department 2) Department of Land Transport 3) Department of Local Administration
	Engineering → Speed	(−)	Promoting awareness about technologies, such as warning signs and speed limiters, can contribute to reducing overspeeding.	✓			
	Behavioral intentions → Speed	(+)	Promoting consistent encouragement for peers to not exceed the legal speed limits.	✓			
	Attitude → Behavioral intentions	(+)	Promoting attitudes and awareness regarding the impacts of speeding can help prevent continuous traffic crashes involving pedestrians and animals.	✓			
	Subjective Norm → Behavioral intentions	(+)	Promoting positive examples of responsible speed riding is key to fostering safer roads.	✓			

Table 4.4 Appropriate policies and guidelines proposed based on the findings using the model (Continued)

Policy	Variable	Indicator	Guidelines	Planning S	Planning I	Planning L	Responsible department
	Perceived Behavioral Control → Behavioral intentions	(−)	Promoting awareness of the risks of speeding under adverse weather conditions (such as rain, fog, or heat)	✓			
	AF_Y → Subjective Norm	(+)	Promoting awareness of the consequences of crashes through the experiences of those who have encountered such unforeseen events can be a powerful strategy for educating the community.	✓			
1) Education and Awareness (Targeted promotion)	AGE2 → Attitude	(+)	Promoting a positive attitude toward the risks of exceeding the legal limit can be targeted at two specific groups: riders under and over ages 26 and 35 years, respectively.	✓			1) Government Public Relations Department 2) Department of Land Transport 3) Department of Local Administration
	STATUS1 (Single) → Attitude	(−)	Promoting a positive attitude toward the risks of exceeding the legal speed limit among single riders	✓			

Table 4.4 Appropriate policies and guidelines proposed based on the findings using the model (Continued)

Policy	Variable	Indicator	Guidelines	Planning S	Planning I	Planning L	Responsible department
	INCOME3 → Behavioral intentions	(+)	Promoting awareness of the consequences of exceeding the legal speed limit among riders with an income of less than 20,001 baht can be beneficial.	✓			
	EXPERIENCE (<5 Y) → Behavioral intentions	(−)	Promoting awareness of the consequences of exceeding the legal speed limit among riders with less than five years of riding experience can be effective.	✓			
2) Engineering and Infrastructural Improvements	Engineering → Speed	(−)	Designing roads with the consideration of reducing riding speeds and the impact of speed enforcement can be beneficial.			✓	1) Department of Highways 2) Department of Rural Roads
			Installing speed-camera devices in high-risk areas can effectively deter speeding.		✓		1) Royal Thai Police 2) Department of Highways 3) Department of Rural Roads

Table 4.4 Appropriate policies and guidelines proposed based on the findings using the model (Continued)

Policy	Variable	Indicator	Guidelines	Planning			Responsible department
				S	I	L	
3) Legislation and Enforcement	Enforcement → Speed	(+)	Regular maintenance of infrastructure is key to ensuring road safety.		✓		1) Department of Highways 2) Department of Rural Roads
			Establishing speed enforcement checkpoints in high-risk areas	✓			1) Royal Thai Police 2) Department of Highways 3) Department of Rural Roads
	TICKET_Y → Perceived Behavioral Control	(+)	Temporarily suspending their riding licenses		✓		
4) Emergency Response and Post-Crash Care	Emergency response → Speed	(+)	Training emergency medical services (EMS) personnel	✓			1) Ministry of Public Health of Thailand 2) National Institute for Emergency Medicine 3) Emergency Medical System of Local Administrative Organizations
			Preparation for Emergency Medical Equipment		✓		
			The development of advanced back-end systems, such as a unified communication platform		✓		
			Establishing emergency service points in high-risk areas	✓			

Table 4.4 Appropriate policies and guidelines proposed based on the findings using the model (Continued)

Policy	Variable	Indicator	Guidelines	Planning			Responsible department
				S	I	L	
	ACCIDENT_Y → Emergency response	(+)	Promoting feedback on the conduct of officials from individuals who have experienced unexpected events. This serves as a pathway to enhancing the emergency-response capabilities of safety organizations.	✓			

(+) Indicates a high possibility of exhibiting safe behaviors.

(-) Indicates a high possibility of exhibiting risky behaviors.

S = Short-range plan refers to a plan with a duration of up to one year.

I = Intermediate-range plan refers to a plan with a duration of one to five years.

L = Long-range plan refers to a plan with a duration of five years or more.

Table 4.4 reveals the challenges of managing some policies and guidelines. These policies and guidelines may involve complex factors that are challenging in some areas owing to resource constraints or the lack of central support, as well as factors that cannot be directly controlled owing to budget limitations. However, these policies and approaches can drive results if they rely on cooperation among multiple parties, including the government, the private sector, and the general public, to bring about beneficial changes. Additionally, planning for various timeframes and designating responsible departments helps in setting clearer goals and policies. Short-range planning helps address the current problems or challenges and facilitates rapid changes. Intermediate-range planning aids sustainable development and problem-solving at a broader level. Long-range planning supports the creation of a vision and the setting of directions to prepare for future changes. Planning across these different timeframes ensures that road-safety efforts are systematic and capable of effectively managing challenges. Additionally, the monitoring and evaluating the outcomes of the measures by collecting crash data before and after implementation, this data will be utilized to assess the results and refine policies and measures for future improvements.

4.8 Limitation of the study

This study has offered valuable and novel insights in many aspects. However, it was accompanied by several limitations arising from its focus on examining the speeding behavior of motorcycle riders in industrial zones characterized by heavy traffic and road designs primarily tailored to accommodate trucks and commuter vehicles, such as motorcycles. Additionally, the study centers on riders within industrial areas, who are predominantly working-age individuals. This demographic may exhibit driving behaviors and commuting patterns distinct from those of riders in other areas. As such, applying the recommendations and policy measures derived from this study to other areas or regions with differing environmental conditions should be approached with caution. Future research should broaden the scope to encompass a diverse range of areas, such as urban zones, rural regions, and commercial districts, to compare driving behaviors across varied contexts. Moreover, to effectively mitigate road crashes, future studies should aim to expand their scope by exploring secondary factors or other causes influencing risky behaviors among motorcycle riders. These factors may include road infrastructure, technological advancements, innovations, and law enforcement practices. A more comprehensive understanding of these elements would support the development of tailored policies for different contexts, enabling policymakers to identify and implement more effective strategies for reducing road crashes.

4.9 Acknowledgments

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CHAPTER V
CONCLUSION AND RECOMMENDATION

Road traffic crashes remain a critical global issue, as they continue to claim lives worldwide. Current statistics indicate that approximately 1.19 million people die each year due to road traffic crashes, equating to a fatality rate of 15 deaths per 100,000 population. This issue has posed a significant challenge for countries worldwide, particularly in developing nations, which account for 92% of all traffic-related fatalities. As a result, the number of injuries and fatalities in developing countries remains substantially higher than in developed nations.

Thailand, as a developing country undergoing social, economic, and industrial growth, continues to face persistent road safety challenges. Consequently, the country ranks among the leading nations in Asia experiencing severe road traffic crash problems. Statistical analyses have shown that road traffic crashes in Thailand are predominantly concentrated in industrial areas. The complexity of driving conditions, particularly in densely populated and high-traffic areas, significantly elevates the risk of crashes, especially those involving motorcycles and trucks, which contribute to some of the highest fatality rates. Furthermore, when classifying crashes by vehicle type, statistical data indicate that crashes involving motorcycles and trucks account for more than 50% of all reported road traffic crashes. Given these circumstances, a comprehensive understanding of the key factors influencing risk behaviors and crash severity is crucial. Implementing precise, evidence-based measures tailored to specific geographic contexts will ultimately enhance the effectiveness of road safety strategies. To achieve these objectives, this study aims to investigate the critical factors influencing risk behaviors and crash severity within industrial areas. The research is structured around three primary objectives: 1) To develop a model for predicting the factors influencing the severity of truck-involved and non-truck- involved collisions in industrial areas in

Thailand 2) To develop a model for predicting the factors influencing the risky behaviors of truck drivers in industrial areas in Thailand 3) To develop a model for predicting the factors influencing the speed-related behaviors of motorcycle riders in industrial areas in Thailand using Structural Equation Models. The details and conclusions are as follows:

5.1 Factors Influencing the Severity of Truck-Involved and Non-Truck-Involved Crashes

This specific objective utilizes road traffic crash data from Thailand from 2020 to 2022 to examine factors influencing the severity of injuries and fatalities in both truck-involved and non-truck-involved crashes. Four key factors were analyzed: 1) Roadway Characteristics 2) Cause of Assumption 3) Crash Characteristics and 4) Weather Conditions. The severity levels of injuries and fatalities were classified into two categories: PDO/minor injury and severe/fatal injury. The analysis of crash models for truck-involved crashes identified three major factors that significantly increased injury severity: Darting in front of a vehicle, Head-on collisions, Pedestrian collisions, These factors were found to contribute to a higher likelihood of severe injuries and fatalities.

For the analysis of crash models in non-truck-involved crashes, the following factors were found to significantly increase injury severity: Tailgating, Running signs/signals, Angle collisions, Head-on collisions, Overtaking collisions, Pedestrian collisions, Obstruction collisions, Collisions during overcast conditions, these factors were found to contribute to a higher likelihood of severe injuries and fatalities. Furthermore, a comparative analysis of both models revealed that head-on collisions and pedestrian collisions were statistically significant factors contributing to increased injury severity in both truck-involved and non-truck-involved crashes. Based on these findings, road safety policies and measures have been established and categorized into two main strategies: Safety policies and measures for trucks and Safety policies and measures for general vehicles

5.2 Factors Influencing Risky Driving Behavior of Truck Drivers

This specific objective focuses on developing a model to identify factors influencing risky driving behavior among truck drivers in major industrial areas of Thailand. The study involved a survey of 600 truck drivers operating in these key industrial areas. A correlated random parameter logit model was applied, incorporating unobserved heterogeneity in driver behavior. The analysis was based on two psychological theories: the Health Belief Model (HBM) and the Protection Motivation Theory (PMT). The findings provided in-depth insights, uncovering key overlooked variables. The study revealed several significant factors influencing risk-taking behavior among truck drivers: perceived susceptibility (When drivers perceive the risk of crashes while driving), perceived severity (When drivers feel that crashes will impact their work), perceived barriers (when truck drivers perceive that fastening seat belts causes discomfort, and when they perceive safety equipment for vehicles as expensive and unaffordable), cues to action (When truck drivers encounter safe driving campaigns), and health motivation (When truck drivers prioritize adequate rest and relaxation). These factors significantly impact truck drivers' risky behaviors. Upon examining the differences that influence the mean of random parameters, it was found that truck drivers who feel uncomfortable wearing a seatbelt tend to show a lower mean of familiarity with the routes they drive. This indicates that truck drivers who are familiar with the routes and find seatbelt use uncomfortable tend to engage in riskier driving behaviors. Similarly, truck drivers who are familiar with the routes and perceive safety equipment in the vehicle as expensive and unaffordable also exhibit increased risky driving behavior. Additionally, the study proposes several useful recommendations for developing road safety policies and measures aimed at reducing risky driving behaviors among truck drivers, ultimately aiming to decrease injury and fatality rates on the roads. These recommendations can be categorized into seven main measures, derived from the findings of the model: 1) Promoting Perceived Susceptibility 2) Promoting Perceived Severity 3) Promoting Perceived Benefits 4) Promoting Perceived Barriers 5) Promoting Cues to Action 6) Promoting Health Motivation 7) Promoting Response Efficacy These strategies can help reduce the risk-taking behavior of truck drivers, enhancing road safety and minimizing crashes and fatalities.

5.3 Factors Influencing the Speeding Behavior of Motorcycle Riders

This specific objective examines the factors that influence the speeding behavior of motorcycle riders. The study surveyed 1,200 motorcycle riders in industrial areas of Thailand, using both the traditional Theory of Planned Behavior (TPB) framework and a newly proposed 3Es+Es framework, which has been overlooked in many previous studies. The application of these two frameworks provides new insights and perspectives into the speeding behavior of motorcycle riders. The study identified several key factors that predict the intention to engage in speeding behavior on the roads. Notably, the Engineering factor was found to significantly increase speeding behavior. Additionally, Attitude, Subjective Norm, and Perceived Behavioral Control all key components of TPB were found to significantly influence the intention to engage in safer driving behaviors, leading to reduced speeding.

To gain deeper insights into risky behavior in this context, the study also examined latent factors from the socio-demographic and personal data of the riders. The factors that significantly influenced risky behavior included age, marital status, income, driving experience, crash history, and traffic violations. Among these, it was found that riders who are single tend to have a lower attitude toward safety, while those with less than 5 years of driving experience are more likely to speed or show a reduced intention to engage in safe driving behaviors. Furthermore, important guidelines were proposed, including policies and measures to manage and address risky behaviors leading to speeding among motorcycle riders. These policies and measures can be divided into four main strategies: 1) Education and Awareness 2) Engineering and Infrastructure Improvements 3) Legislation and Enforcement 4) Emergency Response and Post-crash Care.

These strategies aim to address the root causes of risky driving behaviors and contribute to enhanced safety on the roads, specifically targeting motorcycle riders.

5.4 Recommendations

The three key research findings reveal important factors influencing risky behavior and the severity of crashes in industrial areas, along with suitable recommendations and strategies to enhance road safety. Regarding the results from examining the factors affecting crash severity, it is evident that the factors influencing the severity of crashes involving trucks and those not involving trucks differ. Therefore, it is crucial for policymakers to prioritize safety measures appropriately, ensuring that no specific factors are overlooked, in order to achieve comprehensive and effective road safety improvements in Thailand. The results from examining the behavior of truck and motorcycle drivers reveal that the psychological perspectives of the Health Belief Model (HBM) and Protection Motivation Theory (PMT) remain powerful concepts and factors for assessing driver behavior. These concepts provide valuable insights into the behavior of truck drivers, which are beneficial for policymakers involved in promoting and raising awareness about road safety for truck drivers. Additionally, these insights can assist transportation authorities in incorporating specific safety lessons and content related to truck drivers in the driver's license testing process. Furthermore, the application of the 3Es+Es safety framework, combined with the traditional Theory of Planned Behavior (TPB) framework, in examining motorcycle rider behavior provides a new perspective on rider behavior. This approach reveals valuable insights that benefit organizations involved in safety efforts, including the Ministry of Public Health, the Department of Highways, the Department of Rural Roads, the Department of Land Transport, local administrative organizations, the Royal Thai Police, the Public Relations Department, the National Institute for Emergency Medicine, and the emergency medical systems of local administrative organizations. These findings are crucial for the formulation of policies and measures to address and reduce risky behaviors among motorcycle riders.

5.5 Limitations and Future Direction

Although this study provides valuable insights and numerous benefits, it does have limitations. Firstly, the factors influencing the severity of crashes may not encompass all the relevant variables. Therefore, to gain a more comprehensive understanding, it is necessary to further consider additional factors, such as road characteristics (e.g., the number of lanes) and traffic conditions (e.g., traffic volume). Nevertheless, if efforts are made to gather a more extensive dataset by examining these factors, it would significantly improve the accuracy and comprehensiveness of the analysis in the future, addressing the limitations and enhancing the examination of factors influencing crash severity. Secondly, the examination of truck drivers' behavior without considering demographic factors such as gender, age, and income may result in missing important information. Therefore, future research should investigate driver behavior in a more comprehensive manner while taking into account the demographic factors of the drivers as well. This would provide a more complete understanding of the influences on driver behavior. Thirdly, the examination of motorcycle rider behavior may not fully address other causes such as alcohol consumption or tailgating, which are leading factors influencing risky driving behavior. To gain deeper insights into driving behavior, investigating additional factors or causes beyond speed-related behaviors would be beneficial for policymakers in developing comprehensive and effective safety measures for motorcyclists. Finally, this study focused on the industrial areas in Thailand. Therefore, the implementation of the policies and safety measures proposed in this study should be carried out cautiously, especially when extending to regions outside industrial zones or areas with different context

APPENDIX A

List of Publications

List of Publications

Seefong M, Wisutwattanasak P, Se C, Theerathitichaipa K, Jomnonkwao S, Champahom T, et al. Big Data Analytics with the Multivariate Adaptive Regression Splines to Analyze Key Factors Influencing Accident Severity in Industrial Zones of Thailand: A Study on Truck and Non-Truck Collisions. Big Data and Cognitive Computing. 2023;7(3):156.

Seefong, M., Wisutwattanasak, P., Se, C. *et al.* A study of motorcycle riders related to speeding behavior in Thailand’s Industrial zones. *Sci Rep* **14**, 29889 (2024). https://doi.org/10.1038/s41598-024-81793

APPENDIX B

Data description of the truck and non-truck crash severity model.

Data description of the truck and non-truck crash severity model.

Table B1 Data description of the truck and non-truck crash severity model

Variables	Truck				Non-truck			
	Severe/Fatal		PDO/Minor		Severe/Fatal		PDO/Minor	
	Freq	%	Freq	%	Freq	%	Freq	%
Roadway Characteristics Factor								
1) Interchange road/Ramps (1 If crash occurred on interchange road/ramps, 0 Otherwise)	1	1.28	77	98.72	0	0.00	0	0.00
2) Access road (1 if crash occurred on access road, 0 Otherwise)	0	0.00	0	0.00	6	27.27	16	72.73
3) Wide curved road (1 if crash occurred on wide curved road, 0 Otherwise)	0	0.00	35	100.00	0	0.00	0	0.00
4) Curved road (1 if crash occurred on curved road, 0 Otherwise)	33	10.68	276	89.32	60	15.15	336	84.85
5) Curved slope road (1 if crash occurred on curved slope road, 0 Otherwise)	23	13.53	147	86.47	21	15.79	112	84.21
6) Sharp curve road (1 if crash occurred on sharp curve road, 0 Otherwise)	0	0.00	0	0.00	4	28.57	10	71.43
7) Expressway (1 if crash occurred on expressway, 0 Otherwise)	9	2.43	362	97.57	0	0.00	0	0.00
8) Straight road (1 if crash occurred on straight road, 0 Otherwise)	596	9.69	5554	90.31	716	8.91	7319	91.09
9) Gradient road (1 If crash occurred on gradient road, 0 Otherwise)	24	21.05	90	78.95	7	15.22	39	84.78
10) T-junction (1 if crash occurred at the T-junction, 0 Otherwise)	3	60.00	2	40.00	14	41.18	20	58.82
11) Y-junction (1 if crash occurred on Y-junction, 0 Otherwise)	0	0.00	11	100.00	0	0.00	0	0.00
12) 4-leg intersection (1 if crash occurred on 4-leg intersection, 0 Otherwise)	5	35.71	9	64.29	0	0.00	0	0.00
Cause of Assumption Factor								
13) DUI (1 if driver was under influence of alcohol, 0 Otherwise)	8	23.53	26	76.47	15	23.81	48	76.19
14) Illegal overtaking (1 if driver made an illegal overtaking, 0 Otherwise)	0	0.00	0	0.00	6	24.00	19	76.00
15) Unfamiliar route (1 if driver was not familiar with the route, 0 Otherwise)	0	0.00	0	0.00	1	7.69	12	92.31
16) Exceeding the speed limit (1 if driver exceeded the speed limit, 0 Otherwise)	663	10.20	5837	89.80	681	8.92	6952	91.08

Table B1 Data description of the truck and non-truck crash severity model (Continued)

Variables	Truck				Non-truck			
	Severe/Fatal		PDO/Minor		Severe/Fatal		PDO/Minor	
	Freq	%	Freq	%	Freq	%	Freq	%
17) Tailgating (1 if driver tailgated the vehicle in front, 0 Otherwise)	0	0.00	0	0.00	9	56.25	7	43.75
18) Wrong direction (1 if driver drove in the wrong direction/against the traffic, 0 Otherwise)	0	0.00	0	0.00	7	41.18	10	58.82
19) Darting in front of a vehicle (1 if cause was due to darting in front of a vehicle, 0 Otherwise)	58	22.22	203	77.78	59	14.43	350	85.57
20) Overloading (1 if the vehicle was overloaded, 0 Otherwise)	1	4.35	22	95.65	0	0.00	0	0.00
21) Running signs/signals (1 if driver conducted a running signs/signal, 0 Otherwise)	22	32.35	46	67.65	21	50.00	21	50.00
22) Obstruction (1 if obstruction on the road, 0 Otherwise)	0	0.00	0	0.00	0	0.00	34	100.00
23) Doze Off (1 if driver dozed off, 0 Otherwise)	23	9.20	227	90.80	21	10.50	179	89.50
24) Malfunctioning equipment (1 if the vehicle had malfunctioning equipment, 0 Otherwise)	9	2.81	311	97.19	7	3.15	215	96.85
Crash Characteristics Factor								
25) Angle collision (1 if crash type was angle collision, 0 Otherwise)	9	25.71	26	74.29	9	45.00	11	55.00
26) Head-on collision (1 if crash type was head-on collision, 0 Otherwise)	84	48.55	89	51.45	63	48.46	67	51.54
27) Overtaking collision (1 if crash type was collision while overtaking, 0 Otherwise)	0	0.00	0	0.00	7	50.00	7	50.00
28) Pedestrian collision (1 if crash involved pedestrian, 0 Otherwise)	24	80.00	6	20.00	77	68.14	36	31.86
29) Sideswipe collision (1 if crash type was sideswipe collision, 0 Otherwise)	4	4.26	90	95.74	0	0.00	0	0.00
30) Rear-end collision (1if crash type was rear-end collision, 0 Otherwise)	412	10.50	3511	89.50	278	7.32	3522	92.68
31) Obstruction Collision (1 if the crash was against the obstruction on the road, 0 0therwise)	46	25.56	134	74.44	46	23.23	152	76.77
32) Curved-road rollover (1 if crash type was rollover on a curved road, 0 Otherwise)	20	4.58	417	95.42	57	12.93	384	87.07
33) Straight-road rollover (1 if crash type was rollover on a straight road, 0 Otherwise)	138	4.86	2704	95.14	291	7.34	3673	92.66
Weather Conditions Factor								
34) Fine weather (1 if crash occurred under fine weather, 0 Otherwise)	716	10.70	5973	89.30	751	9.79	6923	90.21
35) Rain (1 if crash occurred during rain, 0 Otherwise)	79	6.25	1186	93.75	58	5.99	911	94.01

Table B1 Data description of the truck and non-truck crash severity model (Continued)

Variables	Truck				Non-truck			
	Severe/Fatal		PDO/Minor		Severe/Fatal		PDO/Minor	
	Freq	%	Freq	%	Freq	%	Freq	%
36) Storm/flooding (1 if crash occurred under Storm/flooding, 0 Otherwise)	0	0.00	0	0.00	0	0.00	2	100.00
37) Fog/smoke/dust (1 if crash occurred during fog, smoke or dust, 0 Otherwise)	0	0.00	0	0.00	0	0.00	3	100.00
38) Overcast (1 if crash occurred during overcast weather, 0 Otherwise)	0	0.00	0	0.00	16	69.57	7	30.43

APPENDIX C

Definitions, descriptive statistics and statistical analysis results

Sociodemographic characteristics of motorcyclists

Table C1 Participants' sociodemographic characteristics

Variable		Frequency	Percentage (%)
Age	≤25	379	18.95
	26-35	745	37.25
	36-45	538	26.9
	≥46	338	16.9
Gender	Male	1,184	59.20
	Female	816	40.80
Status	Single	1,006	50.3
	Married	863	43.15
	Otherwise	131	6.55
Education	Primary school	173	8.65
	Lower secondary school	348	17.4
	Higher secondary	509	25.45
	Diploma/high vocational certificate	316	15.8
	Bachelor's degree	573	28.65
	Postgraduate	40	2
	Other	41	2.05
Income	≤10,000	149	7.45
	10,000-20,000	1,482	74.1
	20,001-30,000	296	14.8
	30,001-40,000	42	2.1
	≥40,000	31	1.55
Occupation	Student	93	4.65
	Government/State enterprise officer	126	6.3
	Private company	1,054	52.7
	Private business	187	9.35
	Farmer	60	3
	Laborer	418	20.9
	others	62	3.1
License	NO	416	20.8
	Yes	1,584	79.2
Experience	≤5	227	11.35
	5-10 Years	725	36.25
	11-15 Years	319	15.95

Table C1 Participants' sociodemographic characteristics (Continued)

Variable		Frequency	Percentage (%)
	16-20 Years	392	19.6
	≥20 Years	337	16.85
Ticket	Never	1,189	59.45
	At least 1 time	811	40.55
Own crash	Never	872	43.6
	At least 1 time	1,128	56.4
Relative's crash	Never	798	39.9
	At least 1 time	1,202	60.1
Relative killed in a crash	Never	1,552	77.6
	At least 1 time	448	22.4
Time	0:00-6:00 AM (Late night)	60	3
	6:00-12:00 PM (Morning)	1,355	67.75
	12:00-6:00 PM (Afternoon)	358	17.9
	6:00-12:00 AM (Night)	227	11.35

Table C2 Definition and Descriptive Statistics of Dependent Variables

Indicators	Code	Level in evaluation					
		Never	Almost never	Sometimes	Fairly often	Often	Always
Do you ride faster than the legal speed limit?	IS1	650 (32.5%)	379 (18.95%)	497 (24.85%)	267 (13.35%)	144 (7.2%)	63 (3.15%)
Do you ride into curves so fast that you think you might not be able to control the vehicle?	IS2	849 (42.45%)	478 (23.90%)	352 (17.60%)	196 (9.80%)	98 (4.90%)	27 (1.35%)
Do you ignore speed limits, especially late at night and early in the morning?	IS3	803 (40.15%)	427 (21.35%)	409 (20.45%)	229 (11.45%)	91 (4.55%)	41 (2.05%)
Do you ride faster than the legal speed limit in residential or village areas?	IS4	835 (41.75%)	495 (24.75%)	387 (19.35%)	167 (8.35%)	86 (4.30%)	30 (1.50%)
Do you ride faster than the legal speed limit when you see an open road?	IS5	696 (34.8%)	362 (18.1%)	451 (22.55%)	279 (13.95%)	133 (6.65%)	79 (3.95%)

Definition and Descriptive Statistics of Independent Variables

Table C3 Definition and Descriptive Statistics of Independent Variables

Factor	Code	Min	Max	Mean	Std. Deviation	Skewness	Kurtosis
Attitude							
1) I believe that speeding increases the risk of crashes.	SA1	1	7	6.453	0.924	−1.917	4.149
2) I believe that speeding may result in hitting pedestrians/animals.	SA2	1	7	6.334	1.021	−1.755	3.287
3) I believe that speeding leads to excessive fuel consumption.	SA3	1	7	6.015	1.208	−1.226	1.236
Subjective Norm							
4) My family and those around me do not ride faster than the legal speed limit.	SS4	1	7	5.694	1.481	−1.103	0.594
5) Passengers (rear-seat passengers) advise me not to exceed the legal speed limit.	SS5	1	7	5.675	1.505	−1.156	0.736
6) The people around me advise me not to ride faster than the legal speed limit.	SS6	1	7	5.841	1.409	−1.380	1.685
Perceived Behavioral Control							
7) I can control the vehicle even when ride faster than the legal speed limit.	SP7	1	7	3.287	1.974	0.395	−1.084
8) I can avoid crashes even when riding faster than the legal speed limit.	SP8	1	7	2.985	1.909	0.637	−0.738
9) I can ride faster than the legal speed limit even in unfavorable weather conditions such as rain, fog, or heat.	SP9	1	7	2.64	1.799	0.939	−0.148
10) I can ride faster than the legal speed limit even in heavy traffic conditions (lots of vehicles).	SP10	1	7	2.634	1.785	0.89	−0.265
11) I can ride faster than the legal speed limit even if there are police officers/speed cameras.	SP11	1	7	2.575	1.784	1.01	0.002
Behavioral intentions							
12) I will not exceed the legal speed limit when riding in the future.	SB12	1	7	5.781	1.33	−1.089	0.953
13) I am determined not to exceed the legal speed limit.	SB13	1	7	5.982	1.204	−1.279	1.554

Table C3 Definition and Descriptive Statistics of Independent Variables (Continued)

Factor	Code	Min	Max	Mean	Std. Deviation	Skewness	Kurtosis
14) I will advise my family and those around me not to exceed the legal speed limit.	SB14	1	7	6.051	1.163	−1.196	1.093
Education							
15) I have noticed that campaigns about the risks of speeding constantly remind me of safety.	SE15	1	7	5.985	1.217	−1.484	2.447
16) I believe that rider training courses on the risks of speeding would help reduce speeding.	SE16	1	7	5.915	1.191	−1.223	1.465
17) I believe that raising awareness in the community about the risks of speeding would help reduce speeding.	SE17	1	7	5.932	1.169	−1.177	1.554
Engineering							
18) I believe that designing separate lanes for high-speed vehicles would help reduce crashes.	SG18	1	7	5.743	1.314	−1.187	1.474
19) I believe that installing warning and speed-limiting signs would help reduce speeding.	SG19	1	7	5.793	1.2	−1.021	1.061
20) I believe that installing speed warning and limiting devices (traffic bollards) would help reduce speeding.	SG20	1	7	5.797	1.198	−1.027	1.12
21) I believe that implementing speed limit zones, such as around schools, communities, and pedestrian areas, would help reduce speeding.	SG21	1	7	5.992	1.143	−1.179	1.321
Enforcement							
22) I believe that strict law enforcement on speeding would help reduce speeding.	SF22	1	7	6.007	1.097	−1.166	1.39
23) I believe that strict traffic discipline enforced by police would help reduce speeding.	SF23	1	7	5.997	1.116	−1.250	1.685
24) I believe that increasing penalties for speeding would help reduce speeding.	SF24	1	7	6.000	1.151	−1.329	2.004

Table C3 Definition and Descriptive Statistics of Independent Variables (Continued)

Factor	Code	Min	Max	Mean	Std. Deviation	Skewness	Kurtosis
Emergency response							
25) I believe that improving the standards of care by organizations when crashes occur due to speeding would reduce injuries and fatalities.	SM25	1	7	5.999	1.107	−1.111	1.239
26) I believe that quick access to crash scenes by organizations when crashes occur due to speeding would reduce injuries and fatalities.	SM26	1	7	6.036	1.159	−1.294	1.646
27) I believe that training and developing emergency responders effectively when crashes occur due to speeding would reduce injuries and fatalities.	SM27	1	7	6.004	1.165	−1.324	1.865
28) I believe that upgrading the standards of rescue equipment by organizations when crashes occur due to speeding would reduce injuries and fatalities.	SM28	1	7	6.048	1.144	−1.309	1.744

Table C4 Model results of exploratory factor analysis

Item	Component				Cronbach's alpha
	1	2	3	4	
TPB Factor					
Attitude					0.818
SA1	0.849				
SA2	0.806				
SA3	0.789				
Subjective Norm					0.733
SS4		0.687			
SS5		0.801			
SS6		0.871			
Perceived Behavioral Control					0.944
SP7			0.842		
SP8			0.911		
SP9			0.935		
SP10			0.932		

Table C4 Model results of exploratory factor analysis (Continued)

Item	Component				Cronbach's alpha
	1	2	3	4	
SP11			0.905		
Behavioral intentions					0.884
SB12				0.875	
SB13				0.828	
SB14				0.775	
3Es+Es Factor					
Education					0.879
SE15	0.848				
SE16	0.865				
SE17	0.779				
Engineering					0.863
SG18		0.839			
SG19		0.779			
SG20		0.721			
SG21		0.679			
Enforcement					0.9
SF22			0.763		
SF23			0.782		
SF24			0.807		
Emergency response					0.921
SM25				0.774	
SM26				0.85	
SM27				0.853	
SM28				0.861	

Note: 3Es+Es factor: KaiserMeyer-Olkin (KMO) = 0.899 and total variance explained 79.968% and TPB Factor: KaiserMeyer-Olkin (KMO) = 0.805 and total variance explained 79.494%

Table C5 Model results of confirmatory factor analysis

Variable	Loading	S.E.	t-Stat	P-Value	CR	AVE
TPB Factor						
Attitude					0.781	0.544
SA1	0.696	0.023	30.542	0		
SA2	0.818	0.020	40.648	0		
SA3	0.692	0.021	33.668	0		
Subjective Norm					0.749	0.5
SS4	0.637	0.013	48.74	0		
SS5	0.734	0.014	50.684	0		
SS6	0.746	0.012	59.78	0		
Perceived Behavioral Control					0.933	0.736
SP7	0.729	0.013	54.985	0		
SP8	0.827	0.009	88.352	0		
SP9	0.949	0.005	175.501	0		
SP10	0.91	0.007	138.825	0		
SP11	0.859	0.009	99.835	0		
Behavioral intentions					0.853	0.662
SB12	0.708	0.018	39.201	0		
SB13	0.835	0.015	54.975	0		
SB14	0.887	0.014	63.603	0		
3Es+Es Factor						
Education					0.853	0.663
SE15	0.649	0.019	33.559	0		
SE16	0.882	0.011	81.573	0		
SE17	0.889	0.011	83.571	0		
Engineering					0.862	0.615
SG18	0.596	0.018	32.56	0		
SG19	0.904	0.009	99.351	0		
SG20	0.856	0.01	88.418	0		
SG21	0.744	0.015	48.113	0		
Enforcement					0.886	0.721
SF22	0.822	0.011	76.515	0		
SF23	0.883	0.009	101.909	0		
SF24	0.841	0.010	84.452	0		
Emergency response					0.897	0.686
SM25	0.817	0.011	72.838	0		
SM26	0.869	0.009	92.213	0		
SM27	0.852	0.010	86.143	0		
SM28	0.772	0.014	53.794	0		

Table C5 Model results of confirmatory factor analysis (Continued)

Variable	Loading	S.E.	t–Stat	P-Value	CR	AVE
Speeding Behavior					0.925	0.713
IS1	0.772	0.011	70.877	0		
IS2	0.848	0.009	98.927	0		
IS3	0.919	0.006	153.19	0		
IS4	0.899	0.007	133.825	0		
IS5	0.774	0.012	66.644	0		

BIOGRAPHY

Ms. Mallika Seefong was born on January 9, 1997, in Phichit Province, Thailand. She completed her primary education at Kitipittaya School and her lower and upper secondary education at Khaosai Thapklo Phittaya School. She earned her bachelor's degree in Logistics Engineering from Pibulsongkram Rajabhat University and a Master's degree in Logistics and Supply Chain from Naresuan University. She was awarded a scholarship to pursue a degree of Doctor of Philosophy in Civil, Transportation, and Geo-resources Engineering at Suranaree University of Technology.