MODELLING IN MOTORCYCLIST NEAR MISSES

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แบบจำลองการเกือบเกิดอุบัติเหตุในผู้ขับขี่รถจักรยานยนต์

นางสาวณัฏฐาภรณ์ หาญทนงค์

วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิศวกรรมศาสตรดุษฎีบัณฑิต
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MODELLING IN MOTORCYCLIST NEAR MISSES

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คำสำคัญ: ประเทศที่มีรายได้ต่ำและปานกลาง/ความปลอดภัยบนท้องถนน/เหตุการณ์เกือบเกิดอุบัติเหตุ/การวิเคราะห์สมการโครงสร้างหลายกลุ่ม/รถจักรยานยนต์

การป้องกันการเกือบเกิดอุบัติเหตุ (Near miss) เป็นมาตรการเชิงรุกที่สำคัญ เนื่องจากสามารถป้องกันเหตุการณ์ที่มีความเสี่ยงไม่ให้กลายเป็นอุบัติเหตุที่ส่งผลเสียหายทั้งชีวิตและทรัพย์สินได้ อีกทั้งยังเป็นการสร้างสังคมที่ปลอดภัย ซึ่งเป็นการยกระดับมาตรฐานคุณภาพชีวิตของประชาชนให้สูงขึ้นและเป็นองค์ประกอบสำคัญของการเป็นสังคมหรือชุมชนที่ยั่งยืน ในปัจจุบัน ประเทศที่มีรายได้ต่ำและปานกลาง (LMIC) มีอัตราการเสียชีวิตจากอุบัติเหตุรถจักรยานยนต์สูงที่สุดเป็นอันดับต้น ๆ ของโลก ส่วนใหญ่เป็นกลุ่มผู้ใช้ถนนที่เปราะบาง (vulnerable road users) ได้แก่ ผู้ขับขี่รถจักรยานยนต์ ดังนั้น การมุ่งเน้นหาแนวทางการลดความเสี่ยงในการเกิดอุบัติเหตุ หนึ่งในองค์ความรู้ที่สำคัญคือ การป้องกันการเกือบเกิดอุบัติเหตุ (Near miss) จึงเป็นสิ่งที่จำเป็นอย่างยิ่ง จากการทบทวนงานวิจัย พบว่ามิติสำคัญที่เกี่ยวข้องกับความเสี่ยงในการเกือบเกิดอุบัติเหตุ (Near miss) หากทำการศึกษาอย่างละเอียด จะช่วยลดความเสี่ยงในการเกิดอุบัติเหตุได้ ซึ่งหมายถึงการลดจำนวนผู้เสียชีวิตและบาดเจ็บจากอุบัติเหตุในรถจักรยานยนต์ จากผลการทบทวนงานวิจัย พบว่ามี 3 มิติที่สำคัญ โดยแบ่งเป็น 3 ผลการศึกษา ได้แก่

การศึกษาที่ 1 การเปรียบเทียบปัจจัยเสี่ยงต่อการเกือบเกิดอุบัติเหตุระหว่างพื้นที่เขตเมืองและเขตชนบท: เนื่องจากลักษณะกายภาพของถนนในเขตเมืองและชนบทแตกต่างกัน ทำให้มีปัจจัยเสี่ยงต่อการเกือบเกิดอุบัติเหตุที่แตกต่างกัน การศึกษานี้มีวัตถุประสงค์เพื่อพัฒนาแบบจำลองพฤติกรรมเสี่ยงในการเกือบเกิดอุบัติเหตุในผู้ขับขี่รถจักรยานยนต์ของประเทศไทย และเปรียบเทียบแบบจำลองในพื้นที่เขตเมืองและชนบท โดยใช้ Multi-group Structural Equation Modeling (SEM) การรวบรวมข้อมูลทำใน 6 ภูมิภาคจากผู้ขับขี่ 2,002 คน พบว่าปัจจัยด้านความผิดพลาดในการควบคุม (Control errors), การละเมิดกฎจราจร (Violations) และการใช้อุปกรณ์เพิ่มความปลอดภัย (Safety equipment) ส่งผลต่อการเกือบเกิดอุบัติเหตุอย่างมีนัยสำคัญ ซึ่งคำแนะนำจากผลการศึกษานี้สามารถช่วยเพิ่มมาตรการด้านความปลอดภัยในการขับขี่

การศึกษาที่ 2 การเปรียบเทียบปัจจัยเสี่ยงต่อการเกือบเกิดอุบัติเหตุระหว่างผู้ขับขี่รถจักรยานยนต์ในกลุ่มวัยรุ่นและผู้สูงอายุ: เนื่องจากกลุ่มเยาวชนหรือวัยรุ่นมีจำนวนอุบัติเหตุทางรถจักรยานยนต์ที่สูงมาก อีกทั้งกลุ่มบุคคลเหล่านี้ยังมีบทบาทสำคัญในการพัฒนาประเทศในอนาคต ขณะเดียวกันจำนวนผู้สูงอายุทั่วโลกมีแนวโน้มเพิ่มขึ้นอย่างต่อเนื่องพร้อมกับจำนวนอุบัติเหตุเช่นกัน โดยเฉพาะในประเทศที่มีรายได้ต่ำและปานกลาง (LMIC) การศึกษานี้จึงมุ่งพัฒนาแบบจำลองพฤติกรรมเสี่ยงในการเกือบเกิดอุบัติเหตุในผู้ขับขี่รถจักรยานยนต์ของประเทศไทย และเปรียบเทียบแบบจำลองในกลุ่มวัยรุ่นและผู้สูงอายุ โดยใช้ Multi-group Structural Equation Modeling (SEM) การรวบรวมข้อมูลจาก 6 ภูมิภาค พบว่าปัจจัยด้านความผิดพลาดในการควบคุม (Control errors) ส่งผลต่อการเกือบเกิดอุบัติเหตุในทั้งสองกลุ่มอย่างมีนัยสำคัญ ซึ่งคำแนะนำจากผลการศึกษานี้สามารถช่วยเพิ่มมาตรการป้องกันอุบัติเหตุที่เหมาะสมสำหรับทั้งกลุ่มวัยรุ่นและผู้สูงอายุ

การศึกษาที่ 3 การพัฒนาแบบจำลองความสัมพันธ์ระหว่างทัศนคติและการรับรู้ต่อการเกิด Near miss ของผู้ขับขี่รถจักรยานยนต์ในประเทศกำลังพัฒนา: การศึกษานี้ใช้ Structural Equation Modeling (SEM) ในการพิจารณาปัจจัยด้านการรับรู้เกี่ยวกับความกลัวในการขับขี่ (Fear of Traffic), ทัศนคติเกี่ยวกับความประมาท (Attitude for Distracted Riding), การรับรู้เกี่ยวกับการหลีกเลี่ยงการขับขี่ในการจราจรแบบผสม (Avoidance of Mixed Traffic) และการรับรู้ความสามารถในการควบคุมพฤติกรรม (Perceived Behavioral Control) จากการศึกษาพบว่า การรับรู้ความสามารถในการควบคุมพฤติกรรม (Perceived Behavioral Control) มีความสัมพันธ์เชิงบวกกับความเสี่ยงต่อเหตุการณ์เกือบเกิดอุบัติเหตุ โดยเฉพาะเมื่อใช้โทรศัพท์มือถือขณะขับขี่หรือขับขี่ด้วยความเร็วสูงในทางโค้ง ขณะที่การหลีกเลี่ยงการขับขี่ร่วมกับการจราจรแบบผสม (Avoidance of Mixed Traffic) มีความสัมพันธ์เชิงลบ ข้อเสนอแนะจากการศึกษานี้ประกอบด้วยการบังคับใช้กฎหมาย มาตรการด้านความปลอดภัย การปรับปรุงโครงสร้างพื้นฐานและสภาพแวดล้อมถนน รวมถึงการอบรมเพื่อเพิ่มความรู้และทักษะในการขับขี่รถจักรยานยนต์อย่างปลอดภัย

สาขาวิชาวิศวกรรมขนส่ง ลายมือชื่อนักศึกษา..........ณัฏฐาภรณ์..........

ปีการศึกษา 2566 ลายมือชื่ออาจารย์ที่ปรึกษา..........................

ลายมือชื่ออาจารย์ที่ปรึกษาร่วม..........................

NATTHAPORN HANTANONG: MODELLING IN MOTORCYCLIST NEAR MISSES. THESIS ADVISOR: VATANAVONGS RATANAVARAHA, Ph.D. 212 PP.

Keyword: Low- and Middle-Income Countries (LMICs)/Road traffic safety/Near-crash/ Multi-group SEM/Motorized Two-Wheelers (MTWs)

Preventing near misses is a crucial proactive measure, as it can avert high-risk events from escalating into accidents that cause significant damage to life and property. Furthermore, it contributes to building a safer society, thereby elevating the standard of living for citizens and constituting a key component of a sustainable society or community. Currently, low- and middle-income countries (LMICs) have some of the highest rates of motorcycle accident fatalities globally, primarily affecting vulnerable road users, including motorcyclists. Therefore, focusing on ways to reduce the risk of accidents is essential, and an important area of knowledge in this regard is the prevention of near-misses. A review of the research identifies key dimensions related to the risk of near misses, which, if studied in detail, can help reduce the occurrence of accidents, subsequently decreasing fatalities and injuries from motorcycle accidents. The review delineates three significant dimensions, categorized into three studies:

Study 1: Analyzing near-miss incidents and risky riding behavior in Thailand: A comparative study of urban and rural areas. The physical characteristics of roads in urban and rural areas differ, leading to varying risk factors for near-misses. This study aims to develop a model of risky behaviors leading to near-misses among motorcyclists in Thailand and compare models between urban and rural areas using multi-group structural equation modeling (SEM). Data was collected from 2,002 riders across six regions. The study found that control errors, traffic violations, and the use of safety equipment significantly impact near-misses. Recommendations from this study can enhance safety measures for motorcyclists.

Study 2: Assessing the self-report instruments of younger versus older riders involved in near-miss motorcycle incidents. Adolescents and young adults have high

rates of motorcycle accidents and play a crucial role in the future development of the country. Simultaneously, the global elderly population is increasing, along with accident rates, particularly in LMICs. This study aims to develop a model of risky behaviors leading to near-misses among motorcyclists in Thailand and compare models between adolescents and the elderly using SEM. Data were collected from six regions, revealing that control errors significantly impact near misses in both groups. Recommendations from this study can inform appropriate accident prevention measures for both adolescents and the elderly.

Study 3: The role of perception failures in near-misses among motorcyclists. This study employs structural equation modeling (SEM) to examine factors such as fear of traffic, attitude toward distracted riding, avoidance of mixed traffic, and perceived behavioral control. The study found that perceived behavioral control positively correlates with the risk of near misses, particularly when using a mobile phone while riding or speeding on curves. Conversely, avoidance of mixed traffic negatively correlates with near misses. Recommendations from this study include law enforcement, safety measures, infrastructure and environmental improvements, and training to enhance knowledge and skills for safe motorcycle riding.

School of Transportation Engineering

Academic Year 2023

Student's Signature......ณัฏฐาภรณ์......

Advisor's Signature..........................

Co-advisor's Signature..........................

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LIST OF ABBREVIATIONS

α	Statistically significant level
β	Structural coefficient
M	Mean
SD	Standard deviation
SK	Skewness
KU	Kurtosis
SE_{SK}	Standard error of skewness
SE_{KU}	Standard error of kurtosis
n	Sample size
Z	Z-Score
χ^2	Chi-squared statistic
df	Degree of freedom
p	Level of significance
CFI	Comparative fit index
TLI	Tucker Lewis index
SRMR	Standardized root mean square residual
RMSEA	Root mean square error of approximation
SEM	Structural equation modeling
CFA	Confirmatory factor analysis

LIST OF ABBREVIATIONS (Continued)

EFA	Exploratory factor analysis
CR	Composite reliability
AVE	Average variance extracted

CHAPTER I

INTRODUCTION

1.1 Rationale for the research

1.1.1 Excursion

Motorcycle usage is prevalent in developing countries, especially in Thailand, due to its convenience, speed, fuel efficiency, and cost-effectiveness. However, the increased use of motorcycles has led to a corresponding rise in motorcycle-related accidents (Liao, Lin, & Park, 2019). The fatality risk for motorcyclists is nearly eight times higher than that for car drivers (Keall & Newstead, 2012) and up to forty times higher when compared to car passengers (Šraml, Tollazzi, & Renčelj, 2012). According to the World Health Organization, approximately 1.35 million people worldwide die each year from road accidents, with an additional 20–50 million people suffering injuries or disabilities. Despite global efforts, road fatalities in low-income countries have not decreased. Low- and middle-income countries (LMICs) constitute about 85% of the world’s population and possess only 60% of the world’s registered vehicles, but they account for 93% of all road traffic deaths (Haghani, Behnood, Dixit, & Oviedo-Trespalacios, 2022). Approximately 54% of road accident fatalities occur among vulnerable road users, with the South-East Asia region experiencing the highest number of motorcycle-related deaths at 43% (World Health Organization, 2018a). These countries often lack comprehensive road user training, adherence to traffic laws, and sufficient health and road infrastructure, which significantly impacts the mortality rate of road users (Fitzpatrick & O’Neill, 2017). Consequently, it is unsurprising that Thailand ranks ninth globally and first in Asia for road accident fatalities (World Health Organization, 2018b). In Thailand, there are 21 million registered motorcycles, comprising 70% of all vehicles (Department of Land Transport, 2022).

1.1.2 The importance of Near misses

In the context of safety, Heinrich's Safety Triangle model places accidents at the apex of the pyramid, with near misses at the bottom, signifying their higher frequency and lower severity (Hamann & Peek-Asa, 2017). Although near-miss events do not result in damage, they can serve as indicators of potential collisions because they share common causation factors with actual accidents (Wright & Van der Schaaf, 2004). Moreover, lower-severity safety outcomes, such as near misses, occur more frequently, thus offering more opportunities for study (Laureshyn, Goede, Saunier, & Fyhri, 2017). A near-miss incident, also known as a near-crash, near-miss crash, or near-miss accident, is a situation where a collision or accident is narrowly avoided without causing damage (Aldred & Crosweller, 2015; Sanders, 2015; Young, Sobhani, Lenné, & Sarvi, 2014). These events can act as 'early warnings' of situations or behaviors that may lead to accidents (Aldred, Elliott, Woodcock, & Goodman, 2017), helping to identify risk factors that could lead to actual incidents. Studying and reporting near misses provides insight into situations or behaviors likely to cause accidents, allowing for timely preventive measures. Currently, near-miss incidents are used alongside police-reported crashes to identify crash hotspots in road networks and to develop safety measures and strategies (Park, Kim, & Kim, 2023). Therefore, near misses are crucial for promoting safety and reducing accident risks. Emphasizing the reporting and analysis of near misses helps identify risk factors, improve preventive measures, and foster a sustainable safety culture in society.

1.1.3 Understanding risky riding behaviors in different physical and environmental settings

Currently, motorcycles in Thailand commonly share lanes with other vehicles like cars and trucks, and fatal accidents often occur on major roads or highways (Se, Champahom, Jomnonkwao, & Ratanavaraha, 2022). A crash severity analysis conducted by Champahom et al. (2023) identified that local roads frequently witness traffic accidents and fatalities, with distinct risky riding behaviors observed between urban and rural roads. Similarly, research in the United States indicates that motorcyclists face a higher risk of fatality in urban areas compared to rural ones (U.S. Department of Transportation's, 2022). Studies such as those by Harnen, Wong, Umar, and Wan Hashim (2003) have shown that Taiwan experiences greater injury severity in motorcycle accidents on rural roads compared to urban ones. Additionally, Budd, Allen, and Newstead (2018) evaluated motorcycle-related accidents and injury risks in rural and urban areas in Australia, revealing higher injury severity in rural areas. Specifically, 35% of injury accidents (and 40% of serious injury and fatal accidents) occur in rural areas, while less than 30% of injury accidents (and more than 30% of serious injury and fatal accidents) happen in areas with speed limits of 80 km/h or higher. These findings underscore significant differences in the physical and environmental characteristics of urban and rural roads, including variances in road networks, land use, and travel patterns. Urban roads typically experience heavier traffic and stricter law enforcement, influencing motorcycle driving behavior such as law violations and speeding. Consequently, it is imperative to develop customized motorcycle safety measures and campaigns tailored to the specific challenges faced in both urban and rural areas to effectively address these issues.

1.1.4 Evaluating risky riding behaviors across age segments

In-depth studies on motorcycle accidents reveal that approximately 50% of these incidents are attributable to riders' perception failures, with the age bracket of 15–24 exhibiting the highest accident rates (ThaiRoads Foundation, 2022). A significant portion of these accidents arise from errors in control, particularly in braking techniques aimed at decelerating or halting the motorcycle. Notably, ninety percent of motorcycle riders involved in accidents, regardless of their licensing status, acquire riding skills through informal means such as friends, family, or self-training, often lacking adequate safety driving skills (ThaiRoads Foundation, 2022). Adolescent drivers face heightened accident risks due to their novice status, limited experience, and incomplete development of the physical, cognitive, and mental capacities required for motorcycle riding. Conversely, the elderly demographic, aged 50 and above, represents another vulnerable group deserving special attention and monitoring, given a sustained uptrend in mortality rates over the past five years, nearing levels comparable to those of adolescents and working-age individuals (ThaiRoads Foundation, 2022). This pattern aligns with Thailand's aging population, emphasizing the imperative of addressing road accident concerns, particularly among adolescents and young adults, to foster advancements in traffic safety.

1.1.5 Considering riders' attitudinal characteristics and risk perception

Research indicates that risk perception plays a significant role in mitigating risky behaviors and improving safety outcomes by facilitating both theoretical understanding and perceptual adjustments (Ba, Zhang, Chan, Zhang, & Cheng, 2016). Both risk perception and perceived competence are fundamental intellectual constructs, crucial in shaping models of road user behavior due to their association with behavior adjustments (Marín Puchades et al., 2018). By perceiving risks, drivers become cognizant of the hazards linked to risky actions like speeding, using mobile phones while driving, or navigating unsafe road conditions. This awareness prompts drivers to diminish such risky behaviors, thereby reducing the probability of accidents. Moreover, risk perception directly impacts safety outcomes while driving, encouraging drivers to exercise greater caution and comply with regulations, consequently lowering accident risks and enhancing road safety. Hence, risk perception stands as a vital element capable of curbing risky behaviors and fostering driving safety, exerting a substantial influence on the construction of driver behavior models and behavior adjustments. Leveraging insights from risk perception in various initiatives such as training programs, public awareness campaigns, and technological innovations can effectively bolster road safety efforts.

1.2 Purpose of the Research

The research aims to achieve the following objectives:

1) Develop models of risky behaviors leading to near-miss accidents among motorcycle riders in Thailand by utilizing the Motorcycle Rider Behavior Questionnaire (MRBQ) and comparing between urban and rural areas.

2) Develop models of risky behaviors leading to near-miss accidents among motorcycle riders in Thailand by utilizing the MRBQ and comparing adolescent and elderly riders.

3) Explore the relationship between attitude, risk perception, and near-miss incidents among motorcycle riders in Thailand.

1.3 Scope of the Research

The research scope encompasses the following aspects:

1) Population: motorcycle riders aged 18 and above residing in Thailand.

2) Study Areas: urban areas, including municipal areas, and rural areas, including tambon administrative organizations (TAOs).

3) Research Focus: Investigating driver behaviors using adapted questions from the MRBQ, studying risky behaviors of motorcycle riders in urban and rural areas regarding near-miss events, studying risky behaviors of adolescent and elderly motorcycle riders regarding near-miss events, and investigating the influence of attitude and risk perception on near-miss incidents.

1.4 Research Questions

The research seeks to address the following questions:

1) What are the risky riding behaviors associated with near-miss accidents, and how do the behavior models compare between urban and rural areas?

2) What are the risky riding behaviors associated with near-miss accidents, and how do the behavior models compare between adolescent and elderly riders?

3) What factors of attitude and risk perception contribute to near-miss incidents?

4) How can the findings contribute to the enhancement of existing safety policies?

1.5 Contribution of the Research

The research is expected to make the following contributions:

1) Provide insights into factors influencing near-miss accidents among motorcycle riders, aiding in the enhancement of existing safety policies tailored to both urban and rural contexts. Additionally, it can serve as a basis for developing self-assessment tools for riders to better understand their riding risks.

2) Offer insights into factors influencing near-miss accidents among motorcycle riders, supporting the adjustment of existing safety policies to better suit the characteristics of different age groups. Moreover, it can aid in developing self-assessment tools for adolescent and elderly riders to enhance their awareness of riding risks.

3) Provide insights into the influence of attitude and risk perception on near-miss incidents among motorcycle riders, contributing to the refinement of existing safety policies.

1.6 Organization of the Research

The research comprises five chapters, structured as follows:

1) Chapter 1: Research Principles and Justification, including Background Information, Research Objectives, Scope, Research Questions, and Contributions.

2) Chapter 2: Study to develop models of risky behaviors leading to near-miss accidents using the MRBQ, comparing urban and rural areas.

3) Chapter 3: Study to develop models of risky behaviors leading to near-miss accidents using the MRBQ, comparing adolescent and elderly riders.

4) Chapter 4: Study to explore the relationship between attitude, risk perception, and near-miss incidents among motorcycle riders in Thailand.

5) Chapter 5: Summary and Analysis of the Three Studies (Chapters 2–4).

1.7 Reference

Aldred, R., & Crosweller, S. (2015). Investigating the rates and impacts of near misses and related incidents among UK cyclists. *Journal of Transport & Health,* 2(3), 379-393. doi:https://doi.org/10.1016/j.jth.2015.05.006

Aldred, R., Elliott, B., Woodcock, J., & Goodman, A. (2017). Cycling provision separated from motor traffic: a systematic review exploring whether stated preferences vary by gender and age. *Transport Reviews,* 37(1), 29-55. doi:10.1080/01441647.2016.1200156

Ba, Y., Zhang, W., Chan, A. H. S., Zhang, T., & Cheng, A. S. K. (2016). How drivers fail to avoid crashes: A risk-homeostasis/perception-response (RH/PR) framework evidenced by visual perception, electrodermal activity and behavioral responses. *Transportation Research Part F: Traffic Psychology and Behaviour,* 43, 24-35. doi:https://doi.org/10.1016/j.trf.2016.09.025

Budd, L., Allen, T., & Newstead, S. (2018). Current Trends in Motorcycle Related Crash and Injury Risk in Australia by Motorcycle Type and Attributes.

Champahom, T., Se, C., Aryuyo, F., Banyong, C., Jomnonkwao, S., & Ratanavaraha, V. (2023). Crash Severity Analysis of Young Adult Motorcyclists: A Comparison of Urban and Rural Local Roadways. *Applied Sciences,* 13(21), 11723. Retrieved from https://www.mdpi.com/2076-3417/13/21/11723

Department of Land Transport. (2022). Statistical Data on Registered Vehicles in Thailand. Retrieved from https://web.dlt.go.th/statistics/

Fitzpatrick, D., & O'Neill, D. (2017). The older motorcyclist. *European Geriatric Medicine,* 8(1), 10-15. doi:https://doi.org/10.1016/j.eurger.2016.10.004

Haghani, M., Behnood, A., Dixit, V., & Oviedo-Trespalacios, O. (2022). Road safety research in the context of low- and middle-income countries: Macro-scale literature analyses, trends, knowledge gaps and challenges. *Safety Science,* 146, 105513. doi:https://doi.org/10.1016/j.ssci.2021.105513

Hamann, C. J., & Peek-Asa, C. (2017). Examination of adult and child bicyclist safety-relevant events using naturalistic bicycling methodology. *Accident Analysis & Prevention,* 102, 1-11. doi:https://doi.org/10.1016/j.aap.2017.02.017

Harnen, S., Wong, S. V., Umar, R. S. R., & Wan Hashim, W. I. (2003). MOTORCYCLE CRASH PREDICTION MODEL FOR NON-SIGNALIZED INTERSECTIONS. *IATSS Research,* 27(2), 58-65. doi:https://doi.org/10.1016/S0386-1112(14)60144-8

Keall, M. D., & Newstead, S. (2012). Analysis of factors that increase motorcycle rider risk compared to car driver risk. *Accident Analysis & Prevention,* 49, 23-29.

Laureshyn, A., Goede, M. d., Saunier, N., & Fyhri, A. (2017). Cross-comparison of three surrogate safety methods to diagnose cyclist safety problems at intersections in Norway. *Accident Analysis & Prevention,* 105, 11-20. doi:https://doi.org/10.1016/j.aap.2016.04.035

Liao, Y., Lin, C.-Y., & Park, J.-H. (2019). Is motorcycle use associated with unhealthy lifestyles? Findings from Taiwan. *Journal of Transport & Health,* 15, 100659. doi:https://doi.org/10.1016/j.jth.2019.100659

Marín Puchades, V., Fassina, F., Fraboni, F., De Angelis, M., Prati, G., de Waard, D., & Pietrantoni, L. (2018). The role of perceived competence and risk perception in cycling near misses. *Safety Science,* 105, 167-177. doi:https://doi.org/10.1016/j.ssci.2018.02.013

Park, J.-I., Kim, S., & Kim, J.-K. (2023). Exploring spatial associations between near-miss and police-reported crashes: The Heinrich’s law in traffic safety. *Transportation Research Interdisciplinary Perspectives,* 19, 100830. doi:https://doi.org/10.1016/j.trip.2023.100830

Sanders, R. L. (2015). Perceived traffic risk for cyclists: The impact of near miss and collision experiences. *Accident Analysis & Prevention,* 75, 26-34. doi:https://doi.org/10.1016/j.aap.2014.11.004

Se, C., Champahom, T., Jomnonkwao, S., & Ratanavaraha, V. (2022). Motorcyclist injury severity analysis: a comparison of Artificial Neural Networks and random parameter model with heterogeneity in means and variances. *International Journal of Injury Control and Safety Promotion,* 29(4), 500-515. doi:10.1080/17457300.2022.2081985

Šraml, M., Tollazzi, T., & Renčelj, M. (2012). Traffic safety analysis of powered two-wheelers (PTWs) in Slovenia. *Accident Analysis & Prevention,* 49, 36-43.

ThaiRoads Foundation. (2022). Key fact on road safety situations in Thailand 2018 - 2021 Retrieved from https://www.roadsafetythai.org/project_download_bookdetail-edoc-636-.html

U.S. Department of Transportation's. (2022). Fatality Analysis Reporting System (FARS). Retrieved from https://www-fars.nhtsa.dot.gov/Main/index.aspx

World Health Organization. (2018a). *GLOBAL STATUS REPORT ON ROAD SAFETY*. Retrieved from https://apps.who.int/iris/bitstream/handle/10665/276462/9789241565684-eng.pdf?ua=1

World Health Organization. (2018b). *Road traffic injuries*. Retrieved from https://www.who.int/news-room/fact-sheets/detail/road-traffic-injuries

Wright, L., & Van der Schaaf, T. (2004). Accident versus near miss causation: a critical review of the literature, an empirical test in the UK railway domain, and their implications for other sectors. *Journal of hazardous materials,* 111(1-3), 105-110.

Young, W., Sobhani, A., Lenné, M. G., & Sarvi, M. (2014). Simulation of safety: A review of the state of the art in road safety simulation modelling. *Accident Analysis & Prevention,* 66, 89-103.

CHAPTER II

ANALYZING NEAR-MISS INCIDENTS AND RISKY RIDING BEHAVIOR IN THAILAND: A COMPARATIVE STUDY OF URBAN AND RURAL AREAS

2.1 Abstract

Preventing near-miss incidents is considered a proactive measure, as it aims to prevent events that have a risk of resulting in accidents. This is regarded as a vital component of building a sustainable and secure society within communities. In the present day, low- and middle-income countries (LMICs) often experience the highest fatality rates from motorcycle accidents, which frequently involve mixed traffic scenarios with other vehicles. The distinct physical characteristics and environmental conditions of roads in urban and rural areas significantly contribute to different riding behaviors. Therefore, the objective of this study is to develop a behavioral model related to near-miss incidents among motorcycle riders in both urban and rural regions using multi-group structural equation modeling (SEM). Data collected from six Thai regions via adapted MRBQ assessed control errors, violations, and safety equipment use in a sample of 2002 riders (1066 urban, 936 rural). Through parameter invariance testing, differences in factor loadings, intercepts, and structural paths were identified between urban and rural areas. All three of these factors significantly influenced near-miss incidents among motorcycle riders in both urban and rural areas. The policy recommendations resulting from this study can contribute to enhancing safety measures for motorcycle riders.

2.2 Introduction

In the 2018 Global Status Report on Road Safety, it is explicitly stated that road traffic accidents constitute a significant cause of global fatalities. This is compounded by the continuous growth of the global population, resulting in a consistent upward trend in road accident-related fatalities. Despite concerted global efforts to improve road safety, as documented by Bhatti and Ahmed (2014), there has been no substantial reduction in the number of road-traffic-accident-related deaths in low-income countries since 2013, which reveals that low- and middle-income countries (LMICs) collectively represent approximately 85% of the world's population while accounting for only 60% of registered vehicles globally. Paradoxically, these countries experience a disproportionately high fatality rate, contributing to 93% of all road traffic accident fatalities, as observed in the study by Haghani, Behnood, Dixit, and Oviedo-Trespalacios (2022).

Of particular note is the finding that 54% of all road traffic accident fatalities occur within the category of vulnerable road users. Among these, the Southeast Asian region stands out with the highest percentage of fatalities, primarily attributed to motorcycle riders and constituting 43% of the total fatalities, as reported by the World Health Organization (2018).

Thailand, located in Southeast Asia and categorized as a middle-income country according to the The World Bank (2022), exhibits a notable prevalence of motorcycles. This popularity is attributed to their practicality, efficiency in reaching destinations, fuel economy, cost-effectiveness in maintenance, and relatively affordable pricing, as observed by Haworth (2012). According to the Department of Land Transport in Thailand, the country has recorded a staggering 21 million registered motorcycles, which make up 53% of the total registered vehicles within the nation (Department of Land Transport, 2022). Thailand secures the third position globally in terms of the highest motorcycle numbers. However, when assessing the fatality rate per 100,000 individuals, Thailand ranks ninth on a global scale, with a fatality rate of

32.7 per 100,000 people. Furthermore, Thailand retains its status as the leading country in the ASEAN region, as reported by the World Health Organization (2018). Notably, a significant proportion of road fatalities in Thailand involve motorcycle users, comprising 74% of all road users (World Health Organization, 2018). Motorcycle riders face a substantially elevated risk of injury or fatality in road accidents, with a likelihood exceeding 30 times that of car drivers per kilometer traveled, as indicated by the OECD/ITF (2015).

2.3 Literature Review

2.3.1 Urban and Rural Areas

At present, Thailand sees motorcycles sharing the road with other vehicles, such as cars and trucks. Notably, accidents resulting in fatalities are frequently observed on major arterial roads and highways (Se, Champahom, Jomnonkwao, & Ratanavaraha, 2022). A recent study conducted by Champahom, Se, et al. (2023) involved a comprehensive analysis of crash severity and revealed notable disparities in risk behaviors among motorcycle riders in urban and rural areas. Furthermore, studies from the United States suggest that motorcycle riders face a higher likelihood of fatal accidents in urban areas compared to rural areas (U.S. Department of Transportation's, 2022). Harnen, Wong, Umar, and Wan Hashim (2003) have pointed out that Taiwan experiences a higher level of severity of injuries in motorcycle accidents on rural roads in comparison to urban roads. Similarly, Budd, Allen, and Newstead (2018) assessed accidents involving motorcycles and injury risks in both rural and urban areas in Australia. Their findings indicated a higher proportion of injury accidents, including fatal ones, occurring in rural areas, with less than 30% of these incidents taking place in areas with speeds of 80 km/h or higher. The study by Islam and Brown (2017) highlighted the significant impact of alcohol consumption, the absence of helmet use, and speeding on the severity of injuries in both urban and rural areas. Brenac, Clabaux, Perrin, and Elslande (2006) found that high-speed riding in urban areas is notably associated with higher motorcycle accident rates compared to rural areas. Furthermore, Gkritza (2009) and Li, Li, Cai, Zhang, and Lo (2008) concluded that helmet usage among motorcycle riders is lower in urban areas compared to rural areas.

The urban environment is distinguished by the construction of towering structures that function as hubs for commerce and business activities, housing a variety of shops and restaurants. Diverse amenities are readily available, complemented by a well-organized transportation system featuring numerous intersections and junctions on the roads. This infrastructure, however, contributes to significant traffic congestion, particularly during peak hours. In contrast, rural areas are predominantly characterized by agricultural landscapes, where a majority of the populace is engaged in farming or animal husbandry. Residents primarily inhabit dispersed villages or communities, resulting in lower population density and less congested traffic conditions. The accessibility of public transportation in rural areas is limited, leading to a prevalent preference for motorcycles as a means of commuting. Riding habits in these regions may involve higher speeds and a reduced adherence to traffic regulations, stemming from lax law enforcement coverage across diverse areas. Figures 2.1 and 2.2 serve to visually depict the pronounced disparities in the physical attributes of roadways and environments between urban and rural landscapes. In the depiction of the urban area in Figure 2.1, numerous cars and motorcycles line the roads, causing traffic hindrances. The presence of intersections and lanes exacerbates traffic disruptions and contributes to heightened congestion. Conversely, Figure 2.2 illustrates the physical characteristics of roads and environments in rural areas, highlighting a conspicuous distinction from their urban counterparts. The limited presence of lightweight vehicles and unobstructed traffic flow further emphasizes the unique features of rural landscapes. These contrasting physical elements significantly influence the riding behaviors of individuals in both urban and rural settings.

Figure 2.1 Physical characteristics of roads and environments in urban areas. Source: Google Maps. Urban area (coordinates: 14.9751957, 102.0855722).

Figure 2.2 Physical characteristics of roads and environments in rural areas. Source: Google Maps. Rural area (coordinates: 17.0303607, 101.2773004).

Hence, it is imperative to separately investigate and address motorcycle safety in urban and rural areas, taking into account the distinctions in road infrastructure, land utilization, and transport models. Urban roads tend to be heavily congested and subject to more stringent regulations, which have a pronounced impact on the riding behavior of motorcycle riders. Implementing safety measures tailored to specific urban and rural contexts is crucial to effectively addressing these challenges.

2.3.2 Near-Miss Incidents

A significant focus of this research is on near-miss incidents, also referred to as near-crashes, near-miss crashes, or near-miss accidents. Near-miss incidents are defined as situations where a collision or accident was narrowly avoided, regardless of whether it was avoided by maneuvering around other vehicles, pedestrians, cyclists, animals, or objects on the road (Aldred & Crosweller, 2015). The use of a near-miss strategy involves collecting and extensively evaluating data and identifying potential issues in advance to prevent accidents (Powell et al., 2007).

Currently, there is a growing body of research on near-miss incidents in road travel. In the realm of bicycle transportation, a study conducted in San Francisco, USA, found that 86% of individuals who ride bicycles at least once a year have experienced near-miss incidents, and 20% of these incidents resulted in actual collisions (Sanders, 2015). Remarkably, near-miss incidents are highly associated with the perception of traffic risk, which holds more significance than actual collisions (Sanders, 2015). In Iceland, a survey on near-miss incidents involving motorcycles revealed that 78.2% of respondents had experienced near-miss incidents (Hardy, 2009). In Australia, it was discovered that 76% of riders involved in crashes had experienced at least one near-miss incident in the past year, with 80% of motorcycle riders between the ages of 15 and 19 having encountered near-miss incidents (Liz de Rome et al., 2016). In the United Kingdom, a comprehensive study was conducted regarding near-miss incidents in bicycle travel as part of the UK Near-Miss Project, which was carried out in collaboration with the government to contribute to transport policies aimed at reducing the risk of accidents (Aldred, 2016). The significance of near-miss incidents lies in their dual nature: firstly, they can predict patterns of behavior or physical road characteristics that may lead to accidents resulting in injuries or fatalities; secondly, they influence cycling experiences and perceptions (Aldred, 2012). It is crucial to note that near-miss incidents are akin to actual collisions, but differ solely in the timing of events when avoidance is still possible. Near-miss incidents occur more frequently than actual collisions (Sanders, 2015). While near-miss incidents may not result in harm, their analysis provides valuable insights into factors associated with personal or environmental conditions that could lead to accidents. Consequently, near-miss incidents have been employed as supplementary data to augment police-reported crashes. This utilization aims to identify crash hotspots within the road network and formulate measures and strategies to enhance safety (Park, Kim, & Kim, 2023). This study adopts a self-report methodology to evaluate risky behaviors and near-miss experiences. The distinction between observing near-misses in the field and relying on self-reported incidents is acknowledged. Observing near-misses in the field entails direct witnessing or real-time recording of incidents within a specific context, such as a workplace or traffic setting. These observations are generally deemed more objective and accurate, rooted in direct, firsthand experiences. Conversely, the self-reported near-miss method relies on individuals voluntarily disclosing their experiences through surveys, questionnaires, or interviews. This approach introduces a degree of subjectivity, as individuals may interpret events differently or may not accurately recall incidents. Variables such as personal bias, interpretation of questions, and the willingness to report can impact the data, imposing limitations on this method (Devaux & Sassi, 2016). Nonetheless, self-reporting can yield detailed insights into aspects that field observations may not capture, such as perceptions, behaviors, attitudes, or satisfaction levels (Warner et al., 2011). For instance, in this study, questionnaires are employed to probe participants' perceptions while assessing their own risky riding behaviors. Hence, in both research and safety assessments, the combined use of both methods may be employed to attain a more holistic comprehension of near-miss occurrences. Each approach possesses inherent strengths and weaknesses, and the selection often hinges on research objectives, available resources, and the specific contextual requirements of the study.

Following the discussion regarding the significance of the aforementioned self-reported near-misses, they can be deemed supplementary data for accident databases. This proactive approach is aimed at preventing accidents and reducing the likelihood of accidents involving injuries or fatalities among motorcycle users. This study seeks to compare risk behaviors linked to near-miss incidents among motorcycle riders in both urban and rural settings while establishing the principal null hypothesis, which is as follows:

Hypothesis 2.1 ($H_{2.1}$): *There is no difference in the invariance between urban and rural*.

2.3.3 Motorcycle Rider Behavior Questionnaire (MRBQ)

Due to the similarities in the physical and psychological characteristics between near-miss incidents and actual collisions, with the only difference being the final time frame during which collisions can be avoided, near-miss incidents can be used as a surrogate measure for accident occurrences under the assumption that near-miss incidents and collisions stem from similar causes (Marín Puchades et al., 2018). Therefore, factors that contribute to near-miss incidents are likely to bear similarities to factors that contribute to accidents.

Based on previous research, important factors contributing to accidents include humans, vehicles, and the environment (Evans, 2012; Olson & Dewar, 2002; Ratanavaraha & Amprayn, 2003; Shinar, 2007). Among these factors, those related to humans are considered the most significant in terms of accident occurrence (Olson & Dewar, 2002; Shinar, 2007). The book "Human Factors in Traffic Safety" emphasizes that understanding human behavior begins with comprehending the characteristics of human tasks, skills, and attributes. Relevant factors include driver perception and response, such as where and for how long the driver looks, individual differences, emotions, stress, aggressiveness, motivation, driving skills, risky behaviors, social variables, driver attitudes, gender differences, driving experience, fatigue, alcohol consumption, and impaired driving behaviors (Olson & Dewar, 2002). Unsafe and risky behaviors are primarily attributed to individuals and encompass various factors, such as unsafe driving behaviors, including drunk driving (Ameratunga, Herman, Wainiqolo,

& Kafoa, 2015) and speeding (Agusdinata, van der Pas, Walker, & Marchau, 2009), among others. Studies on factors influencing motorcycle accidents have identified economic and social factors as well as driving behaviors, including gender, age, possession of a driver's license, driving experience, motorcycle ownership, alcohol consumption, sleep medication use, speed, helmet use, and risky behaviors (Chang & Yeh, 2007; L. de Rome et al., 2011; Lin & Kraus, 2009; Vlahogianni, Yannis, & Golias, 2012). The study on risky behaviors contributing to near-misses involving motorcycles specifies that road and environmental factors have a significant impact on near-miss frequency (Jomnonkwao, Champahom, Se, Hantanong, & Ratanavaraha, 2023). These factors may contribute to near-miss incidents or collisions resulting in injuries or fatalities.

In their study, Elliott, Baughan, and Sexton (2007) aimed to develop a questionnaire capable of assessing motorcycle rider behaviors and determining which factors associated with these behaviors could predict the risk of collisions. To achieve this, they employed the Motorcycle Rider Behavior Questionnaire (MRBQ) and conducted a principal component analysis (PCA) to identify the underlying patterns of the factors involved. The MRBQ consisted of a total of 43 questions, which were categorized into five groups: traffic errors, control errors (consisting of 7 items), speed violations (12 items), performance of stunts (7 items), and use of safety equipment (4 items). Following the development of the MRBQ, numerous researchers have utilized this instrument and made adaptations to the factor items, considering variations in physical characteristics and traffic regulations across different countries. These adjustments aimed to ensure that the questionnaire aligned with the specific context of motorcycle rider behaviors in each country. Further details and information can be found in Table 2.1. The additional main null hypothesis for this study is as follows:

Hypothesis 2.2 ($H_{2.2}$): *Control errors have a negative effect on near-misses in urban areas.*

Hypothesis 2.3 ($H_{2.3}$): *Violations have a negative effect on near-misses in urban areas.*

Hypothesis 2.4 ($H_{2.4}$): *Safety equipment has a negative effect on near-misses in urban areas*.

Hypothesis 2.5 ($H_{2.5}$)*: Control errors have a negative effect on near-misses in rural areas.*

Hypothesis 2.6 ($H_{2.6}$): *Violations have a negative effect on near-misses in rural areas*.

Hypothesis 2.7 ($H_{2.7}$): *Safety equipment has a negative effect on near-misses in rural areas*.

Table 2.1 Summary of motorcycle riding behavior from related research works

Country (Author)	Sample Size	Items	Demographic Characteristics	Other Data	Factor Structure	Factor Analysis Method	Technique
United Kingdom (Elliott et al., 2007)	8666	43	Age, gender, riding experience (y), and riding mileage (km per year)	Self-reported crash data	5-factor (traffic errors, speed violations, stunts, safety equipment, and control errors)	Principle component analysis with varimax rotation	Generalized linear modeling
India (Chouhan, Kathuria, & Sekhar, 2021)	392	32	Age, gender, riding experience(y), riding purpose, riding frequency, license holding, riding mileage (km per day.), marital status, and education level	Self-reported near-crash and crash data, self-reported traffic violation data	4-factor (traffic errors, stunts, speed violations, and control errors)	Exploratory factor analysis	Negative binomial regression

Table 2.1 Summary of motorcycle riding behavior from related research works (Continued)

Country (Author)	Sample Size	Items	Demographic Characteristics	Other Data	Factor Structure	Factor Analysis Method	Technique
India (Sumit, Ross, Brijs, Wets, & Ruiter, 2021)	300	43	Age, gender, occupation, type of motorcycle, riding exposure (hours per week), and education level	Self-reported near-crash and crash data, Self-reported traffic violation data	5-factor (traffic errors, violations, stunts, safety equipment, and control errors)	Exploratory factor analysis	Logistic regression model
Australia (Sakashita et al., 2014)	1305	43	Age, gender, riding experience (y), riding exposure (hours per week)	Self-reported near crash and crash data, police-reported crash and offense data	4-factor (errors, speed violation, stunts, and protective gear)	Confirmatory factor analysis and principal axis factoring	Zero-inflated Poisson regression model and logistic regression model

Table 2.1 Summary of motorcycle riding behavior from related research works (Continued)

Country (Author)	Sample Size	Items	Demographic Characteristics	Other Data	Factor Structure	Factor Analysis Method	Technique
Australia (Stephens et al., 2017)	470	29	Age, gender, riding experience(y), riding exposure (hours per week), marital status, and employment level	Self-reported near-crash and crash data, self-reported traffic violation data	5-factor (traffic errors, speed violations, stunts, protective gear, and control errors)	Principal axis factoring	Logistic regression model
Vietnam (Trung Bui, Saadi, & Cools, 2020)	2254	43	Age, gender, riding experience(y), riding purpose, riding frequency, and education level	Self-reported traffic accidents and traffic violation data	4-factor (traffic errors, speed- and alcohol-related violations, safety equipment, and control errors)	Confirmatory factor analysis and principal axis factoring	Negative binomial regression

Table 2.1 Summary of motorcycle riding behavior from related research works (Continued)

Country (Author)	Sample Size	Items	Demographic Characteristics	Other Data	Factor Structure	Factor Analysis Method	Technique
Iran (Motevalian, Asadi-Lari, Rahimi, & Eftekhar, 2011)	518	48	Age, gender, riding experience (y), marital status, and education level	Self-reported crash data	6-factor (traffic errors, speed violations, stunts, safety violations, traffic violations, and control errors)	Principle component analysis with varimax rotation	Pearson's correlation coefficient
Turkey (Özkan, Lajunen, Doğruyol, Yıldırım, & Çoymak, 2012)	451	43	Age, gender, riding experience (y), riding mileage (km per y), and education level	Self-reported crash data, self-reported offense data	5-factor (traffic errors, speed violations, stunts, safety equipment, and control errors)	Principal component analysis	Hierarchical regression and the regression models

Table 2.1 Summary of motorcycle riding behavior from related research works (Continued)

Country (Author)	Sample Size	Items	Demographic Characteristics	Other Data	Factor Structure	Factor Analysis Method	Technique
Slovenia (Topolšek & Dragan, 2016)	205	43 + 11	Age, riding experience(y), riding purpose, license holding years, riding frequency, and engine capacity	Self-reported traffic accidents	7-factor (safety equipment, errors, stunts, helmet, clothing, speed violations, and alcohol)	Exploratory and second-order confirmatory factor analysis	Structural equation modeling
Nigeria (Sunday, 2010)	500	40	Age, gender, riding experience(y), motorcycle usage, and alcohol use	Self-reported crash data, self-reported traffic violation data	4-factor (control/safety, stunts, errors, speeding/impatience)	Principal component analysis	Generalized linear modeling

Table 2.1 Summary of motorcycle riding behavior from related research works (Continued)

Country (Author)	Sample Size	Items	Demographic Characteristics	Other Data	Factor Structure	Factor Analysis Method	Technique
Thailand (Uttra, Jomnonkwao, Watthanaklang, & Ratanavaraha, 2020)	1516	38	Age, gender, riding experience(y), riding purpose, riding frequency, and license-holding years	Helmet-wearing behavior	4-factor (traffic errors, stunts, safety equipment, and control errors)	Exploratory and second-order confirmatory factor analysis	Structural equation modeling

2.3.4 Objective and Contributions

The preceding research has delved into the study of risk behavior factors, specifically in India (Chouhan et al., 2021; Sumit et al., 2021) and Australia (Sakashita et al., 2014; Stephens et al., 2017), utilizing self-reported near-miss incidents to evaluate behaviors that have a high risk of leading to accidents. However, there has yet to be a comparative analysis of riding behaviors in urban and rural settings. As previously mentioned in Section 2.3.1, this underscores the significance of examining the risk behaviors of drivers in both urban and rural areas. Consequently, this study places its primary focus on investigating the risk behavior factors contributing to near-miss incidents, drawing a comparison between urban and rural areas that is characterized by distinct physical differences. Although near-miss events do not result in actual accidents, they provide valuable insight for the analysis of potential accidents and the formulation of preventive policies. The objective of this study is to intervene in risky events to prevent their progression into accidents. By understanding the underlying causes that lead to unsafe situations, our research searches for proactive measures to prevent accidents and enhance overall safety. This approach yields crucial insights for authorities to improve, plan, and precisely address issues. In light of the current global scenario, there is heightened awareness of the widespread occurrence of road accidents worldwide, impacting both developed and developing countries. As previously noted, near-miss events occur more frequently than actual accidents. In Thailand, a developing country characterized by a middle-income status and a high prevalence of motorcycle usage, road accident statistics rank among the highest globally. The study of near-miss incidents presents a novel and compelling focus, extending benefits not only to Thailand, but also to other developing countries grappling with similar challenges. This research can serve as a blueprint for addressing road accident issues and implementing proactive measures to reduce accident occurrences. Furthermore, it has the potential to significantly contribute to reducing injuries and fatalities on roads, addressing a fundamental need for humanity by enhancing overall safety and quality of life within society.

2.4. Materials and Methods

2.4.1 Research Procedures

In the previous study, the primary objective was to examine and explore the Motorcycle Rider Behavior Questionnaire (MRBQ) as a tool for investigating motorcycle rider behaviors. The original MRBQ, initially developed by Elliott et al. (2007), underwent adaptations and modifications by researchers from different countries (refer to Table 2.1 for detailed information). These adjustments involved altering, removing, or adding new questions to enhance their contextual relevance to motorcycle riders in each specific country.

In the present study, expert opinions and feedback were sought to revise the questionnaire. After incorporating the necessary modifications, a pilot test was conducted to ensure the questionnaire's validity and reliability before proceeding with the actual data collection. The study adhered to ethical principles governing research involving human participants, with a particular focus on safeguarding the rights and well-being of the volunteers. An assessment of ethical considerations determined that the study posed a low risk to the participants.

Following the questionnaire's revision, it was distributed to motorcycle riders nationwide, and the collected data underwent a normality check. Exploratory factor analysis (EFA) was employed to identify the underlying components, leading to the identification of three key components: control error, violation, and safety equipment. To assess the measurement quality of the latent structure tested within a structural equation modeling (SEM) framework, confirmatory factor analysis (CFA), a statistical technique, was utilized.

Finally, a multi-group SEM analysis was conducted to compare and evaluate the factors that influence near-misses in urban and rural areas. The research procedures are visually presented in Figure 2.3.

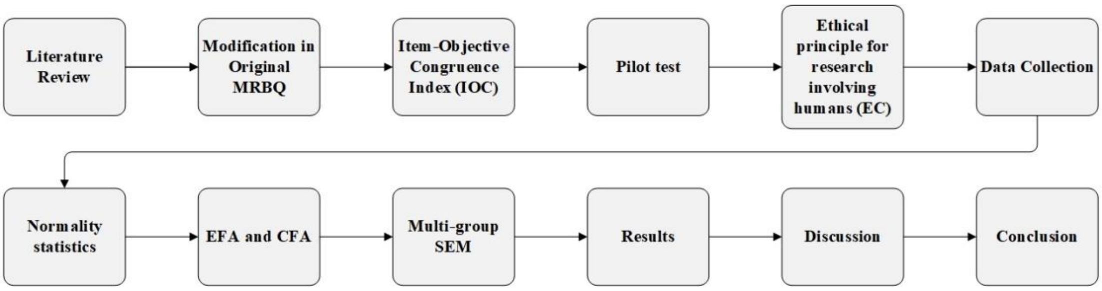


Figure 2.3 Research procedures

2.4.2 Questionnaire Design

1) Demographic and Riding Information

In this section, the questionnaire includes socio-demographic information such as gender, age, marital status, highest level of education, individual income (THB/month), household income (THB/month), household members, occupation, holding a license, riding experience, riding frequency, main reason for riding, average speed (km/h), and self-reported accidents and traffic violations. Specifically, regarding collisions and traffic law violations, there are targeted questions, including "Have you received any fines or traffic tickets for your car or motorcycle in the past 3 years?" and "How many times have you been involved in an accident or near-miss within the past year?". In this research study, "near-miss" and "near-crash" are defined as "unsafe traffic incidents in which riders somehow managed to escape from the accident," and "crash" is defined as "a collision leading to injuries or vehicle damage" (Chouhan et al., 2021; Trung Bui et al., 2020).

2) Motorcycle Rider Behavior Questionnaire (MRBQ)

In this study, we utilized the Motorcycle Rider Behavior Questionnaire (MRBQ), developed by Elliott et al. (2007), as the primary instrument for investigating motorcycle rider behavior. This questionnaire has been employed in various countries, such as Iran (Motevalian et al., 2011), Turkey (Özkan et al., 2012), Australia (Sakashita et al., 2014; Stephens et al., 2017), Slovenia (Topolšek & Dragan, 2016), Nigeria (Sunday, 2010), Vietnam (Trung Bui et al., 2020), and India (Chouhan et al., 2021; Sumit et al., 2021). These studies have adapted the MRBQ to suit the particular rider behaviors and contexts in each respective country. Further information regarding the literature review is presented in Table 2.1.

For this specific study, the MRBQ was adapted and implemented in Thailand, which is a middle-income country characterized by a significant number of traffic accidents and high-risk riding behaviors. Riding behaviors in Thailand differ from those in higher-income or developed countries due to variations in geographical features, traffic regulations, culture, and beliefs. Consequently, modifications were made to the questionnaire to enhance its appropriateness for Thai motorcycle riders. The questionnaire comprised a total of 17 items, with 11 items derived from the original research and an additional 6 items addressing mobile phone usage while riding, alcohol consumption, helmet use behavior, and daytime headlight usage. This adaptation aligned with studies conducted in India and Iran (Chouhan et al., 2021; Motevalian et al., 2011), which also adjusted the questionnaire to encompass helmet use behavior. However, our study further expanded the scope by including questions pertaining to mobile phone usage while riding and alcohol consumption to more accurately reflect the riding behaviors observed in Thailand. The questionnaire employed in this research study uses a Likert scale with a rating scale ranging from 1 (never) to 5 (always) to evaluate participants' responses.

2.4.3 Data Collection

The primary objective of data collection in this study was to ensure comprehensive representation across the entire country. To achieve this, a sampling methodology was devised that would provide a representative sample from all regions. The selection of provinces for the sample distribution was based on the number of registered motorcycles in each province, taking into account the Human Achievement Index (HAI). The HAI is an index that assesses the quality of life by considering eight sub-indices related to various aspects of individuals' lives, such as health, education, employment, income, housing, family life, transportation, communication, and social participation. This composite index measures development outcomes at the provincial level. The provinces were categorized into four quartiles, ranging from Q1 (highest HAI scores) to Q4 (lowest HAI scores).

The data collection process covered six regions: the central region, with six provinces; the eastern region, with five provinces; the northeastern region, with six provinces; the northern region, with seven provinces; the western region, with five provinces; and the southern region, with five provinces. The number of data points collected was determined based on the appropriate sample size, which was derived from analyzing the structural equation model. It was recommended that the sample size for estimating the maximum likelihood be at least ten times the number of observable variables (Golob, 2003). Consequently, a total of 2002 sample sets were collected, ensuring an even distribution across all six regions. The research employed stratified sampling as the sampling technique. The target population consisted of the general population residing in the designated areas for at least one year, aged 18 years or older, capable of riding motorcycles, and with registered vehicles. The selection process for the sample group is illustrated in Figure 2.4, and data collection took place in various administrative areas, including both urban areas and rural areas. In the segment related to the Motorcycle Rider Behavior Questionnaire (MRBQ), participants in the survey were provided with clarifications for the questions prior to engaging in the survey. These clarifications encompassed the characteristics of risk behaviors associated with motorcycle riding, offering participants the chance to watch videos that elucidated the meaning and provided examples of “near miss” incidents. Particular emphasis was placed on the thoroughness and precision of these explanations.

The participant characteristics are presented in Table 2.2, which provides an overview of the respondents who completed the questionnaire. The participants were divided into two groups: those residing in urban areas (n = 1066) and those residing in rural areas (n = 936). The sample characteristics of both groups were found to be relatively similar. In terms of demographic characteristics, the majority of participants in both urban and rural areas were single. In terms of education, most participants had obtained a bachelor's degree as their highest level of education. Regarding income, participants had an average personal monthly income of less than THB 18,000. The majority of participants' household monthly income ranged from THB 30,001 to 50,000. Regarding motorcycle-related factors, less than 50% of the participants possessed a motorcycle rider's license. The majority of the participants used motorcycles on a daily basis, primarily to commute for study or work purposes. The average speed used by most participants while riding motorcycles was below 80 km/hr. In terms of traffic behavior, over 90% of the participants reported not having violated traffic laws within the past 3 years. Additionally, nearly 80% of the participants had experienced near-misses while riding motorcycles. However, more than 90% of the participants had had no prior experience with accidents within the past year.

Table 2.2 Sample characteristics

Variable Name	Category	Urban (*n* = 1066)	Rural (*n* = 936)
		% (n)	% (n)
Gender	Male	48.1% (513)	47.3% (443)
	Female	51.9% (553)	52.7% (493)
Age	20 or less	6.8% (72)	7.1% (66)
	21 to 25	6.1% (65)	7.4% (69)
	26 to 39	29.9% (319)	28.4% (266)
	40 to 59	35.5% (187)	36.1% (338)

Table 2.2 Sample characteristics (Continued)

Variable Name	Category	Urban (*n* = 1066) % (n)	Rural (*n* = 936) % (n)
	60 and older	21.8% (232)	21% (197)
Marital status	Single	57.5% (613)	53.7% (503)
	Married	33.6% (358)	36% (337)
	Divorce	8.9% (95)	10.3% (96)
Highest education level	Diploma	42.1% (449)	43.1% (403)
	Bachelor’s degree	55.1% (587)	52.8% (494)
	Postgraduate or PhD	2.8% (30)	4.2% (39)
Individual income (THB/month)	18,000 or less	34.4% (367)	34% (318)
	18,001 to 25,000	36.8% (392)	35.8% (335)
	25,001 or more	28.8% (307)	30.2% (283)
Household income (THB/month)	30,000 or less	20.1% (214)	21.6% (202)
	30,001 to 50,000	32.8% (350)	33.1% (310)
	50,001 to 70,000	27.2% (290)	25.4% (238)
	70,001 or more	19.9% (212)	19.9% (186)
Household members	1 to 2	30.2% (322)	34% (318)
	3 to 4	55.4% (591)	54.7% (512)
	5 or more	14.4% (153)	11.3% (106)
Occupation	Student	7.3% (78)	7.4% (69)
	Civil servant/state enterprise employee	3.8% (40)	3.7% (35)
	Private companies	38.8% (414)	41.2% (386)
	Personal business/trading owner	23.3% (248)	25.9% (242)
	Agriculturist	8% (85)	7.7% (72)
	Contractors	17.4% (185)	12.5% (117)
	Housewife	1.4% (15)	1.4% (13)
	Other	0.1% (1)	0.2% (2)

Table 2.2 Sample characteristics (Continued)

Variable Name	Category	Urban (*n* = 1066) % (n)	Rural (*n* = 936) % (n)
Holding license	Yes	46% (490)	38.6% (361)
	No	54% (576)	61.4% (575)
Riding experience (years)	5 or fewer	1.41% (15)	1.7% (16)
	6 to 10	8.91% (95)	10.5% (98)
	11 to 20	21.11% (225)	21.2% (198)
	21 to 30	21.29% (227)	20.3% (190)
	31 or more	47.3% (504)	46.4% (434)
Riding frequency	Once a week	34.3% (366)	36.1% (338)
	Several times per week	31.1% (332)	29.3% (274)
	Every day	34.6% (368)	34.6% (324)
Main reason for riding	Only for work or study	52% (554)	56% (524)
	Only for recreation	21.9% (233)	20.4% (191)
	Other	26.1% (279)	23.6% (221)
Average speed (km/h)	80 or less	81.2% (866)	81% (758)
	81 or more	18.8% (200)	19% (178)
Traffic violations (past 3 years) for motorcycle only	Yes	5.1% (54)	5.2% (49)
	No	94.9% (1012)	94.8% (887)
Traffic violations (past 3 years) across all vehicles	Yes	8.3% (89)	8.4% (79)
	No	91.7% (977)	91.6% (857)
Near-miss (past 12 months)	None	23.3% (248)	22.1% (207)
	1 to 2	49.2% (524)	49.6% (464)
	3 or more	27.6% (294)	28.3% (265)
Accident (past 12 months)	None	94.7% (1099)	94.6% (885)
	1 or more	5.3% (57)	5.4% (51)

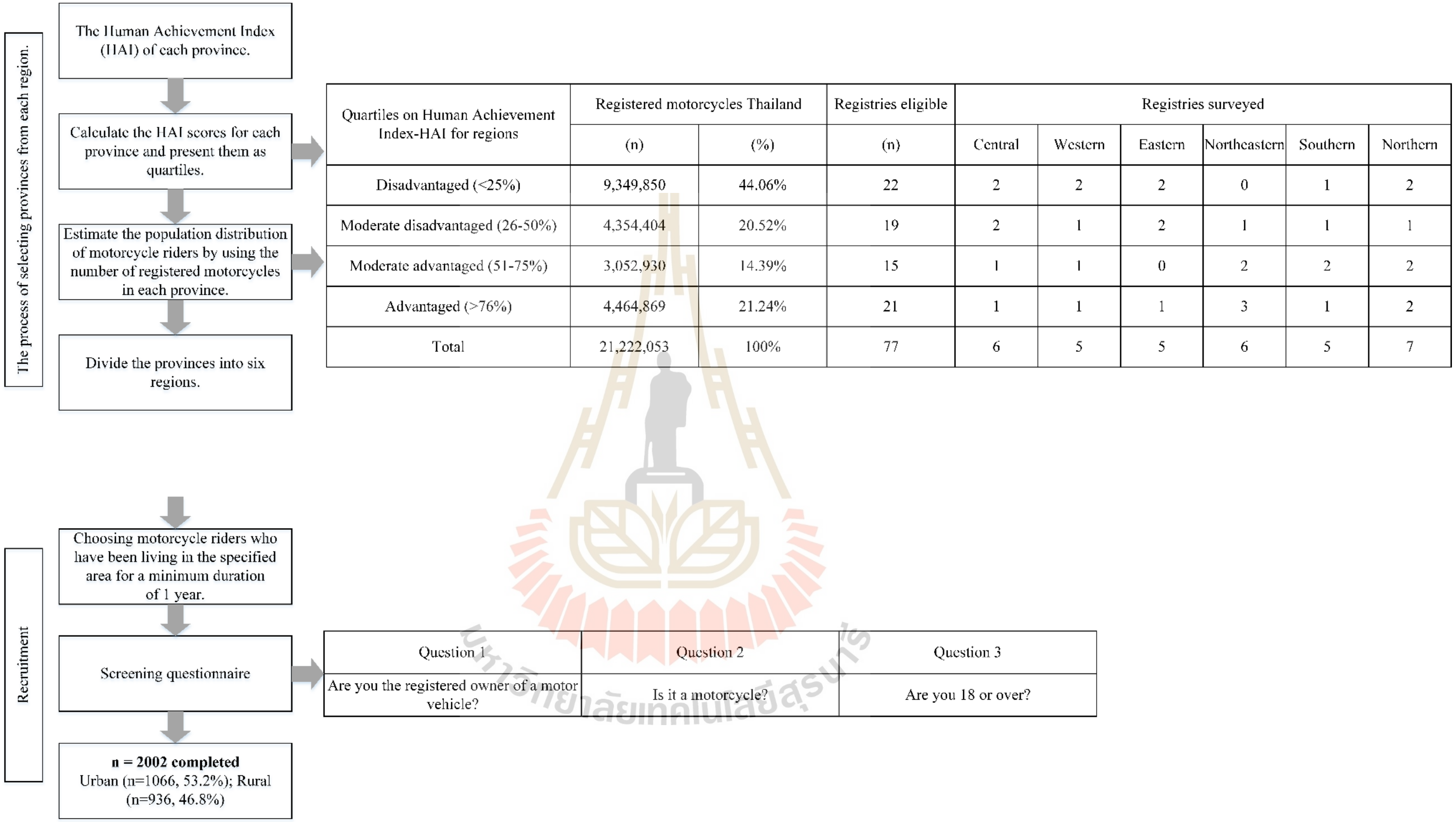
The types of near-miss incidents are shown in Table 2.3, which includes three categories: skidding, loss of motorcycle control, and swerving or braking due to other vehicles (or pedestrians). The analysis revealed that in both urban and rural areas, over 50% of the most common near-miss incidents fell under the category of swerving or braking in response to other vehicles (or pedestrians). The primary causes of these incidents were identified as other vehicles merging or cutting in, sudden lane changes by other vehicles, and other vehicles making right turns and cutting in.

Table 2.3 Type of near-miss incident.

Type of Near-Miss Incident	**Cause of the Near-Miss**	**Urban (*n* = 819)**	**Rural (*n* = 731)**
		% (n)	**% (n)**
Skid	due to water	8.2% (67)	9.6% (70)
	due to mud, wet leaves, or animal manure	1% (8)	0.5% (4)
	due to oil spillage on the road	2.4% (20)	2.1% (15)
	due to slippery or loose road surfaces (e.g., paint or worn asphalt) or loose gravel	3.9% (32)	4.2% (31)
	due to road objects (e.g., clothes, plastic bags, or garbage)	3.3% (27)	2.9% (21)
	Total	18.8% (154)	19.3% (141)
Near loss of control	due to evasion (vehicle in front drives slowly or brakes suddenly)	8.9% (73)	8.9% (65)
	due to a tire puncture	0.7% (6)	0.7% (5)
	due to mechanical failure	0.4% (3)	0.5% (4)
	due to traveling too fast for the conditions	3.5% (29)	5.9% (43)
	due to potholes or grooves in the road	10.4% (85)	9.4% (69)
	due to flying objects (e.g., insects, birds, paper)	1.2% (10)	1.1% (8)

Table 2.3 Type of near-miss incident (Continued)

Type of Near-Miss Incident	Cause of the Near-Miss	Urban (*n* = 819)	Rural (*n* = 731)
		% (n)	% (n)
	due to tiredness or inattention (lack of focus)	2% (16)	0.8% (6)
	Total	27.1% (222)	27.3% (200)
Swerve or brake due to another vehicle (or pedestrian)	overtaking from behind	10.4% (85)	11.1% (81)
	coming towards you in your lane	9.8% (80)	7.5% (55)
	another car turns right, cutting you off	8.7% (71)	10% (73)
	turning into your path from a side road, private driveway, or opposite direction	6.2% (51)	6% (44)
	cutting you off at a junction	4.9% (40)	6.6% (48)
	cutting you off while performing a U-turn	7.7% (63)	7.5% (55)
	cyclist riding into your path	0% (0)	0.1% (1)
	animal(s) walking into your path	6.1% (50)	4% (29)
	Total	53.8% (440)	52.8% (386)
Any other type of near-miss experience		0.4% (3)	0.5% (4)



Quartiles on Human Achievement Index-HAI for regions	Registered motorcycles Thailand		Registries eligible	Registries surveyed					
	(n)	(%)	(n)	Central	Western	Eastern	Northeastern	Southern	Northern
Disadvantaged (<25%)	9,349,850	44.06%	22	2	2	2	0	1	2
Moderate disadvantaged (26-50%)	4,354,404	20.52%	19	2	1	2	1	1	1
Moderate advantaged (51-75%)	3,052,930	14.39%	15	1	1	0	2	2	2
Advantaged (>76%)	4,464,869	21.24%	21	1	1	1	3	1	2
Total	21,222,053	100%	77	6	5	5	6	5	7

Question 1	Question 2	Question 3
Are you the registered owner of a motor vehicle?	Is it a motorcycle?	Are you 18 or over?

Figure 2.4 Recruitment procedure for obtaining a representative sample of riders from Thailand

2.4.4 Methods

The present study has focused on examining the correlation between unsafe riding behaviors and near-miss incidents. The exploration of factors influencing unsafe riding behaviors was facilitated through the utilization of a survey meticulously designed via the questionnaire design process. The questionnaire structure drew inspiration from the well-established Motorcycle Rider Behavior Questionnaire (MRBQ), as delineated in Section 2.3.3, wherein a thorough review of its questions was conducted. To further refine the study's findings, both exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were employed. These statistical techniques served the purpose of categorizing observable variables and validating latent variables, ultimately identifying three key variables: control errors (CE), violations (VI), and safety equipment (SE). Subsequently, the investigation into the relationship between these variables and near-miss incidents was undertaken using structural equation modeling (SEM). SEM enabled the identification of relationships between observed variables and latent variables, encompassing both direct and indirect effects. In order to discern potential disparities between urban and rural settings, the study conducted a comparative analysis through a multi-group analysis. This method was instrumental in testing for parameter differences between the two models. The details are elaborated as follows:

1) Exploratory Factor Analysis (EFA)

Exploratory factor analysis (EFA) is a widely used statistical method in the social sciences. It has been shown to be beneficial for testing learning, cognition, and personality theories, investigating scale validity, and reducing the dimensionality of a group of variables so that they may be used more readily in subsequent statistical studies (finch, 2013). In the context of this study, adjustments were necessary in order to account for the physical and traffic law differences across countries, which contribute to variations in riding behaviors. Consequently, the Motorcycle Rider Behavior Questionnaire (MRBQ) was adapted to suit motorcycle riders in Thailand, even though it had already been validated. The adapted questionnaire consisted of a total of 17 indicators, with 11 indicators derived from previous research and an additional 6 indicators that were modified or added. The original questions focused on speed and vehicle control, while the additional questions addressed topics such as mobile phone usage while riding, alcohol consumption, helmet-wearing behavior, the use of chin straps, and daytime headlight usage. EFA was utilized to group the newly added indicators that were relevant to motorcycle riding behavior.

2) Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis (CFA) is employed to assess the extent to which measured variables effectively explain constructs. A concept-based theory's primary benefit is that it allows for analytical evaluation and provides a framework for understanding how measured quantities indicate psychological, social, and business elements. By combining CFA results with tests of construct validity, researchers gain a comprehensive understanding of the quality of measurement (Champahom, Jomnonkwao, et al., 2023; Rex B Kline, 2015). This study, in the confirmatory factor analysis section, aimed to identify the components of motorcycle rider behavior, including control errors, violations (VI), and safety equipment (SE).

3) Multigroup Analysis (MGA)

Multigroup analysis (MGA) is a popular method that is extensively employed to compare groups. It encompasses a range of sophisticated techniques commonly utilized by researchers to explore variations among categorical variables, such as gender or country (J. Hair, Sarstedt, Ringle, & Gudergan, 2017), as well as continuous variables that can be categorized through dichotomization or cluster analysis (Joseph F. Hair, Risher, Sarstedt, & Ringle, 2019). MGA can be implemented within the context of partial least squares structural equation modeling (PLS-MGA), allowing researchers to evaluate meaningful differences in the structural paths across multiple groups (Henseler, Ringle, & Sarstedt, 2016). This study examines the riding behaviors of motorists in urban and rural areas, aiming to determine whether there are significant differences in the parameters of riding behavior between riders in these two settings.

4) Structural Equation Modeling (SEM)

Structural equation modeling (SEM) is a powerful and widely employed multivariate technique in scientific research for investigating and evaluating complex relationships among variables. SEM combines two statistical methods: confirmatory factor analysis and path analysis. Confirmatory factor analysis is primarily used to estimate latent psychological traits like attitude and satisfaction. On the other hand, path analysis originated in biometrics and aims to identify causal relationships between variables by constructing a path diagram (Fan et al., 2016). In the confirmatory factor analysis section of this study, our objective was to identify the components of motorcycle rider behavior, encompassing control errors, violations (VI), and safety equipment (SE), designated as latent variables. In the path analysis section, our focus was on elucidating the relationships between these latent variables and near-miss incidents, aiming to ascertain whether a correlation exists and, if so, the extent of that correlation.

5) Indices of Goodness of Fit

We investigated the structural validity of the model to assess its compatibility with the empirical data. Five measurement tools, namely, χ^2/df, SRMR, RMSEA, CFI, and TLI, were employed in this study. The evaluation criteria for these indices are as follows:

(1) The χ^2/df is the ratio between the chi-square value and the degrees of freedom. It is advised by Rex B. Kline (2011) that this ratio should not exceed 3. However, in cases where the model is highly complex, Hu and Bentler (1999) propose that the ratio should not exceed 5.

(2) The standardized root mean residual (SRMR) represents the average of the residuals obtained from comparing the variance–covariance matrix derived from the sample data with the estimated parameter values. Ideally, the SRMR should be below 0.08 (Hu & Bentler, 1999).

(3) The root mean square error of approximation (RMSEA) is a statistical measure used to assess the goodness of fit of a model to the population covariance matrix. It indicates how closely the model fits the observed data. In general, a lower RMSEA value indicates a better fit, and it is ideal for the RMSEA to be below 0.07 (Steiger, 2007).

(4) The comparative fit index (CFI) compares the chi-square value of the model to that of a baseline model in order to evaluate the adequacy of model specification. It investigates whether the sub-model diverges from the overall model. Ideally, the CFI should have a value of 0.90 or higher (Hu & Bentler, 1999).

(5) The Tucker–Lewis Index (TLI) is used to compare the chi-square value of a model with that of a baseline model in order to evaluate the model's specification adequacy. It determines whether the sub-model deviates from the overall model. It is recommended that the TLI have a value of 0.80 or higher (Hooper, Coughlan, & Mullen, 2008; Jomnonkwao, Sangphong, Khampirat, Siridhara, & Ratanavaraha, 2016).

2.5 Results

2.5.1 Descriptive Statistics

The descriptive statistics generated for MRBQ variables, including mean (*M*), standard deviation (*SD*), skewness (*SK*), and kurtosis (*KU*) (Table 2.4), provide insights into the categorization of latent variables into three groups: control error (CE), violation (VI), and safety equipment (SE). The urban group exhibited means ranging from 1.650 to 4.240, while the rural group showed means ranging from 1.580 to 4.290. The standard deviations for the urban group ranged from 0.632 to 0.972, and for the rural group, they ranged from 0.639 to 1.043. Skewness values for the urban group ranged from −1.399 to 0.870, and for the rural group, they ranged from −1.375 to 0.802. Kurtosis values for the urban group ranged from −1.231 to 1.610, and for the rural group, they ranged from −1.446 to 1.591. Based on the analysis, it can be concluded that the skewness and kurtosis values for MRBQ were less than 3 and 10, respectively, in urban and rural areas (Rex B. Kline, 2011).

Table 2.4 Descriptive statistics

Code	Latent Variable/Questionnaire	Urban (n = 1066)				Rural (n = 936)			
		M	*SD*	*SK*	*KU*	*M*	*SD*	*SK*	*KU*
CE1	Find that you have difficulty controlling the bike when riding at speed.	1.660	0.658	0.610	0.008	1.660	0.684	0.558	−0.773
CE2	The road is slippery during the rain, causing sudden braking.	1.700	0.667	0.603	0.046	1.690	0.710	0.717	0.004
CE3	You ride the motorcycle with a wide turning radius, resulting in sharp curves or near collisions with other cars.	1.660	0.632	0.424	−0.679	1.580	0.639	0.636	−0.578
CE4	Having trouble with your visor or goggles fogging up.	1.650	0.692	0.870	0.577	1.660	0.727	0.802	−0.038
VI1	Exceed the speed limit on a residential road.	1.760	0.783	0.457	−1.231	1.810	0.782	0.344	−1.289
VI2	When perceiving clear road conditions, you frequently ride at high speeds without adhering to the legal speed limit.	1.730	0.759	0.489	−1.117	1.810	0.776	0.348	−1.265

Table 2.4 Descriptive statistics (Continued)

Code	Latent Variable/Questionnaire	Urban (n = 1066)				Rural (n = 936)			
		M	*SD*	*SK*	*KU*	*M*	*SD*	*SK*	*KU*
VI3	In situations involving two or more traffic lanes, you typically ride in the middle or far-right lane, avoiding close proximity to the leftmost lane.	1.720	0.765	0.513	−1.125	1.830	0.805	0.315	−1.389
VI4	You engage in behaviors such as interfering with, overtaking, and swerving around other vehicles to accelerate your own speed.	1.710	0.762	0.543	−1.090	1.790	0.785	0.378	−1.286
VI5	When a car cuts in front of you or obstructs your vehicle, you tend to accelerate and brake suddenly to maintain your position.	1.730	0.783	0.516	−1.191	1.790	0.788	0.386	−1.292
VI6	You often resort to honking or tailgating when encountering slow-moving vehicles ahead.	1.690	0.771	0.592	−1.087	1.830	0.820	0.314	−1.446
VI7	While riding, you look at maps (on paper or on a smartphone).	1.980	0.716	0.029	−1.049	2.060	0.685	−0.079	−0.866

Table 2.4 Descriptive statistics (Continued)

Code	Latent Variable/Questionnaire	Urban (n = 1066)				Rural (n = 936)			
		M	*SD*	*SK*	*KU*	*M*	*SD*	*SK*	*KU*
VI8	You use the Internet (Facebook, Instagram, Line, and YouTube) on your phone while riding.	2.000	0.700	0.080	−0.722	2.100	0.749	0.027	−0.781
VI9	You ride a motorcycle after consuming alcohol.	1.950	0.710	0.074	−1.011	2.010	0.725	−0.011	−1.093
VI10	During important festivals such as the New Year, Songkran, or social gatherings, you consume alcohol and often ride a motorcycle.	2.020	0.720	0.109	−0.705	2.060	0.753	0.099	−0.767
SE1	You do not wear a helmet while riding a motorcycle.	4.240	0.971	−1.222	0.801	4.290	0.830	−1.243	1.591
SE2	You wear a helmet but do not fasten the chin strap while riding a motorcycle.	4.240	0.965	−1.399	1.610	4.150	1.043	−1.375	1.386
SE3	You ride without turning on the headlights during the daytime.	4.220	0.972	−1.211	0.844	4.250	0.895	−1.139	0.844

Note: For urban, SE_{SK} = 0.075 and SE_{KU} = 0.150;
For rural, SE_{SK} = 0.080 and SE_{KU} = 0.160.

2.5.2 Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) Results

Based on the factor analysis, the EFA components can be classified into three groups for both urban and rural areas: control error (CE), violation (VI), and safety equipment (SE). These components were derived using principal component analysis (PCA) and subsequently rotated using the Varimax method. The factor loadings indicate the strength of the relationship between each variable and its corresponding component, with a threshold of 0.3 or higher considered statistically significant (Maskey, Fei, & Nguyen, 2018). Additionally, J. Hair, Black, Babin, and Anderson (2006) suggest that the Kaiser–Meyer–Olkin (KMO) measure should exceed 0.5 for acceptable factor analysis. KMO values ranging from 0.5 to 0.7 are considered mediocre, while values between 0.7 and 0.8 are considered good. From Table 2.5, the factor analysis results for the urban area indicate a Kaiser–Meyer–Olkin (KMO) measure of 0.907. The EFA's factor loadings for the control error (CE) ranged from 0.636 to 0.698; for violation (VI), from 0.535 to 0.738; and for safety equipment (SE), from 0.805 to 0.827. Similarly, Table 2.6 presents the factor analysis results for the rural area, with a KMO measure of 0.891. The EFA's factor loadings for control error (CE) ranged from 0.631 to 0.750; for violation (VI), from 0.470 to 0.767; and for safety equipment (SE), from 0.796 to 0.842. The accuracy of the measurement indicators was assessed using Cronbach's α coefficient, which is considered acceptable when the values are equal to or greater than 0.6 (Taber, 2018). In the urban context, the Cronbach's α values for the three variables—control error (CE), violation (VI), and safety equipment (SE)—were 0.644, 0.873, and 0.821, respectively (Table 2.5). Similarly, in the rural area, the Cronbach's α values for the same variables were 0.707, 0.866, and 0.791, respectively (Table 2.6). Table 2.5 displays the factor loadings for the urban model obtained from the CFA. The factor loading values for control error (CE) ranged from 0.646 to 0.730; for violation (VI), from 0.359 to 0.867; and for safety equipment (SE), from 0.356 to 0.426. The statistical values derived from the analysis demonstrated a favorable fit of the model to the observed data. The χ^2/df ratio was 3.499 (Hu & Bentler, 1999), RMSEA was 0.048 (Steiger, 2007), CFI was 0.954 (Hu & Bentler, 1999), TLI was 0.945 (Hooper et al., 2008; Jomnonkwao et al., 2016), and SRMR was 0.052 (Hooper et al., 2008; Jomnonkwao et al., 2016). These values collectively indicate that the model fit well with the observed data. And according to Table 2.6, the CFA's factor loadings for the rural model are presented. The factor loading values for control error (CE) ranged from 0.552 to 0.666; for violation (VI), from 0.367 to 0.856; and for safety equipment (SE), from 0.335 to 0.506. The analysis results provided statistical values indicating the model's good fit to the observed data. The χ^2/df ratio was 4.045 (Hu & Bentler, 1999), RMSEA was 0.057 (Steiger, 2007), CFI was 0.936 (Hu & Bentler, 1999), TLI was 0.923 (Hooper et al., 2008; Jomnonkwao et al., 2016), and SRMR was 0.063 (Hooper et al., 2008; Jomnonkwao et al., 2016). These values demonstrate a satisfactory fit of the model to the observed data.

The assessment of convergent validity aimed to determine whether various indicators would measure the same underlying construct. The composite reliability (CR) and average variance extracted (AVE) were calculated using Equations (2.1) and (2.2):

$$CR = \frac{(\sum_{i=1}^{n} L_i)^2}{(\sum_{i=1}^{n} L_i)^2 + (\sum_{i=1}^{n} e_i)} \tag{2.1}$$

$$AVE = \frac{\sum_{i=1}^{n} L_i^2}{n} \tag{2.2}$$

The standardized factor loadings from confirmatory factor analysis (CFA) are represented by L_i; the number of observed variables within each factor is represented by i; and the error variance terms for each set of measurement models (control error (CE), violation (VI), and safety equipment (SE)) are represented by e_i. For the urban group, the composite reliability (CR) values were 0.645, 0.870, and 0.822, respectively, for control error (CE), violation (VI), and safety equipment (SE) (Table 2.5). The corresponding average variance extracted (AVE) values were 0.313, 0.415, and 0.606, respectively. For the rural group, the CR values were 0.709, 0.862, and 0.794, respectively, for control error (CE), violation (VI), and safety equipment (SE) (Table 2.6). The corresponding AVE values were 0.380, 0.401, and 0.563, respectively. If an AVE value is less than 0.5 but the CR value exceeds 0.6, it is still considered acceptable, according to L. W. Lam (2012).

Table 2.5 Factor analysis for urban areas. *n* = 1066, KMO = 0.907

Variable/ Measurement Model/Cronbach's α	EFA		CFA					
	Communalities	Loading	Loading	Est.\S.E.	*p*-Value	Error Variance	CR	AVE
Control Error (Cronbach's α = 0.644)							0.645	0.313
CE1	0.426	0.636	0.558	18.30	<0.001 **	0.689		
CE2	0.418	0.642	0.519	16.674	<0.001 **	0.730		
CE3	0.455	0.655	0.595	19.849	<0.001 **	0.646		
CE4	0.507	0.698	0.563	18.340	<0.001 **	0.683		
Violation (Cronbach's α = 0.873)							0.870	0.415
VI1	0.614	0.704	0.734	44.601	<0.001 **	0.461		
VI2	0.602	0.717	0.720	42.099	<0.001 **	0.482		
VI3	0.640	0.738	0.801	59.680	<0.001 **	0.359		
VI4	0.576	0.713	0.723	43.225	<0.001 **	0.477		
VI5	0.605	0.714	0.767	51.653	<0.001 **	0.411		
VI6	0.568	0.714	0.725	43.602	<0.001 **	0.474		
VI7	0.420	0.535	0.482	18.903	<0.001 **	0.768		
VI8	0.366	0.555	0.427	15.835	<0.001 **	0.818		

Table 2.5 Factor analysis for urban areas. n = 1066, KMO = 0.907 (Continued)

Variable/ Measurement Model/Cronbach's α	EFA		CFA					
	Communalities	Loading	Loading	Est.\S.E.	*p*-Value	Error Variance	CR	AVE
VI9	0.386	0.589	0.517	21.223	<0.001 **	0.733		
VI10	0.451	0.594	0.365	12.862	<0.001 **	0.867		
Safety Equipment (Cronbach's α = 0.821)							0.822	0.606
SE1	0.710	0.810	0.774	44.728	<0.001 **	0.401		
SE2	0.700	0.805	0.758	42.699	<0.001 **	0.426		
SE3	0.735	0.827	0.802	48.621	<0.001 **	0.356		
χ^2/df = 398.971/114 = 3.499, RMSEA = 0.048 (0.043–0.054), CFI = 0.954, TLI = 0.945, SRMR = 0.052								

Note: ** Standardized estimates are significant at the 0.001 level (two-tailed).

Table 2.6 Factor analysis for rural areas. n = 936, KMO = 0.891

Variable/ Measurement Model/Cronbach's α	EFA		CFA					
	Communalities	Loading	Loading	Est.\S.E.	*p*-Value	Error Variance	CR	AVE
Control Error (Cronbach's α = 0.707)							0.709	0.380
CE1	0.447	0.631	0.587	19.946	<0.001 **	0.655		
CE2	0.503	0.702	0.578	19.504	<0.001 **	0.666		
CE3	0.535	0.725	0.626	21.936	<0.001 **	0.608		
CE4	0.569	0.750	0.670	24.323	<0.001 **	0.552		
Violation (Cronbach's α = 0.866)							0.862	0.401
VI1	0.554	0.711	0.669	32.705	<0.001 **	0.552		
VI2	0.566	0.720	0.679	33.916	<0.001 **	0.539		
VI3	0.644	0.767	0.796	54.449	<0.001 **	0.367		
VI4	0.620	0.742	0.778	50.358	<0.001 **	0.395		
VI5	0.598	0.742	0.741	43.201	<0.001 **	0.451		
VI6	0.619	0.761	0.770	48.725	<0.001 **	0.407		
VI7	0.456	0.470	0.442	15.542	<0.001 **	0.805		
VI8	0.342	0.538	0.379	12.632	<0.001 **	0.856		

Table 2.6 Factor analysis for rural areas. n = 936, KMO = 0.891 (Continued)

Variable/ Measurement Model/Cronbach's α	EFA		CFA					
	Communalities	Loading	Loading	Est.\S.E.	*p*-Value	Error Variance	CR	AVE
VI9	0.414	0.543	0.483	17.788	<0.001 **	0.766		
VI10	0.306	0.497	0.389	13.05	<0.001 **	0.849		
Safety Equipment (Cronbach's α = 0.791)							0.794	0.563
SE1	0.649	0.796	0.703	30.835	<0.001 **	0.506		
SE2	0.711	0.805	0.815	39.427	<0.001 **	0.335		
SE3	0.717	0.842	0.729	33.335	<0.001 **	0.469		
χ^2/df = 461.177/114 = 4.045, RMSEA = 0.057 (0.052–0.063), CFI = 0.936, TLI = 0.923, SRMR = 0.063								

Note: ** Standardized estimates are significant at the 0.001 level (two-tailed).

2.5.3 Multi-Group Analysis Results

Multi-group structural equation modeling (SEM) was employed to examine the invariance between the urban and rural groups (hypothesis 2.1). The findings are displayed in Table 2.7, demonstrating the consistency of invariance measurements, such as factor loadings, intercepts, and structural paths, between the two groups (model 3). The following are the model fit statistics for model 3: χ^2 = 1005.489, df = 258, χ^2/df = 3.897 (Hu & Bentler, 1999), RMSEA = 0.054 (Steiger, 2007), CFI = 0.937 (Hu & Bentler, 1999), TLI = 0.925 (Hooper et al., 2008; Jomnonkwao et al., 2016), and SRMR = 0.056 (Hu & Bentler, 1999). Similarly, with model 4, the factor loadings, intercepts, and structural paths were discovered to be the same in both groups. The model fit statistics for model 4 were as follows: χ^2 = 1128.953, df = 292, χ^2/df = 3.866, RMSEA = 0.054 (0.050–0.057), CFI = 0.929, TLI = 0.926, and SRMR = 0.065. The analytical findings of both models (models 3 and 4) suggested a good fit to the data and satisfied the set criteria.

A comparison was made between model 3 and model 4, revealing a significant difference in the risk behavior model of motorcycle riders between urban and rural areas. This was supported by the statistical analysis, which yielded a Chi-square value of 123.464 with 34 degrees of freedom (df) and a significance level of $p < 0.001$. Therefore, it was necessary to develop separate models to capture the distinct risk behaviors of motorcycle riders in urban and rural areas.

Table 2.7 Model of fit and statistical and multi-group analyses

Model	χ^2	*df*	χ^2/df	RMSEA	CFI	TLI	SRMR	Delta- χ^2	Delta-df	*p*-Value
Individual group										
Model 1: Urban (*n* = 1066)	467.691	129	3.626	0.050	0.946	0.936	0.054	-	-	-
Model 2: Rural (*n* = 936)	537.798	129	4.169	0.058	0.926	0.912	0.065	-	-	-
Measurement of invariance										
Model 3: Simultaneous	1005.489	258	3.897	0.054	0.937	0.925	0.056	-	-	-
Model 4: Factor loading, intercept, and structural path held equal groups	1128.953	292	3.866	0.054	0.929	0.926	0.065	123.464	34	<0.001

Note: χ^2 = chi-squared statistic; df = degree of freedom; *p* = level of significance; CFI = comparative fit index; TLI = Tucker–Lewis index; SRMR = standardized root mean square residual; RMSEA = root mean square error of approximation.

2.5.4 Structural Equation Modeling (SEM) Results

The analysis of the structural equation modeling (SEM) demonstrates that both the urban and rural models exhibited a good fit to the observed data, as evidenced by the statistical results presented in Figures 2.5 and 2.6. The SEM model results can be found in Tables 2.8 and 2.9. Upon examining the individual models, it was evident that all 17 indicators from both groups exhibited statistical significance. In the structural model, the factor with the highest factor loading was control error, with coefficients (coef.) of 0.574 (p-value < 0.001) in the urban model and 0.603 (p-value < 0.001) in the rural model. Conversely, the safety equipment factor in the rural model had the lowest factor loading, with a coefficient (coef.) of 0.260 (p-value < 0.001).

When examining specific indicators in the measurement model, namely, VI7, VI8, and VI10, it became apparent that they have low factor loadings. This indicates a weak relationship between the latent variables and the observed indicators. Changes in the spatial context of motorcycle riding behavior inside the Thai environment might be the underlying reason for this, resulting in differences from the established theoretical framework. However, in previous studies that employed confirmatory factor analysis (CFA), the measurement model continued to be appropriate, as all indicators exhibited statistical significance. Moreover, previous research has established that factor loadings above 0.20 are still considered acceptable (Champahom, Jomnonkwao, et al., 2023; Uttra et al., 2020).

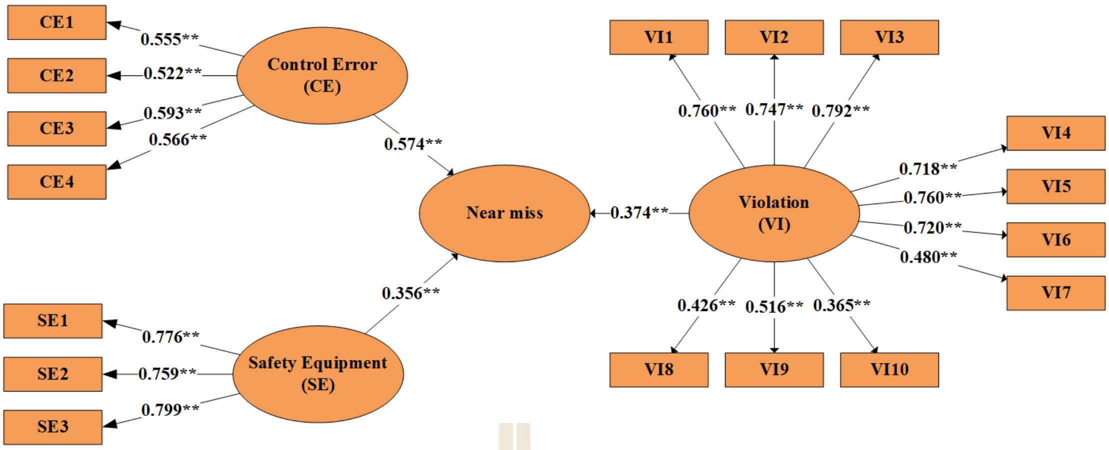


Figure 2.5 Structural equation modeling of near-misses in motorcycle riding for urban society

χ^2/df = 467.691/129 = 3.626, RMSEA = 0.050 (0.045–0.055), CFI = 0.946, TLI = 0.936, SRMR = 0.054,** *p*-value < 0.001 (Mplus 7.0 standardized estimates)

The null hypothesis for the urban model is as stated below:

I. **Hypothesis 2.2 ($H_{2.2}$):** Control error has a negative effect on near-misses in urban areas.

II. **Hypothesis 2.3 ($H_{2.3}$):** Violation has a negative effect on near-misses in urban areas.

III. **Hypothesis 2.4 ($H_{2.4}$):** Safety Equipment has a negative effect on near-misses in urban areas.

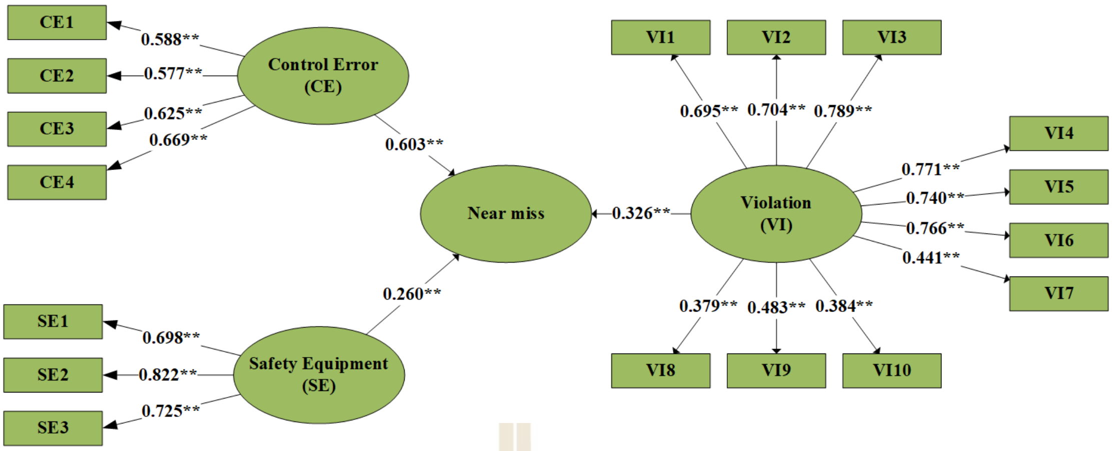


Figure 2.6 Structural equation modeling of near-misses in motorcycle riding in rural areas

χ^2/df = 537.798/129 = 4.169, RMSEA = 0.058 (0.053–0.063), CFI = 0.926, TLI = 0.912, SRMR = 0.065, ** *p*-value < 0.001 (Mplus 7.0 standardized estimates)

The null hypothesis for the rural model is as stated below:

I. **Hypothesis 2.5 ($H_{2.5}$):** Control error has a negative effect on near-misses in rural areas.

II. **Hypothesis 2.6 ($H_{2.6}$):** Violation has a negative effect on near-misses in rural areas.

III. **Hypothesis 2.7 ($H_{2.7}$):** Safety equipment has a negative effect on near-misses in rural areas.

Table 2.8 Parameter estimate of the measurement model

Variable	Urban					Rural				
	Standardized Estimates	S.E.	Est.\S.E.	*p*-Value	R^2	Standardized Estimates	S.E.	Est.\S.E.	*p*-Value	R^2
Control error by										
CE1	0.555	0.030	18.233	<0.001 **	0.308	0.588	0.029	20.178	<0.001 **	0.346
CE2	0.522	0.031	16.838	<0.001 **	0.272	0.577	0.029	19.594	<0.001 **	0.333
CE3	0.593	0.030	19.874	<0.001 **	0.351	0.625	0.028	22.091	<0.001 **	0.391
CE4	0.566	0.030	18.740	<0.001 **	0.321	0.669	0.027	24.388	<0.001 **	0.448
Violation by										
VI1	0.760	0.015	50.877	<0.001 **	0.578	0.695	0.019	36.617	<0.001 **	0.484
VI2	0.747	0.016	48.177	<0.001 **	0.558	0.704	0.019	37.841	<0.001 **	0.496
VI3	0.792	0.014	58.522	<0.001 **	0.627	0.789	0.015	53.682	<0.001 **	0.623
VI4	0.718	0.017	42.869	<0.001 **	0.516	0.771	0.016	49.519	<0.001 **	0.594
VI5	0.760	0.015	50.786	<0.001 **	0.577	0.740	0.017	43.551	<0.001 **	0.548
VI6	0.720	0.017	43.155	<0.001 **	0.518	0.766	0.016	48.390	<0.001 **	0.586
VI7	0.480	0.025	18.966	<0.001 **	0.230	0.441	0.028	15.606	<0.001 **	0.194

Table 2.8 Parameter estimate of the measurement model (Continued)

Variable	Urban					Rural				
	Standardized Estimates	S.E.	Est.\S.E.	*p*-Value	R^2	Standardized Estimates	S.E.	Est.\S.E.	*p*-Value	R^2
VI8	0.426	0.027	15.953	<0.001 **	0.182	0.379	0.030	12.675	<0.001 **	0.143
VI9	0.516	0.024	21.300	<0.001 **	0.266	0.483	0.027	17.884	<0.001 **	0.233
VI10	0.365	0.028	12.917	<0.001 **	0.133	0.384	0.030	12.918	<0.001 **	0.148
Safety equipment by										
SE1	0.776	0.017	45.377	<0.001 **	0.602	0.698	0.022	31.523	<0.001 **	0.488
SE2	0.759	0.018	43.214	<0.001 **	0.577	0.822	0.019	42.366	<0.001 **	0.675
SE3	0.799	0.016	48.462	<0.001 **	0.638	0.725	0.021	33.830	<0.001 **	0.526

Note: ** Standardized estimates are significant at the 0.001 level (two-tailed).

Table 2.9 Parameter estimates of the structural model

Hypothesis	Urban				Rural			
	Standardized estimates	Standard Error	*p*-Value	Result	Standardized estimates	Standard Error	*p*-Value	Result
1 Control error →Near-miss	0.574	0.039	<0.001 **	Supported	0.603	0.039	<0.001 **	Supported
2 Violation →Near-miss	0.374	0.015	<0.001 **	Supported	0.326	0.016	<0.001 **	Supported
3 Safety equipment →Near-miss	0.356	0.015	<0.001 **	Supported	0.260	0.013	<0.001 **	Supported

Note: ** Standardized estimates are significant at the 0.001 level (two-tailed).

2.6 Discussion

This section's primary topics are the measurement model and the structural model. The measuring model section explores the noticeable differences in the behavior of motorcycle riders in urban and rural locations, making preliminary suggestions. The structural model section investigates and clarifies the finding of the relationship between latent factors that influence near-misses, in addition to describing a comparison study between the two populations.

2.6.1 The MRBQ Factor Structure

1) Control Errors (CE)

The control error factor is comprised of four items, and it is clear that the loading factor adequately encompasses the non-intentional aspects of this factor. For instance, CE2 reflects sudden braking due to slippery road conditions during rainfall, while CE4 relates to difficulties caused by fogging visors or goggles. Furthermore, this factor is associated with speeding, which entails riding in a reckless and inattentive manner. CE1 captures the challenge of controlling the bike at high speeds, while CE3 pertains to wide turns that result in sharp curves or near-collisions with other vehicles.

The findings of this study align with previous research conducted by Chouhan Chouhan et al. (2021), Elliott et al. (2007), Özkan et al. (2012), and Sumit et al. (2021). These studies also incorporated all four indicators within the measurement model of control errors (CE), which is recognized as a risk factor that can potentially lead to near-misses.

2) Violations (VI)

When analyzing the factors associated with violations in this research, several key risky behavior variables emerged, including speeding and reckless behavior, as well as the use of mobile phones and alcohol consumption while riding motorcycles. These risky behaviors align with findings from previous studies on risky riding behaviors. Upon examining the loading values of this research, it became evident that VI3 ("In situations involving two or more traffic lanes, you typically ride in the middle or far-right lane, avoiding close proximity to the leftmost lane") carried the most weight in both models. In this particular study, the questionnaire items were tailored to the riding behavior context of Thai riders, whereas in earlier research, these items fell within the "stunts" category (Elliott et al., 2007). The original question, "Ride between two lanes of fast-moving traffic," represents a hazardous action on Indian roads and could be deemed a violation under the Motor Vehicles Act (Sumit et al., 2021). Other reckless behaviors characterize VI4: "You engage in behaviors such as interfering with, overtaking, and swerving around other vehicles to accelerate your own speed," VI5: "When a car cuts in front of you or obstructs your vehicle, you tend to accelerate and brake suddenly to maintain your position," and VI6: "You often resort to honking or tailgating when encountering slow-moving vehicles ahead." Distracted riding manifests as a behavior resulting from a lack of awareness regarding the associated dangers (SaveLIFE Foundation, 2017).

Moreover, another significant identified factor is speeding, specifically relating to item VI1, "Exceed the speed limit on a residential road." Previous research, such as the study by Elliott et al. (2007), categorized this item under the speed violations factor. Numerous studies have consistently shown that speeding plays a major role in contributing to accidents. For example, research conducted in New South Wales, Australia, by Stephens et al. (2017) found a significant association between risky behavior (stunts) and speed violations, as well as a higher likelihood of accidents and severe consequences. Similar findings were reported by Özkan et al. (2012) in Turkey.

Another factor associated with violations is alcohol consumption. The questionnaire items VI9, "You ride a motorcycle after consuming alcohol," and VI10, "During important festivals such as New Year, Songkran, or social gatherings, you consume alcohol and often ride a motorcycle," were categorized under the violation factor. This finding aligns with studies conducted in various countries, including

Vietnam, where research by Vu, Nguyen, Nguyen, and Khuat (2020) revealed that alcohol consumption while riding increases the likelihood of engaging in risky behaviors and leads to significant accidents. These behaviors include higher average speed, average lateral overtaking distance, longer brake reaction time, increased acceleration and deceleration, and more frequent lane changes, resulting in a significant decrease in overall performance.

Additionally, previous research conducted in Cambodia by Roehler, Ear, Parker, Sem, and Ballesteros (2015) identified speeding and alcohol consumption as major factors contributing to motorcycle fatalities. Similar findings were reported in studies conducted in Thailand by Tongklao, Jaruratanasirikul, and Sriplung (2016), which highlighted speeding and alcohol consumption while riding as risky behaviors leading to motorcycle injuries.

According to traffic accident statistics in Thailand, the primary causes of fatalities on the roads include riding above the speed limit, accounting for the highest proportion, as well as alcohol consumption, which is also a significant contributor to road traffic deaths (Injury Data Collaboration Center (IDCC), 2021). In recent years, campaigns promoting "don't drink and drive" have been launched, particularly during important festivals like the New Year and Songkran, accompanied by stringent law enforcement measures.

In addition, the violation factor encompasses indicators related to the use of mobile phones. Specifically, the items VI7 "While riding, you look at maps (on paper or on a smartphone)" and VI8 "You use the internet (Facebook, Instagram, Line, and YouTube) on your phone while riding" are classified within the violation factor. These findings are supported by studies conducted in Mexico and Vietnam. A study conducted in Mexico by Pérez-Núñez et al. (2014) revealed that the use of mobile phones is highly prevalent among motorcycle riders across all age groups. Similarly, in Vietnam, Truong, Nguyen, and De Gruyter (2018) reported that mobile phone usage is particularly common among adolescent motorcycle riders. Moreover, frequent texting or searching for information on mobile phones while riding significantly increases the risk of accidents (Truong, Nguyen, & De Gruyter, 2019). Furthermore, research conducted in India has identified a higher inclination among male riders to ride under the influence of alcohol and use mobile phones while riding (Hassan, Vinodkumar, & Vinod, 2017). These ten indicators, classified under the Violations (VI) model, represent risk factors that can contribute to near-miss incidents.

3) Safety Equipment (SE)

Finally, the safety equipment factor focuses on two aspects: wearing helmets and turning on motorcycle headlights. The items SE1 ("You do not wear a helmet while riding a motorcycle") and SE2 ("You wear a helmet but do not fasten the chin strap while riding a motorcycle") are considered indicators of safety equipment. Previous research conducted in Iran by Motevalian et al. (2011) categorized these items as safety violations and control errors. A study by Zamani-Alavijeh, Bazargan, Shafiei, and Bazargan-Hejazi (2011) reported that more than 67% of Iranian riders do not wear helmets while riding. Similar findings of low helmet usage among motorcycle riders have been observed in Ghana and Jamaica (Zamani-Alavijeh et al., 2011).

In addition to helmet usage, the item SE3 "You ride without turning on the headlights during the daytime" is considered an indicator of safety equipment. It falls under the broader safety factor (Elliott et al., 2007; Sakashita et al., 2014). Research has shown that using daytime running lights on motorcycles significantly reduces the risk of accidents (D'Elia & Newstead, 2023). By activating motorcycle headlights during the daytime, the risk of motorcycle collisions can be reduced by approximately 4% to 20% (Davoodi & Hossayni, 2015).

Overall, these three indicators, classified under the Safety Equipment (SE) model, represent risk factors that contribute to near-miss incidents.

Proper helmet usage and the use of motorcycle headlights are crucial for promoting safety and reducing the likelihood of accidents.

2.6.2 An Evaluation of Factors Influencing the Risk of Accidents in Urban and Rural Areas

The results of the structural model analysis revealed significant disparities between the two groups. The factor loading of the control error factor exhibited the most substantial positive impact on near-misses in both models. As a result, Hypotheses 2.2 ($H_{2.2}$) and 2.5 ($H_{2.5}$) were rejected, with a significance level set at 0.001. Research conducted in India by Chouhan et al. (2021) supports this finding and indicates that control error is significantly correlated with an elevated risk of accidents. The frequency of control errors is also related to age and gender. In the rural model, the indicator with the highest factor loading was CE4, which refers to the problem of the visor or goggles fogging up. In rural areas, weather conditions often change suddenly, such as rain or fog, which reduces the rider's visibility. This combined with the indicator CE2, indicating slippery roads during rain and sudden braking, affects the riding conditions. The road surface becomes even more slippery, posing a challenge for motorcycle riders. Nguyen et al. (2022) also mentioned that riding in dusty or rainy conditions increases the likelihood of errors for motorcycle riders. Similarly, Sangkharat, Thornes, Wachiradilok, and Pope (2021) confirmed that road accidents significantly increase due to higher rainfall levels, particularly when riding at high speeds. Accidents occur due to the inability to control the motorcycle on changing road surfaces, inappropriate speeds while entering curves, and a lack of road grip. Rural roads, which are often winding and uneven, present additional challenges for motorcycle riders and contribute to increased accident risks. To minimize errors in motorcycle control in rural areas, riders should adhere to safe riding speeds, maintain a safe distance from other vehicles, and continuously monitor changes in road and weather conditions. It is essential to wear appropriate protective gear and ensure the proper maintenance of motorcycles, including headlights, taillights, brakes, and tires. In the urban model, the indicator with the highest factor loading on control error was CE3, which refers to riding the motorcycle with a wide turning radius, resulting in sharp curves or near-collisions with other cars. This is primarily due to the characteristics of urban environments, including heavy traffic and bustling city areas with pedestrians, bicycles, and other vehicles. These factors increase the risk of collisions and necessitate quick responses from riders to avoid accidents. Furthermore, the indicator CE4, which indicates having trouble with the visor or goggles fogging up, is relevant in urban areas experiencing increased levels of PM2.5 air pollution. This pollution can impair visibility and make it challenging for riders to anticipate changes in road conditions or traffic, thereby increasing the chances of accidents. This aligns with research conducted in China by Wan, Li, Liu, and Li (2020) which confirmed a significant association between the daily number of traffic accidents and particulate matter (PM10 and PM2.5), resulting in a 35% increase in traffic accidents.

The factor ranked second in terms of its significant positive impact on the occurrence of near-miss events was violations. As a result, Hypothesis 2.3 ($H_{2.3}$) and Hypothesis 2.6 ($H_{2.6}$) were rejected at a significance level of 0.001. The analysis showed that the factor loading of the violation factor was slightly higher in the urban model compared to the rural model. Of particular interest is the indicator VI3, which relates to the behavior of riding in the middle or rightmost lane, avoiding close proximity to the leftmost lane, when there are at least two lanes. VI3 had the highest factor loading in both urban and rural areas, indicating that the practice of riding motorcycles between lanes alongside other vehicles increased the risk of accidents in both models. This behavior is a significant issue that frequently leads to accidents involving motorcycles and larger vehicles. The mixed traffic condition, where motorcycles and other vehicles such as cars and trucks share the same road space, creates conflict and ultimately contributes to accidents. To tackle this problem and reduce accidents, including fatalities, other countries have implemented strategies to separate motorcycles from the main traffic flow by establishing exclusive motorcycle lanes

(EMCL). This approach has been proven successful in countries like Malaysia, Taiwan, and Indonesia. Studies have demonstrated that the implementation of EMCL significantly reduces motorcycle accidents and fatalities, particularly in Malaysia, where mixed traffic conditions contribute to motorcycle accidents (Saini, Chouhan, & Kathuria, 2022). The introduction of EMCL has led to a substantial reduction in accidents by up to 39% and a significant decrease in fatalities by up to 600% (Ibrahim, Hamid, Law, & Wong, 2018; Radin Umar, 2006). Similar studies have been conducted in Colombia, where the implementation of EMCL has been found to decrease the occurrence of accidents and injuries among motorcycle users. Additionally, motorcycle riders perceive that EMCL improves the ease of riding and reduces travel time (Osorio-Cuéllar et al., 2017).

In the context of near-misses and their contributing factors, safety equipment (SE) was identified as the factor with the lowest rank that positively influenced such incidents in both the urban and rural models. As a result, Hypotheses 4 (H4) and 7 (H7) were rejected at a significance level of 0.001. In the urban model, SE3, which refers to riding without turning on the headlights during daylight hours, was the indicator with the greatest factor loading. This behavior relates to the widely recognized principle of “see and be seen,” where perceiving motorcycles or other motorcyclists in time allows for adequate reaction to avoid accidents or minimize their impact. To enhance visibility, many countries have implemented the use of daytime running lights on cars and motorcycles (Ivanišević et al., 2022). Urban areas are characterized by their city-like nature and high traffic density, with pedestrians, bicycles, and various vehicles bustling around. The ability to observe and promptly respond to the surrounding environment is crucial. Therefore, the utilization of daytime running lights while riding motorcycles serves as a valuable tool to improve visibility, enabling other road users to easily spot motorcycles and reducing the risk of accidents. In the rural model, SE2, which pertains to wearing a helmet without fastening the chin strap while riding a motorcycle, had the highest factor loading. A study conducted in India revealed that individuals who wore helmets without securing the chin strap had a higher incidence of severe head injuries resulting from road accidents compared to those who wore helmets with properly fastened chin straps. Among motorcycle riders who wore helmets, only 4.8% experienced severe head injuries, whereas this rate was 23.7% for those who did not wear helmets at all. Moreover, full-face helmets were found to be particularly effective in preventing head injuries (Tripathi, Tewari, Mukherjee, & Mathuriya, 2014). Another study by Arif, B, and Prasad (2019) also highlighted that the number of injuries was significantly higher among individuals who did not fasten their helmets compared to those who did. Therefore, both the correct fixation and type of helmet play crucial roles in the effectiveness and safety of helmets for motorcyclists.

Furthermore, research indicates that rural areas have higher fatality rates resulting from road accidents compared to urban areas (Henning-Smith & Kozhimannil, 2018). Thus, ensuring strict adherence to wearing helmets with securely fastened chin straps while riding motorcycles becomes another essential measure to mitigate the risk of accidents in both urban and rural areas.

2.7 Conclusions and Implementation

This study aimed to create a model to prevent accidents by examining the near-miss behavior of motorcycle riders in urban and rural areas in countries with moderate-to-low incomes, where road safety laws and enforcement are often inadequate. The study utilized the Motorcycle Rider Behavior Questionnaire (MRBQ) to analyze three factors of risky behavior (control error, violation, and safety equipment) and their impact on near-miss incidents. To collect data, the study focused on Thailand and included a sample group of 2002 participants from six regions nationwide, with 1066 participants from urban areas and 936 participants from rural areas.

The first issue identified in the study was control error (CE), which was discovered to be the most important element contributing to near-miss incidents in both urban and rural areas. This factor encompasses four main concerns: visibility issues during adverse weather conditions caused by dust or smoke, slippery roads due to heavy rain, and difficulties in maneuvering wide turns. To address these concerns, suggested policy recommendations should focus on raising awareness of the risks associated with riding in unfavorable weather conditions, particularly in rural areas, where higher speeds are possible. The relevant agencies responsible for rider training and licensing should emphasize safe riding practices during rainy weather, including maintaining an appropriate speed for safety and employing safe cornering techniques under normal and abnormal conditions. Moreover, in areas with high levels of fog, dust, or smoke, especially in urban regions with elevated particulate matter (PM10 and PM2.5) levels, road safety agencies should raise awareness and promote precautionary measures. These measures can include using headlights to enhance visibility, reducing riding speed to compensate for reduced visibility, and wearing protective equipment such as full-face helmets and suitable eyewear to prevent direct eye contact with particles. Additionally, regular motorcycle maintenance is crucial to ensure readiness for constantly changing weather conditions. This maintenance should encompass checking and preparing essential components such as headlights, taillights, brake lights, and motorcycle tires to ensure they are in good condition and ready for use.

Violation was identified as the second-most significant factor contributing to near-miss incidents in both the urban and rural models. This factor involves the behavior of motorcycle riders frequently encroaching into the traffic lanes of other vehicles, whether they are riding in the middle or the far right of the traffic lane. It is crucial for the relevant agencies to be highly aware of this issue. As one of the strategies to enhance motorcyclist safety and overall road safety, the implementation of an exclusive motorcycle lane (EMCL) is recommended. Extensive research conducted in foreign countries has confirmed its effectiveness. Therefore, it is advisable for experts, academics, and related agencies to initiate studies and adapt the EMCL concept to suit the country’s specific context, taking into account factors such as physical infrastructure and riding behavior. Moreover, the design of the EMCL should align with traffic conditions and undergo evaluation in terms of safety and economic viability.

In the urban model, safety equipment (SE) was identified as the least influential factor in near-miss incidents. It is recommended that relevant agencies highlight the significance of using headlights during daytime riding to promote safe riding practices. Additionally, traffic officers should conduct comprehensive inspections to ensure that motorcycle headlights are in optimal working condition. In the rural model, agencies responsible for promoting safe riding should address the consequences of not wearing or improperly securing safety helmets. There should be a focus on educating riders about the correct usage of helmets and proper fastening techniques, including the use of chin straps. It is crucial for the government and law enforcement teams to prioritize raising awareness about this issue.

2.8 Limitations and Further Research

This study is primarily centered on motorcycle riders, and there is a need for further research to explore near-miss incidents with other vehicle types, including cars, trucks, and others. Additionally, it is important to note that this study did not specifically examine riders who are under the age of 18, even though statistics indicate that this age group accounts for one in three fatalities in road accidents. Consequently, future research should encompass this demographic to gain a more comprehensive understanding of the subject. Moreover, conducting comparative studies on risky behaviors that may contribute to near-miss incidents among different groups, such as comparing teenage motorcycle riders with older adults, would be valuable.

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2.10 References

Agusdinata, D. B., van der Pas, J. W. G. M., Walker, W. E., & Marchau, V. A. W. J. (2009). Multi-criteria analysis for evaluating the impacts of intelligent speed adaptation. *Journal of Advanced Transportation, 43*(4), 413-454. doi:10.1002/atr.5670430402

Aldred, R. (2012). Governing transport from welfare state to hollow state: The case of cycling in the UK. *Transport Policy, 23*, 95-102. doi:https://doi.org/10.1016/j.tranpol.2012.05.012

Aldred, R. (2016). Cycling near misses: Their frequency, impact, and prevention. *Transportation Research Part A: Policy and Practice, 90*, 69-83. doi:https://doi.org/10.1016/j.tra.2016.04.016

Aldred, R., & Crosweller, S. (2015). Investigating the rates and impacts of near misses and related incidents among UK cyclists. *Journal of Transport & Health, 2*(3), 379-393. doi:https://doi.org/10.1016/j.jth.2015.05.006

Ameratunga, S., Herman, J., Wainiqolo, I., & Kafoa, B. (2015). A83 Road traffic injuries and Alcohol: Double jeopardy in Pacific Island nations fuelled by inequitably distributed determinants of health. *Journal of Transport & Health, 2*(2, Supplement), S48-S49. doi:https://doi.org/10.1016/j.jth.2015.04.571

Arif, M. Z., B, R. R., & Prasad, K. (2019). The Role of Helmet Fastening in Motorcycle Road Traffic Accidents. *Craniomaxillofac Trauma Reconstr, 12*(4), 284-290. doi:10.1055/s-0039-1685458

Bhatti, J. A., & Ahmed, A. (2014). Evaluating performance of a Lead Road Safety Agency (LRSA) in a low-income country: a case study from Pakistan. *International Journal of Injury Control and Safety Promotion, 21*(2), 136-143. doi:10.1080/17457300.2013.792282

Brenac, T., Clabaux, N., Perrin, C., & Elslande, P. (2006). Motorcyclist conspicuity-related accidents in urban areas: A speed problem? *Advances in Transportation Studies*, 23-29.

Budd, L., Allen, T., & Newstead, S. (2018). Current Trends in Motorcycle Related Crash and Injury Risk in Australia by Motorcycle Type and Attributes.

Champahom, T., Jomnonkwao, S., Thotongkam, W., Jongkol, P., Rodpon, P., & Ratanavaraha, V. (2023). Investigating Parents’ Attitudes towards the Use of Child Restraint Systems by Comparing Non-Users and User Parents.

Sustainability, 15(4), 2896. Retrieved from https://www.mdpi.com/2071-1050/15/4/2896

Champahom, T., Se, C., Aryuyo, F., Banyong, C., Jomnonkwao, S., & Ratanavaraha, V. (2023). Crash Severity Analysis of Young Adult Motorcyclists: A Comparison of Urban and Rural Local Roadways. *Applied Sciences, 13*(21), 11723. Retrieved from https://www.mdpi.com/2076-3417/13/21/11723

Chang, H.-L., & Yeh, T.-H. (2007). Motorcyclist accident involvement by age, gender, and risky behaviors in Taipei, Taiwan. *Transportation Research Part F: Traffic Psychology and Behaviour, 10*(2), 109-122. doi:https://doi.org/10.1016/j.trf.2006.08.001

Chouhan, S. S., Kathuria, A., & Sekhar, C. R. (2021). Examining risky riding behavior in India using Motorcycle rider behavior questionnaire. *Accident Analysis & Prevention, 160*, 106312. doi:10.1016/j.aap.2021.106312

D'Elia, A., & Newstead, S. (2023). Evaluation of the effectiveness of daytime running lights (DRLs). *Journal of Safety Research*. doi:https://doi.org/10.1016/j.jsr.2023.01.009

Davoodi, S. R., & Hossayni, S. M. (2015). Role of Motorcycle Running Lights in Reducing Motorcycle Crashes during Daytime; A Review of the Current Literature. *Bulletin of Emergency and Trauma, 3*(3), 73-78.

de Rome, L., Fitzharris, M., Baldock, M., Fernandes, R., Ma, A., & Brown, J. (2016). The prevalence of crash risk factors in a population-based study of motorcycle riders. *Injury, 47*(9), 2025-2033. doi:https://doi.org/10.1016/j.injury.2016.03.033

de Rome, L., Ivers, R., Fitzharris, M., Du, W., Haworth, N., Heritier, S., & Richardson, D. (2011). Motorcycle protective clothing: protection from injury or just the weather? *Accident Analysis & Prevention, 43*(6), 1893-1900. doi:10.1016/j.aap.2011.04.027

Department of Land Transport. (2022). Statistical Data on Registered Vehicles in Thailand. Retrieved from https://web.dlt.go.th/statistics/

Devaux, M., & Sassi, F. (2016). Social disparities in hazardous alcohol use: self-report bias may lead to incorrect estimates. *European Journal of Public Health, 26*(1), 129-134. doi:10.1093/eurpub/ckv190

Elliott, M. A., Baughan, C. J., & Sexton, B. F. (2007). Errors and violations in relation to motorcyclists' crash risk. *Accident Analysis & Prevention, 39*(3), 491-499. doi:https://doi.org/10.1016/j.aap.2006.08.012

Evans, L. (2012). *Human Behavior and Traffic Safety*: Springer US.

Fan, Y., Chen, J., Shirkey, G., John, R., Wu, S. R., Park, H., & Shao, C. (2016). Applications of structural equation modeling (SEM) in ecological studies: an updated review. *Ecological Processes, 5*(1), 19. doi:10.1186/s13717-016-0063-3

finch, W. H. (2013). *Exploratory Factor Analysis*. Rotterdam: SensePublishers.

Gkritza, K. (2009). Modeling motorcycle helmet use in Iowa: Evidence from six roadside observational surveys. *Accident Analysis & Prevention, 41*(3), 479-484. doi:https://doi.org/10.1016/j.aap.2009.01.009

Golob, T. F. (2003). Structural equation modeling for travel behavior research. *Transportation Research Part B: Methodological, 37*(1), 1-25. doi:https://doi.org/10.1016/S0191-2615(01)00046-7

Haghani, M., Behnood, A., Dixit, V., & Oviedo-Trespalacios, O. (2022). Road safety research in the context of low- and middle-income countries: Macro-scale literature analyses, trends, knowledge gaps and challenges. *Safety Science, 146*, 105513. doi:https://doi.org/10.1016/j.ssci.2021.105513

Hair, J., Black, W., Babin, B., & Anderson, R. (2006). *Multivariate Data Analysis* (6 ed.): Pearson Prentice Hall.

Hair, J., Sarstedt, M., Ringle, C., & Gudergan, S. (2017). *Advanced Issues in Partial Least Squares Structural Equation Modeling*.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2-24. doi:10.1108/EBR-11-2018-0203

Hardy, E. (2009). Near Miss Study and Motorcycles: A Study of Motorcyclists in Northern Ireland, Southern Ireland and Great Britain.

Harnen, S., Wong, S. V., Umar, R. S. R., & Wan Hashim, W. I. (2003). MOTORCYCLE CRASH PREDICTION MODEL FOR NON-SIGNALIZED INTERSECTIONS. *IATSS Research, 27*(2), 58-65. doi:https://doi.org/10.1016/S0386-1112(14)60144-8

Hassan, T., Vinodkumar, M. N., & Vinod, N. (2017). Influence of demographics on risky driving behaviour among powered two wheeler riders in Kerala, India. *Transportation Research Part F: Traffic Psychology and Behaviour, 46*, 24-33. doi:https://doi.org/10.1016/j.trf.2016.11.008

Haworth, N. (2012). Powered two wheelers in a changing world—Challenges and opportunities. *Accident Analysis & Prevention, 44*(1), 12-18. doi:https://doi.org/10.1016/j.aap.2010.10.031

Henning-Smith, C., & Kozhimannil, K. B. (2018). Rural-Urban Differences in Risk Factors for Motor Vehicle Fatalities. *Health Equity, 2*(1), 260-263. doi:10.1089/heq.2018.0006

Henseler, J., Ringle, C. M., & Sarstedt, M. (2016). Testing measurement invariance of composites using partial least squares. *International Marketing Review, 33*(3), 405-431. doi:10.1108/IMR-09-2014-0304

Hooper, D., Coughlan, J. P., & Mullen, M. R. (2008). *Structural equation modelling: guidelines for determining model fit*.

Hu, L. t., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1-55. doi:10.1080/10705519909540118

Ibrahim, M. K. A., Hamid, H., Law, T. H., & Wong, S. V. (2018). Evaluating the effect of lane width and roadside configurations on speed, lateral position and likelihood of comfortable overtaking in exclusive motorcycle lane. *Accident Analysis & Prevention, 111*, 63-70. doi:https://doi.org/10.1016/j.aap.2017.10.023

Injury Data Collaboration Center (IDCC). (2021). Injury surveillance. Retrieved from http://ae.moph.go.th/

Islam, S., & Brown, J. (2017). A comparative injury severity analysis of motorcycle at-fault crashes on rural and urban roadways in Alabama. *Accident Analysis & Prevention, 108*, 163-171. doi:https://doi.org/10.1016/j.aap.2017.08.016

Ivanišević, T., Ivković, I., Čičević, S., Trifunović, A., Pešić, D., Vukšić, V., & Simović, S. (2022). The impact of daytime running (LED) lights on motorcycles speed estimation: A driving simulator study. *Transportation Research Part F: Traffic Psychology and Behaviour, 90*, 47-57. doi:https://doi.org/10.1016/j.trf.2022.08.002

Jomnonkwao, S., Champahom, T., Se, C., Hantanong, N., & Ratanavaraha, V. (2023). Contributing factors to near-miss experiences of motorcyclists in Thailand: A random parameter probit model approach. *Heliyon, 9*(12), e22625. doi:https://doi.org/10.1016/j.heliyon.2023.e22625

Jomnonkwao, S., Sangphong, O., Khampirat, B., Siridhara, S., & Ratanavaraha, V. (2016). Public transport promotion policy on campus: evidence from Suranaree University in Thailand. *Public Transport, 8*(2), 185-203. doi:10.1007/s12469-016-0122-2

Kline, R. B. (2011). *Principles and practice of structural equation modeling*: Third edition. New York : Guilford Press.

Kline, R. B. (2015). *Principles and practice of structural equation modeling*: Guilford publications.

Lam, L. W. (2012). Impact of competitiveness on salespeople's commitment and performance ☆. *Journal of Business Research, 65*, 1328-1334.

Li, L.-P., Li, G.-L., Cai, Q.-E., Zhang, A. L., & Lo, S. K. (2008). Improper motorcycle helmet use in provincial areas of a developing country. *Accident Analysis & Prevention, 40*(6), 1937-1942. doi:https://doi.org/10.1016/j.aap.2008.06.019

Lin, M. R., & Kraus, J. F. (2009). A review of risk factors and patterns of motorcycle injuries. *Accident Analysis & Prevention, 41*(4), 710-722. doi:10.1016/j.aap.2009.03.010

Marín Puchades, V., Fassina, F., Fraboni, F., De Angelis, M., Prati, G., de Waard, D., & Pietrantoni, L. (2018). The role of perceived competence and risk perception in cycling near misses. *Safety Science, 105*, 167-177. doi:https://doi.org/10.1016/j.ssci.2018.02.013

Maskey, R., Fei, J., & Nguyen, H.-O. (2018). Use of exploratory factor analysis in maritime research. *The Asian Journal of Shipping and Logistics, 34*(2), 91-111. doi:https://doi.org/10.1016/j.ajsl.2018.06.006

Motevalian, S. A., Asadi-Lari, M., Rahimi, H., & Eftekhar, M. (2011). Validation of a persian version of motorcycle rider behavior questionnaire. *Ann Adv Automot Med, 55*, 91-98.

Nguyen, D. V. M., Vu, A. T., Ross, V., Brijs, T., Wets, G., & Brijs, K. (2022). Small-displacement motorcycle crashes and risky ridership in Vietnam: Findings from a focus group and in-depth interview study. *Safety Science, 152*. doi:10.1016/j.ssci.2021.105514

OECD/ITF. (2015). Improving Safety for Motorcycle, Scooter and Moped Riders. Retrieved from https://doi.org/10.1787/9789282107942-en

Olson, P. L., & Dewar, R. E. (2002). *Human Factors in Traffic Safety*: Lawyers & Judges Pub.

Osorio-Cuéllar, G. V., Pacichana-Quinayaz, S. G., Bonilla-Escobar, F. J., Fandiño-Losada, A., Jaramillo-Molina, C., & Gutiérrez-Martínez, M. I. (2017). First motorcycle-exclusive lane (Motovia) in Colombia: perceptions of users in Cali, 2012–2013. *International Journal of Injury Control and Safety Promotion, 24*(2), 145-151. doi:10.1080/17457300.2015.1061563

Özkan, T., Lajunen, T., Doğruyol, B., Yıldırım, Z., & Çoymak, A. (2012). Motorcycle accidents, rider behaviour, and psychological models. *Accident Analysis & Prevention, 49*, 124-132. doi:https://doi.org/10.1016/j.aap.2011.03.009

Park, J.-I., Kim, S., & Kim, J.-K. (2023). Exploring spatial associations between near-miss and police-reported crashes: The Heinrich's law in traffic safety. *Transportation Research Interdisciplinary Perspectives, 19*, 100830. doi:https://doi.org/10.1016/j.trip.2023.100830

Pérez-Núñez, R., Hidalgo-Solórzano, E., Vera-López, J. D., Lunnen, J. C., Chandran, A., Híjar, M., & Hyder, A. A. (2014). The Prevalence of Mobile Phone Use Among Motorcyclists in Three Mexican Cities. *Traffic Injury Prevention, 15*(2), 148-150. doi:10.1080/15389588.2013.802776

Powell, N. B., Schechtman, K. B., Riley, R. W., Guilleminault, C., Chiang, R. P., & Weaver, E. M. (2007). Sleepy driver near-misses may predict accident risks. *Sleep, 30*(3), 331-342. doi:10.1093/sleep/30.3.331

Radin Umar, R. S. (2006). Motorcycle safety programmes in Malaysia: how effective are they? *International Journal of Injury Control and Safety Promotion, 13*(2), 71-79. doi:10.1080/17457300500249632

Ratanavaraha, V., & Amprayn, C. (2003). Causative highway accident factors of the expressway system in Thailand. *Journal of the Eastern Asia Society for Transportation Studies, 5*.

Roehler, D. R., Ear, C., Parker, E. M., Sem, P., & Ballesteros, M. F. (2015). Fatal motorcycle crashes: a growing public health problem in Cambodia. *International Journal of Injury Control and Safety Promotion, 22*(2), 165-171. doi:10.1080/17457300.2013.876050

Saini, H. K., Chouhan, S. S., & Kathuria, A. (2022). Exclusive motorcycle lanes: A systematic review. *IATSS Research, 46*(3), 411-426. doi:https://doi.org/10.1016/j.iatssr.2022.05.004

Sakashita, C., Senserrick, T., Lo, S., Boufous, S., Rome, L. d., & Ivers, R. (2014). The Motorcycle Rider Behavior Questionnaire: Psychometric properties and application amongst novice riders in Australia. *Transportation Research Part F: Traffic Psychology and Behaviour, 22*, 126-139. doi:https://doi.org/10.1016/j.trf.2013.10.005

Sanders, R. L. (2015). Perceived traffic risk for cyclists: The impact of near miss and collision experiences. *Accident Analysis & Prevention, 75*, 26-34. doi:https://doi.org/10.1016/j.aap.2014.11.004

Sangkharat, K., Thornes, J. E., Wachiradilok, P., & Pope, F. D. (2021). Determination of the impact of rainfall on road accidents in Thailand. *Heliyon, 7*(2), e06061. doi:https://doi.org/10.1016/j.heliyon.2021.e06061

SaveLIFE Foundation. (2017). *DISTRACTED DRIVING IN INDIA A STUDY ON MOBILE PHONE USAGE, PATTERN & BEHAVIOUR*. Retrieved from https://savelifefoundation.org/wp-content/uploads/2017/04/Distracted-Driving-in-India_A-Study-on-Mobile-Phone-Usage-Pattern-and-Behaviour.pdf

Se, C., Champahom, T., Jomnonkwao, S., & Ratanavaraha, V. (2022). Motorcyclist injury severity analysis: a comparison of Artificial Neural Networks and random parameter model with heterogeneity in means and variances. *International*

Journal of Injury Control and Safety Promotion, 29(4), 500-515. doi:10.1080/17457300.2022.2081985

Shinar, D. (2007). *Traffic Safety and Human Behavior*: Emerald Group Publishing Limited.

Steiger, J. H. (2007). Understanding the limitations of global fit assessment in structural equation modeling. *Personality and Individual Differences, 42*(5), 893-898. doi:https://doi.org/10.1016/j.paid.2006.09.017

Stephens, A. N., Brown, J., de Rome, L., Baldock, M. R. J., Fernandes, R., & Fitzharris, M. (2017). The relationship between Motorcycle Rider Behaviour Questionnaire scores and crashes for riders in Australia. *Accident Analysis & Prevention, 102*, 202-212. doi:https://doi.org/10.1016/j.aap.2017.03.007

Sumit, K., Ross, V., Brijs, K., Wets, G., & Ruiter, R. A. C. (2021). Risky motorcycle riding behaviour among young riders in Manipal, India. *BMC Public Health, 21*(1), 1954. doi:10.1186/s12889-021-11899-y

Sunday, O. K. (2010). The performance of the motorcycle rider behaviour questionnaire among commercial motorcycle riders in Nigeria. *Injury Prevention, 16*, A194 - A194.

Taber, K. S. (2018). The Use of Cronbach's Alpha When Developing and Reporting Research Instruments in Science Education. *Research in Science Education, 48*(6), 1273-1296. doi:10.1007/s11165-016-9602-2

The World Bank. (2022). World Bank Country and Lending Groups. Retrieved from https://datahelpdesk.worldbank.org/knowledgebase/articles/906519

Tongklao, A., Jaruratanasirikul, S., & Sriplung, H. (2016). Risky behaviors and helmet use among young adolescent motorcyclists in Southern Thailand. *Traffic Injury Prevention, 17*(1), 80-85. doi:10.1080/15389588.2015.1045062

Topolšek, D., & Dragan, D. (2016). Relationships between the motorcyclists' behavioural perception and their actual behaviour. *Transport, 33*, 151-164.

Tripathi, M., Tewari, M. K., Mukherjee, K. K., & Mathuriya, S. N. (2014). Profile of patients with head injury among vehicular accidents: an experience from a tertiary care centre of India. *Neurol India, 62*(6), 610-617. doi:10.4103/0028-3886.149382

Trung Bui, H., Saadi, I., & Cools, M. (2020). Investigating on-road crash risk and traffic offences in Vietnam using the motorcycle rider behaviour questionnaire (MRBQ). *Safety Science, 130*, 104868. doi:https://doi.org/10.1016/j.ssci.2020.104868

Truong, L. T., Nguyen, H. T. T., & De Gruyter, C. (2018). Correlations between mobile phone use and other risky behaviours while riding a motorcycle. *Accident Analysis & Prevention, 118*, 125-130. doi:https://doi.org/10.1016/j.aap.2018.06.015

Truong, L. T., Nguyen, H. T. T., & De Gruyter, C. (2019). Mobile phone use while riding a motorcycle and crashes among university students. *Traffic Injury Prevention, 20*(2), 204-210. doi:10.1080/15389588.2018.1546048

U.S. Department of Transportation's. (2022). Fatality Analysis Reporting System (FARS). Retrieved from https://www-fars.nhtsa.dot.gov/Main/index.aspx

Uttra, S., Jomnonkwao, S., Watthanaklang, D., & Ratanavaraha, V. (2020). Development of Self-Assessment Indicators for Motorcycle Riders in Thailand: Application of the Motorcycle Rider Behavior Questionnaire (MRBQ). *Sustainability, 12*(7). doi:10.3390/su12072785

Vlahogianni, E. I., Yannis, G., & Golias, J. C. (2012). Overview of critical risk factors in Power-Two-Wheeler safety. *Accident Analysis & Prevention, 49*, 12-22. doi:https://doi.org/10.1016/j.aap.2012.04.009

Vu, A. T., Nguyen, M. T., Nguyen, D. V. M., & Khuat, V. H. (2020). Investigating the effect of blood alcohol concentration on motorcyclist's riding performance using an advanced motorcycle simulator. *Transportation Research Part F: Traffic Psychology and Behaviour, 73*, 1-14. doi:https://doi.org/10.1016/j.trf.2020.06.010

Wan, Y., Li, Y., Liu, C., & Li, Z. (2020). Is traffic accident related to air pollution? A case report from an island of Taihu Lake, China. *Atmospheric Pollution Research, 11*(5), 1028-1033. doi:https://doi.org/10.1016/j.apr.2020.02.018

Warner, C. H., Appenzeller, G. N., Grieger, T., Belenkiy, S., Breitbach, J., Parker, J., . . . Hoge, C. (2011). Importance of Anonymity to Encourage Honest Reporting in

Mental Health Screening After Combat Deployment. *Archives of General Psychiatry, 68*(10), 1065-1071. doi:10.1001/archgenpsychiatry.2011.112

World Health Organization. (2018). *GLOBAL STATUS REPORT ON ROAD SAFETY*. Retrieved from https://apps.who.int/iris/bitstream/handle/10665/276462/9789241565684-eng.pdf?ua=1

Zamani-Alavijeh, F., Bazargan, M., Shafiei, A., & Bazargan-Hejazi, S. (2011). The frequency and predictors of helmet use among Iranian motorcyclists: A quantitative and qualitative study. *Accident Analysis & Prevention, 43*(4), 1562-1569. doi:https://doi.org/10.1016/j.aap.2011.03.016

CHAPTER III

ASSESSING THE SELF-REPORT INSTRUMENTS OF YOUNGER VERSUS OLDER RIDERS INVOLVED IN NEAR-MISS MOTORCYCLE INCIDENTS

3.1 Abstract

Road accidents pose severe and pervasive consequences, especially in low- and middle-income countries (LMICs), where both the population and fatal accidents among youth and the elderly are steadily increasing. Therefore, this study aims to develop a model for risky behavior in near-miss incidents among motorcycle riders in Thailand. It intends to compare models between younger and older riders utilizing structural equation modeling (SEM) with a multi-group approach. The data were examined employing modified instruments derived from the Motorcycle Rider Behavior Questionnaire (MRBQ). Samples depicting risky riding behavior were obtained from both younger and older rider groups. Parameter invariance testing revealed differences between the two groups. Control errors notably emerged as the predominant factor contributing to near-miss incidents for both age groups. Speeding was identified as the primary concern for the younger group, while adverse weather conditions were deemed crucial for the older group. Based on this study, policy recommendations endorse the creation of targeted training programs for novice riders, emphasizing adherence to legal speed limits and the adoption of safe riding practices. Additionally, the study underscores the importance of preparing riders, especially those in the older age group, for adverse weather conditions.

3.2 Introduction

Annually, the global toll of fatalities resulting from road accidents stands at approximately 1.35 million, as documented by the World Health Organization (2018). In conjunction with this, a significant demographic number of between 20 and 50 million individuals experiences incapacitating injuries or disabilities due to these incidents. Notably, vulnerable road users, encompassing pedestrians, cyclists, and motorcyclists, are disproportionately implicated in nearly 50% of these occurrences. This predilection for vulnerability is particularly pronounced within nations characterized by modest to intermediate economic indicators, a classification delineated by the World Health Organization (2018). Furthermore, prevailing projections, as posited by Haruhiko, Qingfeng, Abdulgafoor, and Adnan (2020), portend a sustained increase in these figures. An especially noteworthy facet is the disproportionate impact on the age group spanning from 5 to 29 years, which comprises children and young adults, as underscored by the World Health Organization (2018). Thailand's motorcycle fatality rate holds the global second position and leads within the Asian region, a classification supported by the World Health Organization (2018). Remarkably, the nation boasts a cumulative registration tally of 21 million motorcycles, representing a substantial 70% portion of the entire vehicular landscape, as evidenced by the Department of Land Transport (2021). The allure of motorcycles can be attributed to their inherent advantages, including convenience, swiftness, fuel efficiency, and cost-effectiveness. However, it is noteworthy that these very attributes contribute to the cultivation of risky driving behaviors, a proposition expounded by Liao, Lin, and Park (2019). This propensity for imprudent driving practices significantly contributes to the prevalence of injuries and fatalities stemming from accidents. Drawing attention to the situation in developing countries, Fitzpatrick and O’Neill (2017) reveal a confluence of factors that accentuate the heightened vulnerability within these regions. Specifically, such countries often exhibit deficient road user training, diminished adherence to traffic regulations, and inadequacies in both road infrastructure and healthcare systems. These deficiencies collectively culminate in elevated rates of injuries and fatalities among their populace.

The ThaiRoads Foundation's report in 2022 highlights that in the year 2021, Thailand confronted a notable fatality rate attributed to motorcycle-related incidents, accounting for approximately 51% of the overall fatalities resulting from road accidents. In-depth analysis of motorcycle accidents further discloses that nearly 50% of these occurrences trace their origins to perceptual lapses among motorcycle riders during the assessment of situations. It is of significance that individuals aged between 15 and 24 years, constituting the adolescent and young adult cohort, exhibit the highest incidence of motorcycle accidents. The principal underlying cause of these incidents predominantly revolves around errors linked to motorcycle control, particularly the mastery of braking techniques for speed moderation and halting. This factor prominently features in 90% of motorcycle accident cases involving riders, irrespective of their possession of a valid driver's license. The acquisition of motorcycle riding skills is frequently influenced by peers, family members, or self-initiated practice, commonly excluding the incorporation of safe driving skills (ThaiRoads Foundation, 2022).

3.3 Literature Review

3.3.1 Younger and older rider

A study conducted by the OECD contends that adolescent drivers lack full preparedness in terms of physical and cognitive development. Notably, the prefrontal cortex, often recognized as the "executive function" of the brain governing decision-making, impulse regulation, and reasoning, remains inadequately matured until the age of 25 (Huang & Winston, 2011). Adolescent drivers, who are commonly identified as high-risk candidates for road accidents, confront limitations stemming from their limited driving experience and an increasing inclination toward risky behaviors (Gershon et al., 2018). Adolescents are substantially more susceptible to severe road accidents compared to adults, often exhibiting a threefold higher propensity (Walshe, Ward McIntosh, Romer, & Winston, 2017). Moreover, the incidence of road traffic crashes per million miles driven is shown to be up to six times greater for adolescents when compared with adults (Banz, Fell, & Vaca, 2019). It is imperative to underscore that adolescent riders are inherently predisposed to an escalated accident risk, primarily due to their status as novice drivers with limited experiential exposure. This vulnerability is compounded by their underdeveloped physical, cognitive, and brain maturation, which compromises their aptitude for proficient motorcycle operation.

Since the beginning of 2020, the COVID-19 pandemic has had a discernible impact on reduced road usage among the population. Despite an overall decrease in the occurrence of road accidents, there has been a troubling trend of significantly increased severity in injuries resulting from these accidents (ThaiRoads Foundation, 2022). Notably, "motorcycles" persist as the predominant high-risk vehicle category, contributing to fatalities arising from road accidents. This fact is vividly portrayed in Figure 3.1, mirroring the pattern delineated in Figure 3.2. These graphical representations underscore that the "working-age group" remains more susceptible to fatalities compared to other age cohorts, with a consistent upward trajectory. An intriguing observation pertains to the "elderly population," specifically individuals aged 50 to 60 years and above. This demographic constitutes an additional vulnerable group that necessitates vigilant attention, as the ascending trend in fatality rates over the past five years is approaching levels almost on par with those of the youth and working-age groups (ThaiRoads Foundation, 2022). This phenomenon is intricately tied to Thailand's progression into an "aged society," as those aged 60 years and older currently comprise 10% of the population. Projections indicate that the elderly population will escalate to 28%, ushering Thailand into the realm of a "super-aged society" within the next decade (World Health Organization, 2023). It is imperative to note that Thailand is not the sole contender grappling with the complexities of an aging society. Lower and middle-income countries (LMICs) are predicted to encompass two-thirds of their populations with elderly individuals by 2050 (Tan, 2022). As a result, the elderly population grapples with a spectrum of issues and requirements, encompassing age-related visual impairments, chronic ailments, and risky behaviors. Of paramount importance, elderly individuals who sustain injuries in road accidents endure more severe ramifications than their younger counterparts. This often necessitates intensive medical care, extended convalescence periods, and heightened possibilities of complications (Fitzpatrick & O'Neill, 2017). The elderly are doubly susceptible to succumbing in road accidents compared to the youth (Azami-Aghdash, Aghaei, & Sadeghi-Bazarghani, 2018; W. Y. Lee, Cameron, & Bailey, 2006), largely attributed to their diminished physical resilience, thereby elevating the risk of fatality (C. Lam et al., 2019). The process of driving mandates faculties such as attention, memory, problem-solving skills, and information processing, all of which tend to wane with advancing age. These cognitive impairments, frequently linked with conditions like Alzheimer's disease and dementia, are more prevalent among the elderly. Common categories of errors committed by elderly drivers encompass pedal misapplications, lane positioning errors, collisions, running red lights, and exceeding speed limits (Freund & Smith, 2011). These errors have significant repercussions on other road users, consequently augmenting the hazards of morbidity and mortality for passengers across diverse modes of transportation (Etehad et al., 2015). This study acknowledges the importance of road accidents, particularly concerning youth and adolescents, who bear a significant role in a country's future development. Furthermore, the globally increasing elderly population is a matter of concern.

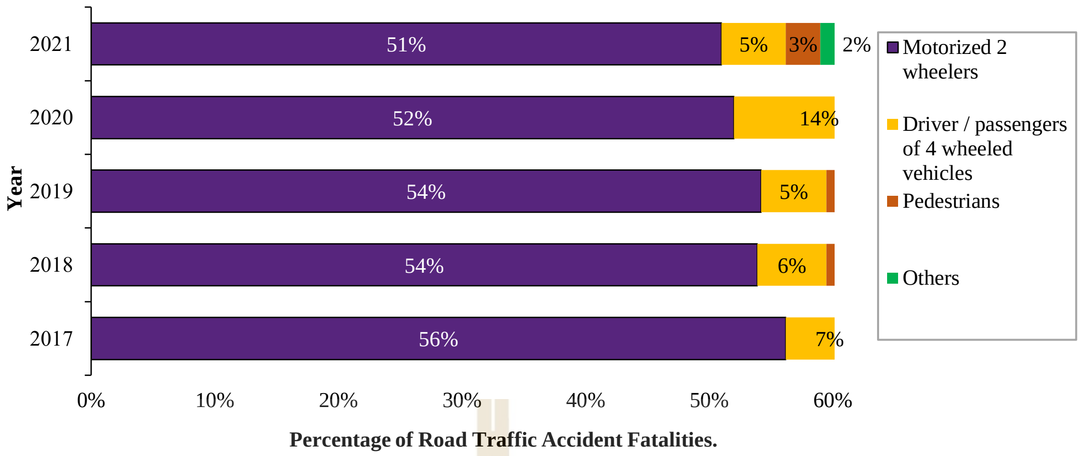

Figure 3.1 The Proportion of Road Traffic Accident Fatalities in Thailand, 2017–2021, Segmented by vehicle type (ThaiRoads Foundation, 2022)

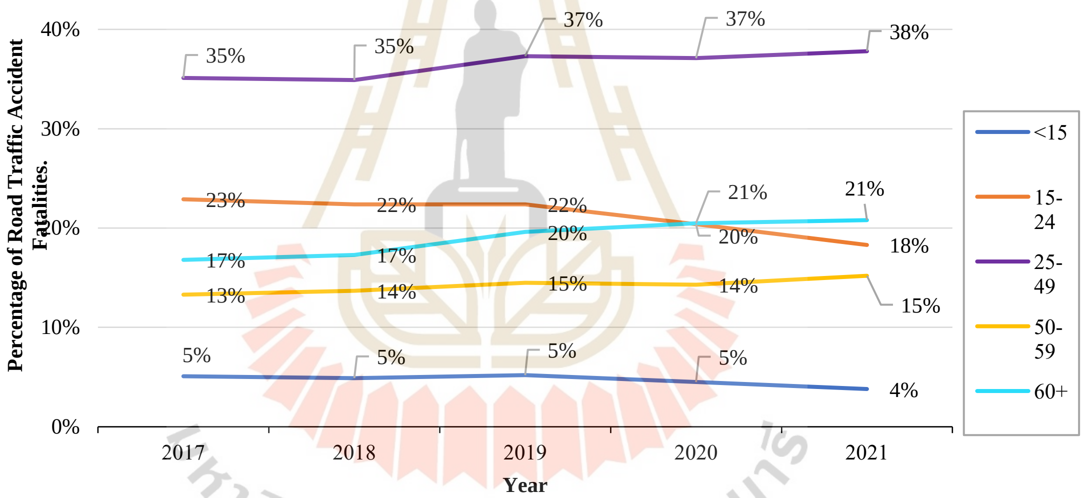

Figure 3.2 The Proportion of Road Traffic Accident Fatalities in Thailand, 2017–2021, Segmented by age groups (ThaiRoads Foundation, 2022)

3.3.2 The importance of a near-miss incident

A crucial aspect emphasized in this study concerning accident prevention is the notion of near-miss incidents or near-crashes. These events involve scenarios in which collisions or accidents are narrowly avoided (Aldred & Crosweller, 2015; Sanders, 2015; Young, Sobhani, Lenné, & Sarvi, 2014). Importantly, research indicates that near-miss incidents can serve as proxies for real accidents (P. Chen, Zeng, Yu, & Wang, 2017; Cho, Rodríguez, & Khattak, 2009; Zheng, Ismail, & Meng, 2014). Wright and Van der

Schaaf (2004) imply a fundamental assumption for utilizing minor incidents as a foundation for accident prevention measures: the common cause hypothesis, positing that the causal pathways of near misses resemble those of actual accidents leading to injuries and damages. As a result, the inclusion of near-miss incidents has been incorporated as additional information alongside police-reported crashes to identify areas prone to accidents within road networks and develop safety measures and strategies. (Park et al., 2023). The origin of the near-miss incident concept traces back to Heinrich's (1941) research in industrial safety, which scrutinized over 75,000 incident reports (Heinrich, 1941). This discovery engendered Heinrich's law, Heinrich's Accident Triangle, or Heinrich's Safety Pyramid, depicted in Figure 3.3. The paramount objective of Heinrich's Safety Pyramid is to broaden the base of the triangle for identifying leading indicators and analyzing risk behaviors, unsafe conditions, unsafe acts, and near misses to forestall first aid, injuries, illnesses, and fatalities. Safety performance indicators are classified into leading and lagging indicators. Lagging indicators might not effectively reflect the severity of hazards, event intensity, or event causation reduction. Conversely, leading indicators involve evaluating processes, activities, and conditions that assess safety efficacy and forecast future outcomes (Awolusi & Marks, 2015). The significance of near-miss incidents in road safety lies in their capacity to predict behavior patterns or physical attributes of roads that could lead to injuries or fatalities (Aldred, 2012). Additionally, near-misses can serve as advanced warning signals for events or behaviors that could potentially lead to accidents (collisions) (Marín Puchades et al., 2018). Importantly, near-misses occur more frequently than actual collisions (Sanders, 2015). Furthermore, the enhancement of risk factors associated with near-misses can substantially curtail or prevent actual collisions or severe events (Matsui et al., 2013).

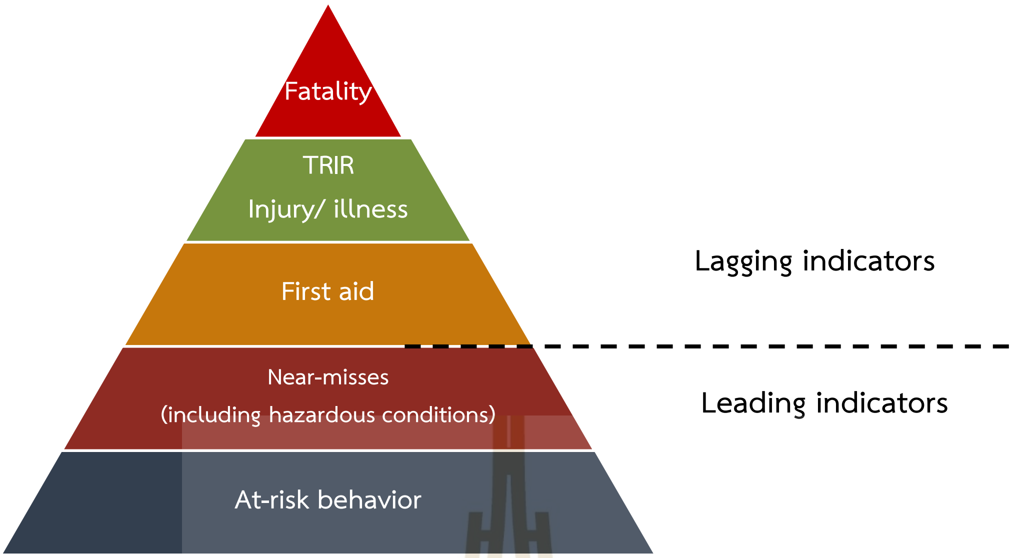

Figure 3.3 Heinrich's Accident Triangle or Heinrich's Safety Pyramid (Awolusi & Marks, 2015)

3.3.3 Measuring rider behavior with self-report: The Motorcycle Rider Behavior Questionnaire (MRBQ)

In prior research, self-reports have been utilized as a means to quantify driving style and driver behavior. The original iteration of the Motorcycle Rider Behavior Questionnaire (MRBQ) was crafted by Elliott et al. (2007) and adapted from the Manchester Driver Behavior Questionnaire (DBQ) formulated by Reason, Manstead, Stradling, Baxter, and Campbell (1990). The MRBQ encompasses a wide array of facets, spanning from errors and violations to the use of safety gear while riding. Elliott et al. (2007) embarked on a study aimed at constructing a survey instrument capable of assessing the behavior of motorcycle riders. This endeavor sought to determine which factors linked to specific behavior patterns could serve as predictors of the likelihood of collisions. The Motorcycle Rider Behavior Questionnaire (MRBQ), comprising 43 items, was employed for this purpose. It incorporates five distinct categories: traffic errors, control errors, speed violations, stunts performance, and use of safety equipment. Within these categories, traffic errors delineate inadvertent errors, while safety equipment pertains to the rider's actions, mechanisms, and protective elements. Stunts involve purposeful maneuvers that engender heightened risks for motorcyclists, while speed violations comprise intentional acts with utilitarian motivations. Control errors encompass both conscious and subconscious mishandling of the motorcycle. Several research investigations have adjusted variables within their questionnaires. This adaptation is driven by disparities in physical attributes and traffic regulations among countries, which give rise to divergent driving behaviors. As a result, the questionnaire's content must be suitably attuned to the motorcycle behavior inherent in each nation. Table 3.1 provides a comprehensive global overview of studies pertaining to the MRBQ tool. It encompasses investigations conducted in both low- and middle-income countries as well as high-income countries. The table serves to delineate the evidence, sample characteristics, and analytical methodologies employed in these studies.

Table 3.1 Literature Review Summary: Motorcycle Rider Behavior Questionnaire (MRBQ)

Country (author)	Compare the rider's age	Sample Type	Sample Size	Items	Factor structure	Factor analysis method
High-income countries						
United Kingdom (Elliott et al., 2007)	No	General Rider Population	8,666	43	5- factors (traffic errors, speed violations, stunts, safety equipment, and control errors)	Principle component analysis with varimax rotation
Netherland (Steg & Brussel, 2009)	No	Young moped riders	146	43	3-factors (errors, lapses, and violation)	Exploratory and confirmatory factor analysis

Table 3.1 Literature Review Summary: Motorcycle Rider Behavior Questionnaire (MRBQ) (Continued)

Country (author)	Compare the rider's age	Sample Type	Sample Size	Items	Factor structure	Factor analysis method
Australia (Sakashita et al., 2014)	No	Australian novice riders	1,305	43	4-factors (errors, speed violation, stunts, and protective gear)	Confirmatory factor analysis and principal axis factoring
Slovenia (Topolšek & Dragan, 2016)	No	General Rider Population	205	43 + 11	7- factors (safety equipment, errors, stunts, helmet, clothing, speed violations, and alcohol)	Exploratory and second-order confirmatory factor analysis
Australia (Stephens et al., 2017)	No	General rider population	470	29	5- factors (traffic errors, speed violations, stunts, protective gear, and control errors)	Principal axis factoring
Low- and middle-income countries						
Iran (Motevalian et al., 2011)	No	General rider population	518	48	6- factors (traffic errors, speed violations, stunts, safety violations, traffic violations, and control errors)	Principle component analysis with varimax rotation

Table 3.1 Literature Review Summary: Motorcycle Rider Behavior Questionnaire (MRBQ) (Continued)

Country (author)	Compare the rider's age	Sample Type	Sample Size	Items	Factor structure	Factor analysis method
Turkey (Özkan et al., 2012)	No	General Rider Population	451	43	5- factors (traffic errors, speed violations, stunts, safety equipment, and control errors)	Principle component analysis
Nigeria (Sunday, 2010)	No	Commercial Motorcycle Riders	500	40	4- factors (Control/Safety, Stunts, Errors, Speeding/Impatience)	Principle component analysis
Vietnam (Trung Bui et al., 2020)	No	General rider population	2,254	43	4- factors (traffic errors, speed and alcohol-related violations, safety equipment, and control errors)	Confirmatory factor analysis and principal axis factoring
Thailand (Uttra et al., 2020)	No	General rider population	1,516	38	4- factors (traffic errors, stunts, safety equipment, and control errors)	Exploratory and second-order confirmatory factor analysis

Table 3.1 Literature Review Summary: Motorcycle Rider Behavior Questionnaire (MRBQ) (Continued)

Country (author)	Compare the rider's age	Sample Type	Sample Size	Items	Factor structure	Factor analysis method
India (Chouhan, Kathuria, & Sekhar, 2021)	No	General rider population	392	32	4-factors (traffic errors, stunts, speed violations, and control errors)	Exploratory factor analysis
India (Sumit et al., 2021)	No	Young Motorcycle Riders	300	43	5- factors (traffic errors, violations, stunts, safety equipment, and control errors)	Exploratory factor analysis
Colombia (Ospina-Mateus, Jiménez, & López-Valdés, 2021)	No	Motorcycle taxi riders	438	45	5- factors (stunts, speed violations, traffic errors, control errors, and safety)	Exploratory factor analysis

Table 3.1 Literature Review Summary: Motorcycle Rider Behavior Questionnaire (MRBQ) (Continued)

Country (author)	Compare the rider's age	Sample Type	Sample Size	Items	Factor structure	Factor analysis method
Thailand (Jomnonkw-ao, Hantanong, Champahom, Se, & Ratanavaraha, 2023)	No	General Rider Population (Compare the rider's zone)	2002	17	3- factors (violation, safety equipment, and control errors)	Exploratory and confirmatory factor analysis
Thailand (This study)	Yes	Young and Older Motorcycle Riders	855	19	3- factors (traffic violation, safety equipment, and control errors)	Exploratory and confirmatory factor analysis

The Motorcycle Rider Behavior Questionnaire (MRBQ) comprises a series of inquiries designed to elicit information about riders' conduct, attitudes, and encounters pertaining to near-miss incidents. The following features are commonly incorporated in the MRBQ to assess near-miss risk behaviors:

(1) *Scenario-Based Questions:* The MRBQ employs hypothetical or real-life scenarios, illustrating situations where a near-miss incident might transpire. Participants are then prompted to respond to these scenarios, offering insights into their potential behavior in comparable situations.

(2) *Frequency of Near-Miss Experiences:* Questions within the questionnaire may address the frequency of near-miss experiences encountered by riders within

a specific timeframe. This aids researchers in comprehending how frequently riders confront situations with the potential for accidents.

(3) *Behavioral Responses:* Riders are queried about their reactions and responses during or after a near-miss incident. This encompasses inquiries about evasive actions taken, alterations in speed, utilization of protective gear, or other behaviors aimed at averting a collision.

(4) *Perceived Causes:* Participants may be prompted to pinpoint factors they believe contributed to the occurrence of near-miss incidents. This involves an assessment of their perception of external elements (e.g., road conditions, weather) and internal factors (e.g., rider's behavior, skills).

(5) *Attitudes and Risk Perception:* Questions may delve into riders' attitudes regarding risk, their perception of the likelihood of being involved in a near-miss incident, and the extent of their concern about such occurrences.

The MRBQ serves as a valuable instrument for researchers, providing a comprehensive understanding of the cognitive and behavioral aspects of riders in situations leading to near-miss incidents. The gathered responses contribute to the identification of patterns and risk factors and the development of targeted interventions and safety measures to mitigate the occurrence of near-miss incidents among motorcycle riders. The research conducted in Thailand by Jomnonkwao, Hantanong, et al. (2023) highlighted the substantial impact of risky motorcycle riding behaviors on the frequency of near-miss incidents, both in urban and rural settings. The study identified three primary risk factors contributing to these incidents. (1) Control Errors: This unintentional factor is linked to the management of motorcycle control, particularly in situations involving speed adjustment, negotiating curves, riding on slippery surfaces, and adverse weather conditions. (2) Violations: This category encompasses variables associated with high-risk behaviors, including speeding, reckless driving, mobile phone use, and driving under the influence of alcohol while operating a motorcycle. (3) Safety Equipment: This factor is associated with the usage of safety equipment, specifically the adherence to wearing helmets and the utilization of motorcycle headlights. The study underscores the pivotal role of these risk factors in influencing the occurrence of near-miss incidents. Understanding these factors enables the development of targeted interventions and safety measures aimed at addressing specific aspects of motorcycle rider behavior, ultimately reducing the likelihood of near-miss accidents.

Drawing insights from a study conducted in India (Chouhan et al., 2021), it was revealed that control errors exhibit a significant correlation with an elevated likelihood of near-miss incidents. Additionally, the study underscored a noteworthy correlation between the frequency of control errors and age categories. This finding substantiates the fundamental null hypothesis pertaining to control error factors among the younger and older groups in the current investigation.

Hypothesis$_{1a}$ (H_{1a}): *Control errors exert an adverse impact on the occurrence of near-miss incidents among younger riders.*

Hypothesis$_{1b}$ (H_{1b}): *Control errors exert an adverse impact on the occurrence of near-miss incidents among older riders.*

Research conducted in various countries, including the UK (Elliott et al., 2007), Colombia (Ospina-Mateus et al., 2021), Vietnam (Trung Bui et al., 2020), and India (Chouhan et al., 2021), has consistently indicated that traffic errors are strongly associated with risky driving behavior and play a pivotal role in contributing to accidents. Studies from Australia have further corroborated these findings by establishing a clear link between errors and speeding in both accidents (Möller et al., 2020) and near-miss incidents (Stephens et al., 2017). Additionally, the occurrence of stunts has also been identified as a contributing factor in these incidents (Özkan et al., 2012; Stephens et al., 2017). These conclusions align harmoniously with the core null hypothesis, which pertains to the influence of traffic violation factors within the younger and older groups investigated in the present study.

***Hypothesis$_{2a}$* *(H$_{2a}$)*:** *Traffic violations exert an adverse impact on the occurrence of near-miss incidents among younger riders.*

***Hypothesis$_{2b}$* *(H$_{2b}$)*:** *Traffic violations exert an adverse impact on the occurrence of near-miss incidents among older riders.*

Regarding the aspect of safety equipment, it is regarded as a safety-conscious driving behavior (Sakashita et al., 2014; Topolšek & Dragan, 2016). The research conducted by Sakashita et al. (2014) pointed out that the use of safety equipment does not exhibit a significant association with either the risk of actual crashes or near-miss incidents. This observation corresponds with the central null hypothesis concerning the safety equipment factors within the younger and older groups under investigation in this present study.

***Hypothesis$_{3a}$* *(H$_{3a}$)*:** *Safety equipment exerts an adverse impact on the occurrence of near-miss incidents among younger riders.*

***Hypothesis$_{3b}$* *(H$_{3b}$)*:** *Safety equipment exerts an adverse impact on the occurrence of near-miss incidents among older riders.*

3.3.4 Purpose and Contributions

Based on previous studies, Table 3.1 presents a succinct summary of the existing literature on the Motorcycle Rider Behavior Questionnaire (MRBQ), delving into risk-behavior factors across both high-income and low- and middle-income countries. The majority of studies predominantly concentrated on scrutinizing driving behavior within the general rider population. A notable exception is the research conducted by Jomnonkwao, Hantanong, et al. (2023), which specifically delved into evaluating risky behaviors contributing to near-miss accidents. The research investigates riding conduct in both urban and rural regions of Thailand, which is a developing nation. However, as noted earlier in Section 3.3.1, this emphasizes the importance of taking into account the hazardous conduct of both younger and older riders. Therefore, the aims of this study encompass the development of a risk behavior model concerning near-miss incidents among Thailand's motorcycle riders. The methodology employs MRBQ and involves a comparison between two distinct cohorts: young riders and elderly riders. The pivotal contributions of this research primarily center on the identification of risk behavior factors that precipitate near-miss incidents while juxtaposing these factors across the two divergent groups characterized by significant differences in physical and psychological attributes. Considering that near-miss incidents represent potential events that have yet to materialize but can nevertheless be harnessed, their study serves as a proactive approach to forestall potentially hazardous situations from escalating into full-fledged accidents. The comprehension of the underlying causes driving unsafe scenarios and their proactive mitigation serves as a pivotal measure to preclude the occurrence of loss of life and property damage, thereby emerging as a consequential proactive strategy in accident prevention and consequently fostering genuine safety. This paradigm can also augment the efficacy of police-reported crash data, empowering pertinent authorities to precisely refine, strategize, and rectify issues within the domain of road safety. Thailand, classified as a developing nation with middle-income status and notable motorcycle utilization, records alarmingly high accident rates on a global scale. Notably, statistical data underscores a marked prevalence of motorcycle accidents involving both the younger and older demographics, with an observable upward trajectory. Therefore, the exploration of near-miss incidents emerges as a fresh and captivating subject of inquiry, endowing a focused comprehension capable of tackling road safety issues and implementing proactive measures to reduce the occurrence of accidents, consequently leading to reductions in both injuries and fatalities. Furthermore, the elevation of safety considerations concerning life and property assumes paramount importance for both the local community and broader society. The elevation of safety standards within society, including the establishment of sustainable communities, would manifest through the creation of a secure milieu, ultimately contributing to an enriched quality of life.

In this study, we undertake a comparison of risk behaviors associated with near-miss incidents among motorcycle riders, with a specific emphasis on the distinctions between young and elderly riders. In this context, the classification "younger" encompasses individuals aged 30 years or below (Alnawmasi & Mannering, 2019), while "older" pertains to those aged 60 years and above (Ashie, Wilhelm, Carney, DiPasquale, & Bush, 2018; S.-J. Chen, Chen, & Lin, 2018). The primary null hypothesis is formulated as follows:

Hypothesis$_0$ (H_0). *There is no difference in invariance between younger and older riders' behaviors.*

3.4 Methods

3.4.1 Research Methods

The original MRBQ questionnaire underwent modifications based on the research conducted by Elliott et al. (2007), with comprehensive particulars elucidated in Table 3.1. These adaptations encompassed both the removal and addition of questions to intricately align with the specific driving contexts characteristic of each respective country. Within the ambit of this study, the original interrogative items underwent refinements guided by the discerning input and recommendations provided by experts specializing in the design of survey questions. Subsequent to this meticulous refinement process, a preliminary pilot test was meticulously executed prior to embarking on the primary phase of data collection. It is crucial to emphasize that the study meticulously followed the ethical principles of experiments involving humans, as stipulated by the Ethical Committee (EC), prior to progressing further. The survey instrument was systematically administered to motorcycle riders across the entirety of the nation. Rigorous scrutiny was directed towards the assessment of data distribution normality, followed by subjecting the dataset to a rigorous exploratory factor analysis (EFA). The outcome of this analytical endeavor revealed the emergence of three distinct factors: control errors, traffic violations, and safety equipment. These identified factors subsequently underwent a confirmatory factor analysis (CFA) aimed at meticulously gauging the precision of measurement inherent within the latent structure within the overarching framework of structural equation modeling (SEM). Furthermore, factors exerting influence on occurrences of near-miss incidents within both the adolescent and elderly demographic cohorts were subjected to a comprehensive examination and comparative analysis using the sophisticated approach of multi-group SEM, as visually depicted in Figure 3.4.

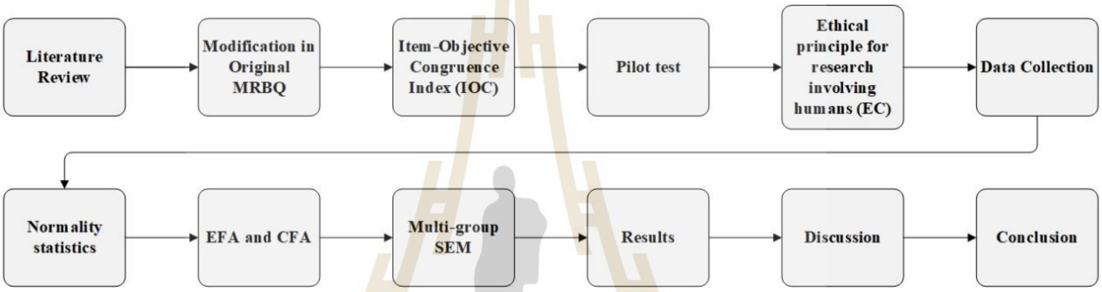

Figure 3.4 Research procedures

3.4.2 Questionnaire Construction

1) General information

Previous research has illuminated the considerable impact of demographic factors and riding experience on distinguishing various cohorts of riders. A wealth of studies underscore that adolescents, owing to their limited driving experience, tend to manifest the highest degree of risky driving behaviors. Their nascent experience often translates into engagement in perilous actions, such as exceeding speed limits and operating vehicles while under the influence. Immediate impulses frequently overshadow their cognizance of potential repercussions (Taubman-Ben-Ari, Mikulincer, & Gillath, 2004). This phenomenon is particularly pronounced among student riders in comparison to their non-student counterparts due to the disparate lifestyles that contribute to behavioral disparities. Adolescents, being both youthful and positioned within a high-risk category concerning driving conduct and traffic incidents, evince an elevated propensity for engaging in unsafe driving practices (Bina, Graziano, & Bonino, 2006). The discourse on riding experience is yet another recurrent theme of significance in the literature. It is closely linked with an augmented likelihood of risky driving conduct and traffic accidents. Novice drivers generally exhibit diminished driving proficiency, thereby engendering more precarious driving scenarios and an increased probability of accidents (Forward, 2010). Conversely, less-seasoned drivers might struggle to anticipate concealed hazards and exhibit an enhanced proclivity for frequent errors due to a misguided allocation of attention (Chan, Pradhan, Pollatsek, Knodler, & Fisher, 2010). Although age and driving experience often correlate, they embody distinct concepts. While young individuals might possess substantial driving experience, particularly if they engage frequently in motorcycle riding, the variance in driving experience between older and younger drivers can lead to judicious and more considered driving choices among the former, attributed to their heightened physical and mental maturity (Chung & Wong, 2012). Furthermore, even within the category of elderly drivers, the presence of risky behaviors is observable. A tendency to be involved in collisions on high-speed roadways and in rural areas is evident. While the proportion of elderly motorcycle riders tends to rise, their driving acumen typically diminishes over time (Fitzpatrick & O'Neill, 2017).

2) Utilization of the Questionnaire

The present research, the utilization of the MRBQ (Motorcycle Rider Behavior Questionnaire) was modified for application in the Thai context, where extremely dangerous riding behavior occurs. This contrasts with higher-income or developed countries, where riding behaviors are molded by distinct contextual elements encompassing geographical topography, traffic regulations, cultural norms, and divergent belief systems. Consequently, adjustments were made to the questionnaire items to effectively capture the riding behavior of motorcyclists in the Thai setting. The questionnaire encompassed a total of 19 items, of which 13 were drawn from previous research while the remaining 6 were refined and incorporated anew. The initial inquiries were focused on elements related to speed and control of the vehicle. However, the supplementary questions revolved around practices such as cell phone usage, drinking alcohol, failure to wear a helmet, donning reflective clothing, and the activation of headlights during daylight hours. This methodological technique is consistent with similar research undertaken in India and Iran (Chouhan et al., 2021; Motevalian et al., 2011), which also undertook adaptations and augmentations to questionnaires, notably in relation to helmet usage. Remarkably, the current study broadened its focus to encompass behaviors such as cell phone engagement while riding and use of alcohol during festive periods (ThaiRoads Foundation, 2022), thereby aligning more closely with the riding habits characteristic of Thailand. To evaluate rider behavior, the research will adopt a questionnaire-based assessment employing a Likert scale. Responses will be categorized across five levels, signifying: 1 (never), 2 (rarely), 3 (sometimes), 4 (often), and 5 (always).

3.4.3 Data Collection

In the data collection phase, the researchers aimed to achieve nationwide representation by distributing the sample across all regions of Thailand. Data gathering encompassed six regions, each with a designated number of provinces: Central (6 provinces), Eastern (5 provinces), Northeastern (6 provinces), Northern (7 provinces), Western (5 provinces), and Southern (5 provinces), totaling 34 provinces, as illustrated in Figure 3.5. The selection of provinces was guided by the evaluation outcomes of the Human Achievement Index (HAI), a composite index gauging provincial-level human development. This index incorporates eight sub-indices, computed to establish proportions and stratified into four quartiles (Q1 = provinces with the highest human development index, up to Q4 = provinces with the lowest human development index). Subsequently, the proportions were determined based on the cumulative registered motorcycle population and the age distribution of the youth and elderly populations in the selected provinces. The sample size, amounting to 815 datasets, was determined through the principles of structural equation modeling analysis. Guided by the recommendation that the sample size for maximum likelihood estimation should be at least 10 times the number of observed variables (Golob, 2003), the research collected a total of 815 samples, comprising 475 from the younger demographic and 340 from the older demographic, as detailed in Table 3.2, which presents the number of samples collected for each region categorized into younger and older groups. The research adopted a stratified sampling approach, randomly choosing individuals who have lived in the designated locations for at least a year, possessing the capability to ride motorcycles, and having their motorcycles registered with the Department of Land Transport.

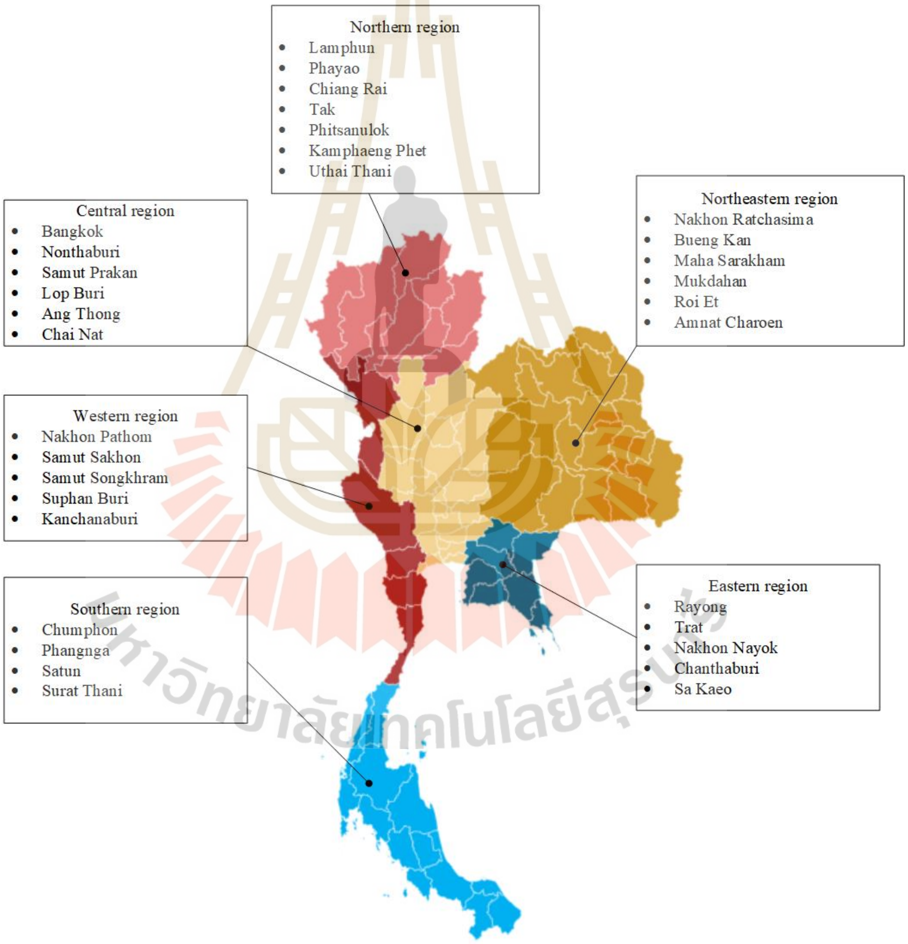

Figure 3.5 Map depicting the provinces selected for collecting questionnaire data from motorcycle riders in Thailand

Table 3.2 The collected and compiled sample sizes for each region were categorized into younger and older groups

Regions	Younger	Older
Western	72	53
North-eastern	74	49
Southern	68	47
Central	94	63
Eastern	70	56
Northern	97	72
Total	**475**	**340**

The individual's characteristics are outlined in Table 3.3 and classified into two distinct groups according to their responses to the questionnaire: (1) younger respondents (*n* = 475) with an average age of 24.4 years, and (2) older respondents (*n* = 340) with an average age of 66.2 years. It was noted that the sample attributes of both groups showed considerable similarity. To elaborate, a significant portion were unmarried and held bachelor's degrees. The mean personal monthly income for the younger group was below 18,000 Baht, whereas for the older group, it ranged between 18,000 and 25,000 Baht. The mean household monthly income primarily fell within the bracket of 30,001 to 50,000 Baht. A noteworthy observation is that more than half of the participants lacked a valid motorcycle driver's license, frequently utilizing motorcycles for commuting to educational institutions or workplaces. The average riding speed predominantly remained below 80 km/hr. It is pertinent to highlight that over 90% of the participants had a clean record with no reported traffic violations within the past three years, while nearly 80% had encountered near-miss incidents. However, over 90% had not experienced any accidents in the preceding year.

Table 3.3 Sample characteristics

Variable name	Category	Younger (n=475)	Older (n=340)
		% (n)	% (n)
Gender	Male	49.7% (236)	46.5% (158)
	Female	50.3% (239)	53.5% (182)
Age	Mean	24.4	66.2
Marital status	Single	77.7% (369)	41.5% (141)
	Married	22.1% (105)	40.6% (138)
	Divorce	0.2% (1)	17.9% (61)
Education level	Diploma	38.1% (181)	39.71% (135)
	Bachelor's degree	60% (285)	55.3% (188)
	Postgraduate or PhD	1.9% (9)	5% (17)
Individual income (THB/month)	18,000 or less	51.6% (245)	26.18% (89)
	18,001 to 25,000	29.7% (141)	37.95% (129)
	25,001 or more	18.5% (89)	35.89% (122)
Household income (THB/month)	30,000 or less	22.7% (109)	18.53% (63)
	30,001 to 50,000	37.4% (179)	32.36% (110)
	50,001 to 70,000	21.9% (105)	27.95% (95)
	70,001 or more	17.1% (82)	21.18% (72)
Household members	1 to 2	32% (152)	33.53% (114)
	3 to 4	54.8% (260)	54.71% (186)
	5 or more	13.3% (63)	11.77% (40)
Occupation	Student	30.9% (147)	-
	Civil servant/state enterprise employee	2.7% (13)	1.8% (6)
	Private companies	34.5% (164)	29.1% (99)
	Personal business/trading owner	14.7% (70)	40.3% (137)

Table 3.3 Sample characteristics (Continued)

Variable name	Category	Younger (n=475)	Older (n=340)
		% (n)	% (n)
	Agriculturist	4.8% (23)	10.3% (35)
	Contractors	12% (57)	14.4% (49)
	Housewife	0.2% (1)	4.1% (14)
Holding License	Yes	41.9% (199)	39.7% (135)
	No	58.1% (276)	60.3% (205)
Riding experience (years)	5 or less	5.8% (28)	-
	6 to 10	38.7% (184)	-
	11 to 20	55.4% (263)	0.59% (2)
	21 to 30	-	2.65% (9)
	31 or more	-	96.77% (329)
Average hours riding per week	5 or less	32.4% (154)	56.48% (192)
	6 to 10	38.4% (183)	39.71% (135)
	11 or more	28.9% (138)	3.83% (13)
Average weekly kilometers	50 km or less	15.8% (75)	29.12% (99)
	51 to 100	30.3% (144)	41.48% (141)
	101 to 200	29% (138)	26.77% (91)
	201 or more	24.7% (118)	2.65% (9)
Frequency of motorcycle riding	Once a week	33.9% (161)	36.8% (125)
	Several times per week	29.7% (141)	31.2% (106)
	Everyday	36.4% (173)	32.1% (109)
Purpose for riding	Only for work or study	58.9% (280)	48.5% (165)
	Only for recreation	20.4% (97)	20.6% (70)
	Shopping	20.6% (98)	30.6% (104)
	Other	-	0.3% (1)

Table 3.3 Sample characteristics (Continued)

Variable name	Category	Younger (n=475)	Older (n=340)
		% (n)	% (n)
Average speed (km/hr)	Less than or equal 80	59.9% (285)	92.36% (314)
	More than 80	40% (190)	7.65% (26)
Motorcycle-specific traffic violations within the last three years	Yes	5.9% (28)	4.1% (14)
	No	94.1% (447)	95.9% (326)
Traffic violations across all types of vehicles within the last three years	Yes	8.2% (39)	8.2% (28)
	No	91.8% (436)	91.8% (312)
Near miss (part 12 months)	None	22.3% (106)	22.6% (77)
	1 to 2	47% (223)	48.9% (89)
	3 or more	30.7% (146)	28.6% (77)
Accident (part 12 months)	None	93.3% (443)	96.5% (328)
	1 or more	6.7% (32)	3.5% (12)

Based on Table 3.4, showing the category of near-miss occurrence, The near-miss occurrences can be divided into three main categories: skidding, nearly losing control of the motorcycle, and using brakes in reaction to interactions with other vehicles or pedestrians. The examination uncovered that both the younger and older cohorts experienced the highest frequency of the "swerving or braking in response to another road user" type of near-miss accident, accounting for more than 50% in each group. The main contributing factors to this type of incident were abrupt lane changes and sudden cuts in front by other vehicles, necessitating sudden braking.

Table 3.4 Category of near-miss occurrence

Category of near-miss	Cause of the near-miss	Younger (n=475)	Older (n=340)
		% (n)	% (n)
Skid	By rain or water.	7.3% (27)	5.71% (15)
	By mud, wet leaves, and animal manure.	0.9% (3)	0.39% (1)
	By oil spillage on the road.	1.9% (7)	2.67% (7)
	By slippery or loose road surfaces (e.g., paint or worn asphalt), loose gravel.	2.5% (9)	3.43% (9)
	By road objects (e.g., clothing, plastic bags, or debris).	3.8% (14)	1.91% (5)
	Total	**16.3% (60)**	**14.11% (37)**
Near loss of control	By evasion (preceding vehicle moving slowly or abruptly applying brakes).	8.4% (31)	6.85% (18)
	By a tire puncture.	0.3% (1)	-
	By mechanical failure.	0.3% (1)	0.39% (1)
	By traveling too fast for the conditions.	3.6% (13)	4.19% (11)
	By potholes or grooves in the road.	9.8% (36)	10.27% (27)
	By flying objects (e.g., insects, birds, paper).	1.4% (5)	1.15% (3)
	By tiredness or inattention (lack of focus).	0.9% (3)	1.53% (4)
	Total	**24.4% (90)**	**24.38% (64)**
Swerving or braking in response to another road user	Overtaking from behind.	12.2% (45)	10.65% (28)
	Coming towards you in your lane.	9.5% (35)	9.13% (24)
	Another car turns right, cutting you off.	12.5% (46)	12.17% (32)

Table 3.4 Category of near-miss occurrence (Continued)

Category of near-miss	Cause of the near-miss	Younger (n=475)	Older (n=340)
		% (n)	% (n)
	Turning into your path from a side road, private driveway, or opposite direction.	7.6% (28)	6.09% (16)
	Cutting you off at a junction.	3.6% (13)	9.13% (24)
	Cutting you off while performing a U-turn.	7.9% (29)	7.61% (20)
	Cyclist riding into your path.	-	0.39% (1)
	Pedestrian walking into your path.	0.3% (1)	-
	Animal(s) walking into your path.	5.7% (21)	6.09% (16)
	Total	**59% (218)**	**61.26% (161)**
Any additional form of near-miss encounter.		0.6% (2)	0.39% (1)
Overall		**100% (370)**	**100% (298)**

3.4.4 Methods

The present research employs a theoretical approach grounded in structural equation modeling (SEM) to analyze the factors influencing near-miss incidents among motorcycle riders, particularly focusing on the differences between younger and older age groups. SEM is a statistical technique that combines factor analysis and multiple regression to examine the complex relationships between observed and latent variables. The research commences by formulating hypotheses concerning control errors, traffic violations, and safety equipment. These hypotheses are then tested using SEM, allowing for the examination of direct and indirect relationships between the variables. Factor analysis is utilized to assess the measurement model, examining the relationships between observed variables and their underlying latent constructs, such as control errors, traffic violations, and safety equipment. This helps in identifying the key factors contributing to near-miss incidents within each age group. The study also employs multi-group SEM to test for invariance between younger and older groups, allowing for the investigation of age-specific differences in the structural relationships between variables. This approach enables a nuanced understanding of how the factors influencing near-miss incidents may vary across different age demographics. Moreover, the research integrates statistical analyses, such as mean, standard deviation, skewness, and kurtosis, to provide a comprehensive overview of the data's distribution characteristics. Descriptive statistics contribute to the interpretation of factor loadings and model fit, offering insights into the reliability and validity of the measurement model. The specifics of the statistical framework are outlined in the following manner:

1) Exploratory Factor Analysis (EFA)

Exploratory factor analysis (EFA) is a very popular statistical tool that is used throughout the social sciences. It has proven useful for reducing the dimensionality of a set of variables (finch, 2013). This research has integrated diverse assessment indicators, validated through the MRBQ. However, owing to differences in physical characteristics and traffic laws across countries, distinct riding behaviors are present. The questionnaire consisted of 19 indicators, with 14 derived from prior research and an additional 5 adjusted and incorporated. Given further deliberation, aspects pertaining to cell phone usage, alcohol drinking, failure to wear a helmet, wearing reflective clothing, and activating headlights during daylight hours were incorporated for additional scrutiny. Subsequently, an EFA was utilized to restructure the indicators pertaining to motorcycle riding behavior, marking its second application in this study.

2) Confirmatory Factor Analysis (CFA)

It is utilized when one wants to determine the number of factors needed to explain the relationships between variables and what these factors represent. It helps identify latent variables and their interpretations, typically after analytic rotation. On the other hand, confirmatory factor analysis starts by defining latent variables based on theory or prior knowledge and then constructs observable variables to measure these latent variables (Jöreskog, Olsson, & Wallentin, 2016).

3) Multi-Group Analysis

This method is a widely utilized approach for conducting group comparisons. It encompasses a range of advanced techniques that researchers typically employ when they intend to investigate variations among categorical variables. (Hair Jr, Sarstedt, Ringle, & Gudergan, 2017). In this study, a comparison was undertaken between young and older motorcycle riders. During the second phase, cross-validation was employed to evaluate measurement models and scrutinize various parameters, encompassing the number of constructs, indicator factor loadings, means, and covariances. For the evaluation, goodness of fit like differences in chi-square (Δ-χ^2) and differences in degrees of freedom (Δ-DF) were utilized (J.F. Hair, Black, & Babin, 2010). The results obtained will reveal whether there are statistically significant differences in the model's parameters between young and older motorcycle riders.

4) Structural Equation Modeling (SEM)

Structural Equation Modeling (SEM) is a complex statistical technique used to estimate the effect of observable factors on a variable that cannot be directly observed. Structural Equation Models (SEM) have two components: the measurement component and the structural component. The measurement component defines latent constructs that reflect study concepts with multiple indicators (Saliya, 2022).

5) Goodness of Fit

The research assessed the structural validity of the model by examining statistical values to gauge the extent to which the model aligns with empirical data. The evaluation criteria were as follows:

i. The chi-square to the degrees of freedom ratio or χ^2/df should not exceed 3 (Rex B. Kline, 2011), or 5 for more complex models (Hu & Bentler, 1999).

ii. The standardized root mean residual (SRMR) should be below 0.08 (Hu & Bentler, 1999).

iii. The Root Mean Square Error of Approximation (RMSEA) should be below 0.07 (Steiger, 2007).

iv. The comparative fit index (CFI) is deemed acceptable if it equals or exceeds 0.90 (Hu & Bentler, 1999).

v. The Tucker-Lewis Index (TLI) is considered satisfactory if it is 0.80 or higher (Hooper et al., 2008; Jomnonkwao et al., 2016).

These criteria were utilized to determine whether the model effectively aligns with empirical data and possesses structural validity.

3.5 Results

3.5.1 Descriptive Statistics

The computed descriptive statistics (see Table 3.5). The dataset will provide descriptive statistics for the younger cohort, encompassing mean values [1.580–4.490], standard deviation (*SD*) [0.639–1.025], skewness [-1.466–0.936], and kurtosis [-1.329–1.922]. Correspondingly, the older group's statistics encompass mean values [1.660–4.460], standard deviation (*SD*) [0.647–1.017], skewness [-1.483–0.744], and kurtosis [-1.326–2.556]. This suggests that the MRBQ variable data conforms to a normal distribution, aligning with the guidelines provided by Rex B. Kline (2011), which stipulate that skewness values should not surpass 3, and kurtosis values should not exceed 10.

Table 3.5 Descriptive statistics

	Questionnaire	Younger (*n* = 475)				Older (*n* = 340)			
		M	*SD*	*SK*	*KU*	*M*	*SD*	*SK*	*KU*
ER1	Experience challenges in maintaining control of the motorcycle when riding at high speeds.	1.640	0.653	0.538	-0.680	1.730	0.702	0.638	0.301
ER2	The roadway becomes slippery in rainy conditions, leading to abrupt braking.	1.730	0.698	0.681	0.259	1.720	0.741	0.712	-0.110
ER3	Experience difficulty in staying within the lane while negotiating a turn.	1.580	0.639	0.643	-0.569	1.660	0.647	0.455	-0.698
ER4	Encounter issues with visor or goggles fogging up.	1.650	0.714	0.936	0.667	1.660	0.720	0.744	-0.205
VI1	Exceed the speed limit on a residential road.	1.780	0.793	0.415	-1.293	1.800	0.796	0.380	-1.326
VI2	Exceed the speed limit on a country/rural road.	1.750	0.766	0.469	-1.158	1.770	0.760	0.405	-1.167
VI3	Overtaking in an overtaking-prohibited area.	1.760	0.760	0.441	-1.150	1.700	0.744	0.555	-1.009
VI4	Disregard the speed limit late at night or in the early hours of the morning.	1.810	0.814	0.450	-0.967	1.710	0.786	0.551	-1.174

Table 3.5 Descriptive statistics (Continued)

	Questionnaire	Younger (n = 475)				Older (n = 340)			
		M	*SD*	*SK*	*KU*	*M*	*SD*	*SK*	*KU*
VI5	Attempt to overtake someone that you had not noticed to be signaling a right turn.	1.760	0.777	0.441	-1.218	1.710	0.767	0.536	-1.113
VI6	When a car abruptly enters your vehicle's path or hinders your progress, you accelerate and swiftly overtake it while applying sudden braking.	1.790	0.801	0.407	-1.329	1.710	0.794	0.563	-1.195
VI7	You will blow your horn or close behind when the car in front drives slowly.	1.760	0.800	0.450	-1.300	1.720	0.789	0.546	-1.189
VI8	During your ride, you consult maps (either on paper or on a smartphone).	2.000	0.675	-0.005	-0.797	2.000	0.716	0.000	-1.044
VI9	You engage with the internet (Facebook, Instagram, Line, and YouTube) on your phone while riding.	2.040	0.726	0.065	-0.762	2.050	0.727	0.058	-0.751
VI10	Ride when you suspect you might be over the legal limit for alcohol.	1.980	0.702	0.023	-0.967	1.970	0.738	0.051	-1.157

Table 3.5 Descriptive statistics (Continued)

Questionnaire		Younger (n = 475)				Older (n = 340)			
		M	*SD*	*SK*	*KU*	*M*	*SD*	*SK*	*KU*
VI11	Significant celebrations like New Year, Songkran, or social events, you partake in alcohol consumption and frequently operate a motorcycle.	2.040	0.752	0.143	-0.712	2.040	0.736	0.123	-0.689
EQ1	Fail to use a helmet while riding a motorcycle.	4.330	0.874	-1.392	1.589	4.290	0.903	-1.310	1.317
EQ2	Wear a helmet on a motorcycle, but neglect to secure the chin strap.	4.210	1.025	-1.466	1.721	4.140	1.017	-1.279	1.162
EQ3	Neglect to activate daytime headlights on your motorcycle.	4.320	0.870	-1.204	0.873	4.190	0.971	-1.158	0.794
EQ4	Wear riding boots?	4.490	0.676	-1.302	1.922	4.460	0.726	-1.483	2.556

Note: For younger, SE_{SK} = 0.112 and SE_{KU} = 0.224;

For older, SE_{SK} = 0.132 and SE_{KU} = 0.264.

3.5.2 Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) results

The results of the exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) are presented in Table 3.6 for younger and Table 3.7 for older, respectively. These tables include variables for the measurement model, Cronbach's α, factor loading of EFA, factor loading of CFA, error variance, CR, and AVE value. Based on the conducted factor analysis for both the younger and older groups, the extracted components from the exploratory factor analysis (EFA) could be categorized into three distinct groups. The elements were derived through the application of the principal component analysis (PCA) method with the varimax rotation technique. The factor loading values set the threshold criterion for considering values greater than 0.3(Maskey et al., 2018). Furthermore, J. Hair et al. (2006) recommended that the Kaiser-Meyer-Olkin (KMO) value be accepted if it exceeds 0.5. Values falling between 0.5 and 0.7 indicate a mediocre level of suitability, while values ranging from 0.7 to 0.8 signify good suitability. To evaluate the reliability of the measurement indicators, Cronbach's α was employed, with values exceeding 0.6 being deemed acceptable (Taber, 2018).

Table 3.6 EFA and CFA for Younger. *n* = 475, KMO = 0.897

Measurement Model	EFA		CFA					
	Communalities	Factor loading	Factor loading	Z	p-Value	Error	CR	AVE
Control error (Cronbach's α = 0.672)							0.678	0.348
ER1	0.498	0.678	0.657	16.287	<0.001**	0.568		
ER2	0.410	0.628	0.480	10.396	<0.001**	0.769		
ER3	0.516	0.707	0.637	15.729	<0.001**	0.594		
ER4	0.522	0.697	0.571	13.136	<0.001**	0.674		
Traffic violation (Cronbach's α = 0.877)							0.875	0.406
VI1	0.672	0.740	0.813	42.802	<0.001**	0.339		
VI2	0.607	0.719	0.765	34.501	<0.001**	0.415		
VI3	0.554	0.701	0.681	24.807	<0.001**	0.536		
VI4	0.558	0.706	0.711	27.748	<0.001**	0.495		
VI5	0.618	0.761	0.729	29.563	<0.001**	0.468		
VI6	0.577	0.712	0.737	30.729	<0.001**	0.457		
VI7	0.584	0.732	0.709	27.243	<0.001**	0.498		
VI8	0.385	0.472	0.430	10.747	<0.001**	0.815		
VI9	0.293	0.502	0.376	8.971	<0.001**	0.858		

Table 3.6 EFA and CFA for Younger. n = 475, KMO = 0.897 (Continued)

Measurement Model	EFA		CFA					
	Communalities	Factor loading	Factor loading	Z	p-Value	Error	CR	AVE
VI10	0.385	0.529	0.452	11.525	<0.001**	0.796		
VI11	0.338	0.543	0.376	8.952	<0.001**	0.859		
Safety equipment (Cronbach's α = 0.772)							0.777	0.480
EQ1	0.672	0.798	0.764	28.358	<0.001**	0.417		
EQ2	0.685	0.778	0.795	30.281	<0.001**	0.368		
EQ3	0.675	0.807	0.741	26.192	<0.001**	0.451		
EQ4	0.365	0.583	0.394	9.013	<0.001**	0.845		
χ^2/df = 356.741/147= 2.427, RMSEA = 0.055 (0.048 - 0.062), CFI = 0.932, TLI = 0.921, SRMR = 0.064								

Note: ** The level of significance at 0.001

Table 3.7 EFA and CFA for Older. n = 340, KMO = 0.874

Measurement Model	EFA		CFA					
	Communalities	Factor loading	Factor loading	Z	p-Value	Error	CR	AVE
Control error (Cronbach's α = 0.695)							0.701	0.373
ER1	0.413	0.630	0.535	10.543	<0.001**	0.714		
ER2	0.508	0.709	0.588	11.860	<0.001**	0.655		
ER3	0.451	0.668	0.569	11.318	<0.001**	0.676		
ER4	0.598	0.771	0.732	15.990	<0.001**	0.465		
Traffic violation (Cronbach's α = 0.881)							0.878	0.405
VI1	0.621	0.763	0.768	29.181	<0.001**	0.411		
VI2	0.538	0.704	0.703	22.596	<0.001**	0.505		
VI3	0.440	0.649	0.635	17.738	<0.001**	0.596		
VI4	0.610	0.760	0.750	27.257	<0.001**	0.437		
VI5	0.576	0.723	0.705	22.642	<0.001**	0.504		
VI6	0.559	0.725	0.720	24.171	<0.001**	0.481		
VI7	0.602	0.760	0.739	26.020	<0.001**	0.453		
VI8	0.425	0.504	0.451	9.727	<0.001**	0.797		
VI9	0.338	0.545	0.433	9.161	<0.001**	0.812		

Table 3.7 EFA and CFA for Older. *n* = 340, KMO = 0.874 (Continued)

Measurement Model	EFA		CFA					
	Communalities	Factor loading	Factor loading	Z	p-Value	Error	CR	AVE
VI10	0.433	0.553	0.494	11.149	<0.001**	0.756		
VI11	0.456	0.574	0.452	9.721	<0.001**	0.796		
Safety equipment (Cronbach's α = 0. 773)							0.776	0.475
EQ1	0.582	0.737	0.656	17.168	<0.001**	0.570		
EQ2	0.675	0.786	0.768	22.959	<0.001**	0.410		
EQ3	0.719	0.831	0.825	26.964	<0.001**	0.319		
EQ4	0.406	0.635	0.447	9.049	<0.001**	0.801		
χ^2/df = 290.799/145= 2.005, RMSEA = 0.054 (0.045 - 0.063), CFI = 0.933, TLI = 0.921, SRMR = 0.063								

Note: ** The level of significance at 0.001.

Table 3.6 reveals that, for the younger group, the KMO value is 0.897. The factor loadings for EFA are as follows: control errors (ER) [0.628–0.707], traffic violations (VI) [0.472–0.761], and safety equipment (SE) [0.583–0.807]. Additionally, the factor loadings for CFA are Control Error (ER) [0.480–0.657], Traffic Violation (VI) [0.376–0.813], and Safety Equipment (SE) [0.394–0.795]. Moving on to Table 3.7, for the older group, the KMO value is 0.874. The factor loadings for EFA are as follows: control errors (ER) [0.630–0.771], traffic violations (VI) [0.504–0.763], and safety equipment (SE) [0.635–0.831]. Additionally, the factor loadings for CFA are Control Error (ER) [0.535–0.732], Traffic Violation (VI) [0.433–0.768], and Safety Equipment (SE) [0.447–0.825].

Additionally, the outcomes illustrate both the younger model presented in Table 3.6 and the older model presented in Table 3.7. It was determined that the χ^2/df ratio (Hu & Bentler, 1999), RMSEA (Steiger, 2007), (Hu & Bentler, 1999), TLI (Hooper et al., 2008; Jomnonkwao et al., 2016), and SRMR (Hooper et al., 2008; Jomnonkwao et al., 2016) all demonstrated a favorable fit with the empirical data, reaching a satisfactory level of agreement. For the purpose of evaluating convergent validity, the composite reliability (CR) and average variance extracted (AVE) values for both the younger model (Table 3.6) and the older model (Table 3.7) are below 0.5, while the composite reliability (CR) values surpass the threshold of 0.6. According to L. W. Lam (2012), it is acceptable if the CR value is greater than 0.6, even when the AVE value does not exceed 0.5.

3.5.3 Multi-Group Analysis results

In testing Hypothesis$_0$, multi-group structural equation modeling (SEM) was employed to assess invariance between the younger and older groups. The analysis outcomes are detailed in Table 3.8 providing insights into the model fit, statistical parameters, and multi-group analysis. The results are structured into four sub-models for a comprehensive evaluation. The initial grouping, referred to as the individual group, encompasses Model 1: Younger and Model 2: Older. This segment presents the goodness of fit for both models, elucidating their overall explanatory capacity. The subsequent grouping, labeled Measurement of Invariance, includes

Model 3: Simultaneous. This model represents an analysis where path coefficients are not constrained to be equal between groups. It serves as a multi-group measurement model analysis, allowing parameters to be freely estimated across groups. Finally, Model 4 involves an analysis with constrained path coefficients set to be equal between groups. This model aims to test the stability of standardized path coefficients when constrained to be equal. Both sets of models 3 and 4 exhibited commendable fit and alignment with the predefined criteria for evaluation. The comparison between model 3 and model 4 yielded a Chi-square value of 55.193 with degrees of freedom (df) equal to 38 at a significance level (p-value) below 0.05. This signifies the existence of noteworthy parameter disparities within the risk behavior model of motorcycle riders when comparing the younger and older groups. This empirical evidence highlights the variance in risk behavior tendencies between these distinct age cohorts.

Table 3.8 Multi-group analysis

Model	χ^2	*df*	χ^2/df	RMSEA	CFI	TLI	SRMR	Delta- χ^2	Delta-df	*p*-Value
Individual Group										
Model 1: Younger (n=475)	357.044	161	2.218	0.051	0.938	0.927	0.062			
Model 2: Older (n=340)	282.888	158	1.790	0.048	0.943	0.932	0.068			
Measurement of Invariance										
Model 3: Simultaneous	732.599	326	2.247	0.055	0.924	0.912	0.064			
Model 4: Factor loading, intercept, and structural path held equal groups	787.792	364	2.164	0.053	0.921	0.918	0.070	55.193	38	<0.05*

Note: ** The level of significance at 0.05

3.5.4 Structural Equation Modeling (SEM) results

The outcomes yield statistical values indicating a well-fitted model for both Model 1 and Model 2, as illustrated in Figure 3.6 and Figure 3.7. These models demonstrate a good fit with the observed data. Table 3.9 provides the parameter estimates of the measurement model for the younger and older groups. Within this table, 19 observed indicators (ER1-ER4, VI1-VI11, and EQ1-EQ4) and three latent indicators (control error, traffic violation, and safety equipment) are considered. The table presents standardized coefficients, standard errors (S.E.), Z values, p-values, and R^2 for each variable. Notably, the standardized coefficients for observed variables surpass 0.30 in both the younger and older groups. Additionally, the results of the structural equation modeling (SEM) for both the younger and older groups are delineated in Table 3.10. This table unveils the factors influencing the occurrence of near-miss incidents in both groups, encompassing three key factors.

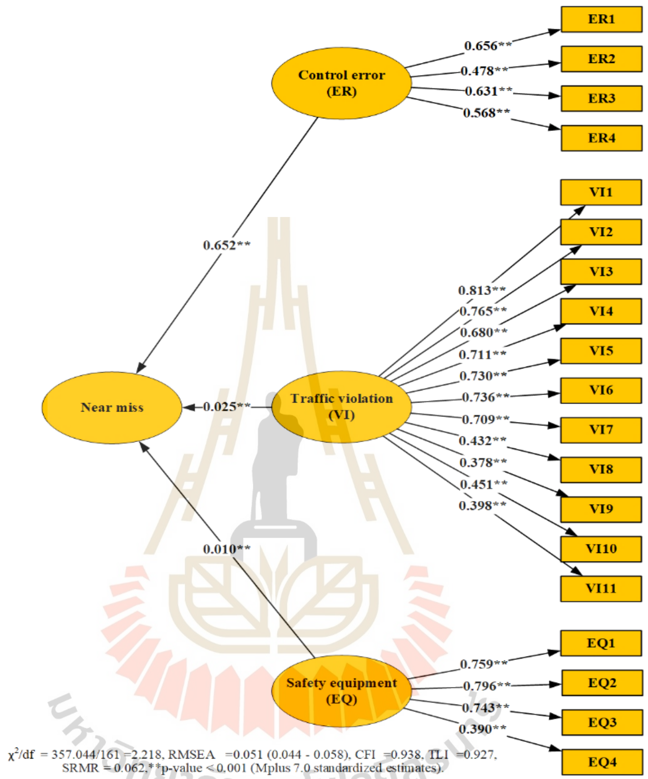

Figure 3.6 Application of structural equation modeling to analyze near-miss incidents in motorcycle riding among younger riders

Hypothesis$_{1a}$ (H$_{1a}$): Control errors exert an adverse impact on the occurrence of near-miss incidents among younger riders.

Hypothesis$_{2a}$ (H$_{2a}$): Traffic violations exert an adverse impact on the occurrence of near-miss incidents among younger riders.

Hypothesis$_{3a}$ (H$_{3a}$): Safety equipment exerts an adverse impact on the occurrence of near-miss incidents among younger riders.

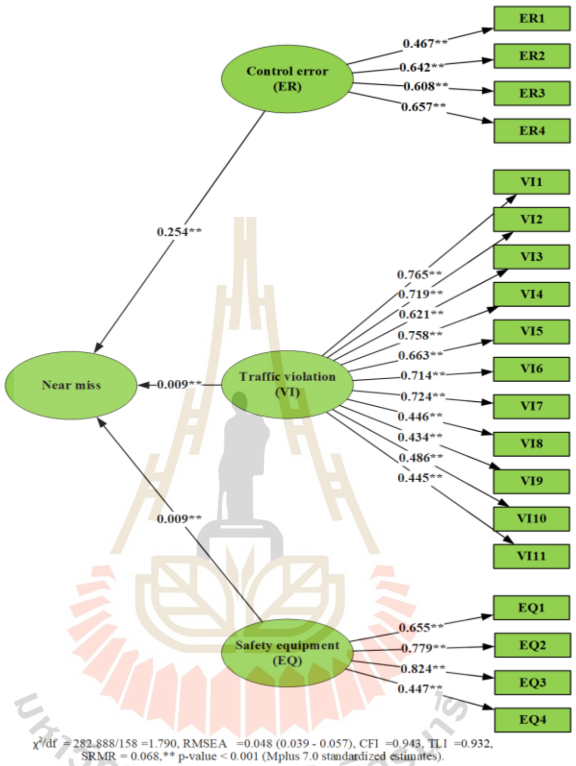

Figure 3.7 Application of structural equation modeling to analyze near-miss incidents in motorcycle riding among older riders

Hypothesis$_{1b}$ (H$_{1b}$): Control errors exert an adverse impact on the occurrence of near-miss incidents among older riders.

Hypothesis$_{2b}$ (H$_{2b}$): Traffic violations exert an adverse impact on the occurrence of near-miss incidents among older riders.

Hypothesis$_{3b}$ (H$_{3b}$): Safety equipment exerts an adverse impact on the occurrence of near-miss incidents among older riders.

Table 3.9 Measurement model

Variable	Younger					Older				
	Standardized coefficients	S.E.	Z	*p*-Value	R^2	Standardized coefficients	S.E.	Z	*p*-Value	R^2
Control error by										
ER1	0.656	0.041	15.979	<0.001**	0.430	0.467	0.060	7.788	<0.001**	0.218
ER2	0.478	0.046	10.305	<0.001**	0.228	0.642	0.051	12.646	<0.001**	0.412
ER3	0.631	0.041	15.526	<0.001**	0.398	0.608	0.051	11.986	<0.001**	0.370
ER4	0.568	0.044	12.875	<0.001**	0.323	0.657	0.052	12.704	<0.001**	0.431
Traffic violation by										
VI1	0.813	0.019	42.942	<0.001**	0.661	0.765	0.027	27.858	<0.001**	0.586
VI2	0.765	0.022	34.676	<0.001**	0.585	0.719	0.031	23.453	<0.001**	0.517
VI3	0.680	0.027	24.759	<0.001**	0.462	0.621	0.038	16.319	<0.001**	0.385
VI4	0.711	0.026	27.803	<0.001**	0.505	0.758	0.028	27.447	<0.001**	0.575
VI5	0.730	0.025	29.680	<0.001**	0.533	0.663	0.035	18.706	<0.001**	0.440
VI6	0.736	0.024	30.668	<0.001**	0.541	0.714	0.031	23.187	<0.001**	0.509
VI7	0.709	0.026	27.321	<0.001**	0.502	0.724	0.030	23.853	<0.001**	0.524
VI8	0.432	0.040	10.824	<0.001**	0.187	0.446	0.047	9.422	<0.001**	0.199

Table 3.9 Measurement model (Continued)

Variable	Younger					Older				
	Standardized coefficients	S.E.	Z	*p*-Value	R^2	Standardized coefficients	S.E.	Z	*p*-Value	R^2
VI9	0.378	0.042	9.039	<0.001**	0.143	0.434	0.048	9.083	<0.001**	0.188
VI10	0.451	0.039	11.509	<0.001**	0.203	0.486	0.045	10.724	<0.001**	0.236
VI11	0.398	0.041	9.727	<0.001**	0.158	0.445	0.047	9.394	<0.001**	0.198
Safety equipment by										
EQ1	0.759	0.027	27.931	<0.001**	0.576	0.655	0.038	17.197	<0.001**	0.429
EQ2	0.796	0.026	30.251	<0.001**	0.634	0.779	0.032	24.157	<0.001**	0.607
EQ3	0.743	0.028	26.309	<0.001**	0.552	0.824	0.031	26.884	<0.001**	0.679
EQ4	0.390	0.044	8.888	<0.001**	0.152	0.447	0.049	9.075	<0.001**	0.200

Note: ** The level of significance at 0.001

Table 3.10 Structural model

Hypothesis	Younger				Older			
	Standardized coefficients	Standard Error	*p*-Value	Result	Standardized coefficients	Standard Error	*p*-Value	Result
1 Control error ⟶ Near miss	0.652	0.055	<0.001**	Supported	0.254	0.037	<0.001**	Supported
2 Traffic violation ⟶ Near miss	0.025	0.001	<0.001**	Supported	0.009	0.001	<0.001**	Supported
3 Safety Equipment ⟶Near miss	0.010	0.000	<0.001**	Supported	0.009	0.001	<0.001**	Supported

Note: ** The level of significance at 0.001

The structural equation modeling (SEM) analysis results for the younger group, depicted in Figure 3.6 and discussed in Hypothesis$_{1a}$ (H$_{1a}$), reveal that control errors exert an adverse impact on the occurrence of near-miss incidents among younger riders. The statistical results strongly support this hypothesis (β = 0.652, $p < 0.001$). Similarly, Hypothesis$_{2a}$ (H$_{2a}$) suggests that traffic violations exert an adverse impact on the occurrence of near-miss incidents among younger riders, and the analysis confirms this hypothesis (β = 0.025, $p < 0.001$). Additionally, Hypothesis$_{3a}$ (H$_{3a}$) posits that safety equipment exerts an adverse impact on the occurrence of near-miss incidents among younger riders, and the results provide substantial support for this hypothesis as well (β = 0.010, $p < 0.001$). These outcomes are visually represented in Figure 3.6 and summarized in Table 3.10. Turning to the SEM analysis results for the older group (Figure 3.7), Hypothesis$_{1b}$ (H$_{1b}$) suggests that control errors exert an adverse impact on the occurrence of near-miss incidents among older riders, and the results significantly support this hypothesis (β = 0.254, $p < 0.001$). Following this, Hypothesis$_{2b}$ (H$_{2b}$) proposes that traffic violations exert an adverse impact on the occurrence of near-miss incidents among older riders, and the analysis affirms this hypothesis (β = 0.009, $p < 0.001$). Finally, in Hypothesis$_{3b}$ (H$_{3b}$), the analysis indicates that safety equipment exerts an adverse impact on the occurrence of near-miss incidents among older riders, with the results providing robust support for this hypothesis as well (β = 0.009, $p < 0.001$). These findings are visually represented in Figure 3.7 and detailed in Table 3.10.

The results of the individual model analysis indicate that all 19 indicators in younger and older groups exhibited strong relationships. Concerning the structural model, control error emerged as the factor with the most significant factor loading values. In the younger model, the coefficient was 0.652 with a significance level of 0.001, while in the older model, the coefficient was 0.254 with a significance level of 0.001. In contrast, traffic violations and safety equipment displayed the lowest factor loading values, both with coefficient values < 0.01 and a significance level of 0.001 in both models.

Upon investigating specific indicators within the measurement model, certain indicators displayed low factor loading values (e.g., VI8, VI9, VI10, VI11, and EQ4). This illustrates that the causal relationships between latent variables and observable indicators are considerably weaker. The observed outcome could potentially be attributed to alterations in contextual factors that exert an influence on motorcycle operating patterns within the specific setting of Thailand. These contextual adjustments could lead to deviations from the established theoretical framework. However, it is important to note that the measurement model retained its congruence with previous discoveries garnered through the utilization of CFA. This congruence was evident, as all indicators exhibited notable statistical significance. It is noteworthy to mention that prior scholarly investigations have also deemed factor loading values surpassing the threshold of 0.20 to be satisfactory and acceptable within this context. (Champahom, Jomnonkwao, et al., 2023; Uttra et al., 2020).

3.6 Discussion

In this section, the discussion focuses on the outcomes of both the measurement model and the structural model. The measurement model involves an assessment of the indicators related to motorcycle rider behavior along with preliminary insights. Regarding the structural model, an analysis and interpretation of the results pertaining to the association between the MRBQ measurement model and its influence on near misses are presented for both the younger and older groups. Furthermore, a comparative analysis is performed between these two population groups.

3.6.1 The factor structure of the MRBQ

1) Control errors (ER) factor

In this investigation, the control error factor comprises a set of four indicators. Within this group, ER2 (the roadway becomes slippery in rainy conditions, leading to abrupt braking) and ER4 (encounter issues with visors or goggles fogging up) are classified as non-intentional factors. Conversely, ER1 (experience challenges in maintaining control of the motorcycle when riding at high speeds) and ER3 (experience difficulty in staying within the lane while negotiating a turn) are behaviors linked to speed control, which could lead to lapses in attention and a lack of vigilance. The outcomes of this study mirror prior research, where all four indicators are categorized under the Control Errors factor (Chouhan et al., 2021; Elliott et al., 2007).

2) Traffic violations (VI) factor

Speeding is acknowledged as a pivotal factor contributing to accidents and is also a notable public health concern. Engaging in excessive speeding (driving beyond the prescribed speed limit) or inappropriate speeding (driving within the limits but excessively fast for the traffic conditions) presents hazards by decreasing the time available for reacting to prevent accidents and amplifying the impact in the event of a collision (Michael et al., 2014). Within the identified indicators, VI1 (exceed the speed limit on a residential road),' VI2 (exceed the speed limit on a country or rural road),' and VI4 (disregard the speed limit late at night or in the early hours of the morning) were formerly classified under speed violations. However, VI5, 'Attempt to overtake someone that you had not noticed to be signaling a right turn, was categorized under traffic errors in the study conducted by Elliott et al. (2007). Furthermore, VI3 (overtaking in an overtaking-prohibited area) was delineated as a traffic error in the research by Uttra et al. (2020) in Thailand.

Subsequently, aggressive riding behavior is considered an intentional action and poses risks not only to the rider but also to others, impacting both their psychological well-being and physical safety. This behavior is acknowledged as provocative and holds relevance in the context of this study. Indicators VI6 (when a car abruptly enters your vehicle's path or hinders your progress, you accelerate and swiftly overtake it while applying sudden braking) and VI7 (you will blow your horn or close behind when the car in front drives slowly) align with the aggressive violations category, previously established in the Driver Behavior Questionnaire (Parker, Lajunen, & Stradling, 1998). This category demonstrates a significant association with an increased likelihood of motorcycle accidents, particularly severe crashes resulting in fatalities (Mohammadpour, Nassiri, & Sullman, 2022).

When considering the use of mobile phones while operating a motorcycle, it is regarded as distracting behavior. Many countries have implemented laws prohibiting the use of handheld phones and texting while riding, a regulation often referred to as the cell phone handheld use and text messaging while riding ban. Thailand is among these countries, having established traffic regulations addressing mobile phone usage while riding. This prohibition stems from the understanding that riding while engaging with a mobile phone poses the risk of diverting attention and leading to distracted riding. Data compiled by The National Highway Traffic Safety Administration (2021) underscores the gravity of this issue by linking texting while riding to numerous fatalities. The act of reading and composing messages introduces visual, manual, and cognitive distractions, contributing to diminished attentiveness and compromised control of the vehicle. This diversion of the driver's focus from the road heightens the likelihood of accidents (Collet, Guillot, & Petit, 2010). In the context of this study, the indicators VI8 (during your ride, you consult maps (either on paper or on a smartphone)) and VI9 (you engage with the internet (Facebook, Instagram, Line, and YouTube) on your phone while riding) on your phone while riding) represent metrics associated with mobile phone use while riding and fall within the category of traffic violations (VI). These findings align with research conducted in Mexico and Vietnam, revealing that the usage of mobile phones while riding is prevalent across various age groups of motorcycle riders (Pérez-Núñez et al., 2014). Moreover, in Vietnam, the utilization of mobile phones while riding is particularly pronounced among adolescent motorcycle riders (Truong et al., 2018). This trend has also been identified in India, where mobile phone usage while riding has surged (Hassan et al., 2017).

Riding under the influence of alcohol poses a significant societal concern due to its substantial contribution to the rise in road accidents. Numerous countries still struggle with the issue of motorcycle riders operating vehicles while intoxicated. This problem is evident in several countries, including Cambodia (Roehler et al., 2015), Ghana (Dapilah, Guba, & Owusu-Sekyere, 2017), the USA (Patrick et al., 2021), Taiwan (Wiratama et al., 2020), Italy (Centola et al., 2020), and the Nordic countries (Mehdizadeh, Nordfjaern, & Klöckner, 2023). It is widely recognized that alcohol has a detrimental effect on riding abilities, impacting areas such as postural control, decision-making, attention, alertness, peripheral vision, contrast sensitivity, responsiveness to external stimuli, and psychomotor coordination and cognition (Kumar Yadav & Velaga, 2021). In the context of this study, indicators VI10 (ride when you suspect you might be over the legal limit for alcohol) and VI11 (significant celebrations like New Year, Songkran, or social events, you partake in alcohol consumption and frequently operate a motorcycle) are categorized as traffic violations (VI). Accident statistics in Thailand highlight alcohol consumption while riding as a leading cause of road fatalities, particularly during significant festivals like New Year and Songkran (Injury Data Collaboration Center (IDCC), 2021). Consequently, campaigns advocating against "don't drink and drive" have been released, accompanied by rigorous law enforcement measures spanning multiple years. The 11 indicators featured in this study are integrated into the traffic violation (VI) measurement model, representing risk factors that could potentially result in near misses.

3) Safety equipment (EQ) factor

The Safety Equipment (EQ) factor pertains to the utilization of safety gear, encompassing helmet usage and the activation of daytime headlights on motorcycles. The inquiries comprise EQ1 (fail to use a helmet while riding a motorcycle) and EQ2 (wear a helmet on a motorcycle, but neglect to secure the chin strap). In prior investigations conducted in Iran (Motevalian et al., 2011), these elements were classified under the safety violation and control error categories. A study by Zamani-Alavijeh et al. (2011) revealed that more than 67% of Iranian motorcycle riders rode without helmets. Similarly, countries such as Ghana and Jamaica have reported limited adoption of helmets among motorcycle riders (Ackaah & Afukaar, 2010;

Fletcher, McDowell, Thompson, & James, 2019). Shifting the focus, the query EQ3 (do not use daytime headlights on your motorcycle) and the question EQ4 (do you wear riding boots?) were formerly associated with the safety factor (Elliott et al., 2007; Sakashita et al., 2014). Research illustrates that the use of daytime running lights (DRL) during daylight hours can substantially diminish the likelihood of accidents (D'Elia & Newstead, 2023). Numerous countries have even enforced legal mandates regarding the use of DRL, leading to a potential reduction of motorcycle collision risks ranging from 4% to 20% (Davoodi & Hossayni, 2015). Studies have indicated that the adoption of DRL can lower fatalities by 24.6%, casualties in multiple daytime crashes by 20%, and multiple daytime crashes by 12.4% (Ivanišević et al., 2022), attributed to augmented vehicle visibility (as per the lighting contrast theory) (Y. M. Lee & Sheppard, 2018).

3.6.2 Comparing Factors Influencing Near Miss Incidents between Younger and Older Individuals

Based on the outcomes of the multi-group analysis model investigating risky behaviors among motorcycle riders and comparing the younger and older age groups, significant distinctions have been identified. The key findings regarding significant differences between younger and older rider groups in terms of factor loadings, intercepts, and structural pathways are crucial for understanding near-miss incidents among different age groups. The SEM analysis indicated that control errors exerted a more pronounced negative impact on near-misses among younger individuals (β = 0.652) in contrast to older individuals (β = 0.254). Traffic violations had a slightly stronger negative effect on near-misses for younger individuals (β = 0.025) compared to older individuals (β = 0.009). Safety equipment exhibited a comparable adverse influence on near-misses for both younger (β = 0.010) and older individuals (β = 0.009). These distinctions underscore the variability in the contributions of control errors, traffic violations, and safety equipment usage to near-miss incidents across diverse age groups. Younger riders seem to be more influenced by control errors. Understanding these nuances can inform targeted interventions and safety measures tailored to specific age demographics, ultimately contributing to the reduction of near-miss incidents.

As a result, the formulation of distinct models to address risky conduct among motorcycle riders became imperative. Research has underscored the contributing elements to risky riding behaviors within both cohorts. Younger riders commonly possess less riding experience relative to their older counterparts, and there is a perception of deficient safe riding skills among them (ThaiRoads Foundation, 2022). Novice drivers, particularly, exhibit an insufficiency in experience and lack comprehensive physical, cognitive, and psychological development, encompassing essential attributes like critical thinking, impulse control, and decision-making proficiencies crucial for adept motorcycle riding (Huang & Winston, 2011). Furthermore, the physiological and cognitive responsiveness of older riders may be diminished, consequently impacting driving competencies tied to vigilance, memory, problem-solving, and information processing (Freund & Smith, 2011). Moreover, an elevated susceptibility to health-related concerns (Fitzpatrick & O'Neill, 2017) could potentially compromise the driving capacities of the elderly population.

In light of the outcomes derived from the structural model, a notable distinction emerged between two distinct cohorts. Notably, the factor loading coefficients attributed to the control error construct provided the most important influence on the occurrence of near-miss events within both model frameworks. This outcome corroborates findings documented in a parallel investigation conducted in India, where a noteworthy correlation was established between control errors and an escalated susceptibility to near-miss incidents. Furthermore, the research underscored a discernible linkage between the frequency of control errors and specific age demographics (Chouhan et al., 2021).

In assessing the key indicators among the younger cohort, two factors emerged with substantial influence: ER1 (experience challenges in maintaining control of the motorcycle when riding at high speeds) and ER3 (experience difficulty in staying within the lane while negotiating a turn). Notably, younger riders typically exhibit significantly higher rates of errors in bike control. This trend is particularly prevalent among adolescents and students, who fall into the category of novice riders. Their limited experience, unfamiliarity with bike control and balance, and diminished alertness due to factors like adrenaline rushes contribute to this phenomenon. When coupled with their lack of experience and occasional disregard for traffic regulations, certain young drivers become more predisposed to risk-taking behaviors such as speeding (Susilo, Joewono, & Vandebona, 2015), ultimately culminating in accidents that carry the potential for injuries or fatalities (P.-L. Chen, Chen, & Pai, 2018).

In Taiwan, the government has integrated the Road Safety Class (RSC) into the rider's licensing process. The RSC involves the presentation of motorcycle accident videos followed by safety-oriented lectures. Its overarching goal is to mitigate road accidents and traffic infractions among novice riders. Results indicate that the RSC yields a temporary reduction in violation incidents by approximately 12%–17% and contributes to an 11% decrease in frequency. Similarly, Australia has embraced a comparable approach by implementing training programs for novice motorcycle riders. These programs encompass three phases: pre-learner (motorcycle permit assessment), learner (check ride), and pre-license (motorcycle licence assessment). The insertion of an intermediate course between the learner permit and license phases serves to extend the novice license duration. Each course mandates on-the-road training and/or assessment components. This initiative has demonstrated its efficacy in ameliorating motorcycle collision concerns among novice riders (Möller et al., 2020).

A study of significance was also conducted in Vietnam, revealing that the formulation of secure riding guidelines for young riders can effectively reduce their involvement in perilous traffic scenarios. Developed through questionnaire surveys, these guidelines contribute to reshaping adolescents' riding behaviors and attitudes, fostering their ability to recognize, avoid, and navigate risks within demanding traffic situations (Luu, Minh, & Long, 2021).

In evaluating the older group, it was observed that the factor loading values for the control error construct also exhibited the highest impact on near-miss incidents. Nevertheless, the magnitude of these factor loading values was not as pronounced as that observed in the younger group. Upon closer examination of the specific indicators, it became apparent that the most substantial loading weights were associated with ER4 (encounter issues with visor or goggles fogging up) and ER2 (the roadway becomes slippery in rainy conditions, leading to abrupt braking). These elements are classified as non-intentional factors and relate to challenges such as impaired visibility due to fog or smoke, as well as treacherous road conditions caused by rain-induced slipperiness. These environmental circumstances accentuate the vulnerability to accidents. The studies carried out in China confirmed a significant correlation between collisions with vehicles and particulate matter (PM) (Wan et al., 2020).

Additionally, inclement weather conditions exacerbate the challenge by rendering road surfaces even more precarious. This corresponds with Nguyen et al. (2022), who assert that motorcycling in conditions characterized by wind, dust, or rain heightens the susceptibility to errors. This effect is compounded among older riders, who, despite possessing extensive riding experience, may confront physical limitations due to the aging process. These challenges impact attention, memory, problem-solving, and information processing capabilities (Freund & Smith, 2011), consequently amplifying the frequency of control errors and, consequently, elevating the accident risk (Chouhan et al., 2021).

The present study shares similarities with the research conducted by Jomnonkwao, Hantanong, et al. (2023), where risk behavior factors in motorcycle riding significantly contributed to near-miss incidents, with control errors being the most influential. These control errors encompass issues related to managing the motorcycle's speed, negotiating curves, driving on slippery surfaces, and navigating unfavorable weather conditions. These findings resonate with the outcomes of the current study. Additionally, another study by Jomnonkwao, Champahom, et al. (2023) identified factors leading to near-miss incidents, encompassing road factors (e.g., road surface, number of traffic lanes, speed limit), environmental factors (e.g., driving at night), and driver factors (e.g., using a phone while driving).

In Japan, a developed nation grappling with pronounced traffic issues among its aging population due to rapid demographic aging (Kurita et al., 2023), several interventions have been enacted. These include statutory mandates necessitating driving proficiency tests and cognitive evaluations for license renewal among individuals aged 75 and above. Initiatives to encourage voluntary license surrender among elderly drivers have been incentivized, offering benefits such as reduced public transport fares or discounted fees for social engagements. Moreover, targeted training programs and safety awareness campaigns tailored for elderly drivers have been implemented, complemented by assessments of driving capabilities under varied conditions (Ishii et al., 2021). Social initiatives providing secure and convenient travel alternatives for seniors, such as group travel arrangements or specialized transportation services, have also been promoted (Chu et al., 2019).

Therefore, control errors, recognized as the most influential factor effecting near-miss incidents, pertain to unintentional mistakes or misjudgments made by motorcycle riders in managing their vehicles. The manifestation of control errors encompasses various critical aspects:

i. *Speed Management:* Riders may misjudge appropriate speeds for different road conditions, leading to situations where they are unable to effectively control their motorcycles.

ii. *Curve Negotiation:* Errors in navigating curves can result in instability, loss of control, and potential near-miss incidents, particularly when riders fail to adjust their speed and positioning adequately.

iii. *Handling on Slippery Surfaces:* Difficulty in managing the motorcycle on slippery or uneven surfaces can contribute to control errors, making riders more susceptible to near-miss situations.

iv. *Adverse Weather Conditions:* Poor weather conditions, such as rain or strong winds, can exacerbate control errors, affecting riders' ability to maintain control of their motorcycles.

Understanding how these control errors manifest is crucial for developing targeted training and awareness programs. For younger riders, emphasis could be placed on improving judgment related to speed management and curve negotiation. Older riders might benefit from training that focuses on enhancing skills in handling motorcycles on slippery surfaces and in adverse weather conditions. Additionally, promoting general awareness about the impact of environmental factors on control errors can contribute to overall rider safety for both age groups.

3.7 Conclusions and Implementation

The aim of this study is to construct a model for understanding near-miss risk behaviors using data gathered from the Motorcycle Rider Behavior Questionnaire (MRBQ) to compare two distinct groups: younger and older riders. The analysis focuses on three factors—control error, traffic violations, and safety equipment—and evaluates their influence on near-miss. The investigation centers on riding behaviors within countries characterized by medium to low income, where road user training is limited and compliance with traffic regulations is lower. The study employs Thailand as a representative sample for questionnaire responses. The collected samples originate from six diverse regions across the country, comprising a total of 815 participants, including 475 younger riders and 340 older riders.

The study's emphasis on speeding as a significant concern, particularly among novice or younger riders, suggests several recommendations for rider's license training and measures to promote safe riding practices:

I. *Incorporate speed management training into licensing programs:* Integrate specific modules on speed management into driver's license training programs, emphasizing the importance of adjusting speeds according to road conditions and surroundings. Include practical scenarios and simulations that allow riders to experience the consequences of inappropriate speeds.

II. *Target Novice and Younger Riders:* Develop specialized training initiatives aimed at novice and younger riders, acknowledging their higher susceptibility to speed-related issues. Emphasize the risks associated with speeding through interactive and engaging educational materials.

III. *Promote defensive riding techniques:* Integrate defensive riding techniques into training programs, teaching riders how to anticipate and respond to potential hazards on the road. Highlight the role of defensive riding in preventing near-miss incidents and enhancing overall safety.

IV. *Use advanced training technologies:* Incorporate advanced training technologies, such as virtual reality (VR) simulations, to provide realistic scenarios that emphasize the consequences of speeding. Utilize technology to assess and improve riders' decision-making skills related to speed management.

V. *Collaborate with riding schools and instructors:* Collaborate with riding schools and instructors to ensure the consistent and effective delivery of speed management training. Encourage riding schools to adopt best practices in teaching speed awareness and control.

VI. *Community awareness campaigns:* Launch community-wide awareness campaigns targeting both riders and the general public to emphasize the dangers of speeding. Use various media channels to disseminate information, including social media, posters, and community events.

VII. *Regular Refresher Courses:* Implement periodic refresher courses for licensed riders to reinforce safe riding practices and update them on any changes in speed regulations or road conditions. Offer incentives for riders who voluntarily participate in refresher training.

By integrating these recommendations into driver's license training and broader awareness campaigns, authorities can address the specific challenges related to speeding among younger riders and enhance overall motorcycle safety.

When considering the older age group, it is evident that the primary issue revolves around adverse weather conditions that are unfavorable for riding. To address visibility-related challenges during adverse weather conditions, especially for older riders who may face heightened risks, policies and recommendations can focus on the following strategies:

I. *Educational Campaigns:* Launch targeted educational campaigns emphasizing the impact of adverse weather on visibility and the specific challenges faced by older riders. Provide information on how adverse weather conditions affect visibility, road conditions, and the importance of adjusting riding behaviors accordingly.

II. *Incorporate weather awareness into training programs:* Integrate weather-specific modules into rider training programs, with a focus on teaching riders, especially older ones, how to adapt to various weather conditions. Emphasize safe riding practices during rain, fog, and other adverse weather scenarios.

III. *Enhanced Licensing Requirements:* Consider implementing enhanced licensing requirements for older riders, including additional training or testing related to riding in adverse weather conditions. Encourage ongoing education and skill development for older riders through refresher courses.

IV. *Promote the Use of Protective Gear:* Encourage the use of high-visibility protective gear, such as reflective clothing and helmets with visibility-enhancing features, to improve older riders' visibility to other road users. Provide information on the effectiveness of such gear in adverse weather conditions.

V. *Weather-Responsive Road Signage:* Implement dynamic road signage that adjusts to weather conditions, providing real-time information to riders about potential hazards and recommended speeds. Include specific signage that warns about reduced visibility and encourages cautious riding.

VI. *Public Transportation Options:* Promote public transportation options during severe weather conditions, offering older riders an alternative to riding in adverse weather. Provide information on accessible and rider-friendly public transportation services.

VII. *Community Workshops and Seminars:* Conduct workshops and seminars in local communities to raise awareness about the challenges of riding in adverse weather, especially for older riders. Facilitate discussions on strategies for mitigating risks and enhancing safety.

By implementing these policies and recommendations, authorities can address the unique challenges older riders face in adverse weather conditions and promote safer riding practices. Additionally, collaboration between government agencies, rider organizations, and other stakeholders is essential to ensuring a comprehensive and effective approach.

While the feasibility of road safety recommendations may be impacted by resource constraints in regions characterized by medium to low income, strategic adaptations, community involvement, and collaboration with external partners can contribute to the successful implementation of these measures. Tailoring initiatives to the specific context and addressing local challenges will be crucial for the effectiveness of road safety efforts in such regions. It's essential to recognize the limitations posed by being a lower- to medium-income country in certain geographic regions. However, by adopting a strategic and localized approach, these challenges can be addressed to enhance road safety. This may involve partnerships with international organizations, leveraging technology for cost-effective solutions, and fostering community engagement to ensure that road safety measures are culturally relevant and well-received.

In summary, while the financial limitations in medium- to low-income regions present challenges, proactive and context-specific strategies can enhance the feasibility and effectiveness of road safety recommendations. The key lies in adapting initiatives to the unique circumstances of each region, considering local resources, and fostering collaboration for sustainable outcomes.

3.8 Limitations and Further Research

While this investigation focuses on motorcycle riders, it is essential to carry out further research on the prevalence of near-miss incidents involving trucks and interactions between smaller and larger vehicles, like motorcycles and trucks. This becomes particularly critical in swiftly developing industrial zones with significant truck traffic. In such industrial areas, the risk of not detecting smaller vehicles, especially at intersections or junctions, is elevated, thereby increasing the likelihood of accidents.

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3.10 References

Ackaah, W., & Afukaar, F. K. (2010). Prevalence of Helmet Use Among Motorcycle Users in Tamale Metropolis, Ghana: An Observational Study. *Traffic Injury Prevention, 11*(5), 522-525. doi:10.1080/15389588.2010.489198

Aldred, R. (2012). Governing transport from welfare state to hollow state: The case of cycling in the UK. *Transport Policy, 23*, 95-102. doi:https://doi.org/10.1016/j.tranpol.2012.05.012

Aldred, R., & Crosweller, S. (2015). Investigating the rates and impacts of near misses and related incidents among UK cyclists. *Journal of Transport & Health, 2*(3), 379-393. doi:https://doi.org/10.1016/j.jth.2015.05.006

Alnawmasi, N., & Mannering, F. (2019). A statistical assessment of temporal instability in the factors determining motorcyclist injury severities. *Analytic Methods in Accident Research, 22*, 100090. doi:https://doi.org/10.1016/j.amar.2019.100090

Ashie, A., Wilhelm, A., Carney, D., DiPasquale, T., & Bush, C. (2018). Comparing fracture patterns of younger versus older riders involved in nonfatal motorcycle accidents. *Traffic Injury Prevention, 19*(7), 761-765. doi:https://doi.org/10.1080/15389588.2018.1494384

Awolusi, I., & Marks, E. (2015). Near-miss reporting to enhance safety in the steel industry. *Iron Steel Technol, 2*, 62-68.

Azami-Aghdash, S., Aghaei, M. H., & Sadeghi-Bazarghani, H. (2018). Epidemiology of Road Traffic Injuries among Elderly People; A Systematic Review and Meta-Analysis. *Bull Emerg Trauma, 6*(4), 279-291. doi:10.29252/beat-060403

Banz, B. C., Fell, J. C., & Vaca, F. E. (2019). Focus: death: complexities of young driver injury and fatal motor vehicle crashes. *The Yale journal of biology and medicine, 92*(4), 725.

Bina, M., Graziano, F., & Bonino, S. (2006). Risky driving and lifestyles in adolescence. *Accid Anal Prev, 38*(3), 472-481. doi:10.1016/j.aap.2005.11.003

Centola, C., Tagliabue, M., Spoto, A., Palpacelli, M., Giorgetti, A., Giorgetti, R., & Vidotto, G. (2020). Enhancement of unsafe behaviors in simulated moped-riding performance under the influence of low dose of alcohol. *Accident*

Analysis & Prevention, 136, 105409. doi:https://doi.org/10.1016/j.aap.2019.105409

Champahom, T., Jomnonkwao, S., Thotongkam, W., Jongkol, P., Rodpon, P., & Ratanavaraha, V. (2023). Investigating Parents’ Attitudes towards the Use of Child Restraint Systems by Comparing Non-Users and User Parents. *Sustainability, 15*(4), 2896. Retrieved from https://www.mdpi.com/2071-1050/15/4/2896

Chan, E., Pradhan, A. K., Pollatsek, A., Knodler, M. A., & Fisher, D. L. (2010). Are Driving Simulators Effective Tools for Evaluating Novice Drivers' Hazard Anticipation, Speed Management, and Attention Maintenance Skills. *Transp Res Part F Traffic Psychol Behav, 13*(5), 343-353. doi:10.1016/j.trf.2010.04.001

Chen, P.-L., Chen, Y.-C., & Pai, C.-W. (2018). Motorcyclist is the right-of-way violator: a population-based study of motorcycle right-of-way crash in Taiwan. *Journal of Advanced Transportation, 2018*.

Chen, P., Zeng, W., Yu, G., & Wang, Y. (2017). Surrogate safety analysis of pedestrian-vehicle conflict at intersections using unmanned aerial vehicle videos. *Journal of Advanced Transportation, 2017*.

Chen, S.-J., Chen, C.-Y., & Lin, M.-R. (2018). Risk factors for crash involvement in older motorcycle riders. *Accident Analysis & Prevention, 111*, 109-114. doi:https://doi.org/10.1016/j.aap.2017.11.006

Cho, G., Rodríguez, D. A., & Khattak, A. J. (2009). The role of the built environment in explaining relationships between perceived and actual pedestrian and bicyclist safety. *Accident Analysis & Prevention, 41*(4), 692-702.

Chouhan, S. S., Kathuria, A., & Sekhar, C. R. (2021). Examining risky riding behavior in India using Motorcycle rider behavior questionnaire. *Accident Analysis & Prevention, 160*, 106312. doi:10.1016/j.aap.2021.106312

Chu, T. D., Miwa, T., Sato, H., Kenmochi, C., & Morikawa, T., 2019. Incorporating Covariance Heterogeneity into Two-level Nested Logit: An Application to a Cooperative Ride System for Elderly People in Rural Areas of Aging Population, Japan. Journal of the Eastern Asia Society for Transportation Studies 13, 698-715.

Chung, Y.-S., & Wong, J.-T. (2012). Beyond general behavioral theories: Structural discrepancy in young motorcyclist's risky driving behavior and its policy implications. *Accident Analysis & Prevention, 49*, 165-176. doi:https://doi.org/10.1016/j.aap.2011.04.021

Collet, C., Guillot, A., & Petit, C. (2010). Phoning while driving I: a review of epidemiological, psychological, behavioural and physiological studies. *Ergonomics, 53*(5), 589-601. doi:10.1080/00140131003672023

D'Elia, A., & Newstead, S. (2023). Evaluation of the effectiveness of daytime running lights (DRLs). *Journal of Safety Research*. doi:https://doi.org/10.1016/j.jsr.2023.01.009

Dapilah, F., Guba, B. Y., & Owusu-Sekyere, E. (2017). Motorcyclist characteristics and traffic behaviour in urban Northern Ghana: Implications for road traffic accidents. *Journal of Transport & Health, 4*, 237-245. doi:https://doi.org/10.1016/j.jth.2016.03.001

Davoodi, S. R., & Hossayni, S. M. (2015). Role of Motorcycle Running Lights in Reducing Motorcycle Crashes during Daytime; A Review of the Current Literature. *Bulletin of Emergency and Trauma, 3*(3), 73-78.

Department of Land Transport. (2021). Number of registered motorcycles in Thailand. Retrieved from https://web.dlt.go.th/statistics/

Elliott, M. A., Baughan, C. J., & Sexton, B. F. (2007). Errors and violations in relation to motorcyclists' crash risk. *Accident Analysis & Prevention, 39*(3), 491-499. doi:https://doi.org/10.1016/j.aap.2006.08.012

Etehad, H., Yousefzadeh-Chabok, S., Davoudi-Kiakalaye, A., Moghadam, D. A., Hemati, H., & Mohtasham-Amiri, Z. (2015). Impact of road traffic accidents on the elderly. *Archives of Gerontology and Geriatrics, 61*(3), 489-493. doi:https://doi.org/10.1016/j.archger.2015.08.008

finch, W. H. (2013). *Exploratory Factor Analysis*. Rotterdam: SensePublishers.

Fitzpatrick, D., & O'Neill, D. (2017). The older motorcyclist. *European Geriatric Medicine, 8*(1), 10-15. doi:https://doi.org/10.1016/j.eurger.2016.10.004

Fletcher, C., McDowell, D., Thompson, C., & James, K. (2019). Helmet use among motorcycle accident victims in the north-east region of Jamaica. *International*

Journal of Injury Control and Safety Promotion, 26(4), 399-404. doi:10.1080/17457300.2019.1653931

Forward, S. E. (2010). Intention to speed in a rural area: Reasoned but not reasonable. *Transportation Research Part F: Traffic Psychology and Behaviour, 13*(4), 223-232. doi:https://doi.org/10.1016/j.trf.2010.04.002

Freund, B., & Smith, P. (2011). Chapter 24 - Older Drivers. In B. E. Porter (Ed.), *Handbook of Traffic Psychology* (pp. 339-351). San Diego: Academic Press.

Gershon, P., Ehsani, J. P., Zhu, C., Sita, K. R., Klauer, S., Dingus, T., & Simons-Morton, B. (2018). Crash Risk and Risky Driving Behavior Among Adolescents During Learner and Independent Driving Periods. *Journal of Adolescent Health, 63*(5), 568-574. doi:https://doi.org/10.1016/j.jadohealth.2018.04.012

Golob, T. F. (2003). Structural equation modeling for travel behavior research. *Transportation Research Part B: Methodological, 37*(1), 1-25. doi:https://doi.org/10.1016/S0191-2615(01)00046-7

Hair, J., Black, W., Babin, B., & Anderson, R. (2006). *Multivariate Data Analysis* (6 ed.): Pearson Prentice Hall.

Hair, J. F., Black, W. C., & Babin, B. J. (2010). *Multivariate Data Analysis: A Global Perspective*: Pearson Education.

Hair Jr, J. F., Sarstedt, M., Ringle, C. M., & Gudergan, S. P. (2017). *Advanced issues in partial least squares structural equation modeling*: saGe publications.

Haruhiko, I., Qingfeng, L., Abdulgafoor, B., & Adnan, A. H. (2020). Forecasting global road traffic injury mortality for 2030. *Injury Prevention, 26*(4), 339. doi:10.1136/injuryprev-2019-043336

Hassan, T., Vinodkumar, M. N., & Vinod, N. (2017). Influence of demographics on risky driving behaviour among powered two wheeler riders in Kerala, India. *Transportation Research Part F: Traffic Psychology and Behaviour, 46*, 24-33. doi:https://doi.org/10.1016/j.trf.2016.11.008

Heinrich, H. W. (1941). Industrial Accident Prevention. A Scientific Approach. *Industrial Accident Prevention. A Scientific Approach.*(Second Edition).

Hooper, D., Coughlan, J. P., & Mullen, M. R. (2008). *Structural equation modelling: guidelines for determining model fit*.

Hu, L. t., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1-55. doi:10.1080/10705519909540118

Huang, P., & Winston, F. K. (2011). Chapter 23 - Young Drivers. In B. E. Porter (Ed.), *Handbook of Traffic Psychology* (pp. 315-338). San Diego: Academic Press.

Injury Data Collaboration Center (IDCC). (2021). Injury surveillance. Retrieved from http://ae.moph.go.th/

Ishii, H., Doi, T., Tsutsumimoto, K., Nakakubo, S., Kurita, S., & Shimada, H., 2021. Long-Term Effects of Driving Skill Training on Safe Driving in Older Adults with Mild Cognitive Impairment. Journal of the American Geriatrics Society 69(2), 506-511.

Ivanišević, T., Ivković, I., Čičević, S., Trifunović, A., Pešić, D., Vukšić, V., & Simović, S. (2022). The impact of daytime running (LED) lights on motorcycles speed estimation: A driving simulator study. *Transportation Research Part F: Traffic Psychology and Behaviour, 90*, 47-57. doi:https://doi.org/10.1016/j.trf.2022.08.002

Jomnonkwao, S., Champahom, T., Se, C., Hantanong, N., & Ratanavaraha, V. (2023). Contributing factors to near-miss experiences of motorcyclists in Thailand: A random parameter probit model approach. *Heliyon, 9*(12), e22625. doi:https://doi.org/10.1016/j.heliyon.2023.e22625

Jomnonkwao, S., Hantanong, N., Champahom, T., Se, C., & Ratanavaraha, V. (2023). Analyzing Near-Miss Incidents and Risky Riding Behavior in Thailand: A Comparative Study of Urban and Rural Areas. *Safety, 9*(4). doi:10.3390/safety9040090

Jomnonkwao, S., Sangphong, O., Khampirat, B., Siridhara, S., & Ratanavaraha, V. (2016). Public transport promotion policy on campus: evidence from Suranaree University in Thailand. *Public Transport, 8*(2), 185-203. doi:10.1007/s12469-016-0122-2

Jöreskog, K. G., Olsson, U. H., & Wallentin, F. Y. (2016). Confirmatory Factor Analysis (CFA). In K. G. Jöreskog, U. H. Olsson, & F. Y. Wallentin (Eds.), *Multivariate Analysis with LISREL* (pp. 283-339). Cham: Springer International Publishing.

Kline, R. B. (2011). *Principles and practice of structural equation modeling*: Third edition. New York : Guilford Press.

Kumar Yadav, A., & Velaga, N. R. (2021). A comprehensive systematic review of the laboratory-based research investigating the influence of alcohol on driving behaviour. *Transportation Research Part F: Traffic Psychology and Behaviour, 81*, 557-585. doi:https://doi.org/10.1016/j.trf.2021.07.010

Kurita, S., Doi, T., Harada, K., Katayama, O., Morikawa, M., Nishijima, C., . . . Shimada, H., 2023. Motoric Cognitive Risk Syndrome and Traffic Incidents in Older Drivers in Japan. JAMA Network Open 6(8), e2330475-e2330475.

Lam, C., Pai, C. W., Chuang, C. C., Yen, Y. C., Wu, C. C., Yu, S. H., . . . Chiu, W. T. (2019). Rider factors associated with severe injury after a light motorcycle crash: A multicentre study in an emerging economy setting. *PLoS One, 14*(6), e0219132. doi:10.1371/journal.pone.0219132

Lam, L. W. (2012). Impact of competitiveness on salespeople's commitment and performance ☆. *Journal of Business Research, 65*, 1328-1334.

Lee, W. Y., Cameron, P. A., & Bailey, M. J. (2006). Road traffic injuries in the elderly. *Emerg Med J, 23*(1), 42-46. doi:10.1136/emj.2005.023754

Lee, Y. M., & Sheppard, E. (2018). The effect of lighting conditions and use of headlights on drivers' perception and appraisal of approaching vehicles at junctions. *Ergonomics, 61*(3), 444-455. doi:10.1080/00140139.2017.1364790

Liao, Y., Lin, C.-Y., & Park, J.-H. (2019). Is motorcycle use associated with unhealthy lifestyles? Findings from Taiwan. *Journal of Transport & Health, 15*, 100659. doi:https://doi.org/10.1016/j.jth.2019.100659

Luu, L. V., Minh, C. C., & Long, N. X. (2021). The development of safe riding guidelines for young riders – A case study of Phu Yen, Vietnam. *IATSS Research, 45*(2), 226-233. doi:https://doi.org/10.1016/j.iatssr.2020.11.001

Marín Puchades, V., Fassina, F., Fraboni, F., De Angelis, M., Prati, G., de Waard, D., & Pietrantoni, L. (2018). The role of perceived competence and risk perception in cycling near misses. *Safety Science, 105*, 167-177. doi:https://doi.org/10.1016/j.ssci.2018.02.013

Maskey, R., Fei, J., & Nguyen, H.-O. (2018). Use of exploratory factor analysis in maritime research. *The Asian Journal of Shipping and Logistics, 34*(2), 91-111. doi:https://doi.org/10.1016/j.ajsl.2018.06.006

Matsui, Y., Hitosugi, M., Doi, T., Oikawa, S., Takahashi, K., & Ando, K. (2013). Features of pedestrian behavior in car-to-pedestrian contact situations in near-miss incidents in Japan. *Traffic Injury Prevention, 14*(sup1), S58-S63.

Mehdizadeh, M., Nordfjaern, T., & Klöckner, C. A. (2023). Drunk or Sober? Number of alcohol units perceived to be safe before riding e-scooter. *Accident Analysis & Prevention, 181*, 106930. doi:https://doi.org/10.1016/j.aap.2022.106930

Michael, R. J., Sharma, M. K., Mehrotra, S., Banu, H., Kumar, R., Sudhir, P. M., & Chakrabarthy, N. (2014). Inclination to speeding and its correlates among two-wheeler riding Indian youth. *Ind Psychiatry J, 23*(2), 105-110. doi:10.4103/0972-6748.151676

Mohammadpour, S. I., Nassiri, H., & Sullman, M. J. M. (2022). Validation of the Driver's Angry Thoughts Questionnaire (DATQ) in a sample of professional drivers in Iran. *IATSS Research, 46*(3), 370-379. doi:https://doi.org/10.1016/j.iatssr.2022.04.002

Möller, H., Senserrick, T., Rogers, K., Sakashita, C., de Rome, L., Boufous, S., . . . Ivers, R. (2020). Crash risk factors for novice motorcycle riders. *Journal of Safety Research, 73*, 93-101. doi:https://doi.org/10.1016/j.jsr.2020.02.003

Motevalian, S. A., Asadi-Lari, M., Rahimi, H., & Eftekhar, M. (2011). Validation of a persian version of motorcycle rider behavior questionnaire. *Ann Adv Automot Med, 55*, 91-98.

Nguyen, D. V. M., Vu, A. T., Ross, V., Brijs, T., Wets, G., & Brijs, K. (2022). Small-displacement motorcycle crashes and risky ridership in Vietnam: Findings from a focus group and in-depth interview study. *Safety Science, 152*. doi:10.1016/j.ssci.2021.105514

Ospina-Mateus, H., Jiménez, L. Q., & López-Valdés, F. J. (2021). The rider behavior questionnaire to explore associations of motorcycle taxi crashes in Cartagena

(Colombia). *Traffic Injury Prevention, 22*(sup1), S99-S103. doi:10.1080/15389588.2021.1970749

Özkan, T., Lajunen, T., Doğruyol, B., Yıldırım, Z., & Çoymak, A. (2012). Motorcycle accidents, rider behaviour, and psychological models. *Accident Analysis & Prevention, 49*, 124-132. doi:https://doi.org/10.1016/j.aap.2011.03.009

Park, J.-I., Kim, S., & Kim, J.-K. (2023). Exploring spatial associations between near-miss and police-reported crashes: The Heinrich's law in traffic safety. *Transportation Research Interdisciplinary Perspectives, 19*, 100830. doi:https://doi.org/10.1016/j.trip.2023.100830

Parker, D., Lajunen, T., & Stradling, S. (1998). Attitudinal predictors of interpersonally aggressive violations on the road. *Transportation Research Part F: Traffic Psychology and Behaviour, 1*(1), 11-24. doi:https://doi.org/10.1016/S1369-8478(98)00002-3

Patrick, M. E., Graupensperger, S., Dworkin, E. R., Duckworth, J. C., Abdallah, D. A., & Lee, C. M. (2021). Intoxicated driving and riding with impaired drivers: Comparing days with alcohol, marijuana, and simultaneous use. *Drug and Alcohol Dependence, 225*, 108753. doi:https://doi.org/10.1016/j.drugalcdep.2021.108753

Pérez-Núñez, R., Hidalgo-Solórzano, E., Vera-López, J. D., Lunnen, J. C., Chandran, A., Híjar, M., & Hyder, A. A. (2014). The Prevalence of Mobile Phone Use Among Motorcyclists in Three Mexican Cities. *Traffic Injury Prevention, 15*(2), 148-150. doi:10.1080/15389588.2013.802776

Reason, J., Manstead, A., Stradling, S., Baxter, J., & Campbell, K. (1990). Errors and violations on the roads: a real distinction? *Ergonomics, 33*(10-11), 1315-1332. doi:10.1080/00140139008925335

Roehler, D. R., Ear, C., Parker, E. M., Sem, P., & Ballesteros, M. F. (2015). Fatal motorcycle crashes: a growing public health problem in Cambodia. *International Journal of Injury Control and Safety Promotion, 22*(2), 165-171. doi:10.1080/17457300.2013.876050

Sakashita, C., Senserrick, T., Lo, S., Boufous, S., Rome, L. d., & Ivers, R. (2014). The Motorcycle Rider Behavior Questionnaire: Psychometric properties and application amongst novice riders in Australia. *Transportation Research Part F: Traffic Psychology and Behaviour, 22*, 126-139. doi:https://doi.org/10.1016/j.trf.2013.10.005

Saliya, C. A. (2022). Structural Equation Modeling (SEM). In C. A. Saliya (Ed.), *Doing Social Research and Publishing Results: A Guide to Non-native English Speakers* (pp. 233-240). Singapore: Springer Nature Singapore.

Sanders, R. L. (2015). Perceived traffic risk for cyclists: The impact of near miss and collision experiences. *Accident Analysis & Prevention, 75*, 26-34. doi:https://doi.org/10.1016/j.aap.2014.11.004

Steg, L., & Brussel, A. v. (2009). Accidents, aberrant behaviours, and speeding of young moped riders. *Transportation Research Part F: Traffic Psychology and Behaviour, 12*(6), 503-511. doi:https://doi.org/10.1016/j.trf.2009.09.001

Steiger, J. H. (2007). Understanding the limitations of global fit assessment in structural equation modeling. *Personality and Individual Differences, 42*(5), 893-898. doi:https://doi.org/10.1016/j.paid.2006.09.017

Stephens, A. N., Brown, J., de Rome, L., Baldock, M. R. J., Fernandes, R., & Fitzharris, M. (2017). The relationship between Motorcycle Rider Behaviour Questionnaire scores and crashes for riders in Australia. *Accident Analysis & Prevention, 102*, 202-212. doi:https://doi.org/10.1016/j.aap.2017.03.007

Sumit, K., Ross, V., Brijs, K., Wets, G., & Ruiter, R. A. C. (2021). Risky motorcycle riding behaviour among young riders in Manipal, India. *BMC Public Health, 21*(1), 1954. doi:10.1186/s12889-021-11899-y

Sunday, O. K. (2010). The performance of the motorcycle rider behaviour questionnaire among commercial motorcycle riders in Nigeria. *Injury Prevention, 16*, A194 - A194.

Susilo, Y. O., Joewono, T. B., & Vandebona, U. (2015). Reasons underlying behaviour of motorcyclists disregarding traffic regulations in urban areas of Indonesia. *Accident Analysis & Prevention, 75*, 272-284.

Taber, K. S. (2018). The Use of Cronbach’s Alpha When Developing and Reporting Research Instruments in Science Education. *Research in Science Education, 48*(6), 1273-1296. doi:10.1007/s11165-016-9602-2

Tan, M. P. (2022). Healthcare for older people in lower and middle income countries. *Age and Ageing, 51*(4), afac016. doi:10.1093/ageing/afac016

Taubman-Ben-Ari, O., Mikulincer, M., & Gillath, O. (2004). The multidimensional driving style inventory—scale construct and validation. *Accident Analysis & Prevention, 36*(3), 323-332. doi:https://doi.org/10.1016/S0001-4575(03)00010-1

ThaiRoads Foundation. (2022). Key fact on road safety situations in Thailand 2018 - 2021 Retrieved from https://www.roadsafetythai.org/project_download_bookdetail-edoc-636-.html

The National Highway Traffic Safety Administration. (2021). Distracted Driving. Retrieved from https://www.nhtsa.gov/risky-driving/distracted-driving

Topolšek, D., & Dragan, D. (2016). Relationships between the motorcyclists' behavioural perception and their actual behaviour. *Transport, 33*, 151-164.

Trung Bui, H., Saadi, I., & Cools, M. (2020). Investigating on-road crash risk and traffic offences in Vietnam using the motorcycle rider behaviour questionnaire (MRBQ). *Safety Science, 130*, 104868. doi:https://doi.org/10.1016/j.ssci.2020.104868

Truong, L. T., Nguyen, H. T. T., & De Gruyter, C. (2018). Correlations between mobile phone use and other risky behaviours while riding a motorcycle. *Accident Analysis & Prevention, 118*, 125-130. doi:https://doi.org/10.1016/j.aap.2018.06.015

Uttra, S., Jomnonkwao, S., Watthanaklang, D., & Ratanavaraha, V. (2020). Development of Self-Assessment Indicators for Motorcycle Riders in Thailand: Application of the Motorcycle Rider Behavior Questionnaire (MRBQ). *Sustainability, 12*(7). doi:10.3390/su12072785

Walshe, E. A., Ward McIntosh, C., Romer, D., & Winston, F. K. (2017). Executive Function Capacities, Negative Driving Behavior and Crashes in Young Drivers. *International Journal of Environmental Research and Public Health, 14*(11). doi:10.3390/ijerph14111314

Wan, Y., Li, Y., Liu, C., & Li, Z. (2020). Is traffic accident related to air pollution? A case report from an island of Taihu Lake, China. *Atmospheric Pollution Research, 11*(5), 1028-1033. doi:https://doi.org/10.1016/j.apr.2020.02.018

Wiratama, B. S., Chen, P.-L., Ma, S.-T., Chen, Y.-H., Saleh, W., Lin, H.-A., & Pai, C.-W. (2020). Evaluating the combined effect of alcohol-involved and un-helmeted riding on motorcyclist fatalities in Taiwan. *Accident Analysis & Prevention, 143*, 105594. doi:https://doi.org/10.1016/j.aap.2020.105594

World Health Organization. (2018). *GLOBAL STATUS REPORT ON ROAD SAFETY*. Retrieved from https://apps.who.int/iris/bitstream/handle/10665/276462/9789241565684-eng.pdf?ua=1

World Health Organization. (2023). Thailand's leadership and innovations towards healthy ageing. Retrieved from https://www.who.int/southeastasia/news/feature-stories/detail/thailands-leadership-and-innovation-towards-healthy-ageing#:~:text=Thailand%20is%20among%20the%20fastest,for%2010%25%20of%20the%20population.

Wright, L., & Van der Schaaf, T. (2004). Accident versus near miss causation: a critical review of the literature, an empirical test in the UK railway domain, and their implications for other sectors. *Journal of hazardous materials, 111*(1-3), 105-110.

Young, W., Sobhani, A., Lenné, M. G., & Sarvi, M. (2014). Simulation of safety: A review of the state of the art in road safety simulation modelling. *Accident Analysis & Prevention, 66*, 89-103.

Zamani-Alavijeh, F., Bazargan, M., Shafiei, A., & Bazargan-Hejazi, S. (2011). The frequency and predictors of helmet use among Iranian motorcyclists: A quantitative and qualitative study. *Accident Analysis & Prevention, 43*(4), 1562-1569. doi:https://doi.org/10.1016/j.aap.2011.03.016

Zheng, L., Ismail, K., & Meng, X. (2014). Traffic conflict techniques for road safety analysis: open questions and some insights. *Canadian journal of civil engineering, 41*(7), 633-641.

CHAPTER IV
THE ROLE OF PERCEPTION FAILURES IN NEAR-MISSES AMONG MOTORCYCLISTS

4.1 Abstract

This study aims to develop a model of the relationship between attitudes and perceptions regarding near-miss incidents among motorcycle riders in developing countries using structural equation modeling. The analysis considers four factors: fear of traffic (FT), attitude toward distracted riding (ADR), avoidance of mixed traffic (AVM), and perceived behavioral control (PBC) to determine their relationships with near-miss incidents. For this study, we selected Thailand as a representative developing country and collected data from a sample of 2,002 individuals across six regions nationwide. The results indicate that perceived behavioral control (PBC) has a significantly positive relationship with the risk of near-miss incidents, particularly when riders use mobile phones while riding or ride at high speeds on curves. Conversely, avoidance of mixed traffic (AVM) has a significantly negative relationship with the risk of near-miss incidents. To mitigate the risk of near-miss incidents, the study recommends enforcing laws and safety measures, improving infrastructure and road environments, and providing training and education to enhance riding knowledge and skills. Furthermore, the study addresses the development limitations in developing countries.

4.2 Introduction

In developing countries such as Thailand, motorcycle usage for transportation is highly prevalent. However, the losses resulting from motorcycle accidents are also increasing (Liao, Lin, & Park, 2019). The risk of death for motorcyclists is nearly eight times higher than for car drivers (Keall & Newstead, 2012) and up to 40 times higher compared to car passengers (Šraml, Tollazzi, & Renčelj, 2012).

Motorcyclists are considered a vulnerable road user group (World Health Organization, 2018). In developing countries, there is a lack of training for road users and insufficient enforcement of traffic laws, coupled with poor health and road infrastructure, significantly impacting road user fatalities (Fitzpatrick & O'Neill, 2017). Consequently, it is not surprising that Thailand ranks among the highest in the world and Asia for traffic accident fatalities (World Health Organization, 2018). In-depth studies of motorcycle accidents reveal that 50% of incidents are due to perception failure (ThaiRoads Foundation, 2022). Theoretical and empirical investigations (Ba, Zhang, Chan, Zhang, & Cheng, 2016) indicate that risk perception plays a crucial role in mitigating risky behaviors and diminishing the probability of adverse safety outcomes. Marín Puchades et al. (2018) emphasize the significance of incorporating risk perception and perceived competence into models of road user behavior, underscoring their substantial influence on behavior modification.

4.2.1 Motorcycle collisions and near-miss incidents

While near misses typically occupy the lower tiers of the safety pyramid, occurring more frequently and with lesser severity compared to actual accidents, they are strategically positioned at the apex in accordance with Heinrich's Safety Triangle model (Hamann & Peek-Asa, 2017). Near-miss events, although devoid of physical damage, can function as substitutes for collisions due to their analogous causal attributes (Wright & Van der Schaaf, 2004). Furthermore, given their higher frequency, safety outcomes with lower severity, such as near misses, are more amenable to research (Laureshyn, Goede, Saunier, & Fyhri, 2017). Typically, a near-miss incident, also known as a near-crash, a near-miss crash, or a near-miss accident, is a situation where a collision or accident almost occurs but is narrowly avoided without causing damage (Aldred & Crosweller, 2015; Sanders, 2015; Young, Sobhani, Lenné, & Sarvi, 2014). However, it can act as a 'warning sign' of situations or behaviors that might lead to accidents (Aldred, Elliott, Woodcock, & Goodman, 2017). Near-miss incidents have been used to supplement police-reported crash data to identify crash hotspots within road networks and to develop safety measures and strategies (Park, Kim, & Kim, 2023).

Recently, a study investigated factors affecting near-misses among motorcyclists. Hantanong, Jomnonkwao, Champahom, Se, and Ratanavaraha (2024) examined the risky behaviors influencing near misses among young and elderly motorcyclists in Thailand. They also compared the risky behaviors affecting near misses among urban and rural riders (Jomnonkwao, Hantanong, Champahom, Se, & Ratanavaraha, 2023). Both studies indicate that risky driving behaviors by the motorcyclists themselves significantly impact the occurrence of near-misses. Additionally, Jomnonkwao, Champahom, Se, Hantanong, and Ratanavaraha (2023) studied risk factors influencing near misses, including road factors, driver factors, and environmental factors. These studies focus on implemented policies and prominent behaviors, whereas the differences in attitudes and perceptions of near misses among motorcyclists have not been deeply explored. Attitudes and perceptions are crucial intermediaries between policy implementation and behavior, as they are essential for public acceptance of transport policy measures (Di Ciommo, Monzón, & Fernandez-Heredia, 2013) and fundamentally influence intentions and decisions in transportation (Sigurdardottir, Kaplan, Møller, & Teasdale, 2013). To complement and expand the existing knowledge on near-miss incidents among motorcyclists, this study aims to explore the relationship between attitudes and perceptions toward near-misses among motorcyclists in developing countries using structural equation modeling.

4.3 Literature review

4.3.1 Fear of traffic (FT)

Riding a motorcycle carries a significant risk of accidents and severe injuries. Fear of motorcycles, also known as the fear of riding, is a common issue among novice riders or those who do not ride frequently. Many riders are particularly afraid of riding on highways due to multiple lanes, high-speed limits, and traffic congestion, which heightens their apprehension about accidents and leads to non-compliance with surrounding traffic conditions (Wong, Chung, & Huang, 2010). The study by Sigurdardottir et al. (2013) identifies fear of traffic and fear of injury as major obstacles to riding. Factors contributing to this fear include traffic volumes, the perception of near-miss incidents, the perception of aggressive behavior by car drivers, driver awareness, the distance traveled by the rider, and vehicle speed.

Therefore, in our model (Figure 4.1), we hypothesize that fear of traffic will have a positive relationship with near-miss incidents (Hypothesis 4.1). In other words, the greater the motorcyclist's fear of traffic, the higher the likelihood of being involved in conflicts (e.g., near misses).

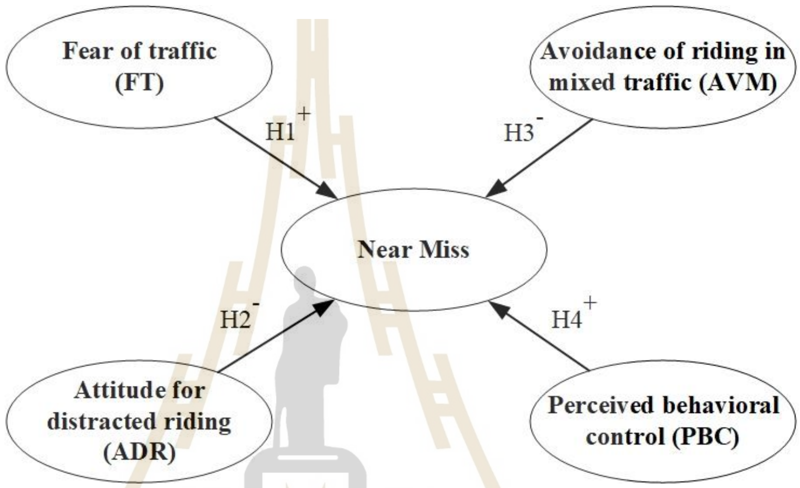


Figure 4.1 Hypothesized path model. The sign of each arrow corresponds to the predicted association and hypothesis

4.3.2 Attitude for distracted riding (ADR)

Attitudes influence behavior directly or indirectly in nearly all social interactions, including driving (Ajzen, 1980; Porter, 2011). Attitude is defined as "a tendency to evaluate an object with varying degrees of favor or disfavor, generally expressed in cognitive, affective, and behavioral responses" (Eagly & Chaiken, 1993). In other words, there are three components that affect and are affected by attitudes: beliefs (cognition), feelings (affect), and behaviors. Drivers may have positive or negative attitudes towards driving safety, which, in turn, influence their driving behavior. Various studies have utilized social cognitive models related to health behavior, such as the theory of reasoned action (Ajzen, 1980), the theory of planned behavior (Ajzen, 1991), and the health belief model (Rosenstock, 1974), to study risky driving behavior

(Ulleberg & Rundmo, 2003). For example, the theory of planned behavior has been used to measure the attitudes of a large sample of drivers towards four driving violations: drunk driving, speeding, tailgating, and dangerous overtaking. The study found that drivers' attitudes were significantly related to the occurrence of accidents (Parker, Manstead, Stradling, Reason, & Baxter, 1992). In another study, Jornet-Gibert, Gallardo-Pujol, Suso, and Andrés-Pueyo (2013) examined antisocial attitudes among drunk driving offenders and found that these offenders were more likely to exhibit antisocial attitudes compared to non-drunk driving offenders. Additionally, Panumasvivat et al. (2024) found that attitudes towards driving are also related to accidents. Their research revealed that although only 13% of drivers listened to music while driving, there was a significant relationship between motorcycle accidents and the attitude disagreeing with the statement "listening to music while driving is dangerous." One of the distractions that can impair driving performance and lead to accidents is listening to music. Activities that most distract motorcycle riders include using navigation maps, listening to music, and adjusting mirrors or other devices on the motorcycle. Not only does listening to music while riding increase motorcycle accidents by 1.53 times, but it is also significantly linked to errors related to attention during riding Panumasvivat et al. (2024).

Therefore, we hypothesize that Attitude for Distracted Riding (ADR) will have a negative relationship with near-miss incidents (Hypothesis 4.2). Put differently, Figure 4.1 illustrates the inverse correlation between a motorcycle rider's likelihood of experiencing a near-miss and their attitude towards distracted riding.

4.3.3 Avoidance of mixed traffic (AVM)

Traffic in developing countries typically features mixed traffic, where motorcycles share lanes with other types of vehicles. This means that vehicles vary in terms of physical characteristics (shape and size) and dynamic characteristics (maximum speed, acceleration, braking, etc.). Furthermore, because mixed traffic comprises various types of vehicles, lane adherence is often quite low. Smaller vehicles tend to fill small gaps created between larger vehicles to reduce travel time.

This contrasts with homogeneous traffic (e.g., a traffic stream consisting mostly of cars), which usually exhibits higher adherence to lane discipline (Damani & Vedagiri, 2021). Motorcycle use can save significant time in congested traffic conditions and requires less road and parking space compared to cars. However, due to having only two wheels, motorcycles are dynamically unstable compared to four-wheeled vehicles. In different traffic conditions, motorcycles often weave through or overtake stationary vehicles at traffic signals, exhibiting poor lane discipline. Other factors that may increase the likelihood of collisions include sudden encounters with animals or other objects on the road (Wang, Lu, Lu, & Wang, 2016), which are common in some developing countries, including Thailand. All these factors imply that motorcycles are significantly different from cars. Therefore, avoiding mixed traffic can help reduce the risk of accidents. Riders may have options to avoid such traffic, including (a) taking an alternative route, (b) opting for a different mode of transport, or (c) avoiding certain sections of the route (Chataway, Kaplan, Nielsen, & Prato, 2014; Marín Puchades et al., 2018).

We hypothesize that Avoidance of Mixed Traffic will have a negative relationship with near-miss incidents (Hypothesis 4.3). Put differently, Figure 4.1 illustrates the inverse correlation between a motorcycle rider's likelihood of experiencing a near-miss and their attitude towards distracted riding.

4.3.4 Perceived behavioral control (PBC)

Perceived behavioral control (PBC) has different names in various frameworks but sometimes refers to similar concepts. For instance, Ajzen (1991) refers to it as perceived behavioral control, while Bandura (1977) calls it self-efficacy, and Boua, Kouabenan, and Belhaj (2022) term it control beliefs. These three concepts are quite similar as they refer to an individual's perception of their ability to influence events affecting them. Perceived driving competence is regarded as an element of riding control (Chaurand & Delhomme, 2013), while perceived behavioral control emerges as a robust predictor of motorcycle riding intention (Satiennam et al., 2023). Perceived behavioral control refers to an individual's perception of their capability to perform a behavior and is a direct predictor of behavior (Ajzen, 1991). According to this concept, people tend to engage in behaviors they believe they can perform. The idea of perceived control over behavior is similar to the concept of self-efficacy (Bandura, 1982). Therefore, perceived control can be defined as an individual's perception of their ability and potential to control their actions in performing a given behavior. Put differently, it outlines how individuals assess their own proficiency and aptitude in a particular scenario. This framework provides a credible basis for asserting that people's sense of control influences their involvement in specific behaviors. As per prior investigations, the readiness to embrace higher risk levels is foreseen by the individual's perception of control over driving conditions (Horswill & McKenna, 1999). Additionally, risks deemed acceptable are more probable to be embraced than those perceived as unacceptable (Nordgren, van der Pligt, & van Harreveld, 2007). Regarding one's capability and efficacy, perceived control could be seen as a favorable attribute (Wohleber & Matthews, 2016). However, when considering future events, scenarios perceived as controllable may lead to cognitive biases that increase the likelihood of their occurrence, leading to unrealistic expectations (Weinstein, 1980). This is confirmed by Măirean and Havârneanu (2018), who observed that riders who overestimate their driving abilities often exhibit verbal and physical anger and risky driving behavior. Feeling more in control, they believe they can avoid accidents more effectively. Similarly, Yang, Feng, Zhao, Jiang, and Huang (2020) reported that drivers who overestimate their driving skills are more likely to engage in queue-jumping behavior. Phongphan Tankasem (2016) study also indicated that perceived behavioral control is significantly related to motorcyclists' intentions to speed. Thus, perceived control that leads to unrealistic expectations results in overconfidence about future events related to one's control, potentially correlating with accident situations.

In the context of this study, we hypothesize that increased perceived behavioral control will have a positive relationship with near-miss incidents (Hypothesis 4.4). In other words, the higher the motorcyclist's perceived behavioral control (PBC), the greater the likelihood of being involved in conflicts (e.g., near misses), as illustrated in Figure 4.1.

4.4 Materials and Method

4.4.1 Data Collection

The researcher aimed for nationwide coverage and thus distributed the sample data across all regions, proportionate to the number of registered motorcycles. We collected the data from various high-traffic areas commonly used by motorcycles, such as shopping malls, government centers, markets, bus stations, universities and educational institutions, business and office districts, tourist spots, and densely populated residential areas. The data collection spanned six regions and 34 provinces, specifically: Central (6 provinces), Eastern (5 provinces), Northeastern (6 provinces), Northern (7 provinces), Western (5 provinces), and Southern (5 provinces). A stratified sampling method was employed to select the sample, targeting residents who had lived in the designated location for at least one year and were aged 18 or older, could ride a motorcycle, and whose motorcycles were registered with the Department of Land Transport. Various guidelines were proposed to determine the appropriate sample size for structural equation modeling (SEM) analysis, including: (a) a minimum sample size of 200 (Hoogland & Boomsma, 1998); (b) a sample size at least 5 to 10 times the number of observed variables (Bollen, 1989); and (c) at least 10 cases per variable (Nunnally, 1994). In this study, a total of 2,002 samples were collected, covering all six regions, thereby ensuring a sufficient sample size for analysis.

The survey included a total of 2,002 participants, as shown in Table 4.1. Of these, 52.2% were female. The largest age group was between 41 and 50 years old, comprising 19.2% of respondents. Other age groups had similar distributions. A significant portion of participants, 54%, held a bachelor's degree, with an average monthly income of 23,142 baht. Alarmingly, 57.5% of participants did not possess a motorcycle driving license. Most rode their motorcycles 1-3 days per week, with an average near-miss experience frequency of 1.64 times and an average accident experience frequency of 0.05 times.

Table 4.1 Sample demographics

Demographics		Quantity	Percentage (%)	Average (*SD*)
Gender	Male	956	47.80%	
	Female	1046	52.20%	
Age (years)	19-20	138	6.9%	
	21-30	369	18.4%	
	31-40	371	18.5%	
	41-50	385	19.2%	
	51-60	369	18.4%	
	>60	370	18.5%	
Highest level of education	Under bachelor's degree	852	42.6%	
	Bachelor's degree	1081	54%	
	Higher than bachelor's degree	69	3.4%	
Income (baht/month)				23,142 (11,952)
Driving license	Yes	851	42.5%	
	No	1151	57.5%	
Frequency of motorcycle riding	1-3 days per week	704	35.2%	
	4-6 days per week.	606	30.3%	
	Every day	692	34.6%	
Accident frequency (Times in the last year)				0.05 (0.23)
Near-miss frequency (Times in the last year)				1.64 (1.30)

4.4.2 Questionnaire

The questionnaire used in this research is divided into two parts. The first part (a) focuses on demographic and riding information, including gender, age, education level, income, possession of a driving license, riding frequency, and near-miss experiences. The second part (b) addresses perceptions of motorcycle riding ability, attitudes toward riding in mixed traffic conditions, distracted riding, and fear of traffic. An acceptable Cronbach's α value of 0.6 or higher, as recommended by Taber (2018), was used in this study. The questions were adapted from studies Marín Puchades et al. (2018) and Chataway et al. (2014), which examined the perceptions and attitudes of cyclists in Italy, Australia, and Denmark to explore their relationship with near-miss incidents among motorcyclists in developing countries.

1) Fear of traffic (FT) measures the perceived skills of motorcyclists when facing traffic. Three items were adapted from Marín Puchades et al. (2018). Respondents were asked to indicate their agreement with each statement on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). The reported items include: "You feel that cars do not give you the right of way as appropriate." "You feel that you almost always have accidents when riding with other types of vehicles," and "you feel unsafe at the speed at which cars are driving." The Cronbach's alpha for this scale was 0.825, indicating acceptable internal consistency.

2) Attitude for distracted riding (ADR) assesses motorcyclists' attitudes toward distracted riding. Four items were adapted from the Attitude Skill Scale by Panumasvivat et al. (2024) and Jornet-Gibert et al. (2013). Respondents were asked to indicate their agreement with each statement on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). Sample items include "Using headphones to listen to music while riding a motorcycle risks accidents" and "Riding after drinking alcohol risks accidents." The Cronbach's alpha for this scale was 0.738, indicating acceptable internal consistency.

3) Avoidance of riding in mixed traffic (AVM) evaluates respondents' attitudes toward avoiding riding in mixed traffic conditions. Three items were adapted from Marín Puchades et al. (2018) and Chataway et al. (2014). Respondents were asked to indicate their agreement with each statement on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). The reported items include: "You avoid using certain routes when there are many vehicles on the road," "You avoid narrow roads with cars coming out," and "When others sit behind the motorcycle, such as children, grandchildren, or siblings, you avoid crowded traffic routes." The Cronbach's alpha for this scale was 0.786, indicating acceptable internal consistency.

4) Perceived behavioral control (PBC) measures participants' perceived control over their motorcycle riding skills. Five items were modified from the Perceived Skill Scale by Marín Puchades et al. (2018). Respondents were asked to indicate their agreement with each statement on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). Sample items include: "You can control the vehicle well, even at high speeds" and "You can talk on the phone while riding a motorcycle, expecting to control the vehicle well and avoid accidents." The Cronbach's alpha for this scale was 0.607, indicating acceptable internal consistency.

4.4.3 Structural equation modelling

Structural Equation Modeling (SEM) is an effective analytical framework used to examine complex relationships among variables within a theoretical model. It allows researchers to investigate both observed and latent structures, providing an in-depth understanding of complex scenarios (Sarstedt, Ringle, & Hair, 2021). SEM comprises two main components: the measurement model and the structural model (Schreiber, Nora, Stage, Barlow, & King, 2006). The measurement model evaluates the validity and reliability of the relationships between latent variables and their indicators, ensuring the robustness of the constructs under examination (Joseph F Hair et al., 2021). In contrast, the structural model explains the connections between latent constructs, elucidating the pathways underlying the hypotheses within the theoretical framework (Joseph F Hair et al., 2021).

Evaluating the fit of an SEM model commonly involves several indices. The chi-square test (χ^2) is used, with a p-value greater than 0.05 indicating a good fit

(Kline, 2011). Additionally, the chi-square ratio (χ^2/df) should be less than 3 for an acceptable fit (Kline, 2011) or not exceed 5 in the case of highly complex models (Hu & Bentler, 1999). The root mean square error of approximation (RMSEA) should be less than or equal to 0.08 (Deb & Ali Ahmed, 2018). The comparative fit index (CFI) should be greater than 0.90 (Hu & Bentler, 1999), while the Tucker Lewis index (TLI) should be 0.8 or higher (Hooper, Coughlan, & Mullen, 2008). Furthermore, the standardized root mean squared residual (SRMR) should not exceed 0.08 (Hu & Bentler, 1999). Reliability testing is assessed using composite reliability (CR), which should be at least 0.70, and the average variance extracted (AVE), which should be at least 0.5 (J. F. Hair, 2006). In some cases, an AVE below 0.5 is acceptable if the CR is above 0.6 (Lam, 2012).

4.5 Results

4.5.1 Preliminary analyses

Descriptive statistics calculated include mean, standard deviation (*SD*), skewness (*SK*), and kurtosis (*KU*), as shown in Table 4.2. This table presents the observed variables of attitudes and perceptions toward near-miss incidents among motorcyclists. According to the preliminary criteria for SEM, normal distribution tests revealed that all observed variables had skewness and kurtosis values less than 3 and 10, respectively. This indicates a normal distribution, as recommended by Kline (2011).

Table 4.2 Mean, Standard Deviation Skewness and kurtosis values of variables used in the model

Variable	Variable description	*M*	*SD*	*SK*	*KU*
Fear of traffic (FT)					
FT1	You feel that cars do not give you the right of way as appropriate.	4.055	0.980	-0.812	-0.255
FT2	You feel that you almost always have accidents when riding with other types of vehicles.	3.919	1.055	-0.621	-0.692
FT3	You feel unsafe at the speed at which cars are driving.	4.015	0.992	-0.701	-0.500
Attitude for distracted riding (ADR)					
ADR1	Using headphones to listen to music while riding a motorcycle risks accidents.	4.059	0.952	-0.743	-0.417
ADR2	While riding, looking at maps (on paper or on smartphones) risks accidents.	4.035	0.989	-0.728	-0.550
ADR3	Using social media (Facebook, Twitter, Instagram, and Line) while riding risks accidents.	4.112	0.955	-0.788	-0.420
ADR4	Riding after drinking alcohol risks accidents.	4.236	0.878	-0.978	0.147
Avoidance of riding in mixed traffic (AVM)					
AVM1	You avoid using certain routes when there are many vehicles on the road.	4.132	0.967	-0.997	0.240
AVM2	You avoid narrow roads with cars coming out.	3.924	1.051	-0.683	-0.492
AVM3	When others sit behind the motorcycle, such as children, grandchildren, or siblings, you avoid crowded traffic routes.	3.970	0.983	-0.641	-0.492
Perceived behavioral control (PBC)					
PBC1	You can control the vehicle well, even at high speeds.	1.991	0.772	0.081	-1.084

Table 4.2 Mean, Standard Deviation Skewness and kurtosis values of variables used in the model (Continued)

Variable	Variable description	*M*	*SD*	*SK*	*KU*
PBC2	You overtake cars in areas with no-overtaking signs, expecting to control the vehicle well and avoid accidents.	1.520	0.687	0.955	-0.340
PBC3	You can talk on the phone while riding a motorcycle, expecting to control the vehicle well and avoid accidents.	1.522	0.656	0.889	-0.283
PBC4	You can ride a motorcycle at high speeds on curves without accidents.	1.489	0.629	0.923	-0.205
PBC5	You can ride a motorcycle at the speed you want.	1.488	0.655	1.035	0.049

Note: SE_{SK} = 0.055 and SE_{KU} = 0.109;

4.5.2 Factor structure

Based on the findings presented in Table 4.3, the exploratory factor analysis (EFA) identified four distinct components: fear of traffic (FT), attitude for distracted riding (ADR), avoidance of riding in mixed traffic (AVM), and perceived behavioral control (PBC). Principal Component Analysis (PCA) with Varimax Rotation was employed as the extraction method. The factor loadings, indicating the strength of each variable's association with the components, should ideally surpass 0.3, following the recommendations of Maskey, Fei, and Nguyen (2018) and J. F. Hair (2006). Moreover, Hair suggested that a Kaiser-Meyer-Olkin (KMO) value exceeding 0.5 is acceptable, with values ranging between 0.5 and 0.7 considered moderate and those surpassing 0.7 considered good. In this study, both the model's KMO value and factor loadings met the prescribed criteria. The results of confirmatory factor analysis (CFA) indicated a good fit between the model and the observed data. Assessing the convergent validity of the CFA model through composite reliability (CR) and average variance extracted (AVE) revealed that although the AVE fell below 0.5, the CR exceeded 0.6, aligning with the acceptable threshold outlined by Lam (2012). Consequently, the model is deemed suitable for further structural equation modeling (SEM) analysis.

Table 4.3 Factor analysis. *n* = 2002, KMO = 0.814

Variable/Measurement Model/Cronbach's α	EFA		CFA					
	Communalities	Loading	Loading	Est.\S.E.	p-Value	Error Variance	CR	AVE
Fear of traffic (FT) (Cronbach's α = 0.825)							0.798	0.568
FT1	0.741	0.798	0.704	27.169	<0.001**	0.504		
FT2	0.744	0.776	0.785	46.261	<0.001**	0.384		
FT3	0.640	0.681	0.770	45.253	<0.001**	0.407		
Attitude for distracted riding (ADR) (Cronbach's α = 0.738)							0.740	0.343
ADR1	0.548	0.706	0.655	18.301	<0.001**	0.571		
ADR2	0.707	0.803	0.837	15.331	<0.001**	0.299		
ADR3	0.619	0.736	0.694	14.943	<0.001**	0.519		
ADR4	0.517	0.464	0.353	12.940	<0.001**	0.875		
Avoidance of riding in mixed traffic (AVM) (Cronbach's α = 0.786)							0.787	0.553
AVM1	0.632	0.779	0.677	42.844	<0.001**	0.542		
AVM2	0.717	0.836	0.819	56.917	<0.001**	0.329		
AVM3	0.655	0.795	0.728	47.581	<0.001**	0.470		

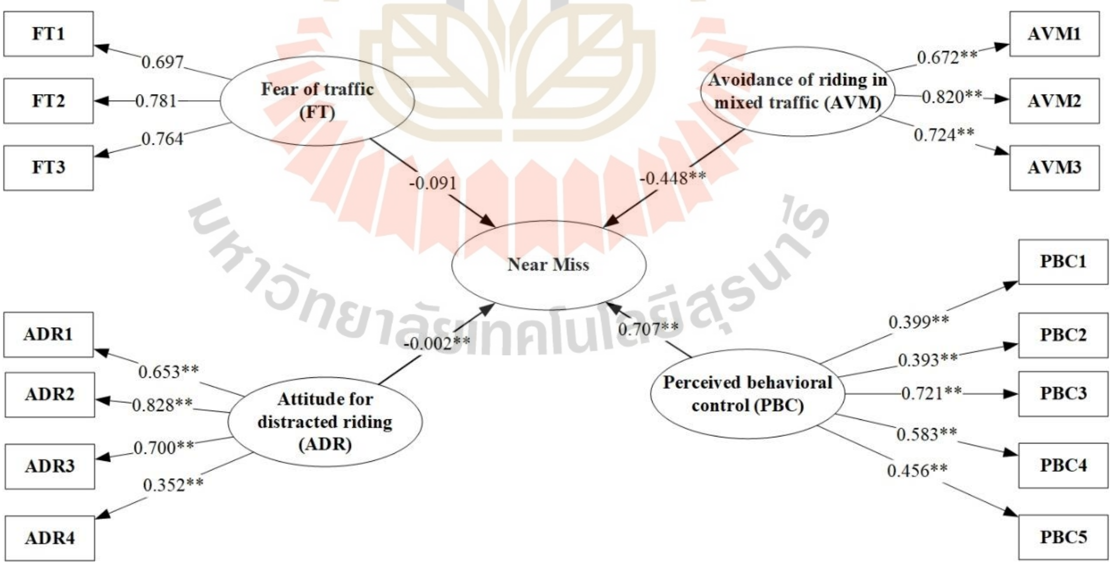
Table 4.3 Factor analysis. *n* = 2002, KMO = 0.814 (Continued)

Variable/Measurement Model/Cronbach's α	EFA		CFA					
	Communalities	Loading	Loading	Est.\S.E.	p-Value	Error Variance	CR	AVE
Perceived behavioral control (PBC) (Cronbach's α = 0.607)							0.668	0.301
PBC1	0.535	0.394	0.482	9.068	<0.001**	0.768		
PBC2	0.510	0.678	0.375	13.542	<0.001**	0.860		
PBC3	0.497	0.690	0.768	18.611	<0.001**	0.409		
PBC4	0.452	0.635	0.609	12.870	<0.001**	0.630		
PBC5	0.430	0.629	0.416	13.229	<0.001**	0.827		
χ^2/df = 168.876/44= 3.838, RMSEA = 0.038 (0.032 - 0.044), CFI = 0. 986, TLI = 0. 966, SRMR = 0. 031								

Note: ** Standardized Estimates is significant at the 0.001 level (two-tailed).

4.5.3 Structural Equation Modeling (SEM) results

The analysis of the SEM model in Figure 4.2 reveals a good fit of the model to the empirical data. Furthermore, the evaluation of the hypothesized path model in Table 4.4 illustrates whether the hypotheses in this study are supported or not. The findings indicate that the paths of Attitude for Distracted Riding (Hypothesis 4.2), Avoidance of Riding in Mixed Traffic (Hypothesis 4.3), and Perceived Behavioral Control (Hypothesis 4.4) significantly differ from zero, supporting the expected relationships. However, the path of fear of traffic (hypothesis 4.1) was found to be nonsignificant. When considering the factor weights of the latent variables, it is evident that perceived behavioral control has the greatest impact on near misses, with a factor weight of 0.707. Following this, the factor of avoidance of riding in mixed traffic has a factor weight of -0.448, indicating a lesser impact. Finally, the factor weight of attitude for distracted riding is the smallest, with a value of -0.002, suggesting the least influence on near misses.



χ^2/df = 210.38/54= 3.896, RMSEA = 0.038 (0.033 - 0.044), CFI = 0. 982, TLI = 0. 961, SRMR = 0.032, **p-value < 0.001 (Mplus 7.0 standardized estimates)

Figure 4.2 Structural equation modeling of safety perception in motorcyclists' near misses

Table 4.4 The evidence corroborates the hypotheses.

Hypotheses	Hypothesis testing in path models	Support provided
H4.1	Fear of traffic is positively associated with near misses.	No
H4.2	Attitude for distracted riding correlates negatively with near misses.	Yes
H4.3	Avoidance of riding in mixed traffic correlates negatively with near misses.	Yes
H4.4	Perceived behavioral control correlates positively with near misses.	Yes

4.6 Discussion

This study investigates the relationship between attitudes and perceptions of near-miss incidents among motorcyclists in developing countries using structural equation modeling (SEM). The results support all hypotheses except Hypothesis 4.1. The path analysis demonstrates a significant positive relationship where perceived behavioral control is most significantly associated with increased near-miss risk, supporting Hypothesis 4.4. This finding aligns with previous studies emphasizing the positive correlation between perceived behavioral control and accident risk. Măirean and Havârneanu (2018) confirmed that riders who overestimate their riding abilities tend to engage in risky behaviors, believing they can avoid accidents due to a perceived sense of control. Similarly, research by Yang et al. (2020) revealed that overconfidence in driving skills often leads to more frequent risky driving behaviors. Phongphan Tankasem (2016) also noted a significant correlation between perceived behavioral control and the intention to speed among motorcyclists.

Considering the observed variables of perceived behavioral control, the item “You can talk on the phone while riding a motorcycle, expecting to control the vehicle well and avoid accidents” has the highest impact. Many countries have laws banning handheld cell phone use and texting while driving (Cell phone handheld use and text messaging while driving ban) because using a mobile phone while driving distracts drivers, increasing the risk of accidents (Hill, Sullman, & Stephens, 2019). This behavior limits the rider's mobility, diverts attention from the road, and reduces reaction time (French & Gumus, 2018). The reduced driving performance due to mobile phone use leads to a higher risk of road accidents (Phuksuksakul, Kanitpong, & Chantranuwathana, 2021). Studies in several countries have explored mobile phone use while riding motorcycles. For example, Pérez-Núñez et al. (2014) reported high mobile phone usage among motorcyclists of all ages in Mexico. Truong, Nguyen, and De Gruyter (2018) noted similar trends among teenage motorcyclists in Vietnam, and Hassan, Vinodkumar, and Vinod (2017) observed increasing mobile phone use in India.

Another notable observed variable of perceived behavioral control is "You can ride a motorcycle at high speeds on curves without accidents." Confidence in high-speed riding is a significant issue, with studies in both developed and developing countries examining this behavior. High-speed riding is considered reckless and careless, posing a risk of crashes and near-misses, as seen in studies from Australia (Stephens et al., 2017), Turkey (Özkan, Lajunen, Doğruyol, Yıldırım, & Çoymak, 2012), Vietnam (Vu, Nguyen, Nguyen, & Khuat, 2020), Cambodia (Roehler, Ear, Parker, Sem, & Ballesteros, 2015), and Thailand (Hantanong et al., 2024). In Thailand, speeding is the leading cause of road accident fatalities (Injury Data Collaboration Center (IDCC), 2021). Research by Elliott and Thomson (2010) and Özkan et al. (2012) examined behavioral intentions from a psychological perspective, highlighting that social norms and perceived acceptability are key factors in shaping behavior and can be used to reduce risky driving. Regular speeders tend to underestimate the risks associated with speeding (Stephens et al., 2017). Targeting speeding behavior with measures to address social acceptability and reduce accident risk is crucial, including law enforcement and media campaigns on driving behavior (Fitzharris et al., 2015).

Conversely, the findings of our analysis reveal a robust negative correlation between near-miss incidents and the avoidance of mixed traffic (AVM), significantly reducing the risk of such events, thereby supporting Hypothesis 4.3. This finding is consistent with previous studies highlighting this relationship. For instance, Marín Puchades et al. (2018) confirmed that cyclists who avoid mixed traffic significantly reduce their near-miss risk. In developing countries, traffic is generally mixed, with motorcycles sharing lanes with other vehicles. Additionally, motorcyclists often weave between traffic lanes, increasing the risk of accidents with larger vehicles, a frequent issue in mixed traffic conditions. The presence of mixed traffic, where motorcyclists share lanes with automobiles and trucks, creates conflict zones on the road, leading to accidents. The observed variables of AVM that had the highest impact were "You avoid narrow roads with cars coming out" and "When others sit behind the motorcycle, such as children, grandchildren, or siblings, you avoid crowded traffic routes." Considering these factors, it is crucial to address infrastructure and road environment issues to reduce accidents caused by mixed traffic. In various countries, the implementation of Exclusive Motorcycle Lanes (EMCL) to divert motorcyclists away from main traffic routes has proven to be an effective measure in enhancing both motorcycle and overall road safety. In countries like Malaysia, Taiwan, and Indonesia, the implementation of EMCLs has significantly reduced motorcycle accidents and fatalities, demonstrating the effectiveness of this strategy (Saini, Chouhan, & Kathuria, 2022). In Malaysia, which has severe issues with motorcycle accidents due to mixed traffic, implementing EMCLs resulted in a 39% reduction in accidents and a 600% decrease in fatalities (Ibrahim, Hamid, Law, & Wong, 2018; Radin Umar, 2006). Similarly, in Colombia, studies on EMCLs found that motorcyclists believe these lanes reduce the likelihood of accidents and injuries. Most motorcyclists also reported that EMCLs made vehicle operation easier and reduced travel time (Osorio-Cuéllar et al., 2017).

4.7 Conclusions and Implementation

This study aims to develop a model examining the relationship between attitudes and perceptions of near-miss incidents among motorcyclists in developing countries using structural equation modeling (SEM). Four factors—Fear of Traffic (FT), Attitude for Distracted Riding (ADR), Avoidance of Mixed Traffic (AVM), and Perceived Behavioral Control (PBC)—were analyzed for their relationship to near-miss incidents, focusing on middle- and low-income countries where traffic safety regulations and enforcement are often insufficient. Thailand was used as a representative case study, with a sample of 2,002 respondents from six regions across the country. The results supported all hypotheses except Hypothesis 4.1.

The study found that perceived behavioral control (PBC) has a significant positive relationship with the risk of near-miss incidents, particularly when motorcyclists use mobile phones while riding or ride at high speeds on curves. Conversely, avoidance of mixed traffic (AVM) has a significant negative relationship with the risk of near-miss incidents. Based on these findings, we propose the following recommendations to reduce near-miss risks:

1) Law Enforcement and Safety Measures:
   - I. Enforce strict laws prohibiting mobile phone use while riding, including public awareness campaigns about the dangers of such behavior.
   - II. Implement strict speed limit enforcement, especially in high-risk areas such as curves and narrow roads.

2) Infrastructure and Road Environment Improvements:
   - I. Establish Exclusive Motorcycle Lanes (EMCL) to separate motorcycles from mixed traffic, reducing conflict points on the road.
   - II. Improve road safety by widening lanes to meet standards and installing warning signs and signals at high-risk locations.

3) Training and Education:
   - I. Provide safe riding training for motorcyclists to enhance their knowledge and skills, including risk assessment and emergency management.
   - II. Launch public awareness campaigns to change attitudes and behaviors, focusing on reducing risky behaviors such as mobile phone use while riding and high-speed riding.

However, these recommendations must consider the limitations of developing countries, particularly financial constraints. Developing infrastructure such as EMCLs requires significant investment, which may be challenging for countries with limited budgets. Additionally, enforcing laws and safety measures, such as installing speed cameras or running public awareness campaigns, requires ongoing funding for implementation and maintenance. There are also management and enforcement challenges, such as difficulty in monitoring compliance with mobile phone use and speed limit laws due to a lack of personnel and necessary technology. In some areas, social and cultural factors may hinder strict law enforcement, resulting in non-compliance. Another significant issue is the limited awareness and acceptance among the public. In some areas, people may have low awareness of the risks associated with motorcycle riding, making behavior change difficult. New measures, such as establishing EMCLs, may face resistance or a lack of understanding about their benefits. Existing road infrastructure in some areas may not be suitable for improvements or new developments, such as narrow roads or complex routes, making it difficult to establish EMCLs. Infrastructure improvements can also be time-consuming and complex due to varying geographical and environmental factors. Considering these limitations is crucial for planning and implementing measures to reduce the risk of accidents and near-miss incidents among motorcyclists in developing countries.

4.8 Limitations and Further Research

The study's utilization of Thailand as a representative case for developing countries might not comprehensively encapsulate the diversity of traffic conditions and cultural disparities present in other developing nations, thereby restricting the applicability of the findings to broader regions. Moreover, the study heavily relied on self-reported data from participants, a methodology susceptible to biases like social desirability bias and recall bias, potentially resulting in the underreporting of hazardous behaviors or the exaggeration of safety practices. Furthermore, the research adopted a cross-sectional design, collecting data at a single time point, consequently limiting the capacity to establish causal relationships between the examined factors and near-miss incidents; longitudinal investigations would offer more robust insights into these causal connections.

4.9 References

Ajzen, I. (1980). Understanding attitudes and predictiing social behavior. *Englewood cliffs*.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179-211. doi:https://doi.org/10.1016/0749-5978(91)90020-T

Aldred, R., & Crosweller, S. (2015). Investigating the rates and impacts of near misses and related incidents among UK cyclists. *Journal of Transport & Health, 2*(3), 379-393. doi:https://doi.org/10.1016/j.jth.2015.05.006

Aldred, R., Elliott, B., Woodcock, J., & Goodman, A. (2017). Cycling provision separated from motor traffic: a systematic review exploring whether stated preferences vary by gender and age. *Transport Reviews, 37*(1), 29-55. doi:10.1080/01441647.2016.1200156

Ba, Y., Zhang, W., Chan, A. H. S., Zhang, T., & Cheng, A. S. K. (2016). How drivers fail to avoid crashes: A risk-homeostasis/perception-response (RH/PR) framework evidenced by visual perception, electrodermal activity and behavioral responses. *Transportation Research Part F: Traffic Psychology and Behaviour, 43*, 24-35. doi:https://doi.org/10.1016/j.trf.2016.09.025

Bandura, A. (1977). Self-efficacy: toward a unifying theory of behavioral change. *Psychological review, 84*(2), 191.

Bandura, A. (1982). Self-efficacy mechanism in human agency. *American psychologist, 37*(2), 122.

Bollen, K. A. (1989). *Structural equations with latent variables* (Vol. 210): John Wiley & Sons.

Boua, M., Kouabenan, D. R., & Belhaj, A. (2022). Road safety behaviors: Role of control beliefs and risk perception. *Transportation Research Part F: Traffic Psychology and Behaviour, 91*, 45-57. doi:https://doi.org/10.1016/j.trf.2022.09.021

Chataway, E. S., Kaplan, S., Nielsen, T. A. S., & Prato, C. G. (2014). Safety perceptions and reported behavior related to cycling in mixed traffic: A comparison between Brisbane and Copenhagen. *Transportation Research Part F: Traffic Psychology and Behaviour, 23*, 32-43. doi:https://doi.org/10.1016/j.trf.2013.12.021

Chaurand, N., & Delhomme, P. (2013). Cyclists and drivers in road interactions: A comparison of perceived crash risk. *Accident Analysis & Prevention, 50*, 1176-1184. doi:https://doi.org/10.1016/j.aap.2012.09.005

Damani, J., & Vedagiri, P. (2021). Safety of motorised two wheelers in mixed traffic conditions: Literature review of risk factors. *Journal of Traffic and Transportation Engineering (English Edition), 8*(1), 35-56. doi:https://doi.org/10.1016/j.jtte.2020.12.003

Deb, S., & Ali Ahmed, M. (2018). Determining the service quality of the city bus service based on users' perceptions and expectations. *Travel Behaviour and Society, 12*, 1-10. doi:https://doi.org/10.1016/j.tbs.2018.02.008

Di Ciommo, F., Monzón, A., & Fernandez-Heredia, A. (2013). Improving the analysis of road pricing acceptability surveys by using hybrid models. *Transportation Research Part A: Policy and Practice, 49*, 302-316. doi:https://doi.org/10.1016/j.tra.2013.01.007

Eagly, A. H., & Chaiken, S. (1993). *The psychology of attitudes*: Harcourt brace Jovanovich college publishers.

Elliott, M. A., & Thomson, J. A. (2010). The social cognitive determinants of offending drivers' speeding behaviour. *Accident Analysis & Prevention, 42*(6), 1595-1605. doi:https://doi.org/10.1016/j.aap.2010.03.018

Fitzharris, M., Liu, S., Peiris, S., Devlin, A., Young, K., Lenne, M., . . . Gatof, J. (2015). *Options to extend coverage of alcohol interlock programs* (1925294757). Retrieved from

Fitzpatrick, D., & O'Neill, D. (2017). The older motorcyclist. *European Geriatric Medicine, 8*(1), 10-15. doi:https://doi.org/10.1016/j.eurger.2016.10.004

French, M. T., & Gumus, G. (2018). Watch for motorcycles! The effects of texting and handheld bans on motorcyclist fatalities. *Social Science & Medicine, 216*, 81-87. doi:https://doi.org/10.1016/j.socscimed.2018.09.032

Hair, J. F. (2006). *Multivariate data analysis*. Upper Saddle River, NJ [etc.]: Pearson Prentice Hall.

Hair, J. F., Astrachan, C. B., Moisescu, O. I., Radomir, L., Sarstedt, M., Vaithilingam, S., & Ringle, C. M. (2021). Executing and interpreting applications of PLS-SEM: Updates for family business researchers. *Journal of Family Business Strategy, 12*(3), 100392.

Hamann, C. J., & Peek-Asa, C. (2017). Examination of adult and child bicyclist safety-relevant events using naturalistic bicycling methodology. *Accident Analysis & Prevention, 102*, 1-11. doi:https://doi.org/10.1016/j.aap.2017.02.017

Hantanong, N., Jomnonkwao, S., Champahom, T., Se, C., & Ratanavaraha, V. (2024). Assessing the Self-Report Instruments of Younger Versus Older Riders Involved in Near-Miss Motorcycle Incidents. *Civil Engineering Journal, 10*(2), 628-654.

Hassan, T., Vinodkumar, M. N., & Vinod, N. (2017). Influence of demographics on risky driving behaviour among powered two wheeler riders in Kerala, India. *Transportation Research Part F: Traffic Psychology and Behaviour, 46*, 24-33. doi:https://doi.org/10.1016/j.trf.2016.11.008

Hill, T., Sullman, M. J. M., & Stephens, A. N. (2019). Mobile phone involvement, beliefs, and texting while driving in Ukraine. *Accident Analysis & Prevention, 125*, 124-131. doi:https://doi.org/10.1016/j.aap.2019.01.035

Hoogland, J. J., & Boomsma, A. (1998). Robustness studies in covariance structure modeling: an overview and a metaanalysis. *Sociological Methods and Research, 26*, 329-333.

Hooper, D., Coughlan, J., & Mullen, M. R. (2008). Structural Equation Modelling: Guidelines for Determining Model Fit. *Electronic Journal of Business Research Methods, 6*(1), 53-61.

Horswill, M. S., & McKenna, F. P. (1999). The effect of perceived control on risk taking 1. *Journal of Applied Social Psychology, 29*(2), 377-391.

Hu, L. t., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1-55. doi:10.1080/10705519909540118

Ibrahim, M. K. A., Hamid, H., Law, T. H., & Wong, S. V. (2018). Evaluating the effect of lane width and roadside configurations on speed, lateral position and likelihood of comfortable overtaking in exclusive motorcycle lane. *Accident Analysis & Prevention, 111*, 63-70. doi:https://doi.org/10.1016/j.aap.2017.10.023

Injury Data Collaboration Center (IDCC). (2021). Injury surveillance. Retrieved from http://ae.moph.go.th/

Jomnonkwao, S., Champahom, T., Se, C., Hantanong, N., & Ratanavaraha, V. (2023). Contributing factors to near-miss experiences of motorcyclists in Thailand: A random parameter probit model approach. *Heliyon, 9*(12), e22625. doi:https://doi.org/10.1016/j.heliyon.2023.e22625

Jomnonkwao, S., Hantanong, N., Champahom, T., Se, C., & Ratanavaraha, V. (2023). Analyzing Near-Miss Incidents and Risky Riding Behavior in Thailand: A Comparative Study of Urban and Rural Areas. *Safety, 9*(4), 90. Retrieved from https://www.mdpi.com/2313-576X/9/4/90

Jornet-Gibert, M., Gallardo-Pujol, D., Suso, C., & Andrés-Pueyo, A. (2013). Attitudes do matter: The role of attitudes and personality in DUI offenders. *Accident Analysis & Prevention, 50*, 445-450. doi:https://doi.org/10.1016/j.aap.2012.05.023

Keall, M. D., & Newstead, S. (2012). Analysis of factors that increase motorcycle rider risk compared to car driver risk. *Accident Analysis & Prevention, 49*, 23-29.

Kline, R. B. (2011). *Principles and Practice of Structural Equation Modeling*. New York: The Guilford Press.

Lam, L. W. (2012). Impact of competitiveness on salespeople's commitment and performance ☆. *Journal of Business Research, 65*, 1328-1334.

Laureshyn, A., Goede, M. d., Saunier, N., & Fyhri, A. (2017). Cross-comparison of three surrogate safety methods to diagnose cyclist safety problems at intersections in Norway. *Accident Analysis & Prevention, 105*, 11-20. doi:https://doi.org/10.1016/j.aap.2016.04.035

Liao, Y., Lin, C.-Y., & Park, J.-H. (2019). Is motorcycle use associated with unhealthy lifestyles? Findings from Taiwan. *Journal of Transport & Health, 15*, 100659. doi:https://doi.org/10.1016/j.jth.2019.100659

Măirean, C., & Havârneanu, C.-E. (2018). The relationship between drivers' illusion of superiority, aggressive driving, and self-reported risky driving behaviors. *Transportation Research Part F: Traffic Psychology and Behaviour, 55*, 167-174. doi:https://doi.org/10.1016/j.trf.2018.02.037

Marín Puchades, V., Fassina, F., Fraboni, F., De Angelis, M., Prati, G., de Waard, D., & Pietrantoni, L. (2018). The role of perceived competence and risk perception in cycling near misses. *Safety Science, 105*, 167-177. doi:https://doi.org/10.1016/j.ssci.2018.02.013

Maskey, R., Fei, J., & Nguyen, H.-O. (2018). Use of exploratory factor analysis in maritime research. *The Asian Journal of Shipping and Logistics, 34*(2), 91-111. doi:https://doi.org/10.1016/j.ajsl.2018.06.006

Nordgren, L. F., van der Pligt, J., & van Harreveld, F. (2007). Unpacking perceived control in risk perception: the mediating role of anticipated regret. *Journal of Behavioral Decision Making, 20*(5), 533-544. doi:https://doi.org/10.1002/bdm.565

Nunnally, J. C. (1994). Psychometric Theory 3E: Tata McGraw-Hill Education.

Osorio-Cuéllar, G. V., Pacichana-Quinayaz, S. G., Bonilla-Escobar, F. J., Fandiño-Losada, A., Jaramillo-Molina, C., & Gutiérrez-Martínez, M. I. (2017). First motorcycle-exclusive lane (Motovia) in Colombia: perceptions of users in Cali, 2012–2013. *International Journal of Injury Control and Safety Promotion, 24*(2), 145-151. doi:10.1080/17457300.2015.1061563

Özkan, T., Lajunen, T., Doğruyol, B., Yıldırım, Z., & Çoymak, A. (2012). Motorcycle accidents, rider behaviour, and psychological models. *Accident Analysis & Prevention, 49*, 124-132. doi:https://doi.org/10.1016/j.aap.2011.03.009

Panumasvivat, J., Kitro, A., Samakarn, Y., Pairojtanachai, K., Sirikul, W., Promkutkao, T., & Sapbamrer, R. (2024). Unveiling the road to safety: Understanding the factors influencing motorcycle accidents among riders in rural Chiang Mai, Thailand. *Heliyon, 10*(3), e25698. doi:10.1016/j.heliyon.2024.e25698

Park, J.-I., Kim, S., & Kim, J.-K. (2023). Exploring spatial associations between near-miss and police-reported crashes: The Heinrich's law in traffic safety. *Transportation Research Interdisciplinary Perspectives, 19*, 100830. doi:https://doi.org/10.1016/j.trip.2023.100830

Parker, D., Manstead, A. S., Stradling, S. G., Reason, J. T., & Baxter, J. S. (1992). Intention to commit driving violations: An application of the theory of planned behavior. *Journal of applied psychology, 77*(1), 94.

Pérez-Núñez, R., Hidalgo-Solórzano, E., Vera-López, J. D., Lunnen, J. C., Chandran, A., Híjar, M., & Hyder, A. A. (2014). The Prevalence of Mobile Phone Use Among Motorcyclists in Three Mexican Cities. *Traffic injury prevention, 15*(2), 148-150. doi:10.1080/15389588.2013.802776

Phongphan Tankasem, T. S. W. S. (2016). Psychological Factors Influencing Speeding Intentions of Car Drivers and Motorcycle Riders in Urban Road Environments. *International Journal of Technology, 7*(7), 291-319. doi:https://doi.org/10.14716/ijtech.v7i7.4698

Phuksuksakul, N., Kanitpong, K., & Chantranuwathana, S. (2021). Factors affecting behavior of mobile phone use while driving and effect of mobile phone use on driving performance. *Accident Analysis & Prevention, 151*, 105945. doi:https://doi.org/10.1016/j.aap.2020.105945

Porter, B. E. (2011). *Handbook of traffic psychology*: Academic press.

Radin Umar, R. S. (2006). Motorcycle safety programmes in Malaysia: how effective are they? *International Journal of Injury Control and Safety Promotion, 13*(2), 71-79. doi:10.1080/17457300500249632

Roehler, D. R., Ear, C., Parker, E. M., Sem, P., & Ballesteros, M. F. (2015). Fatal motorcycle crashes: a growing public health problem in Cambodia. *International Journal of Injury Control and Safety Promotion, 22*(2), 165-171. doi:10.1080/17457300.2013.876050

Rosenstock, I. M. (1974). Historical Origins of the Health Belief Model. *Health Education Monographs, 2*(4), 328-335. doi:10.1177/109019817400200403

Saini, H. K., Chouhan, S. S., & Kathuria, A. (2022). Exclusive motorcycle lanes: A systematic review. *IATSS Research, 46*(3), 411-426. doi:https://doi.org/10.1016/j.iatssr.2022.05.004

Sanders, R. L. (2015). Perceived traffic risk for cyclists: The impact of near miss and collision experiences. *Accident Analysis & Prevention, 75*, 26-34. doi:https://doi.org/10.1016/j.aap.2014.11.004

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2021). Partial least squares structural equation modeling. In *Handbook of market research* (pp. 587-632): Springer.

Satiennam, T., Akapin, N., Satiennam, W., Kumphong, J., Kronprasert, N., & Ratanavaraha, V. (2023). Wrong way driving intention and behavior of young motorcycle riders. *Transportation Research Interdisciplinary Perspectives, 19*, 100827. doi:https://doi.org/10.1016/j.trip.2023.100827

Schreiber, J., Nora, A., Stage, F., Barlow, L., & King, J. (2006). Confirmatory factor analyses and structural equations modeling: an introduction and review. *Journal of Educational Research, 99*(6).

Sigurdardottir, S. B., Kaplan, S., Møller, M., & Teasdale, T. W. (2013). Understanding adolescents' intentions to commute by car or bicycle as adults. *Transportation Research Part D: Transport and Environment, 24*, 1-9. doi:https://doi.org/10.1016/j.trd.2013.04.008

Šraml, M., Tollazzi, T., & Renčelj, M. (2012). Traffic safety analysis of powered two-wheelers (PTWs) in Slovenia. *Accident Analysis & Prevention, 49*, 36-43.

Stephens, A. N., Brown, J., de Rome, L., Baldock, M. R. J., Fernandes, R., & Fitzharris, M. (2017). The relationship between Motorcycle Rider Behaviour Questionnaire scores and crashes for riders in Australia. *Accident Analysis & Prevention, 102*, 202-212. doi:https://doi.org/10.1016/j.aap.2017.03.007

Taber, K. S. (2018). The Use of Cronbach's Alpha When Developing and Reporting Research Instruments in Science Education. *Research in Science Education, 48*(6), 1273-1296. doi:10.1007/s11165-016-9602-2

ThaiRoads Foundation. (2022). Key fact on road safety situations in Thailand 2018 - 2021 Retrieved from https://www.roadsafetythai.org/project_download_bookdetail-edoc-636-.html

Truong, L. T., Nguyen, H. T. T., & De Gruyter, C. (2018). Correlations between mobile phone use and other risky behaviours while riding a motorcycle. *Accident Analysis & Prevention, 118*, 125-130. doi:https://doi.org/10.1016/j.aap.2018.06.015

Ulleberg, P., & Rundmo, T. (2003). Personality, attitudes and risk perception as predictors of risky driving behaviour among young drivers. *Safety Science, 41*(5), 427-443. doi:https://doi.org/10.1016/S0925-7535(01)00077-7

Vu, A. T., Nguyen, M. T., Nguyen, D. V. M., & Khuat, V. H. (2020). Investigating the effect of blood alcohol concentration on motorcyclist's riding performance using an advanced motorcycle simulator. *Transportation Research Part F: Traffic Psychology and Behaviour, 73*, 1-14. doi:https://doi.org/10.1016/j.trf.2020.06.010

Wang, C., Lu, L., Lu, J., & Wang, T. (2016). Correlation between crash avoidance maneuvers and injury severity sustained by motorcyclists in single-vehicle crashes. *Traffic injury prevention, 17*(2), 188-194.

Weinstein, N. D. (1980). Unrealistic optimism about future life events. *Journal of personality and social psychology, 39*(5), 806.

Wohleber, R. W., & Matthews, G. (2016). Multiple facets of overconfidence: Implications for driving safety. *Transportation Research Part F: Traffic Psychology and Behaviour, 43*, 265-278. doi:https://doi.org/10.1016/j.trf.2016.09.011

Wong, J.-T., Chung, Y.-S., & Huang, S.-H. (2010). Determinants behind young motorcyclists' risky riding behavior. *Accident Analysis & Prevention, 42*(1), 275-281. doi:https://doi.org/10.1016/j.aap.2009.08.004

World Health Organization. (2018). *Road traffic injuries*. Retrieved from https://www.who.int/news-room/fact-sheets/detail/road-traffic-injuries

Wright, L., & van der Schaaf, T. (2004). Accident versus near miss causation: a critical review of the literature, an empirical test in the UK railway domain, and their implications for other sectors. *Journal of Hazardous Materials, 111*(1), 105-110. doi:https://doi.org/10.1016/j.jhazmat.2004.02.049

Yang, L., Feng, Z., Zhao, X., Jiang, K., & Huang, Z. (2020). Analysis of the factors affecting drivers' queue-jumping behaviors in China. *Transportation Research Part F: Traffic Psychology and Behaviour, 72*, 96-109. doi:https://doi.org/10.1016/j.trf.2020.05.008

Young, W., Sobhani, A., Lenné, M. G., & Sarvi, M. (2014). Simulation of safety: A review of the state of the art in road safety simulation modelling. *Accident Analysis & Prevention, 66*, 89-103.

CHAPTER V
CONCLUSION AND RECOMMENDATION

5.1 Conclusions

This research is dedicated to investigating near-miss incidents and implementing accident prevention measures among motorcycle riders. The escalating rates of fatalities and injuries stemming from motorcycle accidents in low- and middle-income countries (LMICs) have prompted significant concerns. Among vulnerable road users (VRUs), motorcycle riders face the highest risk of accidents. Hence, it is imperative to explore methodologies for mitigating accident risks and near-misses. Despite near-miss incidents typically not resulting in severe damage akin to actual accidents, they serve as invaluable proxies for examining and assessing potential accident risks. The primary objective of this study is to devise effective strategies for accident prevention and reduction. Through a comprehensive literature review, three pivotal dimensions associated with near-miss incidents were identified, thus informing the tripartite structure of this investigation.

5.1.1 Analyzing Near-Miss Incidents and Risky Riding Behavior in Thailand: A Comparative Study of Urban and Rural Areas.

Study 1: This study endeavors to construct a model delineating risky behaviors culminating in near-miss incidents through the utilization of the Motorcycle Rider Behavior Questionnaire (MRBQ). It juxtaposes urban and rural areas in Thailand, indicative of low- to middle-income countries (LMICs). The aggregate sample comprised 2,002 participants randomly drawn from six regions nationwide, comprising 1,066 urban dwellers and 936 rural inhabitants. Findings from data analysis elucidated that the preeminent contributing factor to near-miss incidents in both locales was control error (CE), characterized by challenges such as diminished visibility during adverse weather conditions, executing wide turns, and navigating slippery or uneven road surfaces amidst weather fluctuations. Subsequently, vibration (VI) emerged as a salient factor, encompassing behaviors like lane splitting and a dearth of safety equipment (SE) usage. Notably, urban settings predominantly grappled with issues such as daytime headlight negligence, while rural areas confronted concerns regarding helmet usage without chin strap fastening. Recommendations emanating from this inquiry underscore the imperative for pertinent authorities to deliberate and execute measures aimed at mitigating these challenges to bolster road safety. Proposals include advocacy for safe driving protocols in adverse weather conditions, contemplation of Exclusive Motorcycle Lanes (EMCL) deployment, and accentuating the significance of appropriate headlight utilization and helmet adherence. It is envisaged that adherence to these recommendations will engender a reduction in accidents and foster an augmented safety milieu for motorcycle riders in Thailand.

5.1.2 Assessing the Self-Report Instruments of Younger Versus Older Riders Involved in Near-Miss Motorcycle Incidents.

Study 2: This research aims to develop a model of risky behavior leading to near-miss incidents by utilizing the Motorcycle Rider Behavior Questionnaire (MRBQ) to compare teenage and elderly motorcycle riders. Participants were surveyed from six regions across Thailand, totaling 815 individuals, with 475 classified as teenagers and 340 as elderly. The study findings highlighted control errors as the most significant factor contributing to near-miss incidents. Several recommendations were proposed, primarily focusing on speed management, particularly for novice or younger motorcycle riders. Measures to promote safe driving included integrating speed management training into driver's license programs, targeting new and young drivers, advocating for cautious driving techniques, utilizing advanced training technologies such as simulated scenario simulations, collaborating with driving schools and instructors, and promoting the use of highly visible protective equipment.

In contrast, elderly drivers faced primary challenges related to adverse weather conditions. Recommendations for this group included enhancing training programs, advocating for the use of protective equipment in changing weather conditions, disseminating community knowledge to enhance driver safety, and presenting localized training and knowledge dissemination guidelines tailored to regional conditions. These recommendations are anticipated to effectively reduce the risk of near-miss incidents.

5.1.3 Study of the Relationship between Motorcycle Riders' Attitudes and Perceptions towards Near-Miss Incidents

Study 3: The aim of this study is to construct a model delineating the interplay between attitudes and perceptions regarding near-miss incidents among motorcycle riders within a developing country milieu, employing structural equation modeling. Four key factors—Fear of Traffic (FT), Attitude for Distracted Riding (ADR), Avoidance of Mixed Traffic (AVM), and Perceived Behavioral Control (PBC)—were scrutinized for their correlation with near-miss incidents. Thailand was chosen as a prototypical example of a developing nation.

The investigation revealed that perceived behavioral control exhibited a notable positive correlation with near-miss incident occurrences, notably when riders engaged in mobile phone usage while riding or traversed bends at elevated speeds. Conversely, a significant negative correlation was observed between the avoidance of mixed traffic and the likelihood of near-miss incidents. To mitigate the risk of near-miss incidents, recommendations include stringent enforcement of laws and safety regulations, enhancement of road infrastructure and surroundings, provision of comprehensive training and education to bolster driving aptitude and competence, and tackling developmental challenges in developing countries.

5.2 Recommendations

This research focuses on studying the concept of near-miss incidents among motorcycle riders to develop effective accident prevention and reduction strategies. These strategies aim to shape policies that reduce the risk of near-miss incidents. The policies emphasize collaboration between the government, relevant agencies, and society to create a safe road environment and sustainably reduce road accidents in

Thailand. Implementing these policies in practice could enhance safety and reduce road accidents in the long term, especially in the challenging driving conditions of Thailand. Each study offers specific recommendations:

5.2.1 Recommendations for Analyzing Near-Miss Incidents and Risky Riding Behavior in Thailand: A Comparative Study of Urban and Rural Areas.

The policy of this study focuses on improving and enhancing road safety in Thailand by examining the riding behaviors of motorcycle riders and considering factors contributing to near-miss incidents in urban and rural areas. The policy principles focus on three main aspects:

1) Control Error: The survey found that the most influential factor contributing to near-miss incidents in both the urban and rural models is control error. This includes issues such as poor visibility while riding in adverse weather and taking wide turns. The recommended policy emphasizes increasing awareness and training for riders to prepare for challenging weather conditions.

2) Violation: Violating traffic laws while riding is a significant factor contributing to near-miss incidents. Policies in this area might prioritize the use of Exclusive Motorcycle Lanes (EMCL) and designing dedicated motorcycle paths to reduce the risk of riding in the lanes of other vehicles.

3) Safety Equipment: The policy highlights the correct and appropriate use of safety equipment, such as wearing standard-compliant helmets and rigorously checking the readiness of motorcycles.

5.2.2 Recommendations for Assessing the Self-Report Instruments of Younger Versus Older Riders Involved in Near-Miss Motorcycle.

The policy recommendations from this study focus on improving and enhancing road safety in Thailand by examining the riding behaviors of teenage and elderly motorcycle riders and identifying factors contributing to near-miss incidents. The policy principles emphasize three main areas:

Additional Training:

1) Speed Learning Program:

   I. Appropriate Speed Assessment: Train riders to assess safe speeds in various situations, such as riding in urban areas, highways, and rural roads.

   II. Awareness and Compliance with Traffic Signals: Emphasize the importance of adhering to speed limit signs and traffic signals.

2) Speed Control Skills Training:

   I. Safe Acceleration and Braking: Practice balanced and safe acceleration and braking to prevent loss of motorcycle control.

   II. Emergency Braking: Train emergency braking in various scenarios to ensure riders are confident and able to handle situations effectively.

3) Specific training for younger riders: Focus on educating them about the risks of motorcycle riding and varying road conditions.

Knowledge Dissemination:

1) Community campaigns and activities: Raise awareness about safe motorcycle riding and the potential risks involved.

2) Utilize technology for knowledge dissemination: use social media, create guides, or produce online training videos.

Technology to Enhance Safety:

1) Support the use of risk-reducing technologies: promote intelligent braking systems (ABS) and wheel skid control systems.

2) Encourage the use of appropriate protective gear. Recommend high-visibility clothing for low-light conditions and helmets with impact protection systems.

Building Partnerships:

1) Form alliances: Collaborate with local agencies, community organizations, and the private sector to support additional safety-related projects and measures for motorcycle riding.

5.2.3 Recommendations for the Study of the Relationship between Motorcycle Riders' Attitudes and Perceptions towards Near-Miss.

The policies and recommendations from this study focus on enhancing motorcycle safety through improved training and knowledge dissemination. These can be categorized into several key areas:

Law Enforcement and Safety Measures:

1) Strict enforcement of laws prohibiting mobile phone use while riding: Implement and promote campaigns to raise awareness of the dangers of using phones while riding.

2) Enforce strict speed limits, particularly in high-risk areas such as curves and narrow roads.

Infrastructure Improvement and Road Environment:

1) Create exclusive motorcycle lanes (EMCL): Separate motorcycles from mixed traffic to reduce conflict points and enhance safety.

2) Improve road safety infrastructure: widen lanes to meet safety standards and install warning signs and traffic signals at high-risk locations.

Training and Education:

1) Provide safe riding training: Enhance the knowledge and skills of motorcycle riders, including risk assessment and emergency handling techniques.

2) Public awareness campaigns: Use various media to change rider attitudes and behaviors, focusing on reducing risky behaviors such as phone use while riding and speeding.

APPENDIX A

TESTING THE INVARIANCE OF THE MEASUREMENT MODEL FOR URBAN AND RURAL RIDERS

TESTING THE INVARIANCE OF THE MEASUREMENT MODEL FOR URBAN AND RURAL RIDERS

Step 1: Separate Each Group Model and analyze the measurement model separately for each group.

Table 1 Command: Separate each group model for **Model 1: Urban**

```
    TITLE:  urban group
     DATA:
     FILE IS "C:\Users\asus\OneDrive\Desktop\Data_1.dat";
     VARIABLE:
           NAMES ARE ZONE ACD NMS TF1-TF14 SL1-SL12 SV1-SV9 TV1-TV6
AV1-AV7
                     SE1-SE8 CE1-CE5 SM1-SM5 AL1-AL3 VC1-VC7 FM1-
FM13;
           USEOBSERVATIONS ARE ZONE EQ 1; !1== urban
           USEVARIABLES ARE CE1 CE2 CE3 CE4 SV3 SV4 TV6 AV1 AV2 AV3
                         SM4 SM5 AL1 AL2 SE1 SE2 SE3;
     MODEL: ERROR BY CE1 CE2 CE3 CE4;
            VION  BY SV3 SV4  TV6 AV1 AV2 AV3 SM4 SM5 AL1 AL2;
            SAFE  BY SE1 SE2 SE3 ;
```

Table 2 The analysis results yielded the following statistics for evaluating the model fit:

```
MODEL FIT INFORMATION
Number of Free Parameters                       56
Loglikelihood
          H0 Value                      -17752.699
          H1 Value                      -17553.214

Information Criteria
          Akaike (AIC)                   35617.399
          Bayesian (BIC)                 35895.812
          Sample-Size Adjusted BIC       35717.946
            (n* = (n + 2) / 24)

Chi-Square Test of Model Fit
          Value                            398.971
          Degrees of Freedom                   114
          P-Value                           0.0000

RMSEA (Root Mean Square Error Of Approximation)
          Estimate                           0.048
          90 Percent C.I.                    0.043  0.054
          Probability RMSEA <= .05           0.683

CFI/TLI
          CFI                                0.954
          TLI                                0.945

Chi-Square Test of Model Fit for the Baseline Model
          Value                           6344.531
```

Table 2 The analysis results yielded the following statistics for evaluating the model fit: (Continued)

```
          Degrees of Freedom                       136
          P-Value                               0.0000

SRMR (Standardized Root Mean Square Residual)
          Value                                  0.052
```

Based on the model fit statistics, the measurement model for urban riders demonstrated a good fit with the empirical data.

Table 3 Command: Separate each group model for **Model 2: Rural**

```
    TITLE:  rural group
    DATA: FILE IS "C:\Users\asus\OneDrive\Desktop\Data_1.dat";
    VARIABLE:
          NAMES ARE ZONE ACD NMS TF1-TF14 SL1-SL12 SV1-SV9 TV1-TV6
AV1-AV7
                    SE1-SE8 CE1-CE5 SM1-SM5 AL1-AL3 VC1-VC7 FM1-
FM13;
          USEOBSERVATIONS ARE ZONE EQ 2; !2== rural
          USEVARIABLES ARE CE1 CE2 CE3 CE4 SV3 SV4 TV6 AV1 AV2 AV3
                           SM4 SM5 AL1 AL2 SE1 SE2 SE3;
          MODEL: ERROR BY CE1 CE2 CE3 CE4;
                 VION  BY SV3 SV4  TV6 AV1 AV2 AV3 SM4 SM5 AL1 AL2;
                 SAFE  BY SE1 SE2 SE3 ;
```

Table 4 The analysis results yielded the following statistics for evaluating the model fit:

```
MODEL FIT INFORMATION
Number of Free Parameters                           56
Loglikelihood

          H0 Value                          -15908.667
          H1 Value                          -15678.078

Information Criteria
          Akaike (AIC)                       31929.334
          Bayesian (BIC)                     32200.464
          Sample-Size Adjusted BIC           32022.613
            (n* = (n + 2) / 24)

Chi-Square Test of Model Fit
          Value                                461.177
          Degrees of Freedom                       114
          P-Value                               0.0000

RMSEA (Root Mean Square Error Of Approximation)
          Estimate                               0.057
          90 Percent C.I.                        0.052  0.063
          Probability RMSEA <= .05               0.016
```

Table 4 The analysis results yielded the following statistics for evaluating the model fit: (Continued)

```
CFI/TLI
          CFI                                0.936
          TLI                                0.923

Chi-Square Test of Model Fit for the Baseline Model
          Value                           5520.312
          Degrees of Freedom                   136
          P-Value                           0.0000

SRMR (Standardized Root Mean Square Residual)
          Value                              0.063
```

Based on the model fit statistics, the measurement model for rural riders demonstrated a good fit with the empirical data.

Step2: Model 3: Configural invariance (base line) model

Table 5 Command: Configural invariance (base line) model

```
  TITLE:  Configural invariance (base line)
    DATA:
    FILE IS "C:\Users\asus\OneDrive\Desktop\Data_1.dat";
    VARIABLE:
          NAMES ARE ZONE ACD NMS TF1-TF14 SL1-SL12 SV1-SV9 TV1-TV6
AV1-AV7
                    SE1-SE8 CE1-CE5 SM1-SM5 AL1-AL3 VC1-VC7 FM1-
FM13;
          USEVARIABLES ARE ZONE CE1 CE2 CE3 CE4 SV3 SV4 TV6 AV1 AV2
AV3
                      SM4 SM5 AL1 AL2 SE1 SE2 SE3;
          GROUPING IS ZONE (1 =urban 2=rural);
    ANALYSIS:
      MODEL        = NOMEAN;
      INFORMATION = EXPECTED;
    MODEL:        ERROR BY CE1 CE2 CE3 CE4;
                  VION  BY SV3 SV4 TV6 AV1 AV2 AV3 SM4 SM5 AL1 AL2;
                  SAFE  BY SE1 SE2 SE3 ;
    MODEL rural:  ERROR BY CE1@1 CE2 CE3 CE4;
                  VION  BY SV3@1 SV4 TV6 AV1 AV2 AV3 SM4 SM5 AL1
AL2;
                  SAFE  BY SE1@1 SE2 SE3 ;
```

Table 6 The analysis results yielded the following statistics for evaluating the model fit of the Configural Invariance (baseline) model:

```
MODEL FIT INFORMATION
Number of Free Parameters                       74
Loglikelihood
          H0 Value                      -33789.366
          H1 Value                      -33231.292
```

Table 6 The analysis results yielded the following statistics for evaluating the model fit of the Configural Invariance (baseline) model: (Continued)

```
Information Criteria
          Akaike (AIC)                    67726.733
          Bayesian (BIC)                  68141.274
          Sample-Size Adjusted BIC        67906.172
            (n* = (n + 2) / 24)


Chi-Square Test of Model Fit
          Value                            1116.149
          Degrees of Freedom                    232
          P-Value                            0.0000

Chi-Square Contributions From Each Group
          URBAN                             502.893
          RURAL                             613.257

RMSEA (Root Mean Square Error Of Approximation)
          Estimate                            0.062
          90 Percent C.I.                     0.058  0.065
          Probability RMSEA <= .05            0.000

CFI/TLI
          CFI                                 0.924
          TLI                                 0.911

Chi-Square Test of Model Fit for the Baseline Model
          Value                           11864.842
          Degrees of Freedom                    272
          P-Value                            0.0000

SRMR (Standardized Root Mean Square Residual)
          Value                               0.063
```

The analysis of the Configural Invariance (baseline) model, which imposed identical measurement model structures for both groups or the same measurement scheme with independent parameter estimation, showed that the model fit statistics indicated a strong fit with the empirical data. This suggests that both groups share an equivalent measurement model structure.

Step3: Model 4 Factor loading invariance model

Table 7 Command: Factor loading invariance model

```
TITLE:  Metrix invariance model
    DATA:
    FILE IS "C:\Users\asus\OneDrive\Desktop\Data_1.dat";
    VARIABLE:
          NAMES ARE ZONE ACD NMS TF1-TF14 SL1-SL12 SV1-SV9 TV1-TV6
AV1-AV7
                    SE1-SE8  CE1-CE5  SM1-SM5  AL1-AL3  VC1-VC7  FM1-
FM13;
          USEVARIABLES ARE ZONE CE1 CE2 CE3 CE4 SV3 SV4 TV6 AV1 AV2
AV3
                      SM4 SM5 AL1 AL2 SE1 SE2 SE3;
          GROUPING IS ZONE (1 =urban 2=rural);
    ANALYSIS:
      MODEL        = NOMEAN;
      INFORMATION = EXPECTED;
    MODEL:         ERROR BY CE1 CE2 CE3 CE4;
                   VION  BY SV3 SV4 TV6 AV1 AV2 AV3 SM4 SM5 AL1 AL2;
                   SAFE  BY SE1 SE2 SE3 ;
    MODEL rural:
```

Table 8 The analysis results yielded the following statistics for evaluating the model fit of the factor loading invariance model:

```
MODEL FIT INFORMATION
Number of Free Parameters                        60
Loglikelihood
          H0 Value                       -33820.132
          H1 Value                       -33231.292

Information Criteria
          Akaike (AIC)                    67760.264
          Bayesian (BIC)                  68096.378
          Sample-Size Adjusted BIC        67905.755
            (n* = (n + 2) / 24)

Chi-Square Test of Model Fit
          Value                            1177.680
          Degrees of Freedom                    246
          P-Value                            0.0000

Chi-Square Contributions From Each Group
          URBAN                             527.614
          RURAL                             650.066

RMSEA (Root Mean Square Error Of Approximation)
          Estimate                            0.062
          90 Percent C.I.                     0.058  0.065
          Probability RMSEA <= .05            0.000

CFI/TLI
          CFI                                 0.920
          TLI                                 0.911
```

Table 8 The analysis results yielded the following statistics for evaluating the model fit of the factor loading invariance model: (Continued)

```
Chi-Square Test of Model Fit for the Baseline Model
          Value                           11864.842
          Degrees of Freedom                    272
          P-Value                            0.0000

SRMR (Standardized Root Mean Square Residual)
          Value                               0.067
```

Table 9 Results of Testing Measurement Model Invariance between Urban and Rural Areas

Description	χ^2	*df*	*χ2/df*	CFI	TLI	RMSEA	SRMR	Δχ2	Δdf	*P*
Individual group										
Model 1: Urban	398.971	114	3.499	0.954	0.945	0.048	0.052			
Model 2: Rural	461.177	114	4.045	0.936	0.923	0.057	0.063			
Measurement invariance										
Model 3: Configural invariance (base line) model	1116.149	232	4.811	0.924	0.911	0.062	0.063			
Model 4: Factor loading invariance model	1177.680	246	4.787	0.920	0.911	0.062	0.067	61.53	14	<0.001

Based on Table 9, the analysis of the measurement model invariance test between urban and rural areas, the finding of a p-value < 0.001 indicates significant variance in model weights. This suggests differences in factor loadings between urban and rural rider groups.

APPENDIX B

TESTING THE INVARIANCE OF THE MEASUREMENT MODEL FOR YOUNGER AND OLDER RIDERS

TESTING THE INVARIANCE OF THE MEASUREMENT MODEL FOR YOUNGER AND OLDER RIDERS

Step 1: Separate each group model and analyze the measurement model separately for each group.

Table 10 Command: Separate each group model for **Model 1: younger**

```
    TITLE:  younger group
    DATA:
    FILE IS "C:\Users\asus\OneDrive\Desktop\ALL2.dat";
    VARIABLE:
          NAMES ARE AGE ACD NMS TF1-TF14 SL1-SL12 SV1-SV9 TV1-TV6
AV1-AV7
                    SE1-SE8 CE1-CE5 SM1-SM5 AL1-AL3 VC1-VC7 FM1-
FM13;
          USEOBSERVATIONS ARE AGE EQ 1; !1== younger
          USEVARIABLES ARE CE1 CE2 CE3 CE4 SV3 SV4 SV5 SV6 AV1 AV2
AV3
                          SM4 SM5 AL1 AL2 SE1 SE2 SE3 SE4;
          MODEL: ERROR BY  CE1 CE2 CE3 CE4;
                 VION  BY  SV3 SV4 SV5 SV6 AV1 AV2 AV3 SM4 SM5 AL1
AL2;
                 SAFE  BY  SE1 SE2 SE3 SE4;
```

Table 11 The analysis results yielded the following statistics for evaluating the model fit:

```
MODEL FIT INFORMATION
Number of Free Parameters                      62
Loglikelihood
          H0 Value                      -8856.177
          H1 Value                      -8677.806

Information Criteria

          Akaike (AIC)                  17836.354
          Bayesian (BIC)                18094.479
          Sample-Size Adjusted BIC      17897.700
            (n* = (n + 2) / 24)

Chi-Square Test of Model Fit
          Value                           356.741
          Degrees of Freedom                  147
          P-Value                          0.0000

RMSEA (Root Mean Square Error Of Approximation)
          Estimate                          0.055
          90 Percent C.I.                   0.048  0.062
          Probability RMSEA <= .05          0.133
```

Table 11 The analysis results yielded the following statistics for evaluating the model fit: (Continued)

```
CFI/TLI
          CFI                                 0.932
          TLI                                 0.921

Chi-Square Test of Model Fit for the Baseline Model
          Value                            3261.680
          Degrees of Freedom                    171
          P-Value                            0.0000

SRMR (Standardized Root Mean Square Residual)
          Value                               0.064
```

Based on the model fit statistics, the measurement model for younger riders demonstrated a good fit with the empirical data.

Table 12 Command: Separate each group model for **Model 2: older**

```
    TITLE: older group
    DATA:
    FILE IS "C:\Users\asus\OneDrive\Desktop\ALL2.dat";
    VARIABLE:
          NAMES ARE AGE ACD NMS TF1-TF14 SL1-SL12 SV1-SV9 TV1-TV6
AV1-AV7
                    SE1-SE8 CE1-CE5 SM1-SM5 AL1-AL3 VC1-VC7 FM1-
FM13;
          USEOBSERVATIONS ARE AGE EQ 2; !2== older
          USEVARIABLES ARE CE1 CE2 CE3 CE4 SV3 SV4 SV5 SV6 AV1 AV2
AV3
                           SM4 SM5 AL1 AL2 SE1 SE2 SE3 SE4;
          MODEL: ERROR BY  CE1 CE2 CE3 CE4;
                 VION  BY  SV3 SV4 SV5 SV6 AV1 AV2 AV3 SM4 SM5 AL1
AL2;
                 SAFE  BY  SE1 SE2 SE3 SE4;
```

Table 13 The analysis results yielded the following statistics for evaluating the model fit:

```
MODEL FIT INFORMATION
Number of Free Parameters                        64
Loglikelihood
          H0 Value                        -6465.585
          H1 Value                        -6320.185

Information Criteria
          Akaike (AIC)                    13059.170
          Bayesian (BIC)                  13304.222
          Sample-Size Adjusted BIC        13101.202
            (n* = (n + 2) / 24)

Chi-Square Test of Model Fit
          Value                             290.799
```

Table 13 The analysis results yielded the following statistics for evaluating the model fit: (Continued)

```
          Degrees of Freedom                       145
          P-Value                               0.0000

RMSEA (Root Mean Square Error Of Approximation)
          Estimate                               0.054
          90 Percent C.I.                        0.045  0.063
          Probability RMSEA <= .05               0.207

CFI/TLI
          CFI                                    0.933
          TLI                                    0.921

Chi-Square Test of Model Fit for the Baseline Model
          Value                               2348.147
          Degrees of Freedom                       171
          P-Value                               0.0000

SRMR (Standardized Root Mean Square Residual)
          Value                                  0.063
```

Based on the model fit statistics, the measurement model for older riders demonstrated a good fit with the empirical data.

Step 2: Model 3: Configural invariance (base line) model

Table 14 Command: Configural invariance (base line) model

```
    TITLE:  Configural invariance (base line)
    DATA:
    FILE IS "C:\Users\asus\OneDrive\Desktop\ALL2.dat";
    VARIABLE:
          NAMES ARE AGE ACD NMS TF1-TF14 SL1-SL12 SV1-SV9 TV1-TV6
AV1-AV7
                    SE1-SE8 CE1-CE5 SM1-SM5 AL1-AL3 VC1-VC7 FM1-
FM13;
          USEVARIABLES ARE CE1 CE2 CE3 CE4 SV3 SV4 SV5 SV6 AV1 AV2
AV3
                           SM4 SM5 AL1 AL2 SE1 SE2 SE3 SE4;
          GROUPING IS AGE (1 =younger 2=older);
    ANALYSIS:
      MODEL       = NOMEAN;
      INFORMATION = EXPECTED;
    MODEL:          ERROR BY CE1 CE2 CE3 CE4;
                    VION  BY SV3 SV4 SV5  SV6 AV1 AV2 AV3 SM4 SM5
AL1 AL2;
                    SAFE  BY SE1 SE2 SE3 SE4;
    Model older:    ERROR BY CE1@1 CE2 CE3 CE4;
                    VION  BY SV3@1 SV4 SV5 SV6 AV1 AV2 AV3 SM4 SM5
AL1 AL2;
                    SAFE  BY SE1@1 SE2 SE3 SE4;
```

Table 15 The analysis yielded statistics for testing the configural invariance (baseline) model as follows:

```
MODEL FIT INFORMATION
Number of Free Parameters                              82
Loglikelihood
          H0 Value                             -15397.950
          H1 Value                             -14997.992

Information Criteria
          Akaike (AIC)                          30959.899
          Bayesian (BIC)                        31345.561
          Sample-Size Adjusted BIC              31085.161
            (n* = (n + 2) / 24)

Chi-Square Test of Model Fit
          Value                                   799.916
          Degrees of Freedom                          298
          P-Value                                  0.0000

Chi-Square Contributions From Each Group
          YOUNGER                                 421.924
          OLDER                                   377.992

RMSEA (Root Mean Square Error Of Approximation)
          Estimate                                  0.064
          90 Percent C.I.                           0.059  0.070
          Probability RMSEA <= .05                  0.000

CFI/TLI
          CFI                                       0.905
          TLI                                       0.891

Chi-Square Test of Model Fit for the Baseline Model
          Value                                  5609.827
          Degrees of Freedom                          342
          P-Value                                  0.0000

SRMR (Standardized Root Mean Square Residual)
          Value                                     0.070
```

The analysis of the Configural Invariance (baseline) model, which imposed identical measurement model structures for both groups or the same measurement scheme with independent parameter estimation, showed that the model fit statistics indicated a strong fit with the empirical data. This suggests that both groups share an equivalent measurement model structure.

Step3: Model 4: Factor loading invariance model

Table 16 Command: Factor loading invariance model

```
    TITLE:  Configural invariance (base line)
    DATA:
    FILE IS "C:\Users\asus\OneDrive\Desktop\ALL2.dat";
    VARIABLE:
          NAMES ARE AGE ACD NMS TF1-TF14 SL1-SL12 SV1-SV9 TV1-TV6
AV1-AV7
                    SE1-SE8 CE1-CE5 SM1-SM5 AL1-AL3 VC1-VC7 FM1-
FM13;
          USEVARIABLES ARE CE1 CE2 CE3 CE4 SV3 SV4 SV5 SV6 AV1 AV2
AV3
                           SM4 SM5 AL1 AL2 SE1 SE2 SE3 SE4;
          GROUPING IS AGE (1 =younger 2=older);
    ANALYSIS:
      MODEL        = NOMEAN;
      INFORMATION = EXPECTED;
    MODEL:          ERROR BY CE1 CE2 CE3 CE4;
                    VION  BY SV3 SV4 SV5  SV6 AV1 AV2 AV3 SM4 SM5
AL1 AL2;
                    SAFE  BY SE1 SE2 SE3 SE4;
    Model older:
```

Table 17 The analysis yielded statistics for testing the factor loading invariance model as follows:

```
MODEL FIT INFORMATION
Number of Free Parameters                        66
Loglikelihood

          H0 Value                       -15412.132
          H1 Value                       -14997.992

Information Criteria
          Akaike (AIC)                    30956.264
          Bayesian (BIC)                  31266.674
          Sample-Size Adjusted BIC        31057.084
            (n* = (n + 2) / 24)

Chi-Square Test of Model Fit
          Value                             828.281
          Degrees of Freedom                    314
          P-Value                            0.0000

Chi-Square Contributions From Each Group
          YOUNGER                           434.027
          OLDER                             394.254

RMSEA (Root Mean Square Error Of Approximation)
          Estimate                            0.063
          90 Percent C.I.                     0.058  0.069
          Probability RMSEA <= .05            0.000

CFI/TLI
          CFI                                 0.902
          TLI                                 0.894
```

Table 17 The analysis yielded statistics for testing the factor loading invariance model as follows: (Continued)

```
Chi-Square Test of Model Fit for the Baseline Model
          Value                               5609.827
          Degrees of Freedom                       342
          P-Value                               0.0000

SRMR (Standardized Root Mean Square Residual)
          Value                                  0.072
```

Table 18 Results for Testing the Invariance of the Measurement Model in the Younger and Older Rider Groups

Description	χ^2	*df*	*χ2/df*	CFI	TLI	RMSEA	SRMR	Δχ2	Δdf	*P*
					Individual group					
Model 1: Younger	356.741	147	2.427	0.932	0.921	0.055	0.064			
Model 2: Older	290.799	145	2.005	0.933	0.921	0.054	0.063			
					Measurement invariance					
Model 3: Configural invariance (base line) model	799.916	298	2.684	0.905	0.891	0.064	0.070			
Model 4: Factor loading invariance model	828.281	314	2.638	0.902	0.894	0.063	0.072	28.365	16	<0.05

Based on Table 18, the analysis of the measurement model invariance test in the younger and older rider groups, with a finding of $p < 0.05$, indicates significant variance in model weights. This suggests that some factor loadings differ between the younger and older rider groups.

APPENDIX C

DEVELOPMENT OF MRBQ

(MOTORCYCLE RIDER BEHAVIOR QUESTIONNAIRE)

DEVELOPMENT OF MRBQ (MOTORCYCLE RIDER BEHAVIOR QUESTIONNAIRE)

Table 19 Principal components analysis (varimax rotation) of the MRBQ items

Item	Traffic errors	Control errors	Stunts	Safety equipment	Speed violations
Fail to notice that pedestrians are crossing when turning into a side street from a main road			.320		
Not notice someone stepping out from behind a parked vehicle until it is nearly too late				.436	
Not notice a pedestrian waiting to cross at a zebra crossing, or a pelican crossing that has just turned red			.704		
Pull out on to a main road in front of a vehicle that you had not noticed, or whose speed you have misjudged				.711	
Miss “GiveWay” signs and narrowly avoid colliding with traffic having the right of way	.713				
Fail to notice or anticipate that another vehicle might pull out in front of you and have difficulty stopping	.769				
Queuing to turn left on a main road, you pay such close attention to the main traffic that you nearly hit the vehicle in front	.750				
Distracted or pre-occupied, you belatedly realise that the vehicle in front has slowed and you have to brake hard to avoid a collision	.772				
Attempt to overtake someone that you had not noticed to be signalling a right turn	.358	.540			
When riding at the same speed as other traffic, you find it difficult to stop in time when a traffic light has turned against you					.737
Ride so close to the vehicle in front that it would be difficult to stop in an emergency			.764		
Run wide when going round a corner					.789
Ride so fast into a corner that you feel like you might lose control		.594			
Exceed the speed limit on a country/rural road					
Disregard the speed limit late at night or in the early hours of the morning 0.15	.728				
Exceed the speed limit on a motorway	.747				
Exceed the speed limit on a residential road	.746				
Open up the throttle and just ‘go for it’ on country roads					
Ride between two lanes of fast moving traffic					
Get involved in unofficial ‘races’ with other riders or drivers	.310				
Ride so fast into a corner that you scare yourself					
Attempt to do, or actually do, a wheelie					
Intentionally do a wheel spin					
Wear riding boots?				-.757	

Table 19 Principal components analysis (varimax rotation) of the MRBQ items (Continued)

Item	Traffic errors	Control errors	Stunts	Safety equipment	Speed violations
Wear a protective jacket (leather or non-leather)?	-.769				
Wear body armour (elbow pads, shoulder pads, knee pads, etc)	-.766				
Wear gloves?	-.766				
Wear bright/fluorescent strips/patches on your clothing	-.770				
Use dipped headlights on your bike?	.402		-.595		
Find that you have difficulty controlling the bike when riding at speed (e.g. steering wobble)		.633			
Skid on a wet road or manhole cover		.759			
Have trouble with your visor or goggles fogging up		.568			
Ride when you suspect you might be over the legal limit for alcohol	.529				

Elliott et al. (2007) originally developed the Motorcycle Rider Behavior Questionnaire (MRBQ), which comprises a table of 43 questions. This study excluded redundant inquiries, such as those concerning leather suits, protective gear, and reflective tape usage, resulting in a refined set of 33 questions. Exploratory Factor Analysis (EFA) was subsequently applied to structure these components using data from 2,002 motorcycle riders in Thailand. From Table 19, it was observed that certain components did not align well with specific factors, posing challenges in component organization. Further statistical analysis revealed that the model lacked practical appropriateness. Consequently, this study undertook a reorganization and categorization of variables, emphasizing the selection of the most significant and impactful ones to enhance the relevance of data for modeling motorcycle rider behavior in Thailand. This methodological adjustment was driven by Thailand's middle-income status, elevated rates of traffic accidents, and prevalent risky driving behaviors, distinct from those studied by Elliott et al. (2007) in the UK. Thus, this research signifies a refinement of theories and models tailored for investigating motorcycle driving behavior specifically in Thailand.

LIST OF PUBLICATIONS

Jomnonkwao, S., Hantanong, N., Champahom, T., Se, C., & Ratanavaraha, V. (2023). Analyzing Near-Miss Incidents and Risky Riding Behavior in Thailand: A Comparative Study of Urban and Rural Areas. *Safety, 9*(4). doi:10.3390/safety9040090

Hantanong, N., Jomnonkwao, S., Champahom, T., Se, C., & Ratanavaraha, V. (2024). Assessing the Self-Report Instruments of Younger Versus Older Riders Involved in Near-Miss Motorcycle Incidents. *Civil Engineering Journal, 10*(2), 628-654. doi: 10.28991/CEJ-2024-010-02-019

BIOGRAPHY

Miss Natthaporn Hantanong, born on April 5th, 2538, in Wang Sai Subdistrict, Pakchong District, Nakhon Ratchasima Province, embarked on her educational journey at Saeng Suriya Wittaya School for her primary education, followed by Pakchong School for her secondary education. With determination and diligence, she successfully completed her undergraduate studies in Transportation and Logistics Engineering at the School of Transportation Engineering, Suranaree University of Technology. Her outstanding academic performance led her to rank first in her class and earn an esteemed academic scholarship for doctoral studies in Transportation Engineering at the same university.

Specializing in research related to road safety and accident modeling, Miss Natthaporn Hantanong has contributed significantly to her field. During her doctoral studies, she presented a noteworthy research paper titled *"Analysis of Factors Affecting In Motorcyclist Near Misses Using Structural Equation Modeling"* at the 2nd International Virtual Conference on Science and Technology (SUT-IVCST 2021), hosted by Suranaree University of Technology, Thailand, on August 6th, 2021.

Furthermore, she has made valuable contributions to academia through her published research papers. These include *"Analyzing Near-Miss Incidents and Risky Riding Behavior in Thailand: A Comparative Study of Urban and Rural Areas"* Safety, 9(4). doi:10.3390/safety9040090 (JIF = 1.9) and *Assessing the Self-Report Instruments of Younger Versus Older Riders Involved in Near-Miss Motorcycle Incidents"* in Civil Engineering Journal, 10(2), doi: 10.28991/CEJ-2024-010-02-019 (JIF = 4.1).

Her dedication to advancing knowledge in transportation engineering and her commitment to improving road safety reflect her exemplary academic and professional achievements.