safety

MDPI

Article

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

Sajjakaj Jomnonkwao [1,*], Natthaporn Hantanong [1], Thanapong Champahom [2], Chamroeun Se [3] and Vatanavongs Ratanavaraha [1]

[1] School of Transportation Engineering, Institute of Engineering, Suranaree University of Technology, 111 University Avenue, Suranaree Sub-District, Muang District, Nakhon Ratchasima 30000, Thailand; d6040086@g.sut.ac.th (N.H.); vatanavongs@g.sut.ac.th (V.R.)
[2] Department of Management, Faculty of Business Administration, Rajamangala University of Technology Isan, 744 Sura Narai Rd, Nai-Muang Sub-District, Muang District, Nakhon Ratchasima 30000, Thailand; thanapong.ch@rmuti.ac.th
[3] Institute of Research and Development, Suranaree University of Technology, 111 University Avenue, Suranaree Sub-District, Muang District, Nakhon Ratchasima 30000, Thailand; chamroeun.s@g.sut.ac.th
* Correspondence: sajjakaj@g.sut.ac.th

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.

Keywords: motorcycle rider behavior questionnaire; low- and middle-income countries (LMICs); road environment; measurement invariance

check for updates

Citation: Jomnonkwao, S.; Hantanong, N.; Champahom, T.; Se, C.; Ratanavaraha, V. Analyzing Near-Miss Incidents and Risky Riding Behavior in Thailand: A Comparative Study of Urban and Rural Areas. *Safety* **2023**, *9*, 90. https://doi.org/10.3390/safety9040090

Academic Editor: Raphael Grzebieta

Received: 3 November 2023
Revised: 6 December 2023
Accepted: 7 December 2023
Published: 12 December 2023

1. 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 [1], 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 et al. [2].

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 [3].

Thailand, located in Southeast Asia and categorized as a middle-income country according to the World Bank [4], 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 [5]. 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 [6]. 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 [3]. Notably, a significant proportion of road fatalities in Thailand involve motorcycle users, comprising 74% of all road users [3]. 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 [7].

2. Literature Review

2.1. 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 [8]. A recent study conducted by Champahom et al. [9] 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 [10]. Harnen et al. [11] 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 et al. [12] 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 [13] 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 et al. [14] found that high-speed riding in urban areas is notably associated with higher motorcycle accident rates compared to rural areas. Furthermore, Gkritza [15] and Li et al. [16] 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. Figure 1 serves 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 1a, 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 1b 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.

(**a**) (**b**)

Figure 1. Physical characteristics of roads and environments in urban and rural areas. Source: Google Maps. (**a**) Urban area (coordinates: 14.9751957, 102.0855722), (**b**) 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.

2.2. 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 [17]. The use of a near-miss strategy involves collecting and extensively evaluating data and identifying potential issues in advance to prevent accidents [18].

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 [19]. Remarkably, near-miss incidents are highly associated with the perception of traffic risk, which holds more significance than actual collisions [19]. In Iceland, a survey on near-miss incidents involving motorcycles revealed that 78.2% of respondents had experienced near-miss incidents [20]. 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 [21]. 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 [22]. 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 [23]. 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 [19]. 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 [24]. 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 [25]. Nonetheless, self-reporting can yield detailed insights into aspects that field observations may not capture, such as perceptions, behaviors, attitudes, or satisfaction levels [26]. 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 1 (H1): *There is no difference in the invariance between urban and rural.*

2.3. 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 [27]. 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 [28–31]. Among these factors, those related to humans are considered the most significant in terms of accident occurrence [28,31]. 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 [31]. Unsafe and risky behaviors are primarily attributed to individuals and encompass various factors, such as unsafe driving behaviors, including drunk driving [32] and speeding [33], 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 [34–37]. 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 [38]. These factors may contribute to near-miss incidents or collisions resulting in injuries or fatalities.

In their study, Elliott et al. [39] 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 1. The additional main null hypothesis for this study is as follows:

Hypothesis 2 (H2): *Control errors have a negative effect on near-misses in urban areas.*

Hypothesis 3 (H3): *Violations have a negative effect on near-misses in urban areas.*

Hypothesis 4 (H4): *Safety equipment has a negative effect on near-misses in urban areas.*

Hypothesis 5 (H5): *Control errors have a negative effect on near-misses in rural areas.*

Hypothesis 6 (H6): *Violations have a negative effect on near-misses in rural areas.*

Hypothesis 7 (H7): *Safety equipment has a negative effect on near-misses in rural areas.*

2.4. Objective and Contributions

The preceding research has delved into the study of risk behavior factors, specifically in India [40,41] and Australia [42,43], 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 2.1, 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.

Table 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 [39]	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 [40]	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
India [41]	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 [42]	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
Australia [43]	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 [44]	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
Iran [45]	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

Table 1. *Cont.*

Country (Author)	Sample Size	Items	Demographic Characteristics	Other Data	Factor Structure	Factor Analysis Method	Technique
Turkey [46]	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
Slovenia [47]	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 [48]	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
Thailand [49]	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

3. Materials and Methods

3.1. 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, Baughan, and Sexton [39], underwent adaptations and modifications by researchers from different countries (refer to Table 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 redesign 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 redesign, 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.

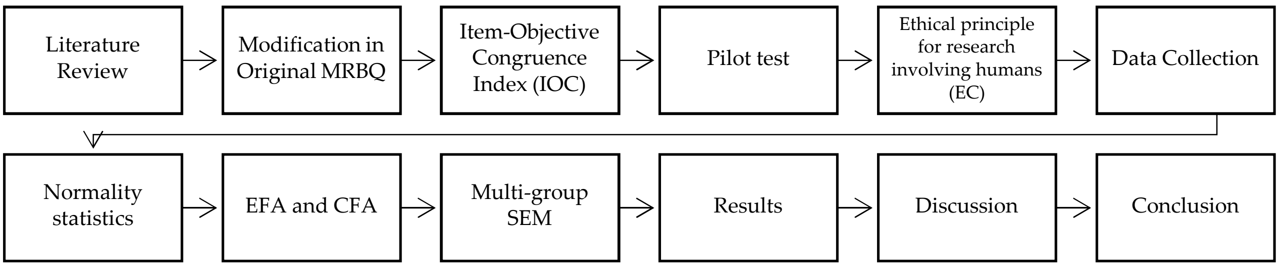

Figure 2. Research procedures.

3.2. Questionnaire Design

3.2.1. 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" [40,44].

3.2.2. Motorcycle Rider Behavior Questionnaire (MRBQ)

In this study, we utilized the Motorcycle Rider Behavior Questionnaire (MRBQ), developed by Elliott et al. [39], as the primary instrument for investigating motorcycle rider behavior. This questionnaire has been employed in various countries, such as Iran [45], Turkey [46], Australia [42,43], Slovenia [47], Nigeria [48], Vietnam [44], and India [40,41].

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 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 [40,45], 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.

3.3. 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 [50]. 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 3, 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, 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.

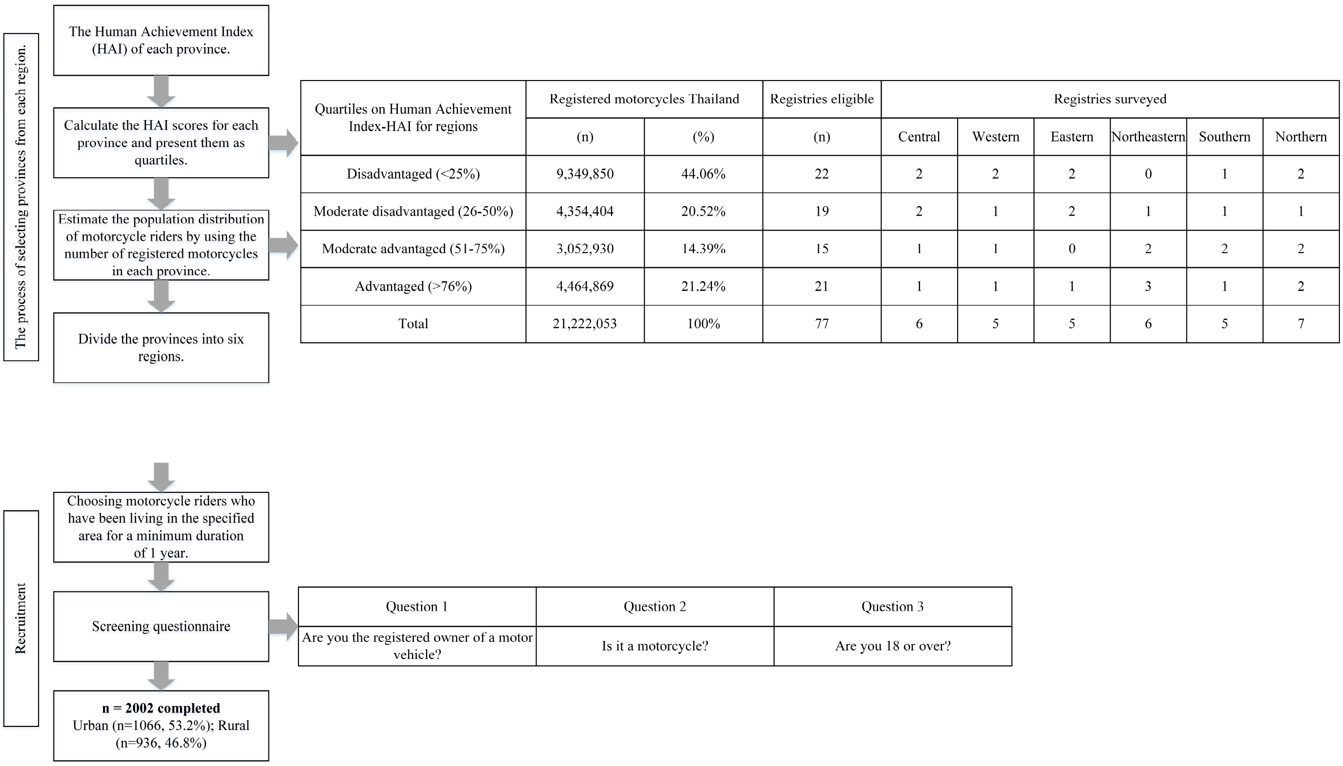

Figure 3. Recruitment procedure for obtaining a representative sample of riders from Thailand.

Table 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)
	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)

Table 2. *Cont.*

Variable Name	Category	Urban (n = 1066)	Rural (n = 936)
		% (n)	% (n)
	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)
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 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 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)
	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)

3.4. 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, 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:

3.4.1. 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 [51]. 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.

3.4.2. 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 [52]. 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).

3.4.3. 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 [53], as well as continuous variables that can be categorized through dichotomization or cluster analysis [54]. 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 [55]. 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.

3.4.4. 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 [56]. 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.

3.4.5. 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:

The χ^2/df is the ratio between the chi-square value and the degrees of freedom. It is advised by Kline [57] that this ratio should not exceed 3. However, in cases where the model is highly complex, Hu and Bentler [58] propose that the ratio should not exceed 5.

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 [58].

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 [59].

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 [58].

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 [60,61].

4. Results

4.1. Descriptive Statistics

The descriptive statistics generated for MRBQ variables, including mean, standard deviation (SD), skewness, and kurtosis (Table 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.

Table 4. Descriptive statistics.

Code	Latent Variable/Questionnaire	Urban (n = 1066)				Rural (n = 936)			
		Mean	SD	SK	KU	Mean	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
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

Table 4. *Cont.*

Code	Latent Variable/Questionnaire	Urban (n = 1066)				Rural (n = 936)			
		Mean	SD	SK	KU	Mean	SD	SK	KU
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
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: SD = standard deviation; SK = skewness; and KU = kurtosis.

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 [57].

4.2. 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 [62]. Additionally, Hair et al. [63] 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 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 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 [64]. 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 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 6). Table 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 [58], RMSEA was 0.048 [59], CFI was 0.954 [58], TLI was 0.945 [60,61], and SRMR was 0.052 [60,61]. These values collectively indicate that the model fit well with the observed data. And according to Table 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 [58], RMSEA was 0.057 [59], CFI was 0.936 [58], TLI was 0.923 [60,61], and SRMR was 0.063 [60,61]. These values demonstrate a satisfactory fit of the model to the observed data.

Table 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	18.309	<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		
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		
χ2/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).

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 (1) and (2):

$$\mathrm{CR} = \frac{\left(\sum_{i=1}^{n} L_i\right)^2}{\left(\sum_{i=1}^{n} L_i\right)^2 + \left(\sum_{i=1}^{n} e_i\right)} \quad (1)$$

$$\mathrm{AVE} = \frac{\sum_{i=1}^{n} {L_i}^2}{n} \quad (2)$$

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 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 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 Lam [65].

Table 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		
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).

4.3. Multi-Group Analysis Results

Multi-group structural equation modeling (SEM) was employed to examine the invariance between the urban and rural groups (hypothesis$_1$). The findings are displayed in Table 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 [58], RMSEA = 0.054 [59], CFI = 0.937 [58], TLI = 0.925 [60,61], and SRMR = 0.056 [58].

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 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.

4.4. 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 4 and 5. The SEM model results can be found in Tables 8 and 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).

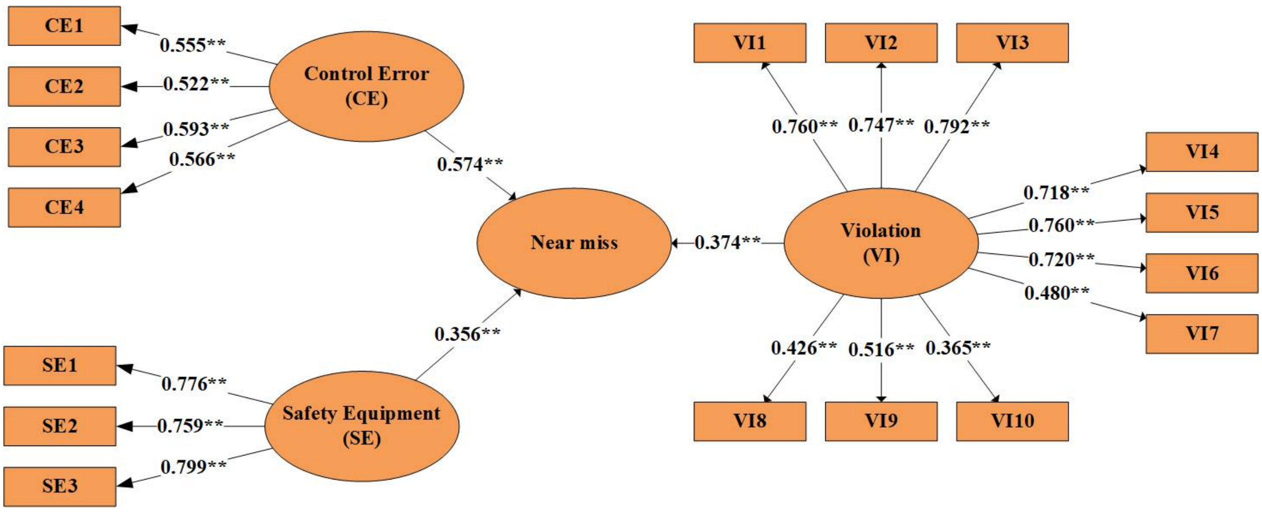

Figure 4. Structural equation modeling of near-misses in motorcycle riding for urban society. χ^2/df = 467.691/129 = 3.626, RMSEA = 0.050 (0.045–0.055), CFI = 0.946, TLI = 0.936, SRMR = 0.054, ** *p*-value < 0.001 (Mplus 7.0 standardized estimates).

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 [49,52].

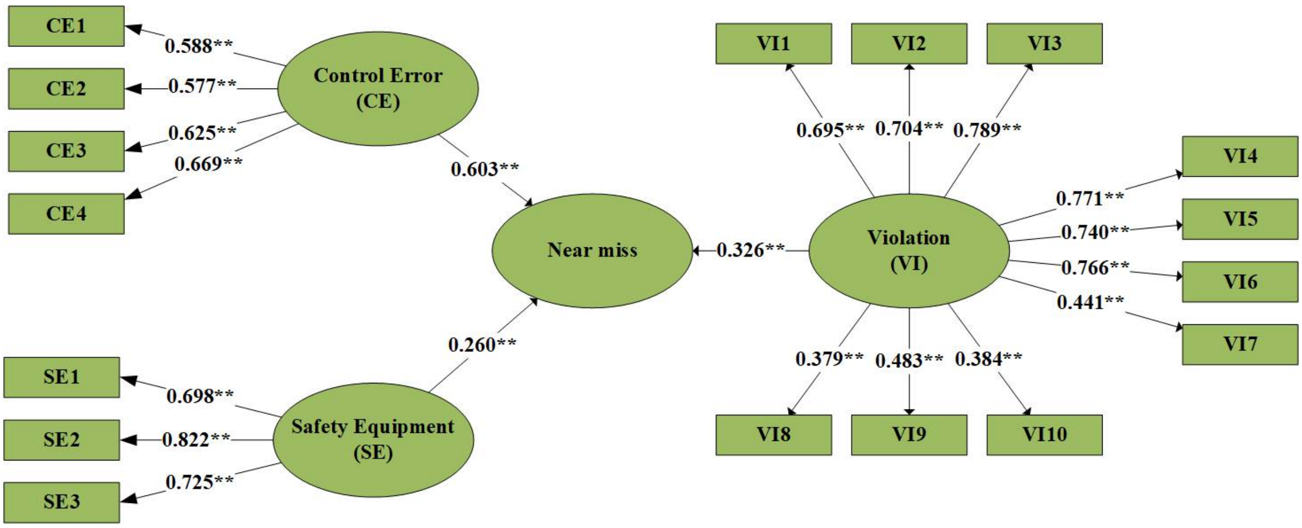

Figure 5. Structural equation modeling of near-misses in motorcycle riding in rural areas. χ^2/df = 537.798/129 = 4.169, RMSEA = 0.058 (0.053–0.063), CFI = 0.926, TLI = 0.912, SRMR = 0.065, ** *p*-value < 0.001 (Mplus 7.0 standardized estimates).

Table 8. Parameter estimate of the measurement model.

	Urban					Rural				
Variable	**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
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 9. Parameter estimates of the structural model.

		Urban				Rural			
	Hypothesis	**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).

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

I. **Hypothesis 2 (H2):** *Control error has a negative effect on near-misses in urban areas.*
II. **Hypothesis 3 (H3):** *Violation has a negative effect on near-misses in urban areas.*
III. **Hypothesis 4 (H4):** *Safety Equipment has a negative effect on near-misses in urban areas.*

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

I. **Hypothesis 5 (H5):** *Control error has a negative effect on near-misses in rural areas.*
II. **Hypothesis 6 (H6):** *Violation has a negative effect on near-misses in rural areas.*
III. **Hypothesis 7 (H7):** *Safety equipment has a negative effect on near-misses in rural areas.*

5. 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.

5.1. The MRBQ Factor Structure

5.1.1. 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 et al. [40], Elliott et al. [39], Özkan et al. [46], and Sumit et al. [41]. 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.

5.1.2. 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 [39]. 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 [41]. 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 [66].

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. [39], 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. [43] 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. [46] 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 et al. [67] 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 et al. [68] identified speeding and alcohol consumption as major factors contributing to motorcycle fatalities. Similar findings were reported in studies conducted in Thailand by Tongklao et al. [69], 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 [70]. 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. [71] revealed that the use of mobile phones is highly prevalent among motorcycle riders across all age groups. Similarly, in Vietnam, Truong et al. [72] 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 [73]. 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 [74]. These ten indicators, classified under the Violations (VI) model, represent risk factors that can contribute to near-miss incidents.

5.1.3. 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. [45] categorized these items as safety violations and control errors. A study by Zamani-Alavijeh et al. [75] 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 [75].

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 [39,42]. Research has shown that using daytime running lights on motorcycles significantly reduces the risk of accidents [76]. By activating motorcycle headlights during the daytime, the risk of motorcycle collisions can be reduced by approximately 4% to 20% [77].

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.

5.2. 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 (H2) and 5 (H5) were rejected, with a significance level set at 0.001. Research conducted in India by Chouhan et al. [40] 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. [78] also mentioned that riding in dusty or rainy conditions increases the likelihood of errors for motorcycle riders. Similarly, Sangkharat et al. [79] 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 et al. [80] 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 3 (H3) and Hypothesis 6 (H6) 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 [81]. 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% [82,83]. 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 [84].

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 [85]. 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 [86]. Another study by Arif et al. [87] 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 [88]. 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.

6. 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.

7. 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.

Author Contributions: Conceptualization, S.J. and N.H.; methodology, N.H.; software, V.R.; validation, C.S., T.C. and N.H.; formal analysis, N.H.; investigation, S.J.; resources, T.C.; data curation, N.H.; writing—original draft preparation, N.H.; writing—review and editing, S.J.; visualization, S.J.; supervision, S.J.; project administration, V.R.; funding acquisition, S.J. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by Office of the Permanent Secretary for Ministry of Higher Education, Science, Research and Innovation (OPS MHESI) and Thailand Science Research and

Innovation (TSRI), [Grant No. RGNS 63-122]. Article Processing Charge (APC) was supported by Suranaree University of Technology (SUT).

Institutional Review Board Statement: The study was conducted following the ethical guidelines outlined in the Helsinki Declaration and received approval from the Suranaree University of Technology Ethics Committee (COA No. 24/2563).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Data available on request due to restrictions, e.g., privacy or ethical.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Bhatti, J.A.; Ahmed, A. Evaluating performance of a Lead Road Safety Agency (LRSA) in a low-income country: A case study from Pakistan. *Int. J. Inj. Control. Saf. Promot.* **2014**, *21*, 136–143. [CrossRef] [PubMed]
2. Haghani, M.; Behnood, A.; Dixit, V.; Oviedo-Trespalacios, O. Road safety research in the context of low- and middle-income countries: Macro-scale literature analyses, trends, knowledge gaps and challenges. *Saf. Sci.* **2022**, *146*, 105513. [CrossRef]
3. World Health Organization. *Global Status Report on Road Safety*; World Health Organization: Geneva, Switzerland, 2018.
4. The World Bank. World Bank Country and Lending Groups. Available online: https://datahelpdesk.worldbank.org/knowledgebase/articles/906519 (accessed on 15 May 2021).
5. Haworth, N. Powered two wheelers in a changing world—Challenges and opportunities. *Accid. Anal. Prev.* **2012**, *44*, 12–18. [CrossRef]
6. Department of Land Transport. Statistical Data on Registered Vehicles in Thailand. Available online: https://web.dlt.go.th/statistics/ (accessed on 20 May 2021).
7. OECD/ITF. Improving Safety for Motorcycle, Scooter and Moped Riders. Available online: https://doi.org/10.1787/25186752 (accessed on 23 May 2021).
8. Se, C.; Champahom, T.; Jomnonkwao, S.; Ratanavaraha, V. Motorcyclist injury severity analysis: A comparison of Artificial Neural Networks and random parameter model with heterogeneity in means and variances. *Int. J. Inj. Control. Saf. Promot.* **2022**, *29*, 500–515. [CrossRef]
9. Champahom, T.; Se, C.; Aryuyo, F.; Banyong, C.; Jomnonkwao, S.; Ratanavaraha, V. Crash Severity Analysis of Young Adult Motorcyclists: A Comparison of Urban and Rural Local Roadways. *Appl. Sci.* **2023**, *13*, 11723. [CrossRef]
10. U.S. Department of Transportation's. Fatality Analysis Reporting System (FARS). Available online: https://www-fars.nhtsa.dot.gov/Main/index.aspx (accessed on 23 May 2021).
11. Harnen, S.; Wong, S.V.; Umar, R.S.R.; Wan Hashim, W.I. Motorcycle Crash Prediction Model for Non-Signalized Intersections. *IATSS Res.* **2003**, *27*, 58–65. [CrossRef]
12. Budd, L.; Allen, T.; Newstead, S. *Current Trends in Motorcycle Related Crash and Injury Risk in Australia by Motorcycle Type and Attributes*; Monash University: Melbourne, VIC, Australia, 2018.
13. Islam, S.; Brown, J. A comparative injury severity analysis of motorcycle at-fault crashes on rural and urban roadways in Alabama. *Accid. Anal. Prev.* **2017**, *108*, 163–171. [CrossRef]
14. Brenac, T.; Clabaux, N.; Perrin, C.; Elslande, P. Motorcyclist conspicuity-related accidents in urban areas: A speed problem? *Adv. Transp. Stud.* **2006**, *8*, 23–29.
15. Gkritza, K. Modeling motorcycle helmet use in Iowa: Evidence from six roadside observational surveys. *Accid. Anal. Prev.* **2009**, *41*, 479–484. [CrossRef]
16. Li, L.-P.; Li, G.-L.; Cai, Q.-E.; Zhang, A.L.; Lo, S.K. Improper motorcycle helmet use in provincial areas of a developing country. *Accid. Anal. Prev.* **2008**, *40*, 1937–1942. [CrossRef]
17. Aldred, R.; Crosweller, S. Investigating the rates and impacts of near misses and related incidents among UK cyclists. *J. Transp. Health* **2015**, *2*, 379–393. [CrossRef]
18. Powell, N.B.; Schechtman, K.B.; Riley, R.W.; Guilleminault, C.; Chiang, R.P.; Weaver, E.M. Sleepy driver near-misses may predict accident risks. *Sleep* **2007**, *30*, 331–342. [CrossRef]
19. Sanders, R.L. Perceived traffic risk for cyclists: The impact of near miss and collision experiences. *Accid. Anal. Prev.* **2015**, *75*, 26–34. [CrossRef] [PubMed]
20. Hardy, E. *Near Miss Study and Motorcycles: A Study of Motorcyclists in Northern Ireland, Southern Ireland and Great Britain*; Right To Ride Ltd.: Chorley, UK, 2009.
21. de Rome, L.; Fitzharris, M.; Baldock, M.; Fernandes, R.; Ma, A.; Brown, J. The prevalence of crash risk factors in a population-based study of motorcycle riders. *Injury* **2016**, *47*, 2025–2033. [CrossRef] [PubMed]
22. Aldred, R. Cycling near misses: Their frequency, impact, and prevention. *Transp. Res. Part A Policy Pract.* **2016**, *90*, 69–83. [CrossRef]
23. Aldred, R. Governing transport from welfare state to hollow state: The case of cycling in the UK. *Transp. Policy* **2012**, *23*, 95–102. [CrossRef]

24. Park, J.-I.; Kim, S.; Kim, J.-K. Exploring spatial associations between near-miss and police-reported crashes: The Heinrich's law in traffic safety. *Transp. Res. Interdiscip. Perspect.* **2023**, *19*, 100830. [CrossRef]
25. Devaux, M.; Sassi, F. Social disparities in hazardous alcohol use: Self-report bias may lead to incorrect estimates. *Eur. J. Public Health* **2016**, *26*, 129–134. [CrossRef]
26. Warner, C.H.; Appenzeller, G.N.; Grieger, T.; Belenkiy, S.; Breitbach, J.; Parker, J.; Warner, C.M.; Hoge, C. Importance of Anonymity to Encourage Honest Reporting in Mental Health Screening After Combat Deployment. *Arch. Gen. Psychiatry* **2011**, *68*, 1065–1071. [CrossRef] [PubMed]
27. Marín Puchades, V.; Fassina, F.; Fraboni, F.; De Angelis, M.; Prati, G.; de Waard, D.; Pietrantoni, L. The role of perceived competence and risk perception in cycling near misses. *Saf. Sci.* **2018**, *105*, 167–177. [CrossRef]
28. Shinar, D. *Traffic Safety and Human Behavior*; Emerald Group Publishing Limited: Bingley, UK, 2007.
29. Evans, L. *Human Behavior and Traffic Safety*; Springer: New York, NY, USA, 2012.
30. Ratanavaraha, V.; Amprayn, C. Causative highway accident factors of the expressway system in Thailand. *J. East. Asia Soc. Transp. Stud.* **2003**, *5*, 2422–2429.
31. Olson, P.L.; Dewar, R.E. *Human Factors in Traffic Safety*; Lawyers & Judges Pub.: Danvers, MA, USA, 2002.
32. Ameratunga, S.; Herman, J.; Wainiqolo, I.; Kafoa, B. A83 Road traffic injuries and Alcohol: Double jeopardy in Pacific Island nations fuelled by inequitably distributed determinants of health. *J. Transp. Health* **2015**, *2*, S48–S49. [CrossRef]
33. Agusdinata, D.B.; van der Pas, J.W.G.M.; Walker, W.E.; Marchau, V.A.W.J. Multi-criteria analysis for evaluating the impacts of intelligent speed adaptation. *J. Adv. Transp.* **2009**, *43*, 413–454. [CrossRef]
34. Chang, H.-L.; Yeh, T.-H. Motorcyclist accident involvement by age, gender, and risky behaviors in Taipei, Taiwan. *Transp. Res. Part F Traffic Psychol. Behav.* **2007**, *10*, 109–122. [CrossRef]
35. Lin, M.R.; Kraus, J.F. A review of risk factors and patterns of motorcycle injuries. *Accid. Anal. Prev.* **2009**, *41*, 710–722. [CrossRef]
36. de Rome, L.; Ivers, R.; Fitzharris, M.; Du, W.; Haworth, N.; Heritier, S.; Richardson, D. Motorcycle protective clothing: Protection from injury or just the weather? *Accid. Anal. Prev.* **2011**, *43*, 1893–1900. [CrossRef]
37. Vlahogianni, E.I.; Yannis, G.; Golias, J.C. Overview of critical risk factors in Power-Two-Wheeler safety. *Accid. Anal. Prev.* **2012**, *49*, 12–22. [CrossRef]
38. Jomnonkwao, S.; Champahom, T.; Se, C.; Hantanong, N.; Ratanavaraha, V. Contributing factors to near-miss experiences of motorcyclists in Thailand: A random parameter probit model approach. *Heliyon* **2023**, *9*, e22625. [CrossRef]
39. Elliott, M.A.; Baughan, C.J.; Sexton, B.F. Errors and violations in relation to motorcyclists' crash risk. *Accid. Anal. Prev.* **2007**, *39*, 491–499. [CrossRef]
40. Chouhan, S.S.; Kathuria, A.; Sekhar, C.R. Examining risky riding behavior in India using Motorcycle rider behavior questionnaire. *Accid. Anal. Prev.* **2021**, *160*, 106312. [CrossRef]
41. Sumit, K.; Ross, V.; Brijs, K.; Wets, G.; Ruiter, R.A.C. Risky motorcycle riding behaviour among young riders in Manipal, India. *BMC Public Health* **2021**, *21*, 1954. [CrossRef] [PubMed]
42. Sakashita, C.; Senserrick, T.; Lo, S.; Boufous, S.; Rome, L.d.; Ivers, R. The Motorcycle Rider Behavior Questionnaire: Psychometric properties and application amongst novice riders in Australia. *Transp. Res. Part F Traffic Psychol. Behav.* **2014**, *22*, 126–139. [CrossRef]
43. Stephens, A.N.; Brown, J.; de Rome, L.; Baldock, M.R.J.; Fernandes, R.; Fitzharris, M. The relationship between Motorcycle Rider Behaviour Questionnaire scores and crashes for riders in Australia. *Accid. Anal. Prev.* **2017**, *102*, 202–212. [CrossRef] [PubMed]
44. Trung Bui, H.; Saadi, I.; Cools, M. Investigating on-road crash risk and traffic offences in Vietnam using the motorcycle rider behaviour questionnaire (MRBQ). *Saf. Sci.* **2020**, *130*, 104868. [CrossRef]
45. Motevalian, S.A.; Asadi-Lari, M.; Rahimi, H.; Eftekhar, M. Validation of a persian version of motorcycle rider behavior questionnaire. *Ann. Adv. Automot. Med.* **2011**, *55*, 91–98.
46. Özkan, T.; Lajunen, T.; Doğruyol, B.; Yıldırım, Z.; Çoymak, A. Motorcycle accidents, rider behaviour, and psychological models. *Accid. Anal. Prev.* **2012**, *49*, 124–132. [CrossRef] [PubMed]
47. Topolšek, D.; Dragan, D. Relationships between the motorcyclists' behavioural perception and their actual behaviour. *Transport* **2016**, *33*, 151–164. [CrossRef]
48. Sunday, O.K. The performance of the motorcycle rider behaviour questionnaire among commercial motorcycle riders in Nigeria. *Inj. Prev.* **2010**, *16*, A194. [CrossRef]
49. Uttra, S.; Jomnonkwao, S.; Watthanaklang, D.; Ratanavaraha, V. Development of Self-Assessment Indicators for Motorcycle Riders in Thailand: Application of the Motorcycle Rider Behavior Questionnaire (MRBQ). *Sustainability* **2020**, *12*, 2785. [CrossRef]
50. Golob, T.F. Structural equation modeling for travel behavior research. *Transp. Res. Part B Methodol.* **2003**, *37*, 1–25. [CrossRef]
51. Finch, W.H. *Exploratory Factor Analysis*; SensePublishers: Rotterdam, The Netherlands, 2013; pp. 167–186.
52. Champahom, T.; Jomnonkwao, S.; Thotongkam, W.; Jongkol, P.; Rodpon, P.; Ratanavaraha, V. Investigating Parents' Attitudes towards the Use of Child Restraint Systems by Comparing Non-Users and User Parents. *Sustainability* **2023**, *15*, 2896. [CrossRef]
53. Hair, J.; Sarstedt, M.; Ringle, C.; Gudergan, S. *Advanced Issues in Partial Least Squares Structural Equation Modeling*; Sage Publications: Thousand Oaks, CA, USA, 2017.
54. Hair, J.F.; Risher, J.J.; Sarstedt, M.; Ringle, C.M. When to use and how to report the results of PLS-SEM. *Eur. Bus. Rev.* **2019**, *31*, 2–24. [CrossRef]

55. Henseler, J.; Ringle, C.M.; Sarstedt, M. Testing measurement invariance of composites using partial least squares. *Int. Mark. Rev.* **2016**, *33*, 405–431. [CrossRef]
56. Fan, Y.; Chen, J.; Shirkey, G.; John, R.; Wu, S.R.; Park, H.; Shao, C. Applications of structural equation modeling (SEM) in ecological studies: An updated review. *Ecol. Process.* **2016**, *5*, 19. [CrossRef]
57. Kline, R.B. *Principles and Practice of Structural Equation Modeling*, 3rd ed.; Guilford Press: New York, NY, USA, 2011.
58. Hu, L.t.; Bentler, P.M. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Struct. Equ. Model. A Multidiscip. J.* **1999**, *6*, 1–55. [CrossRef]
59. Steiger, J.H. Understanding the limitations of global fit assessment in structural equation modeling. *Personal. Individ. Differ.* **2007**, *42*, 893–898. [CrossRef]
60. Hooper, D.; Coughlan, J.P.; Mullen, M.R. *Structural Equation Modelling: Guidelines for Determining Model Fit*; University Press of America: New York, NY, USA, 2008.
61. Jomnonkwao, S.; Sangphong, O.; Khampirat, B.; Siridhara, S.; Ratanavaraha, V. Public transport promotion policy on campus: Evidence from Suranaree University in Thailand. *Public Transp.* **2016**, *8*, 185–203. [CrossRef]
62. Maskey, R.; Fei, J.; Nguyen, H.-O. Use of exploratory factor analysis in maritime research. *Asian J. Shipp. Logist.* **2018**, *34*, 91–111. [CrossRef]
63. Hair, J.; Black, W.; Babin, B.; Anderson, R. *Multivariate Data Analysis*, 6th ed.; Pearson Prentice Hall: Hoboken, NJ, USA, 2006; p. 899.
64. Taber, K.S. The Use of Cronbach's Alpha When Developing and Reporting Research Instruments in Science Education. *Res. Sci. Educ.* **2018**, *48*, 1273–1296. [CrossRef]
65. Lam, L.W. Impact of competitiveness on salespeople's commitment and performance. *J. Bus. Res.* **2012**, *65*, 1328–1334. [CrossRef]
66. SaveLIFE Foundation. Distracted Driving in India a Study on Mobile Phone Usage, Pattern & Behaviour. 2017. Available online: https://savelifefoundation.org/wp-content/uploads/2017/04/Distracted-Driving-in-India_A-Study-on-Mobile-Phone-Usage-Pattern-and-Behaviour.pdf (accessed on 25 May 2021).
67. Vu, A.T.; Nguyen, M.T.; Nguyen, D.V.M.; Khuat, V.H. Investigating the effect of blood alcohol concentration on motorcyclist's riding performance using an advanced motorcycle simulator. *Transp. Res. Part F Traffic Psychol. Behav.* **2020**, *73*, 1–14. [CrossRef]
68. Roehler, D.R.; Ear, C.; Parker, E.M.; Sem, P.; Ballesteros, M.F. Fatal motorcycle crashes: A growing public health problem in Cambodia. *Int. J. Inj. Control. Saf. Promot.* **2015**, *22*, 165–171. [CrossRef] [PubMed]
69. Tongklao, A.; Jaruratanasirikul, S.; Sriplung, H. Risky behaviors and helmet use among young adolescent motorcyclists in Southern Thailand. *Traffic Inj. Prev.* **2016**, *17*, 80–85. [CrossRef] [PubMed]
70. Injury Data Collaboration Center (IDCC). Injury Surveillance. Available online: http://ae.moph.go.th/ (accessed on 20 May 2021).
71. Pérez-Núñez, R.; Hidalgo-Solórzano, E.; Vera-López, J.D.; Lunnen, J.C.; Chandran, A.; Híjar, M.; Hyder, A.A. The Prevalence of Mobile Phone Use Among Motorcyclists in Three Mexican Cities. *Traffic Inj. Prev.* **2014**, *15*, 148–150. [CrossRef] [PubMed]
72. Truong, L.T.; Nguyen, H.T.T.; De Gruyter, C. Correlations between mobile phone use and other risky behaviours while riding a motorcycle. *Accid. Anal. Prev.* **2018**, *118*, 125–130. [CrossRef] [PubMed]
73. Truong, L.T.; Nguyen, H.T.T.; De Gruyter, C. Mobile phone use while riding a motorcycle and crashes among university students. *Traffic Inj. Prev.* **2019**, *20*, 204–210. [CrossRef] [PubMed]
74. Hassan, T.; Vinodkumar, M.N.; Vinod, N. Influence of demographics on risky driving behaviour among powered two wheeler riders in Kerala, India. *Transp. Res. Part F Traffic Psychol. Behav.* **2017**, *46*, 24–33. [CrossRef]
75. Zamani-Alavijeh, F.; Bazargan, M.; Shafiei, A.; Bazargan-Hejazi, S. The frequency and predictors of helmet use among Iranian motorcyclists: A quantitative and qualitative study. *Accid. Anal. Prev.* **2011**, *43*, 1562–1569. [CrossRef]
76. D'Elia, A.; Newstead, S. Evaluation of the effectiveness of daytime running lights (DRLs). *J. Saf. Res.* **2023**, *85*, 95–100. [CrossRef]
77. Davoodi, S.R.; Hossayni, S.M. Role of Motorcycle Running Lights in Reducing Motorcycle Crashes during Daytime; A Review of the Current Literature. *Bull. Emerg. Trauma* **2015**, *3*, 73–78.
78. Nguyen, D.V.M.; Vu, A.T.; Ross, V.; Brijs, T.; Wets, G.; Brijs, K. Small-displacement motorcycle crashes and risky ridership in Vietnam: Findings from a focus group and in-depth interview study. *Saf. Sci.* **2022**, *152*, 105514. [CrossRef]
79. Sangkharat, K.; Thornes, J.E.; Wachiradilok, P.; Pope, F.D. Determination of the impact of rainfall on road accidents in Thailand. *Heliyon* **2021**, *7*, e06061. [CrossRef] [PubMed]
80. Wan, Y.; Li, Y.; Liu, C.; Li, Z. Is traffic accident related to air pollution? A case report from an island of Taihu Lake, China. *Atmos. Pollut. Res.* **2020**, *11*, 1028–1033. [CrossRef]
81. Saini, H.K.; Chouhan, S.S.; Kathuria, A. Exclusive motorcycle lanes: A systematic review. *IATSS Res.* **2022**, *46*, 411–426. [CrossRef]
82. Radin Umar, R.S. Motorcycle safety programmes in Malaysia: How effective are they? *Int. J. Inj. Control. Saf. Promot.* **2006**, *13*, 71–79. [CrossRef]
83. Ibrahim, M.K.A.; Hamid, H.; Law, T.H.; Wong, S.V. Evaluating the effect of lane width and roadside configurations on speed, lateral position and likelihood of comfortable overtaking in exclusive motorcycle lane. *Accid. Anal. Prev.* **2018**, *111*, 63–70. [CrossRef]
84. Osorio-Cuéllar, G.V.; Pacichana-Quinayaz, S.G.; Bonilla-Escobar, F.J.; Fandiño-Losada, A.; Jaramillo-Molina, C.; Gutiérrez-Martínez, M.I. First motorcycle-exclusive lane (Motovia) in Colombia: Perceptions of users in Cali, 2012–2013. *Int. J. Inj. Control. Saf. Promot.* **2017**, *24*, 145–151. [CrossRef]

85. Ivanišević, T.; Ivković, I.; Čičević, S.; Trifunović, A.; Pešić, D.; Vukšić, V.; Simović, S. The impact of daytime running (LED) lights on motorcycles speed estimation: A driving simulator study. *Transp. Res. Part F Traffic Psychol. Behav.* **2022**, *90*, 47–57. [CrossRef]
86. Tripathi, M.; Tewari, M.K.; Mukherjee, K.K.; Mathuriya, S.N. Profile of patients with head injury among vehicular accidents: An experience from a tertiary care centre of India. *Neurol. India* **2014**, *62*, 610–617.
87. Arif, M.Z.; Rajanikanth, B.R.; Prasad, K. The Role of Helmet Fastening in Motorcycle Road Traffic Accidents. *Craniomaxillofac. Trauma Reconstr.* **2019**, *12*, 284–290. [CrossRef]
88. Henning-Smith, C.; Kozhimannil, K.B. Rural-Urban Differences in Risk Factors for Motor Vehicle Fatalities. *Health Equity* **2018**, *2*, 260–263. [CrossRef] [PubMed]