University of Zagreb

Faculty of Transport and Traffic Sciences

Hasselt University

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ASSESSMENT OF INFLUENTIAL FACTORS ON MOTORCYCLISTS' SAFETY ON RURAL ROADS

INTERNATIONAL DUAL DOCTORAL THESIS

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Mentors:
Asst. prof. Dario Babić, Ph.D.
Prof. dr. ir. Ali Pirdavani

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Fakultet prometnih znanosti

Sveučilište u Hasseltu

Marija Ferko

UTBRĐIVANJE UTJECAJNIH ČIMBENIKA NA SIGURNOST MOTOCIKLISTA NA RURALNIM CESTAMA

MEĐUNARODNI DVOJNI DOKTORSKI RAD

Mentori:
Doc. dr. sc. Dario Babić
Prof. dr. ir. Ali Pirdavani

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“I am not the same, having seen the moon shine

on the other side of the world.”

— M. A. Radmacher

Mentors' information

Asst. prof. Dario Babić, Ph.D.

Dario Babić was born on August 27, 1987, in Zagreb, Croatia. He graduated with excellent success in September 2011 from the Faculty of Transport and Traffic Sciences at the University of Zagreb, earning the title of Master of Traffic Engineering. After completing his studies, he enrolled in a postgraduate program (field: Traffic and Transport Technology) at the same faculty and, on January 24, 2018, successfully defended his doctoral dissertation titled "Model for Predicting the Duration of Road Markings."

Since October 2011, he has been employed at the Department of Traffic Signaling at the Faculty of Transport and Traffic Sciences, University of Zagreb. Between 2019 and 2022, he served as the Head of the Testing Laboratory at the Department of Traffic Signaling. Additionally, from 2022 until today, he holds the position of Vice Dean for Science and External Cooperation at the Faculty of Transport and Traffic Sciences.

He is the author of over 60 scientific papers published in international scientific and professional journals and presented at international conferences. Throughout his career, he has participated in several scientific projects such as TWIN-SAFE, CAMBER, IVORY, and eSCRUB. He conducted his postdoc at the Institute of Mobility (IMOB) at Hasselt University (Belgium), working as a principal investigator of the scientific research project titled "Understanding the Impact of Traffic Signaling on Driver Behavior." He is also a recipient of the Fulbright scholarship, under which he stayed at the College of Engineering, Department of Civil and Environmental, Michigan State University (USA), from September 2021 to June 2022, working as a researcher on the project "Speed Feedback Signs for Reducing Run-off-Road Crashes on Freeway Ramps."

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Prof. Dr. ir. Ali Pirdavani

Prof. Dr. ir. Ali Pirdavani (born November 11, 1980, in Tehran, Iran) is an Associate Professor at Hasselt University, Belgium, where he is affiliated with the Faculty of Engineering Technology and the Transportation Research Institute (IMOB). He holds a Bachelor's degree in Civil Engineering (2004) and a Master's in Road & Transportation Engineering (2007). In 2012, he earned his Ph.D. in Transportation Sciences from Hasselt University. Following his doctoral studies, he was awarded a prestigious postdoctoral fellowship from the Research Foundation – Flanders (FWO) in 2013, focusing on crash modeling and road safety impact assessments.

Since joining Hasselt University as a faculty member in 2016, Prof. Pirdavani has established himself as a leading researcher in the fields of road safety, transportation infrastructure, and automated vehicles. His work particularly emphasizes AI-based road safety solutions, digitalization in road design, and infrastructure adaptation for automated and connected mobility. He has coordinated and contributed to numerous national and European research projects, including *AI for Vision Zero in Road Safety (IVORY)*, *Connected and Adaptive Maintenance for Safer Urban and Secondary Roads (CAMBER),* and *Advancing Road Safety Through Twinning (TwinSafe)*.

Prof. Pirdavani has an extensive academic record with more than 100 peer-reviewed journal articles and conference contributions. His research has gained international recognition, reflected in over 1,800 citations, an h-index of 25, and an i10-index of 46 (Google Scholar, 2025). In addition, he has supervised numerous Ph.D. and master's theses, further underlining his dedication to academic mentoring and capacity building.

Beyond his research and teaching activities, Prof. Pirdavani plays an active role in the academic community as an editorial board member of several leading journals, including *Advances in Transportation Sciences*, *KSCE Journal of Civil Engineering*, *Promet – Traffic & Transportation*, and *Sustainability*. His contributions to international collaborations, conferences, and policy discussions position him as a prominent figure in shaping the future of safe and sustainable mobility.

Abstract

This doctoral dissertation investigates motorcyclist safety on rural roads by integrating multiple data sources and analytical methods. It comprises six empirical chapters addressing different dimensions of motorcycle risk. Introductory chapter sets up the methodology and brings up the problem statement. Chapter 2 analyzes single-vehicle crashes using police crash data, identifying key predictors of severe outcomes, including crash type and characteristics, pavement condition, and rider-related factors. Chapter 3 evaluates the safety performance of various roadside barrier types, highlighting the necessity for motorcyclist-friendly solutions. In Chapter 4, speeding behavior is examined through models incorporating temporal, infrastructural, and locational factors, revealing higher speeding likelihood in specific road environments and times. Chapter 5 develops an updated Motorcycle Rider Behavior Questionnaire (MRBQ) based on the sample of Croatian riders. In Chapter 6, MRBQ-based models confirm the predictive value of behavior patterns and perceived infrastructure flaws for crash involvement, near-crashes, and traffic fines. Chapter 7 utilizes smartphone-based naturalistic riding data, demonstrating that aggressive acceleration and higher over-limit speeds predict increased speeding duration, while motorway riding has a mitigating effect. The findings support all three main hypotheses and emphasize the role of contextual, behavioral, and infrastructural influences. The final part of the dissertation concludes with targeted recommendations for rural safety strategies. It outlines future research directions, including geospatial analysis, cross-national comparisons, and applying intelligent safety systems for motorcyclists.

Key words:

Motorcyclist safety; crash severity; MRBQ; road infrastructure; rider behavior.

Sažetak

Doktorska disertacija istražuje sigurnost motociklista na ruralnim cestama integriranjem višestrukih izvora podataka i analitičkih metoda. Sastoji se od šest poglavlja koja obrađuju različite aspekte rizika za motocikliste. Uvodno poglavlje postavlja metodološki okvir i definira istraživački problem. U Poglavlju 2 analizirane su motociklističke prometne nesreće uz korištenje podataka o nesrećama, pomoću čega su identificirani utjecajni čimbenici na posljedice prometnih nesreća, uključujući tip nesreće, stanje kolnika i čimbenike povezane s vozačem. U Poglavlju 3 istraživane su sigurnosne karakteristike različitih vrsta zaštitnih ograda, a naglašena je potreba za rješenjima koja su sigurnija za motocikliste. U Poglavlju 4 istraživano je prekoračenje brzine kroz vremenske, infrastrukturne i lokacijske čimbenike, pri čemu je utvrđena veća vjerojatnost prebrze vožnje u određenim prometnim okruženjima i vremenskom kontekstu. Poglavlje 5 prikazuje razvoj ažuriranog Upitnika o ponašanju motociklista (MRBQ) na uzorku hrvatskih vozača. U Poglavlju 6 modeli temeljeni na MRBQ potvrđuju prediktivnu vrijednost obrazaca ponašanja i percipiranih infrastrukturnih nedostataka u predviđaju prometnih nesreća i policijskih kazni. U Poglavlju 7 korišteni su podaci o vožnji motocikla prikupljeni iz pametnih telefona, koji pokazuju da nagla akceleracija i veća prekoračenja brzine predviđaju duže trajanje vožnje iznad ograničenja, dok vožnja autocestom ima blago obrnuti učinak. Rezultati prikazani u disertaciji potvrđuju sve tri glavne hipoteze i naglašavaju važnost kontekstualnih i infrastrukturnih utjecaja te utjecaja obrazaca ponašanja. Završni dio disertacije donosi ciljanje preporuke za strategije sigurnosti motociklista na ruralnim cestama te iznosi smjernice za buduća istraživanja, uključujući geoprostornu analizu, međudržavne usporedbe i primjenu inteligentnih sigurnosnih sustava za motocikliste.

Ključne riječi:

Sigurnost motociklista; posljedice prometne nesreće; MRBQ; cestovna infrastruktura; ponašanje vozača.

Executive Summary

This doctoral dissertation investigates motorcyclist safety on rural roads through an integrated, multidisciplinary approach, combining traditional crash data, rider behavior surveys, naturalistic trip data, and infrastructure assessments. The work responds to the persistent overrepresentation of riders in road fatalities, especially on rural roads where infrastructure and enforcement limitations heighten the risk. While overall road fatalities in the EU have declined, the share of motorcyclist fatalities has increased relatively, highlighting the need for a focused research effort.

In the Introduction, the background of the topic is explored, including the current state of motorcyclist safety and an overview of specifics related to motorcycle riding. Furthermore, the methodological framework, research questions, objectives, and hypotheses were presented.

The research is structured across six empirical chapters, each targeting a distinct aspect of motorcycle safety. The first analytical chapter (Chapter 2) models the severity of single-vehicle motorcycle crashes using a five-year Croatian police crash database. Results show that crash characteristics (e.g., type, location), infrastructure elements (e.g., pavement condition), and rider attributes (e.g., age, alcohol use) significantly affect the likelihood of fatal outcomes. The second study evaluates the crash risk posed by different types of roadside barriers, and investigating critical locations and recommending implementing motorcyclist-friendly systems over conventional steel guardrails.

The third chapter explores speeding behavior using categorical regression models, revealing that speeding is more frequent in low-traffic areas, on roads with lower speed limits, outside settlements, and further from the intersections. Chapter 4 presents the development and validation of a revised Motorcycle Rider Behavior Questionnaire (MRBQ), with the survey conducted within the Croatian sample (906 respondents). The revised MRBQ demonstrated good psychometric properties and was used in Chapter 5, based on the sample of 842 respondents, to predict involvement in crashes, near-crashes, and traffic fines. Results confirm that specific risky behaviors (errors) significantly predict (near-)crash outcomes, while older riders are less likely to get involved in such events. On the other hand, behaviors including violations and stunts were found to be significant predictors of getting traffic fines.

The final empirical chapter utilizes smartphone-based naturalistic riding data from over 1800 trips (over 36,000 km) by 19 riders. A multiple linear regression model, using a log-transformed speeding variable, reveals that higher average overspeed and aggressive acceleration are strongly associated with prolonged speeding behavior, while riding on

motorways reduces it. This chapter showcases the feasibility and value of smartphone-based methods in rural motorcycle safety research.

Across all analyses, the research confirms three main hypotheses: that crash and behavioral outcomes can be explained by integrated data on infrastructure and riders; that infrastructure and type quality affect rider behavior; and that rider behavior can be systematically measured and modeled to predict safety outcomes. Practical recommendations include improving safety along local roads, applying motorcyclist-friendly road equipment, targeting aggressive riding in safety campaigns, and tailoring interventions to younger rider profiles.

The dissertation concludes with suggestions for future research, emphasizing the need to include multi-vehicle crashes, expand geospatial analyses, compare data across neighboring countries, and explore the role of intelligent systems (e.g., ARAS, airbags, warning technologies) and innovative infrastructure solutions in preventing crashes and mitigating consequences.

This work contributes to traffic safety science by providing a comprehensive, data-driven understanding of the factors influencing motorcyclist risk on rural roads and proposing scalable, evidence-based interventions.

Prošireni sažetak

Ova doktorska disertacija istražuje sigurnost motociklista na ruralnim cestama primjenom integriranog, multidisciplinarnog pristupa koji uključuje podatke o prometnim nesrećama, upitnike o ponašanju vozača motocikala, naturalističke podatke o vožnji te procjenu cestovne infrastrukture. Istraživanje odgovara na problem stalne prekomjerne zastupljenosti motociklista u prometnim nesrećama sa smrtnim ishodom i teškim posljedicama, osobito na ruralnim cestama gdje infrastrukturni nedostaci i provođenje zakonskih kontrola dodatno povećavaju rizik. Iako se broj poginulih u prometu u EU općenito smanjuje, udio poginulih motociklista relativno raste, što ukazuje na potrebu za ciljanijim istraživanjem.

U uvodnom poglavlju prikazana je pozadina teme, uključujući trenutačno stanje sigurnosti motociklista i specifičnosti vožnje motocikla. Nadalje, predstavljen je metodološki okvir, istraživačka pitanja, ciljevi i hipoteze.

Istraživanje je strukturirano u šest empirijskih poglavlja, od kojih se svako bavi posebnim aspektom sigurnosti motociklista. Prvo analitičko poglavlje (Poglavlje 2) modelira težinu ishoda u nesrećama motocikala u kojima je sudjelovalo samo jedno vozilo, koristeći petogodišnju bazu podataka hrvatske prometne policije. Rezultati pokazuju da karakteristike nesreće (npr. tip, lokacija), elementi infrastrukture (npr. stanje kolnika) te obilježja vozača (npr. dob, konzumacija alkohola) značajno utječu na vjerojatnost smrtnog ishoda. Drugo poglavlje procjenjuje rizik od posljedica prometnih nesreća uz različite vrste zaštitnih ograda, i istraživanje kritičnih lokacija, uz preporuku implementacije sustava prilagođenih motociklistima umjesto konvencionalnih čeličnih ograda.

Treće poglavlje istražuje ponašanje pri prekoračenju brzine koristeći kategorijalne regresijske modele, pri čemu se pokazuje da je prekoračenje brzine učestalije u područjima s manjim prometnim opterećenjem, na cestama s nižim ograničenjima brzine, izvan naselja i dalje od raskrižja. Četvrto poglavlje prikazuje razvoj i validaciju revidirane verzije Upitnika o ponašanju motociklista (MRBQ), provedenog na hrvatskom uzorku (od 906 ispitanika). Revidirani MRBQ pokazao je dobre karakteristike te je korišten u Poglavlju 5 (uzorak od 842 ispitanika) za predikciju sudjelovanja u nesrećama i dobivanja kazni u prometu. Rezultati potvrđuju da su određena rizična ponašanja (npr. pogreške) značajni prediktori sudjelovanja u nesrećama, dok su stariji vozači manje skloni takvim ishodima. S druge strane, ponašanja poput kršenja pravila i izvođenja „vratolomija“ pokazala su se značajnim prediktorima dobivanja prometnih kazni.

U završnom empirijskom poglavlju korišteni su naturalistički podaci prikupljeni putem pametnih telefona za više od 1800 vožnji (više od 36.000 km) od strane 19 motociklista. Model višestruke linearne regresije, s log-transformiranom varijablom vremena provedenog u prekoračenju brzine, pokazuje da je visina prosječne brzine iznad ograničenja i agresivna ubrzanja povezani s dužim trajanjem vožnje iznad ograničenja brzine, dok vožnja po autocesti ima suprotni učinak, odnosno manje je trajanje vožnje u prekoračenju brzine. Ovo poglavlje pokazuje mogućnosti i korisnost korištenja pametnih telefona za istraživanja sigurnosti motociklista na ruralnim cestama.

Kroz sva istraživanja potvrđene su tri glavne hipoteze: da se sigurnosni ishodi mogu objasniti integriranim podacima o infrastrukturi i vozačima; da stanje i tip infrastrukture utječu na ponašanje vozača; te da se ponašanje vozača može sustavno mjeriti i modelirati u svrhu predviđanja sigurnosnih ishoda. Praktične preporuke uključuju poboljšanje sigurnosti na lokalnim cestama, primjenu opreme prilagođene motociklistima, ciljanje agresivne vožnje sigurnosnim kampanjama i prilagodbu mjera prema profilu vozača.

Disertacija završava prijedlozima za buduća istraživanja, naglašavajući potrebu uključivanja nesreća s više vozila, proširenje geoprostorne analize, usporedbe s podacima susjednih zemalja te istraživanja uloge inteligentnih sustava (npr. ARAS, zračni jastuci, sustavi upozorenja) i inovativnih infrastrukturnih rješenja u sprječavanju nesreća i ublažavanju njihovih posljedica.

Ovaj rad predstavlja znanstveni doprinos u području sigurnosti cestovnog prometa pružanjem sveobuhvatnog, podatkovno utemeljenog uvida u čimbenike rizika za motocikliste na ruralnim cestama i predlaže primjenjive, znanstveno utemeljene mjere za poboljšanje sigurnosti.

Abbreviations and acronyms

AIC – Akaike Information Criterion
ANN – Artificial Neural Network
ARAS – Advanced Rider Assistance Systems
ASDT – Annual Summer Daily Traffic
AUC – Area Under the Curve
BAC – Blood Alcohol Concentration
BLR – Binary Logistic Regression
BOF – Bijzonder Onderzoeksfonds (Special Research Fund)
CHAID – Chi-squared Automatic Interaction Detection
CI – Confidence Interval
DV – Dependent Variable
DBQ – Driver Behavior Questionnaire
EU – European Union
GIS – Geographic Information System
GPS – Global Positioning System
ID – Identifier
IRTAD – International Road Traffic and Accident Database
IV – Independent Variable
km/h – Kilometers per hour
ML – Machine Learning
MLP – Multilayer Perceptron
MLR – Multinomial Logistic Regression
MLR – Multiple Linear Regression
MPS – Motorcycle Protection System
MRBQ – Motorcycle Rider Behavior Questionnaire
NN – Neural Network
O1-O5 – Objectives 1 to 5
OR – Odds Ratio
PCA – Principal Component Analysis
PPE – Personal Protective Equipment
PTW – Powered Two-Wheeler
R^2 – Coefficient of Determination
RF – Random Forest
ROC – Receiver Operating Characteristic
RQ – Research Question
RQ1-RQ5 – Research Questions 1 to 5
SD – Standard Deviation
SEM – Structural Equation Modeling
SPSS – Statistical Package for the Social Sciences
TPB – Theory of Planned Behavior
VIF – Variance Inflation Factor

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Chapter 1.

Introduction

The road transport system continues to face numerous challenges. It consists of the interaction of different users who use the transport infrastructure and various transport modes to cover a certain distance under the influence of different motives and needs. Despite significant technological and engineering advancements in recent decades, along with sustained efforts to enhance road safety, traffic-related injuries and fatalities remain a critical global issue. The burden of road trauma continues to be substantial, both in terms of individual human suffering and broader societal and economic costs.

The EU has adopted a long-term road safety objective known as “Vision Zero,” aiming to reduce road transport fatalities to near zero by 2050 (“EUROPE ON THE MOVE - Sustainable Mobility for Europe: Safe, Connected, and Clean,” 2018). This ambition extends to serious injuries as well. As part of this strategy, the EU has set interim targets to achieve a 50% reduction in road deaths and serious injuries between 2020 and 2030. To achieve “Vision Zero,” the EU road safety policy framework 2021-2030 was set based on the safe system approach (European Commission, 2020). This is consistent with the UN General Assembly Resolution 74/299, which declared a Decade of Action for Road Safety 2021–2030, setting a global target to reduce road traffic deaths and injuries by at least 50% during this period (WHO, 2021).

Concerns related to road safety vary considerably across the globe, reflecting differences in economic development, motorization, infrastructure quality, and enforcement capacity. Nevertheless, a shared global objective remains – to eliminate road fatalities and reduce the rate and severity of road traffic injuries. In pursuit of this goal, road safety strategies increasingly prioritize the protection of vulnerable road users, including pedestrians, cyclists, and motorcyclists („Directive (EU) 2019/1936,” 2019), who face disproportionately high risks in traffic.

Motorcycling is widely recognized as one of the most unsafe forms of transportation. In contrast to passenger vehicles, motorcycles demand greater physical coordination and balance from the rider while offering minimal structural protection during a crash. The inherent vulnerability of motorcyclists[1] is further exacerbated by the vehicle’s relatively small size, which can reduce its visibility to other road users and increase the severity of outcomes in collisions, particularly those involving larger and heavier vehicles such as cars or trucks.

In the continuation of this chapter, the characteristics of riding a motorcycle, indicators of the state of safety around the world, and why it is important to recognize the key factors that

[1] This thesis will interchangeably use the terms *motorcyclist*, *rider*, or *motorcycle rider* as synonyms. The term *powered two-wheeler (PTW) user/rider* usually considers both motorcycle and moped riders.

can affect the safety of motorcyclists are discussed in detail. Furthermore, the research aim, hypotheses, and methodology approach are presented.

1.1. Background

The *Background* subchapter presents an overview of current motorcycle safety indicators and outlines the unique characteristics distinguishing motorcyclists from other road users. It further examines the influence of vehicle-related, human, and environmental factors contributing to motorcycle safety outcomes based on the existing literature and previous research.

1.1.1. Overview of motorcycle safety indicators across the globe

Globally, road traffic injuries represent the 12th leading cause of death across all age groups (WHO, 2023a). Alarmingly, among individuals aged 5 to 29 years, road injuries are the leading cause of death, stressing the disproportionate impact of road trauma on younger populations. Although the overall number of road deaths has decreased in the last two decades, road safety remains a noteworthy concern due to vulnerable age groups that are most affected, but also due to specific groups of road users (vulnerable road users – cyclists, pedestrians, and motorcyclists). Furthermore, although 12th place in terms of mortality may not seem high, it is worth keeping in mind that road injuries are something that can be addressed relatively quickly and effectively (especially with a holistic approach), unlike, for example, incurable or hereditary diseases.

Fatality rates among motorcyclists remain high despite improvements in helmet use, vehicle manufacturing, and legislation. Between 2010 and 2019, a 7.7% overall reduction in road traffic fatalities was observed across 34 countries with validated data (International Transport Forum, 2022a). However, disaggregated analysis by road user type reveals considerable variation in fatality trends. The most substantial decrease was recorded among car occupants, whose fatalities declined by 19% during this period. In contrast, reductions among vulnerable road users were notably smaller, with pedestrian deaths falling by only 3% and cyclist deaths by 1%. Alarmingly, the number of fatalities among powered two-wheeler (PTW) users, including motorcyclists, increased by 7%, underscoring a divergent and concerning trend for this road user group.

Motorcycle riders are significantly overrepresented in global traffic fatalities (WHO, 2023b). Motorcycles make up only 10% of vehicles but account for over 30% of road deaths in some countries. Between 2010 and 2019, motorcyclist fatalities varied significantly across countries, reflecting divergent regional trends in PTW safety (International Transport Forum, 2022a). According to IRTAD data, South American countries experienced particularly alarming increases: Chile reported an 89% rise in motorcyclist fatalities, followed by Argentina (+70%) and Colombia (+66%). These increases are especially concerning given the high proportion of PTWs in the overall vehicle fleets of these countries.

In contrast, notable reductions were observed in several high-income countries. Switzerland, Norway, and Japan recorded the most substantial decreases, with fatality reductions of 45%, 43%, and 43%, respectively. In total, 18 IRTAD countries experienced either stagnation or a decline in motorcyclist deaths, while 16 countries saw increases. The data underline stark contrasts in motorcyclist safety progress, underlining the need for regionally tailored policy responses and interventions.

Motorcycling experienced a marked increase in popularity in the early 2000s, as evidenced by significant growth in motorcycle registrations and vehicle miles traveled (VMT) during that period (NHTSA's Office of Behavioral Safety Research, 2011, 2023). From 2003 to approximately 2011, both metrics followed a rising trajectory, after which they plateaued, remaining relatively stable through 2021. A temporary decline in both registrations and VMT occurred between 2019 and 2020—likely influenced by the COVID-19 pandemic—followed by a rebound in 2021 (Office of Highway Policy Information, 2025).

A substantial rise in motorcyclist crash involvement paralleled this increase in exposure. Between 2000 and 2008, the number of motorcyclist fatalities in the United States rose by 83%, while injuries increased by 66% (NHTSA's Office of Behavioral Safety Research, 2011). Since 2015, the annual number of motorcyclist fatalities has consistently exceeded 5,000 (NHTSA's Office of Behavioral Safety Research, 2023). Of growing concern is the observed surge in fatal crashes for all road users, including motorcyclists, since the onset of the COVID-19 pandemic (NHTSA's Office of Behavioral Safety Research, 2021). Despite comprising only 3.5% of all registered vehicles, motorcyclists accounted for 14% of all motor vehicle-related fatalities in 2021 (NHTSA's Office of Behavioral Safety Research, 2023). When adjusted for exposure, the disparity becomes even more pronounced: motorcyclists were nearly 24 times more likely to die in a crash per vehicle mile traveled compared to passenger car occupants. Specifically, in 2021, there were 30.68 motorcyclist fatalities per 100 million VMT, compared to 1.22 for passenger car occupants.

According to data for the European region, in 2019, motorcyclists accounted for 16% of all road traffic fatalities within the European Union (Slootmans, 2023b). While motorcycle-related fatalities declined by 14% between 2010 and 2019, this reduction was less pronounced than the overall decrease in road fatalities, which fell by 23% during the same period. In 2023, motorcycle road fatalities accounted for 17% of all road deaths (Atasayar et al., 2025). In contrast, ten years earlier (2013), motorcycle fatalities comprised 14% of road fatalities (Slootmans, 2023b). The overall prevalence of powered two-wheelers (PTWs) has risen considerably over recent decades, increasing from 39.3 vehicles per 1,000 inhabitants in 1994 to 67.8 in 2019 (Vanpée et al., 2022). However, the comparatively modest reduction in motorcycle fatalities contrasts with the substantial 45% decline observed in moped-related fatalities over the 2010-2019 period (Slootmans, 2023b).

Motorcycle-related mortality rates and the proportion of motorcyclist fatalities relative to total road deaths are highest in the southern regions of the European Union; though, their usage is particularly concentrated in southern European countries (Nuyttens, 2020; Slootmans, 2023b).

Regarding the type of crash according to the number of vehicles involved, motorcycles collide most often with passenger vehicles (43%), but the percentage of single-vehicle motorcycle crashes is very high (38%) (European Commission, 2024).

According to statistical data for the Republic of Croatia, the share of motorcycle crashes in the total number of crashes increased from 3.5% in 2013 to 4.4% in 2023 (Ministry of the Interior of the Republic of Croatia, 2024), as shown in Figure 1-1. At the same time, the share of fatalities in the total number of fatalities in the same period increased from 16.4% to 30.7%, which is a significantly higher share compared to the EU average.

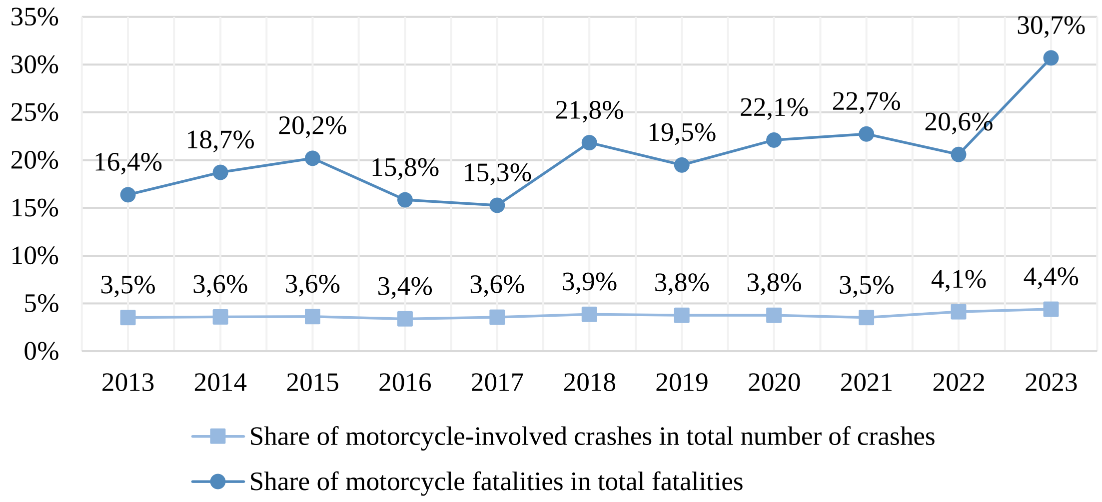


Figure 1-1. Statistics on motorcycle crashes in Croatia

Despite the presence of some of the most advanced transport infrastructure, high standards of personal protective equipment (PPE), and accessible emergency healthcare systems in the European Union, the number of motorcyclist fatalities has shown very modest improvement in recent years. While other categories of road users have benefited from notable declines in fatality rates, motorcyclist deaths have remained relatively stagnant or declined at a much slower pace. This discrepancy highlights persistent challenges unique to motorcycle safety, including behavioral risk factors, exposure patterns, and the limited effectiveness of conventional road safety measures in addressing the specific vulnerabilities of powered two-wheeler users. These trends raise important questions about their safety and emphasize the need for further research.

1.1.2. What is so unique about motorcycles?

Motorcycles are widely used in developed and developing countries, serving various purposes, including daily commuting, recreational riding, and commercial transport (e.g., taxi or delivery). Their popularity is often attributed to several key advantages: motorcycles are generally more affordable and fuel-efficient than cars, they require less space on the road and for parking, and their smaller size and high maneuverability make them particularly well-suited for navigating congested urban environments or areas with limited infrastructure (Fagnant et al., 2013). In many regions, especially in rural or peri-urban areas where public transportation is inadequate or unavailable, motorcycles have become a primary mode of transport (Porter, 2014). Additionally, motorcycles are frequently used for leisure and tourism activities in developed countries and warmer climates or during certain seasons (Illum, 2011). However, despite these benefits, motorcycles also present significant safety challenges. Motorcyclists remain among the most vulnerable road users, with elevated risks of severe injury or death in the event of a crash due to limited physical protection and high exposure to external hazards.

Motorcycles are commonly described as single-track vehicles, requiring the rider to maintain balance and stability actively. This task can become particularly demanding on certain road sections, such as in sharp curves, uneven surfaces, or adverse weather conditions. This characteristic distinguishes motorcyclists from other road users, such as car drivers, who benefit from the inherent stability provided by a multi-track vehicle. Furthermore, unlike occupants of enclosed vehicles, motorcyclists lack structural protection, rendering them significantly more vulnerable in a crash and less resilient to environmental influence.

1.1.2.1. Legal description

Based on European legislation (“Directive 2002/24/EC,” 2002; “Regulation (EU) 168/2013,” 2013), L-category vehicles include powered two-, three-, and four-wheel vehicles, with further classification by design and performance. All L-category vehicles may have a maximum length of 4,000 mm, a width of 2,000 mm, and a height of 2,500 mm. Among these, two-wheel motorcycles[2] fall under category L3e, which includes a range of performance levels and special-use subcategories. These classifications serve technical regulation (e.g., emissions and safety standards) and market surveillance purposes. Within the L3e category, motorcycles are sub-classified by performance level and special use, as shown in Table 1-1.

Table 1-1. Two-wheel motorcycle classification

Subcategory	Description	Use Type
L3e-A1	Low-performance motorcycle	General
L3e-A2	Medium-performance motorcycle	General
L3e-A3	High-performance motorcycle	General
L3e-AxE	Enduro motorcycle (x = 1, 2, 3)	Off-road (enduro use)
L3e-AxT	Trial motorcycle (x = 1, 2, 3)	Specialized (trial riding)

Source: "Regulation (EU) 168/2013," (2013)

In addition to these vehicles being categorized in detail, the driving license levels for L-category vehicles are also categorized. Motorcycle driving licenses in the EU are divided into three main categories, each defined by engine specifications and minimum age requirements (“Directive 2006/126/EC,” 2006). This tiered system is designed to progressively introduce riders to more powerful motorcycles as they gain experience. Category A1 permits riding motorcycles with a cylinder capacity not exceeding 125 cm^3, power output up to 11 kW, and a power-to-weight ratio no greater than 0.1 kW/kg. It also includes motor tricycles with a maximum power of 15 kW. The minimum age for obtaining an A1 license is 16 years. Category A2 covers motorcycles with a maximum power of 35 kW and a power-to-weight ratio not exceeding 0.2 kW/kg. These motorcycles must not be derived from a vehicle producing more than double that power. Riders must be at least 18 years old to obtain an A2 license. Category A is the highest motorcycle license category and includes all motorcycles, regardless of power. Access is granted from age 20, provided the rider has held an A2 license for at least two years. This experience requirement may be waived for individuals aged 24 or older. Additionally, this category includes motor tricycles exceeding 15 kW, for which the minimum age is 21 years.

1.1.2.2. Motorcycle handling and riding dynamics

Handling a motorcycle depends not only on its dimensions but also on its mass or the weight-to-power ratio (Cameron, 2022). The position of the vehicle’s center of gravity is also

[2] In the remainder of this paper, the term *motorcycle* will be used.

important, as it and the weight-to-power ratio affect braking, cornering, and acceleration characteristics. Riders of high-powered motorcycles face an elevated risk of involvement in fatal crashes (Mattsson & Summala, 2010). Research indicates that elevated crash risk among motorcyclists is more strongly associated with high power-to-weight ratios than with engine capacity or absolute power alone (Haworth & Blackman, 2013; Langley et al., 2000). These high ratios are characteristic of sports motorcycles, which consistently exhibit the highest fatality rates among all motorcycle types (Teoh & Campbell, 2010). Motorcycles generally demonstrate significantly higher power-to-weight ratios than passenger cars, with many modern models capable of achieving incredibly high speeds and rapid acceleration (Elliot et al., 2003). However, as single-track vehicles, motorcycles are inherently less stable. Loss of traction, whether due to sudden braking, aggressive acceleration, or slippery road conditions, can easily result in instability and capsize, increasing the risk of a crash.

Motorcycles exhibit distinct handling and braking characteristics compared to other motor vehicles, which adds complexity to their operation. These differences are particularly pronounced during turning maneuvers, at both low and high speeds, and in situations requiring sudden or emergency braking. The need for continuous balance, precise coordination, and sensitivity to weight transfer makes motorcycling a more demanding task, especially under dynamic or hazardous conditions.

Braking performance among motorcyclists shows notable variation depending on pavement conditions. Under wet surface conditions, 90% of riders demonstrated deceleration rates of at least 2.75 m/s^2, whereas 90% achieved decelerations of at least 3.3 m/s^2 on dry pavements (Davoodi & Hamid, 2013). Despite these values, motorcycles generally require a longer braking distance than passenger cars, primarily due to reduced tire contact area, weight distribution, and the complexity of coordinating front and rear braking systems. Additionally, research confirms that motorcycles equipped with anti-lock braking systems (ABS) (Rizzi et al., 2009; Savino et al., 2013) or combined braking systems (CBS) (Ciepka, 2016) exhibit superior braking performance, particularly in deceleration capability, and consequently, in avoiding the collision. Another aspect where proper motorcycle braking comes into play is maintaining a distance between vehicles to avoid rear-end collisions (Sitthiracha & Koetniyom, 2020).

Sharp horizontal curves pose elevated risks for all road users, particularly motorcyclists (Milling et al., 2016). Due to the dynamic handling characteristics of motorcycles, these curves increase the potential for destabilization, especially when riders must make sudden path corrections or engage in emergency braking. Motorcyclists rely on early visual cues to select an appropriate riding path; misinterpretation can lead to trajectory errors, including entry into opposing lanes, particularly in head-on zones.

Curved road segments are characterized by centrifugal force, which acts outward on a moving vehicle and can destabilize its path (Milling et al., 2016). To counteract this force, motorcyclists must lean into the curve during cornering. The lean angle is directly influenced by both speed and curve radius – higher speeds and tighter curves necessitate greater lean angles, thereby increasing the rider's dependence on road surface conditions for maintaining stability and control.

Figure 1-2 depicts forces acting on a motorcycle on a bank at constant speed in a curve (Tollazzi, 2020). When a motorcycle travels through a curve at a constant speed, it must lean to counteract the outward-acting centrifugal force. The diagram illustrates the key forces involved: gravitational force (G), the normal force (N), and the frictional (or traction) force (F_{tr}), along with the centrifugal force (F_c). The rider and motorcycle lean at an angle (α) relative to the vertical to maintain equilibrium. This lean angle is influenced by the curve radius (r), the vehicle speed (v), and the superelevation angle (φ) of the road. The normal and frictional forces must align with the resultant acting from the tire-road contact point to the system's center of mass. Superelevation reduces the required lean angle and improves stability when cornering.

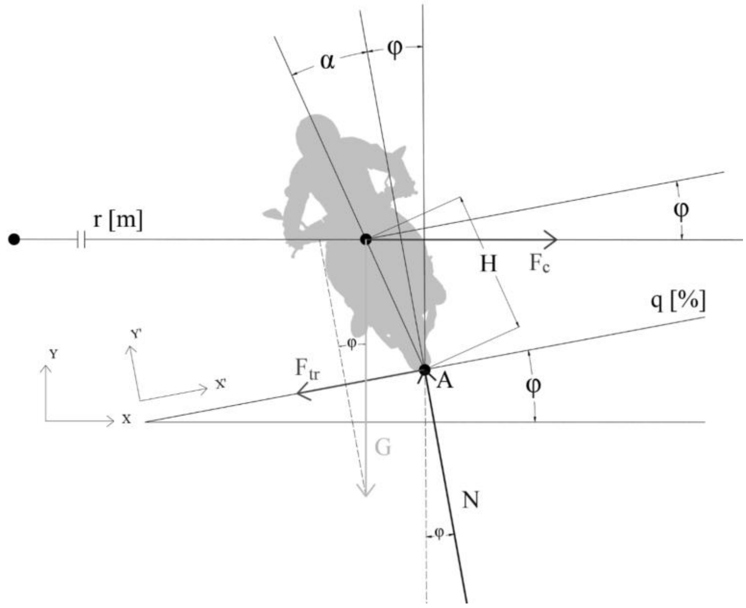


Figure 1-2. Forces acting on a motorcycle on a bank at constant speed in a curve (Tollazzi, 2020)

Motorcyclists are also subject to vibrations transmitted through the handlebars during riding. Prolonged exposure to high vibration levels can result in discomfort and physical strain, leading to symptoms such as numbness, stiffness, and pain in the hands, fingers, shoulders, and neck (Khune & Bhende, 2020). These effects may impair riding performance and contribute to fatigue-related safety risks.

In addition to vehicle dynamics, a motorcyclist's visual strategy plays a critical role in determining lateral positioning within the lane, particularly on curved road sections (Winkelbauer et al., 2017). One notable risk arises when negotiating left-hand curves, where riders may inadvertently shift their visual focus from the center line to the left edge line. This shift can impair curve negotiation and lead to the rider unintentionally cutting the curve, increasing the likelihood of encroachment into the opposing traffic lane and thus elevating the risk of a head-on collision with an oncoming vehicle.

1.1.2.3. Motorcyclist visibility

Motorcyclists' conspicuousness is one of the peculiarities compared to other motorized participants in road traffic, and it differs in urban and rural environments (Gershon et al., 2012). Research has shown that the effectiveness of clothing color, helmet design, and lighting configurations largely depends on environmental conditions (Hole et al., 1996). Studies confirm that the contrast between the motorcyclist and the surrounding environment is crucial in enhancing rider conspicuity (Abdul Khalid et al., 2021; Craen et al., 2011). For example, reflective or brightly colored apparel improves visibility at night, while darker gear may offer better contrast in rural daylight settings. Even studies on daytime running lights (DRL) highlight that their positive impact on conspicuity is context-dependent, as well as design-dependent (Cairney & Styles, 2003; Haferkemper et al., 2010; Ranchet et al., 2016).

One of the key factors contributing to motorcyclists' reduced perceptibility in traffic is the relatively small size of motorcycles compared to other motorized vehicles (Slootmans, 2023b). This reduced visual profile makes motorcycles inherently less conspicuous, particularly in complex or cluttered traffic environments. Unlike larger vehicles, motorcycles may fall outside a driver's immediate field of attention, increasing the likelihood of perceptual errors and contributing to crash risk. Although motorcycles may appear similar in size to cars when viewed from the side, providing drivers with relatively rich motion cues, their frontal profile is significantly narrower, often limited to a single headlight (Craen et al., 2011). This limited visual footprint provides less information for estimating speed and distance, making motorcycles more difficult to detect. Depth and speed perception are especially compromised from the front view, contributing to visibility-related crash risk.

Several studies have investigated the influence of motorcycle speed on conspicuity. In a small in-depth study, the authors found that motorcycles involved in crashes attributed to reduced conspicuity generally traveled at higher speeds than those in crashes caused by other visibility issues, such as view obstruction (Brenac et al., 2006). A follow-up study analyzing 44 intersection crashes likewise reported that motorcyclists in “looked-but-failed-to-see” (LBFTS) crashes were traveling at significantly higher initial speeds (Clabaux et al., 2012). A recent review paper on the role of riders’ conspicuity confirms that their conspicuity is one of the crucial factors in rider safety, as well as the limited environmental awareness and inaccurate speed estimation (Ludfi Pratiwi Bowo et al., 2025).

1.1.2.4. Technical aspect conclusion

In summary, motorcyclists face substantially higher fatality and injury rates compared to car occupants, mainly due to their unique vehicle characteristics and exposure. The high power-to-weight ratio of motorcycles enables rapid acceleration but also increases the severity of crashes. Unlike enclosed vehicles, motorcycles offer limited structural protection and rely heavily on the rider’s skill to maintain balance and stability, particularly under adverse conditions or on challenging road surfaces. Furthermore, motorcyclists are less conspicuous in traffic due to their smaller frontal profile, with visibility further compromised by speed, affecting handling and reducing the likelihood of being detected by other road users. These factors collectively emphasize the heightened vulnerability of motorcyclists.

1.1.3. Human-related aspects in motorcyclist safety

While the human factor is a key element in all aspects of road safety, it plays an especially decisive role for motorcyclists. Many researchers are intrigued by the behavior of road users, especially riders, and are investigating personality traits, attitudes, cultural or peer influence, and other behavior-influencing factors. The complexity of factors contributing to motorcyclists’ behavioral preferences reflects the interplay between individual traits, cognitive evaluations, social influences, and perceived control, all of which shape decisions related to safe and risky riding behaviors. Due to the specifics of motorcycle riding, mistakes and deliberately unsafe actions while riding can have significantly more serious consequences than when driving a passenger or a commercial vehicle. Nevertheless, motorcycle riders often engage in risky behavior that can ultimately result in crash involvement or near-crash situations, endangering others or themselves.

This subchapter presents an overview of the human factor and the behavior of motorcyclists, respectively. A special focus is placed on risky riding, considering that such behavior often leads to unpleasant events and crashes.

1.1.3.1. Human factor in traffic

In traffic management, human factors refer to individual characteristics that influence how people behave and make decisions in traffic (van Schagen & Vissers, 2016). In this context, four key aspects are critical to understanding this behavior: perception (the ability to notice and interpret signs and signals), comprehension (understanding what actions are required), capability (being physically and mentally able to perform the required behavior), and motivation (the willingness to act accordingly).

To understand human behavior, especially in a traffic context, it is essential to consider four fundamental principles (Carter & Kirley, 2017):

1. Behavior is guided by two distinct systems—deliberative (reflective) and intuitive (automatic);
2. Individuals are not purely rational or logical in their decision-making processes;
3. Behavior is powerfully shaped by environmental context;
4. Human error is inevitable, as mistakes are a natural part of human functioning.

The human factor in motorcycling encompasses many aspects, including the rider's physical and psychological condition, such as age, fatigue, or the influence of alcohol and drugs. It also involves cognitive abilities like perception, attention, decision-making, and reaction time – all essential for safe riding. Riders must constantly perceive and interpret the environment, make quick decisions, and control the vehicle effectively. However, distraction, reduced risk awareness, or impaired visual perception, especially at night, can compromise safety. Additionally, experience and familiarity with riding conditions play an important role in effectively performing these tasks.

Psychosocial factors play a significant role in influencing rider behavior and contributing to motorcycle crashes (Zehra et al., 2019). Emotional states, such as mood fluctuations, social or financial stress, and interpersonal conflict, have been associated with aggressive or erratic riding patterns. Riders may respond to stress or frustration by varying speed, exhibiting hostility toward other road users, or engaging in riskier behavior. The presence of pillion passengers can be associated with a reduced risk of fatal motorcycle crashes (Jou et al., 2012). Research shows that pillion passengers generally encourage riders to adopt more cautious riding behaviors, lowering crash severity (Chang et al., 2019). However, some research shows that the presence of pillion passengers in a crash increases the likelihood of fatalities (Champahom et al., 2025).

Vision, or visual perception, stands out as a significant feature when operating a vehicle, since sources say that over 90% of the information the driver receives is visual (Lay, 1986); therefore, the vision sensory channel has the highest importance (Macadam, 2003). Speed information perceived through peripheral vision plays an important role in motion perception, serving as a valuable complement to positional data gathered through central (foveal) vision. This redundancy enhances the rider's ability to maintain spatial orientation and respond effectively to changes in speed and direction; however, due to the helmet and sometimes high speeds, a rider's perception could be impaired. A rider must continuously process visual information, including potential hazards, speed limits, and navigational cues. As speed increases, the volume of visual input that must be interpreted per unit of time also rises (Cunningham et al., 2017). At higher speeds, riders tend to focus their attention narrowly on the area directly ahead, which leads to a phenomenon known as visual tunneling. This effect reduces peripheral awareness and increases the risk that critical objects or events outside the central field of vision will go unnoticed.

Driver fatigue is recognized as a significant factor that compromises road traffic safety (Mofolasayo, 2024). Conditions such as sleep restriction, falling asleep at the wheel, and drowsiness are commonly identified as contributors to road crashes, as they impair alertness, reaction time, and decision-making. Besides fatigue, distractions are also mentioned as one of the harmful factors in traffic. Cognitive distraction is defined as a state of diminished cautiousness concerning the driving environment (Kawanaka et al., 2013). In contrast, visual distraction occurs when the driver's attention is diverted from the vehicle's travel direction. Some researchers classify distractions into physical tasks, auditory or visual diversions, and cognitive activities (Foss & Goodwin, 2014). Moreover, they note that certain activities, such as texting, may simultaneously involve all three forms of distraction, engaging the eyes, mind, and hands in the distracting task.

Alcohol and drug use significantly impair a person's ability to operate the vehicle safely (Garrisson et al., 2022; Goldenbeld, 2024; Tivesten et al., 2023). Intoxication slows reaction times and disrupts fine motor control, making it difficult to maintain balance, maneuver effectively, and respond to sudden hazards. These substances also impair judgment and decision-making, increasing the likelihood of risky behaviors such as reckless maneuvers and excessive speeding. Additionally, alcohol and certain drugs can negatively affect visual perception, reducing peripheral vision, causing blurred vision, and contributing to tunnel vision, all of which limit hazard detection. Cognitive impairments, including reduced concentration and increased distractibility, further compromise the rider's ability to process essential information from the road and surrounding traffic, elevating the crash risk.

Intoxicated riders exhibit prolonged response times and adopt wider safety margins, contributing to increased task performance errors (Creaser et al., 2007). In attempting to maintain motorcycle stability, riders often prioritize balance over other aspects of task execution. Research shows that rider performances are impaired even at BAC = 0.05, and the adverse effects become statistically significant (Vu et al., 2020). In comparing novice and experienced participants at the same level of BAC, the mean speed and acceleration rates of novice participants are significantly higher than those of the experienced participants. The effect of alcohol is particularly pronounced with high-demanding tasks (Creaser et al., 2009).

1.1.3.2. Determinants of risky riding behavior

Every human has specific characteristics and limitations (Macadam, 2003) that result in certain actions, i.e., behavior in traffic. Risky riding behavior usually refers to actions performed by a motorcycle rider that increase the likelihood of a crash or other unwanted event. Regarding behavioral factors, practices such as participating in unofficial races, overtaking in unsafe conditions, and routinely violating traffic signals are commonly observed among crash-involved riders (Zehra et al., 2019).

Risky riding is a term often connected to motorcycle riders. Riding behavior results from a person's cognitive, social, and personality levels (Falco et al., 2013). In other words, individual preferences and attitudes result in a specific behavior. Motorcyclists are not a homogeneous group. Their motivations, behaviors, and risk perceptions vary widely based on age, experience, group affiliation, and personality (Tunnicliff et al., 2011). These insights emphasize that social, identity-related, and moral dimensions are central to understanding motorcyclist behavior.

A multi-group analysis reveals that age and gender are key factors in differentiating motorcyclist groups based on their decision-making processes related to risky riding behavior (Chung & Wong, 2012). In response to adverse traffic conditions, male motorcyclists tend to react impulsively, with road rage significantly increasing their likelihood of engaging in risky behaviors. In contrast, young female riders are more likely to assess perceived risk before taking such actions. Furthermore, the analysis indicates a significant relationship between risk perception and traffic condition awareness among more experienced riders (ages 25–28), a link that is not evident in younger riders (ages 18–24).

The motorcyclist's age indicates a relationship between motorcyclist behavior and perceived safety, and this relationship differs across age groups (Islam, 2021). Higher perceived crash risk is associated with a decrease in the likelihood of engaging in risky behaviors, including phone use, speeding, red-light violations, riding against traffic, and sidewalk riding (Truong et al., 2018). On the other hand, some research shows that even though riders know the crash risk, they do not use the PPE correctly (Seerig et al., 2016). One aspect of the human factor related to motorcyclists' safety is closely linked to the training and riding technique level. For instance, a study from Egypt reports that among 319 motorcyclists hospitalized due to crashes, 87.1% did not possess a valid driving license (Bolbol & Zalat, 2018). Some authors highlight that the learning processes differ between unsupervised novice motorcyclists and supervised novice riders (De Rome et al., 2010).

A lack of riding knowledge and experience, as well as certain personality traits, contribute significantly to the adoption of risky riding behaviors (Romero et al., 2019). Sensation seeking and aggression are strongly linked to speeding, stunt riding, and riding errors, while conscientiousness and agreeableness are associated with safer behavior (Antoniazzi & Klein, 2019). Moreover, motorcyclists who exhibit dangerous attitudes and behaviors, as well as younger riders, are more likely to have been involved in a traffic crash (Theofilatos & Yannis, 2014). Findings confirm that older motorcyclists are less likely to engage in risky riding behavior while on the road (Antoniazzi & Klein, 2019; Goh et al., 2020), suggesting that age is inversely associated with the likelihood of adopting unsafe riding practices.

The findings identify three primary personality traits among young motorcyclists: sensation seeking, amiability, and impatience (Wong et al., 2010). Amiable riders tend to be relatively mature and cautious, displaying safer riding behavior. In contrast, sensation-seeking riders exhibit high self-confidence and comfort with unsafe riding practices, driven by the perceived utility or thrill they derive from such behaviors. Although they demonstrate high traffic awareness, which may reduce crash likelihood, any crash involving this group will likely be severe. Impatient riders display low riding confidence and poor traffic awareness. While they also seek utility from certain risky behaviors, their heightened fear of crashing often leads to reduced attention to surrounding traffic conditions. In Brazil, motorcyclists exhibit higher levels of novelty seeking and persistence and lower levels of harm avoidance and reward dependence compared to their general population, suggesting a distinct temperament profile associated with greater risk tolerance and sensation-seeking tendencies (Romero et al., 2019).

According to an Iranian study, there are four distinct categories of motorcycle riders, each characterized by a specific cognitive bias to justify risky riding behaviors (Bazargan-

Hejazi et al., 2013). *Risk managers* believe that their competence minimizes the likelihood of adverse outcomes. *Risk utilizers* view risky riding as a practical necessity for managing daily responsibilities more efficiently. *Risk calculators* perceive risky behavior as a strategy to avoid crashes by maintaining control in dynamic traffic situations. Finally, *risk-takers* associate risky riding with excitement and social recognition, emphasizing thrill-seeking and a peer-driven nature.

Results from a Serbian study indicate a significant link between riders' lifestyle and their engagement in risky behaviors and crash involvement (Stanojević et al., 2020). Two high-risk rider profiles emerge: the *thrill-seeker*, marked by motorcycle addiction, aggression, and substance use, and the *athletic overconfident* rider, who takes risks due to high self-confidence. In contrast, cultural engagement, religiousness, and socially grounded activities are associated with safer riding behavior.

The findings from an Australian study show that intentions to perform safe riding behaviors are most consistently predicted by perceived behavioral control (PBC), whereas intentions to engage in risky behaviors are primarily driven by attitudes and sensation seeking (Tunnicliff et al., 2012). Riding attitude and risk perception act as mediating variables between personality traits and riding self-confidence in influencing risky riding behaviors (Vuong et al., 2023). Both personality traits and self-confidence also have direct effects on the likelihood of engaging in risky behaviors. Further, riding attitude plays a particularly significant role in promoting risky riding practices. Another study from Iran identifies several key predictors of risky riding behavior, including occupation, average riding frequency, absence of a valid riding license, type of motorcycle used, previous police warnings, unfastened helmet straps, speeding, rider fatigue, and riding without hands on the handlebars (Setoodehzadeh et al., 2021).

Riding errors are associated with greater engagement in distracting activities and a higher daily inattention propensity. Research from Vietnam indicates that motorcyclists with generally unhealthy lifestyles are more likely to engage in high-risk behaviors such as smoking while riding and riding under the influence of alcohol (Nguyen-Phuoc et al., 2020). Smoking habits have been linked to smoking during rides and failure to wear a helmet, while alcohol consumption shows broader associations with a range of risky riding behaviors. Notably, significant correlations have been observed between both drink riding and smoke riding and the overall prevalence of other hazardous behaviors, suggesting a clustering of risk-taking tendencies among specific rider profiles. Riders who engage in reckless overtaking or riding on sidewalks are approximately twice as likely to use a mobile phone (for calling, texting, or searching for information) while riding (Truong et al., 2018). Similarly, those who ride under the influence of alcohol are nearly twice as likely to call or text while riding.

Human factors contributing to motorcycle-related road traffic crashes in Africa include alcohol consumption, smoking, use of illicit drugs, rider fatigue, and limited knowledge of traffic regulations (Konlan & Hayford, 2022). Additional risk factors involve carrying multiple pillion passengers, lack of a valid rider's license, non-compliance with traffic laws, and failure to use personal PPE. Crashes are disproportionately common among younger riders and males. Among young riders in India, risky behaviors include mobile phone use while riding, non-compliance with traffic regulations, and failure to wear a helmet (Sumit et al., 2022).

On the other hand, the most commonly self-reported distractions in a Spanish study include using map navigation, listening to the radio or music, and adjusting vehicle devices, while mobile phone use is reported less frequently (Ledesma et al., 2023). Younger riders report higher levels of engagement in such distracting behaviors and a greater number of riding errors, indicating increased vulnerability to inattention-related risks.

Authors state that the importance of riding style should be emphasized and that it is necessary to further research the concepts of different riding behaviors to deepen the knowledge about the influence of human factors on road crashes (Cheng et al., 2011).

1.1.3.3. Summary and reflections on human factors

The schematic presentation in Figure 1-3 was developed based on a comprehensive review of the literature addressing the role of human factors in motorcycle safety, and it offers a simplified yet structured overview of the complex interplay of human factors that influence rider behavior in traffic. Although the reality of road safety is multifaceted and context-dependent, this framework is a useful conceptual tool for illustrating the key elements contributing to risky riding. It shows how external factors, such as road conditions, traffic density, or weather, can directly or indirectly affect a rider's physical and mental state, for instance, by causing fatigue, stress, or distraction. The impact of these external influences is further shaped by individual characteristics, including age, riding experience, personality traits, and attitudes, which determine how each rider perceives and reacts to the environment.

The interdependence of physical and mental conditions with individual characteristics forms the foundation of a rider's behavior in traffic. When these factors lead to risky behavior (e.g., speeding, poor decision-making, or inattention), the likelihood of being involved in a crash increases. While simplified, the model highlights the importance of considering the rider as a dynamic and context-sensitive component of the traffic system.

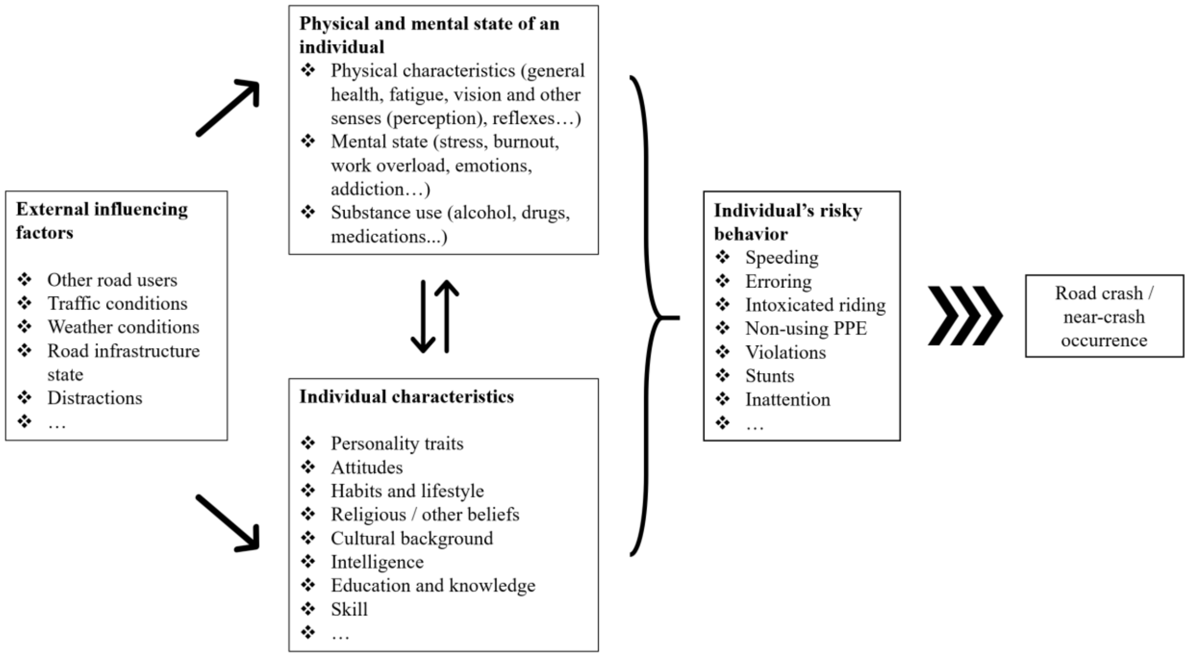


Figure 1-3. Conceptual framework illustrating the interaction between external factors, individual characteristics, and the physical and mental state of a rider in contributing to risky behavior

It is important to emphasize that human-related risk factors and distraction patterns vary across regions, reflecting differences in infrastructure, enforcement, riding culture, and socioeconomic context. Nevertheless, despite global concern regarding motorcyclist safety, there is still a notable lack of comprehensive studies focused on European riders, especially those using naturalistic or behaviorally grounded methods.

Existing research confirms the influence of numerous human factors, including personality traits, emotional and cognitive states, lifestyle, and social norms. The overarching goal is to identify specific behaviors that can be clearly defined, monitored, and influenced through policy, education, or enforcement strategies. While many reviewed studies successfully identify such behaviors, they are often limited in scope, focusing heavily on younger riders or relying on self-reported data. There is a need for broader research that includes older and more diverse rider populations, considers the long-term influence of rider training, and investigates the interaction of multiple human factors in real-world conditions.

In conclusion, understanding the human factor is an important approach to improving motorcycle safety. The insights presented in this subchapter highlight the importance of treating motorcyclists not only as vehicle operators but as complex individuals whose behavior is shaped by a dynamic interplay of inner and external influences.

1.1.4. Exclusive features and challenges of rural roads

Rural roads, situated outside cities and densely populated areas, typically serve to connect sparsely inhabited regions with larger towns or urban centers. These routes frequently traverse forested or agricultural landscapes, which can present unique challenges for road safety and mobility. The traffic on such roads varies; usually, the traffic is the lowest on the lowest-ranked roads. The design and alignment of such roads vary depending on the area, maintenance, importance of the road, etc. Generally, it has been reported that rural roads are deadlier compared to other road types (International Transport Forum, 2022a).

There are different definitions of rural roads. For instance, rural and remote roads in Australia are defined as non-urban roadways that pass through environments with minimal or no roadside development (Tziotis et al., 2018). This classification includes undivided roads with a speed limit of 80 km/h, typically indicative of sparse roadside infrastructure, as well as all other roads where the posted speed limit exceeds 80 km/h. For the EU statistical reports, rural roads are public roads outside urban boundary signs, excluding motorways (Fleischer et al., 2024).

For this research project, all categorized public roads outside the bigger urban area were considered rural, with speed limits ranging from 30 to 90 km/h. Other characteristics are the various roadway widths and passing through different surroundings, such as agricultural and tourist areas.

Globally, developing and upgrading transport infrastructure in rural areas is increasingly supported and encouraged. It has been reported that in developing countries, such improvements contribute to trade and economic development; for instance, in rural development (Wang & Sun, 2016), farm-to-market access (Jenkins et al., 2020), enhancing local mobility (Oloo, 2018), improving living standards (Abdul Latiff et al., 2021; Wiegand et al., 2023), reducing income inequality (Charlery et al., 2016), and supporting rural income growth (Wondemu et al., 2012). The benefits of upgrading rural footpaths into motorcycle-accessible tracks are particularly promoted, as such improvements can significantly enhance rural mobility (Jenkins et al., 2020; Jenkins & Peters, 2016). It is highlighted that such upgrades also positively affect women’s accessibility to essential services and facilities, enhancing women’s well-being and social inclusion (Jenkins, Mokuwa, et al., 2020; Nandwani & Roychowdhury, 2024).

Regarding powered two-wheelers in the European context, while mopeds are more favorable in urban areas, motorcycles are more commonly used in rural areas (Nuyttens, 2020;

Slootmans, 2023b). According to available data, rural road fatalities do not decrease at the same rate as urban ones. Single-vehicle fatalities are disproportionately more frequent on rural roads, while they occur less often on urban roads relative to the overall distribution of road fatalities (Slootmans, 2023a).

Leisure motorcyclists are generally exposed to a higher level of risk on rural roads (ACEM, 2006). While the overall number of motorcycle crashes tends to be greater in urban areas, fatalities are more frequent in rural environments, where higher speeds, limited infrastructure, and longer emergency response times contribute to more severe outcomes. These patterns reflect motorcyclists' different challenges in urban versus rural settings, stressing the need for context-specific safety strategies. According to some studies, drivers experience rural roads as less risky than urban roads, regardless of their age (Cox et al., 2017), which may be because there are fewer other traffic participants and may result in riders and drivers being less careful on rural roads.

Areas with challenging and curvy roads are often preferred for motorcycle riding for recreational purposes, as these routes offer a more dynamic and enjoyable riding experience (Flask & Schneider, 2013). Motorcyclists also point out that they prefer a well-maintained and tidy rural landscape, particularly with water in the foreground (Merry et al., 2020). On the other hand, variability in rural road design contributes to higher crash risk (International Transport Forum, 2020).

The results show that horizontal alignment has a more pronounced impact on single motorcycle crashes than lane or shoulder width (Kvasnes et al., 2021). Road segments featuring multiple adjacent reverse curves and tight curvature (radius less than 200 meters) are associated with a significantly higher likelihood of crashes, highlighting the critical role of geometric road design in motorcyclist safety. Speed is a predominant factor contributing to fatalities and serious injuries in single-motorcycle crashes on rural curves (Wang et al., 2018). Research shows that speeding increases the likelihood of a fatal or serious injury in such crashes by 16.8%, underscoring the critical impact of excessive speed in these high-risk scenarios. Areas around curves present a heightened risk of head-on crashes involving motorcycles due to limited visibility at the point of corner entry (Champahom et al., 2025).

Research on intersections shows that they play a role in the frequency and severity of motorcycle-related crashes, but the results are not uniform (Dumbaugh et al., 2023). Most motorcycle-car crashes have been associated with uncontrolled intersections, where the contributing factor appears to be drivers' low expectation of encountering motorcycles in such locations (Walton et al., 2013). Some authors found that crashes at intersections were associated with minor injuries (Rahman et al., 2021; Salum et al., 2019). Further, research shows that intersections were associated with slight- and no-injury crashes in urban and rural area (Geedipally et al., 2011; S. Islam & Brown, 2017). Single-vehicle motorcycle crashes tend to be less severe at intersections compared to those occurring at locations between intersections (Farid & Ksaibati, 2021), likely due to lower travel speeds and increased rider alertness at intersections (Geedipally et al., 2011). In contrast, according to some research, the likelihood of fatal crashes increases at three-legged intersections, as well as at stop, yield, and uncontrolled intersections (Abrari Vajari et al., 2020).

Hazard detection on rural roads significantly decreases during nighttime (Asadamraji et al., 2018). In suburban and rural areas, one of the common events is a vehicle hitting an animal on the road (Khodadadi-Hassankiadeh et al., 2021; Nelli et al., 2018; Wilkins et al., 2019). Research shows that motorcyclists are disproportionately involved in animal-related serious crashes, with 51.7% of such incidents involving motorcyclists – significantly higher than their representation in other types of serious injury crashes (Rowden et al., 2008). Animal-motorcycle collisions often occur with clear weather and on straight rural roads (R. L. Langley et al., 2006), also during the nighttime, and mainly include older male riders, resulting in a high mortality rate (Bramati et al., 2012). Cases were reported in which riders in animal-motorcycle collisions were under the influence of alcohol (Nelson et al., 2006).

A positive relationship between mean speeds and crash occurrence on single-carriageway roads has been observed, indicating that higher average speeds are associated with increased crash frequency (Gitelman et al., 2017). Two-lane roadways are associated with a higher likelihood of fatal, incapacitating, and non-incapacitating injuries in both single-vehicle and non-intersection-related multi-vehicle crashes (Schneider & Savolainen, 2011). This may be attributed to narrower lanes, limited separation between traffic streams, and less forgiving roadside environments.

Higher traffic volume on low-traffic roads is associated with an increase in crashes (Gitelman et al., 2014). Shoulder widening up to 2–2.5 m initially leads to a rise in crashes, after which further widening contributes to crash reduction. Similarly, increasing lane width up to 3–3.25 m reduces most crash types, while additional widening is linked to more single-vehicle and overall crashes. A larger minimum horizontal curve radius is associated with fewer injury crashes, and improved roadside conditions help reduce single-vehicle crashes. Additionally, steeper vertical grades are correlated with an increase in total crash frequency.

Crashes on rural roads are often severe because of the higher speeds and lack of protective infrastructure (e.g., no median separation, narrow shoulders, no motorcyclist-friendly safety barriers). When the posted limit is too high for the road, drivers who attempt to travel at that speed (or above) are at elevated risk of run-off-road crashes, head-on collisions, and rollovers. Studies on geometric design consistency show that inconsistencies (like a design speed or curve radius that demands a lower speed than the posted limit) are associated with more frequent and severe crashes (Cefalo et al., 2024). Roadside hazards such as trees, barriers, and other fixed objects pose a significant danger to motorcyclists, particularly during curve negotiation, as they increase the risk of severe injury or fatality in the event of a run-off-road crash (Wang et al., 2018).

Some authors emphasize optimizing current road safety inspection procedures and adapting them to secondary and local rural roads (Cantisani et al., 2023).

To conclude, the poor condition of rural road networks significantly contributes to the vulnerability of road users, particularly motorcyclists. Inadequate maintenance, lack of proper signaling, uneven or damaged surfaces, poor care of roadside vegetation, and limited lighting increase the risk of crashes and reduce the ability of riders to respond effectively to unexpected hazards. Additionally, inadequate rain drainage, falling rocks, and debris or dirt on the road surface can pose particular hazards for motorcyclists, as their smaller contact area and balance-dependent operation make them especially vulnerable to sudden loss of traction or control. Horizontal and vertical curves, small curve radii, high-speed limits, and inconsistent road design increase crash risk for motorcyclists – particularly when combined with poor sight distance, narrow or absent shoulders, and visual obstructions. A notable safety concern arises from the discrepancy between posted speed limits and actual road infrastructure conditions, which can create misleading expectations and reduce the rider’s ability to respond effectively to hazards.

1.1.5. Importance of studying influential factors with different approaches

In order to be able to act concretely towards the goal of reducing and eliminating road fatalities and severe injuries, it is inevitable to detect which causes can significantly affect the occurrence or frequency of motorcycle crashes. At the same time, the need to study the interplay of different factors is often emphasized, with the justified assumption that the desired results can be achieved by acting on several factors. The research highlights that the perceived causes of motorcycle crashes are multidimensional, encompassing factors related to rider behavior, environmental conditions, and individual beliefs or perceptions (Cheng & Ng, 2012).

For example, a study on run-off-road crashes on two-lane highways revealed several significant crash characteristics (Rahman et al., 2021). Key factors include the presence of animals on the roadway, adverse weather conditions (snow, sleet, hail), speed limits of 50–55 mph, moderate traffic volumes (i.e., AADT of 1,001–5,000 vehicles/day), drug and alcohol intoxication, motorcycle involvement, nighttime driving, curve radii between 501–1,000 ft, and the absence of street lighting. Further analysis highlights strong crash patterns, such as the increased likelihood of those crashes when animal presence coincides with poor lighting, male drivers operating alone during early morning hours, and dual intoxication by drugs and alcohol. These findings emphasize the importance of addressing environmental, behavioral, and roadway design factors in preventing motorcycle crashes.

Furthermore, speeding, alcohol-impaired riding, and poor motorcycle maintenance are identified as major contributing factors to crash occurrence (Sumit et al., 2022). In another study, motorcyclists perceived that the attitudes of other road users were the primary contributors to motorcycle crashes, whereas cognitive mapping techniques identified poor road conditions as a significant underlying cause (Abdul Sukor et al., 2016).

It is interesting and valuable to compare data-driven findings (objective) with qualitative findings (subjective). In a focus group study, the riders emphasized the need for improved infrastructure, targeted education and training, mutual respect on the road, and technological advancements to support safer riding (Huth et al., 2014). Many concerns revolve around a lack of visibility, insufficient consideration in infrastructure design, and interactions with uninformed or inattentive drivers. From the above, it can be concluded that riders are aware of their role as persons participating in traffic, as well as potential risks caused by other factors.

Suppose we assume that infrastructure and vehicles develop over time and become more advanced and user-oriented. In that case, two factors remain that do not change: the environmental influence (e.g., weather, which can be influenced relatively minorly but can be monitored in advance) and the influence of the person himself (driver, rider, other participants). The above leads to whether it is possible to indirectly and directly affect the human factor and how that can be done efficiently.

Many studies have shown how the age of a motorcyclist affects their behavior in traffic, but none have reported how an individual's behavior changes over time; in other words, does a person behave the same way in a young age group as when they reach older age? Because of temporal influence (Alnawmasi & Mannering, 2019), research must be repeated, given that people, infrastructure, and vehicles change over time. Temporal stability tests additionally indicate that the impact of external variables on motorcyclist injury severity is inconsistent over time, with their influence varying across different years (Li et al., 2024). The overall temporal instability in motorcyclist crash injury severity was observed in another study (Ye et al., 2025), with violations such as alcohol-impaired riding, speeding, and unlicensed riding showing significant influence. Furthermore, the findings reveal evidence of a risk compensation mechanism where riders tend to adjust their behavior under adverse riding conditions, potentially increasing crash risk.

Regional influence is significant in road safety and cannot be neglected. A study in which participants were asked about road infrastructure, trip characteristics, and experiences on daily trips across different countries revealed significant differences in their responses (Azık et al., 2021).

1.2. Problem statement

Despite continuous progress in road safety over recent decades, motorcyclists remain one of the most vulnerable groups in traffic. Across many regions, including the European Union, motorcycle riders account for a disproportionately high share of total road fatalities when compared to car occupants. The lack of structural protection inherent to motorcycles and the distinct dynamics of motorcycle operation compound this elevated risk. Unlike car drivers, motorcyclists must actively balance the vehicle, navigate diverse terrain with limited traction, and rely heavily on visibility to other road users to avoid conflicts.

Motorcyclist conspicuity has been consistently identified as a major contributor to collisions. The relatively small frontal profile of motorcycles, combined with environmental and situational factors, often leads to situations where other road users do not see riders until it is too late. This issue is particularly pronounced on rural roads, where reduced lighting, curves, and obstructions further diminish visibility.

Single-vehicle crashes, many of which occur on rural roads, represent a significant portion of serious and fatal motorcycle incidents. While the role of road infrastructure and environmental conditions in such crashes is well acknowledged, there is insufficient understanding of how these factors interact with rider behavior, vehicle dynamics, and perceptual challenges. Rural roads are often characterized by variable design standards, limited maintenance, and reduced opportunities for evasive maneuvers—factors that heighten the risk for motorcyclists.

According to the literature, speed is particularly critical in motorcycle safety. It not only affects the physical control of the vehicle, particularly in curves and on variable surfaces, but also alters the rider’s visibility to others and their ability to detect and react to hazards. Given its multidimensional influence, speed brings specific attention as both a behavioral and contextual risk factor in rural motorcycle crashes.

Moreover, rider behavior – shaped by personal characteristics, training, experience, and psychological traits – is frequently a dominant factor in crash causation. Behavioral tendencies such as sensation seeking, risk underestimation, fatigue, distraction, and impaired riding due to alcohol or drugs all contribute to increased vulnerability. The diversity of the rider population, spanning wide variations in age, experience, and riding style, makes it challenging to identify universally effective interventions.

While motorcycle safety has been the subject of growing academic interest, existing literature reveals several notable gaps that justify further investigation. First, much research has focused on urban areas or general road user populations, often marginalizing the specific experiences and risks motorcyclists face on rural roads. Particularly within Europe, there is a marked imbalance in research output compared to other world regions, such as Southeast Asia or Latin America, where motorcycles form a larger share of the vehicle fleet and crash statistics.

A significant limitation in traditional crash data is the lack of detail regarding rider behavior, road context, environmental conditions, and motorcycle-specific factors. Conventional databases often overlook near-crashes and minor incidents, especially common on rural roads, that could serve as early indicators of high-risk locations. Exposure data, such as precise mileage, travel patterns, and time-of-day usage for motorcycles, is also scarce or inconsistently recorded. This makes accurate risk estimation and comparative analysis across rider subgroups difficult.

Furthermore, motorcycle safety research faces several methodological challenges. The variability in motorcycle types, rider characteristics, and rural road design undermines the applicability of one-size-fits-all solutions. Psychological and behavioral dimensions, such as risk perception and cognitive workload, are difficult to measure yet critically influence riding behavior. Rural infrastructure is often undocumented or lacks granular detail on factors like surface condition, signage, or line of sight, potentially important for understanding crash causation. Weather and lighting conditions, which could affect visibility and control, are rarely captured in standard datasets.

While naturalistic riding studies and survey-based behavior assessments offer promising avenues to overcome these data limitations, they are resource-intensive and raise issues related to privacy, sensor reliability, and data integration (e.g., synchronizing GPS, speed, and rider input). Therefore, these studies are not often conducted. Moreover, despite implementing advanced safety technologies such as ABS[3], there is limited research evaluating their real-world impact, particularly across motorcycles of different production years.

Finally, motorcyclists in rural areas remain underrepresented in road safety interventions and policy agendas. Given their heightened vulnerability and the complex interplay of environmental and behavioral risks, targeted research is needed to identify modifiable risk factors and develop context-appropriate safety measures.

These limitations underscore the need for further research to comprehensively understand the multifaceted factors contributing to motorcycle crashes and their consequences. In particular, the relationship between risky riding behavior, road geometry, and infrastructure elements remains insufficiently explored.

1.3. Research objectives, questions, and hypotheses

This doctoral research aims to comprehensively assess factors influencing motorcyclist safety on rural roads through a multidisciplinary approach incorporating crash data analysis, behavioral surveys, and naturalistic riding data. This section presents the proposed research objectives, questions, and hypotheses.

1.3.1. Objectives

The overarching purpose is to improve the understanding of the interplay between rider behavior, road infrastructure, and crash outcomes, with a special emphasis on risky riding behaviors and their contextual motivations. The entire research aims to find and generate measures and efforts for proactive action to eliminate severe motorcyclist injuries and deaths on the road. Furthermore, the research aims to propose evidence-based recommendations for improving safety outcomes for motorcyclists in rural environments. The specific research objectives were established to provide a clear direction for the study and to fulfill its overarching aim.

O1. To identify key factors influencing the severity of motorcycle crashes on rural roads and to assess how specific infrastructure affects motorcycle crash outcomes.

This objective analyzes official crash datasets to uncover the most critical variables associated with motorcycle crash risk and injury outcomes in rural environments. Special emphasis is placed on crash type (e.g., single-vehicle), severity level, and contextual factors

[3] Mandatory on new motorcycles in the EU since 2013 (Slootmans, 2023b)

such as road classification, visibility, and temporal conditions. This analysis contributes to identifying infrastructure-related and situational risks that disproportionately affect motorcyclists.

O2. To assess how specific infrastructure characteristics influence motorcycle rider behavior.

This objective examines how rural infrastructure elements – including geometric design, signage, surface conditions, and delineation – affect riders' behavioral responses. Special attention is given to speed selection and the impact of road infrastructure on rider's behavior, which are closely linked to crash likelihood. By identifying infrastructural features that either aid or undermine safe riding behavior, the study delivers insights for targeted interventions and safer road design.

O3. To investigate the relationship between self-reported rider behavior, road perception, and crash history.

Utilizing a structured survey based on the motorcycle rider behavior questionnaire (MRBQ) and supplementary context-specific items, this objective explores how motorcyclists' behavior patterns correlate with perceived road risks, prior crash involvement, and fines issued by the police. It considers cognitive and affective dimensions of risk perception, sensation seeking, and self-assessed riding style to better understand behavioral predispositions that elevate crash risk.

O4. To explore rider behavior and risk perception differences across road types and conditions.

This objective assesses how different infrastructure scenarios (e.g., motorway vs. rural road) and demographic characteristics (e.g., age, experience) influence behavioral choices and risk awareness. The examination aspires to uncover whether certain types of riders or environments require differentiated safety strategies.

O5. To demonstrate the naturalistic riding data's applicability and added value in rural safety research.

This objective involves the analysis of GPS-based smartphone data collected from real-world motorcycle trips. The aim is to assess whether such data can seize subtle aspects of rider behavior (such as speed variability and braking intensity), which are often missed in crash statistics or self-reports. The findings will serve as a methodological contribution, supporting the more comprehensive use of naturalistic methods in motorcycle safety research.

O6. To derive scientific and practical recommendations for improving motorcycle safety on rural roads.

This concluding objective integrates insights from statistical analysis, behavioral surveys, and naturalistic data to formulate recommendations for researchers, infrastructure planners, policymakers, and safety practitioners. Emphasis is placed on identifying modifiable factors, improving rider awareness and training, and informing infrastructure design to reduce fatal and serious motorcycle crashes in rural contexts.

1.3.2. Research questions

Based on the problem statement, the recognized research gaps, and the established objectives, the following research questions were developed:

RQ1. What are the key factors influencing the occurrence and severity of motorcycle crashes on rural roads?

RQ2. How do infrastructure conditions – such as road geometry, signage, equipment, and road surface – affect motorcycle crash outcomes?

RQ3. How do infrastructure conditions – such as road geometry, signage, equipment, and road surface – affect motorcycle rider behavior, particularly speed selection and visual attention?

RQ4. To what extent does rider behavior, measured through self-reports and observed data, correlate with crash involvement and perceived road risks in rural areas?

RQ5. Are there measurable differences in the behavior and perception of motorcyclists when riding on different road types or infrastructure conditions?

1.3.3. Hypotheses

Through this investigation, the study seeks to provide a deeper understanding of how infrastructure features interact with rider behavior and human-related factors to influence crash risk. Also, the aim is to investigate historical crash data to potentially reveal critical aspects. Based on this objective and established research questions, the following main research hypotheses were formulated:

H1. By integrating data on crashes, infrastructure conditions, traffic signaling, and road equipment, and crash participants, it is possible to develop a model that identifies factors influencing the frequency and consequences of motorcycle crashes on rural roads.

H2. The state of road infrastructure, traffic signaling, and road equipment on rural roads influence motorcycle rider behavior in terms of speed, visual scanning of the environment, and perception of road elements.

H3. Conducting an extended questionnaire on motorcycle rider behavior can help determine the relationship between behavior patterns, road infrastructure conditions, and the occurrence of crashes.

1.4. Methodology outline

This doctoral research adopts a multi-method quantitative approach. It incorporates analyses of historical crash data, speed measurements, survey responses, and naturalistic riding data collected via a mobile application. Each method contributes to a holistic understanding of the factors influencing motorcycle safety, particularly on rural roads. Although behavioral dimensions are considered, all data sources are quantitatively analyzed. The rationale behind using multiple data types and analytical methods is to comprehensively understand motorcycle safety from infrastructural and human behavior perspectives.

1.4.1. Theoretical foundations

This doctoral research does not rely on a single unified theory; it is conceptually grounded in an interdisciplinary framework that integrates perspectives from traffic safety, behavioral science, and human factors engineering. These foundations guide the selection of variables, interpretation of rider behavior, and the understanding of crash mechanisms in rural environments.

The human-related analyses are underpinned by risk perception, behavioral adaptation, and cognitive decision-making theories, recognizing that motorcyclist behavior results from an interplay of personal traits, situational awareness, and real-time judgment. The concepts of human error, visual perception, and task workload are central to interpreting rider responses to environmental stimuli, particularly speed selection, distraction, and responses to road geometry and signage.

From the infrastructure perspective, the research draws upon principles of road safety engineering and crash causation models, particularly those emphasizing the role of horizontal alignment, roadside features, and speed-environment interaction. These frameworks help explain how physical road characteristics influence crash likelihood and severity, especially in single-vehicle incidents.

While not tied to a specific psychological model (e.g., Theory of Planned Behavior), the research is informed by empirical behavior-based approaches, supported by survey instruments like the Motorcycle Rider Behavior Questionnaire (MRBQ) and supplemented by observational and crash data. This combination of behavioral and engineering foundations allows for a comprehensive investigation into motorcyclist safety on rural roads.

1.4.2. Data sources and instruments

This research used two approaches when it came to data collection. First, secondary data is collected by official institutions and provided for research purposes. These data include historical crash data based on the database collected by the Ministry of Interior of the Republic of Croatia. On their behalf, the traffic police (trained employees and crash experts) systematically record data on each crash, assigning each crash a unique ID code. In addition, data on vehicle speeds at counting points throughout state roads (secondary roads) were used; the collection of which in Croatia is the responsibility of the road authority (state company Croatian Roads Ltd). Additional data (e.g., the presence of a protective barrier, the size of the curve radius, etc.) were collected using additional tools (official GIS online portals, Google Street View, field surveys).

In addition, the data was collected using a smartphone application (naturalistic riding data) that records basic parameters of movement, such as GPS traces, riding speed, speeding, harsh events (braking, acceleration), use of mobile phones, and proportion of driving on the motorway. The application named *Toecan* was developed under the i-DREAMS project, where the riding and driving data were collected with this application within the Horizon Europe TWIN-SAFE project (Grant agreement ID: 101159114). Part of the collected data (related to motorcycle riding) was utilized for this doctoral research.

Next, primary data was collected within the framework of this doctoral project. For this purpose, an extensive survey was conducted among motorcyclists to determine their demographic characteristics, behavior while riding a motorcycle, perception of infrastructure, and involvement in crashes and traffic fines. The central part of the survey was the modified MRBQ. The modified MRBQ captures individual differences in rider behavior and risk perception, while additional items explore attitudes toward road infrastructure and traffic regulation. Through the survey, participants reported their involvement in crashes, near-crashes, and the traffic fines they received in the past three years. The primary tool used to create and conduct this survey was *Qualtrics*, and all participants completed the survey online via an anonymous link.

Figure 1-4 presents a hierarchical overview of the research data sources employed in the doctoral study, categorized into primary and secondary data, as described above. Each data stream is linked to a specific chapter or chapters where it was applied for analysis, supporting the investigation of motorcyclist safety across diverse methodological approaches. Furthermore, using different sources and forms of data (police-recorded data, measured data, observed data, self-reported data) contributes to a broader understanding of motorcyclist safety.

Further data processing and analysis, collection period, inclusion/exclusion criteria, sample size, and other important data-related protocols are described in detail in each chapter.

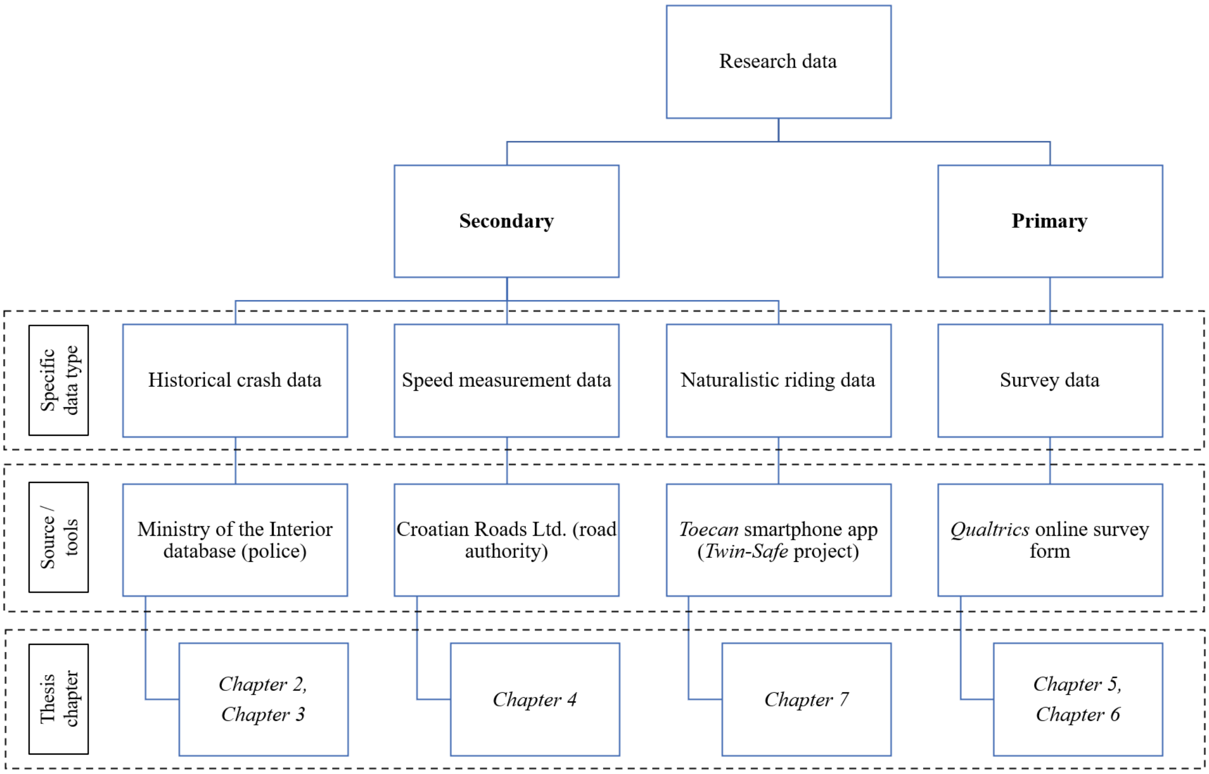


Figure 1-4. Classification and sources of research data used in the thesis

1.4.3. Analytical techniques

A range of analytical procedures was employed across different studies to address this doctoral thesis's research objectives and hypotheses, depending on the type and structure of the data, the research question, and the nature of the dependent variables. The methodological design reflects a quantitative, data-driven approach using classical statistical and machine learning-based methods. Analyses were carried out using software tools such as SPSS, R, and Excel.

The analytical approach in this doctoral research reflects the diversity of data sources and research objectives, requiring a combination of statistical and exploratory techniques. Descriptive analysis was the backbone of every further investigation. Each method was selected to best suit the structure of the data and the specific research question under investigation, ensuring valid interpretation and robust results.

A comprehensive analytical framework addresses the research questions and aims to reach the stated objectives. Each chapter presents and explains in detail the methods and tools used in the analysis and drawing conclusions, depending on the data used and the goal of the individual paper.

Table 1-2 summarizes the type of data used (i.e., crash, speed, survey, and naturalistic), the key observed and dependent variables, the primary analytical methods applied (e.g., logistic regression, Principal component analysis (PCA), neural networks, etc.), and the software tools employed (i.e., SPSS, R). Each row is linked to the corresponding empirical chapter in the thesis, underlining the integration of diverse methods to address the research questions comprehensively.

Table 1-2. Overview of observed variables, analytical procedures, and tools applied across doctoral thesis chapters

Data type	Observed variables	Dependent variable	Main methods used	Tools used	Incorporated in
Crash data	Road type, road characteristics, speed limit, road surface condition, weather conditions, year and day part, crash type and circumstances, citizenship, gender, and alcohol	Crash severity (no injury, mild injury, death/severe injury)	Multinomial logistic regression (MLR) Random Forest (RF)	SPSS, R	Chapter 2
	Crash type, road characteristics, inappropriate speed, visibility conditions, road barrier presence and type, and curve radius	Crash severity (death or severe injury occurred – yes/no)	Binary logistic regression (BLR)	SPSS	Chapter 3
Speed data	Vehicle group, roadside state, in settlement, overtaking allowed, weekday, day part, speed limit, roadway width, ASDT, distance to the closest intersection	Speeding (yes/no)	Multiple comparisons BLR Neural network (NN) Chi-square Automatic Interaction Detector (CHAID) (RF)	SPSS, R	Chapter 4
Survey data	MRBQ items	-	Principal component analysis (PCA)	SPSS	Chapter 5
	MRBQ items (components) Infrastructure perception items (components) Annual mileage, rider age, license age, motorcycle engine capacity, having children, and own riding assessment	Crash involvement Near-crash involvement Traffic fines	PCA Correlations (Spearman 2-tailed tests) BLR	SPSS	Chapter 6

Data type	Observed variables	Dependent variable	Main methods used	Tools used	Incorporated in
Naturalistic data	Average speed, average overspeed, number of harsh events, percentage of time with mobile use and speeding, km driven on motorway, and part of the day	Percentage of time spent speeding	Linear regression	SPSS	Chapter 7

The following subsections further elaborate on the data summarized in Table 1-2.

1.4.3.1. Crash data analysis

In Chapters 2 and 3, historical crash data from the Ministry of the Interior were used to analyze single-vehicle motorcycle crash severity. In Chapter 2, crash severity was treated as a multinomial outcome with three levels (no injury, mild injury, and fatal/severe injury). A multinomial logistic regression and RF were applied to estimate the effects of road characteristics, environmental conditions, and behavioral factors. To complement this, a random forest model was used to assess the relative importance of variables and capture potential nonlinear interactions.

In Chapter 3, the focus shifted to horizontal curves and road safety barriers. Here, crash severity was defined as a binary outcome (whether a severe or fatal injury occurred). A binary logistic regression model examined associations between curve features, inappropriate speed, and injury outcomes.

1.4.3.2. Speed data analysis

Chapter 4 used vehicle speed data to examine factors influencing speeding behavior among motorcyclists. Speeding was coded as a binary outcome (speeding vs. not speeding), and several analytical techniques were applied:

- Multiple comparisons were conducted to examine group differences across road features;
- Binary logistic regression modeled the relationship between infrastructure characteristics and the probability of speeding;
- CHAID and RF models were employed to identify complex interaction structures further and rank predictor importance;
- Neural network model was developed to explore the nonlinear effects of road and contextual variables.

These analyses provided insight into how road geometry, intersection proximity, and other features influence speeding, supporting RQ3 and Objective 2. In addition to testing the possibility of speeding prediction, this approach also investigated and compared different analytical approaches.

1.4.3.3. Survey data analysis

In Chapter 5, a PCA was performed to explore the factor structure of a modified MRBQ adapted for the Croatian context. This statistical technique validated the instrument's internal consistency and derived behavior dimensions, serving as a foundation for further behavioral analysis. In Chapter 6, the survey data were further utilized. Self-reported data on crash history, near-crash experiences, and traffic fines were used as binary outcome variables, while components extracted from the survey parts were used as predicting variables. The following procedures were conducted:

- PCA was again used to reduce infrastructure perception variables to key components;
- Spearman correlation (2-tailed) tested associations between behavioral factors and risky events;
- Binary logistic regression modeled the likelihood of crash/near-crash involvement and traffic fines, using MRBQ components, infrastructure perception components, and sociodemographic variables as predictors.

1.4.3.4. Naturalistic data analysis

In Chapter 7, real-world riding behavior was analyzed. Variables included distance and riding time, average and excessive speed information, harsh events, and trip-level characteristics (e.g., distance on motorways, daytime/nighttime riding, weekend riding).

A method used in this chapter was linear regression, with the time spent speeding (percentage of riding time spent speeding) as a dependent variable, to examine which factors are potentially linked to extended riding time spent above the posted speed limit.

These analyses provided insight into observed rider behavior under actual conditions, helping to triangulate findings from the survey data and contributing to RQ5 and Objectives 4 and 5.

1.4.4. Ethical considerations

The relevant ethics committees approved all data collection procedures involving human participants. Ethics Committees of Hasselt University (SMEC) and the University of

Zagreb – Ethical Committee of the Faculty of Transport and Traffic Sciences considered and approved data collection and analyses procedures.

Ethical approval for survey data collection was obtained through institutional review protocols. Survey respondents and app users were informed of the purpose and scope of the study, and consent was obtained before data collection. Identifiable information was not collected or stored. Naturalistic data were anonymized and encrypted, with data access restricted to the research team.

1.4.5. Justification of the chosen methodology

Integrating multiple data sources and methods allows for triangulation and validation of results across independent datasets. Traditional crash databases lack behavioral context, while survey data alone may suffer from self-report biases. Integrating naturalistic data addresses exposure measurement challenges and objectively complements reported behaviors. Together, these methods offer a multi-layered perspective on risk factors specific to rural motorcycling. Combining quantitative modeling and data-rich empirical approaches strengthens the study’s capacity to identify actionable safety recommendations.

1.5. Doctoral research and thesis structure

This section outlines the overall design of the doctoral research and explains how the thesis is organized to address the proposed research questions and objectives. It first presents a conceptual framework that guided the research process, followed by a detailed explanation of the thesis structure. Together, these elements demonstrate how the research was methodically planned and executed and how each part of the thesis contributes to the overarching aim of improving motorcycle safety on rural roads.

1.5.1. Doctoral research framework

Figure 1-5 presents the overarching framework guiding doctoral research. The process is divided into three related phases. Phase 1 involves identifying the research problem and conducting a thorough literature review to define key knowledge gaps. This phase also includes formulating research objectives, questions, and hypotheses. Phase 2 focuses on establishing a research methodology, including the design of empirical studies, data collection methods, and analytical approaches. It leads to the generation of results and findings across different components of the research. Phase 3 synthesizes these results through critical discussion, drawing out scientific and practical implications, and concluding with final insights and recommendations. This structured progression ensures methodological rigor, theoretical alignment, and relevance to real-world motorcycle safety challenges.

The outcome of each phase is one or more chapters of the doctoral thesis, which is further described in subsection 1.5.2.

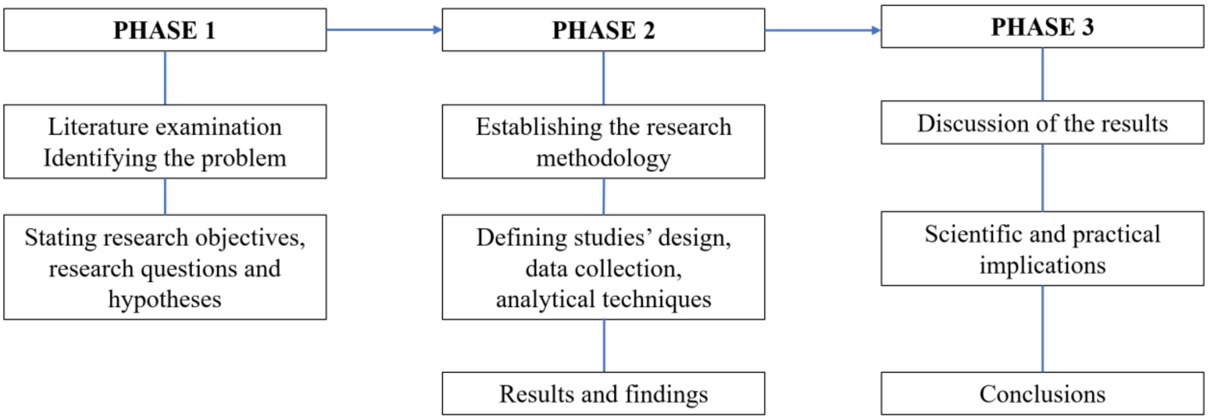


Figure 1-5. Structured framework of the doctoral research, comprising three phases: conceptualization, methodology and analyses, and synthesis

1.5.2. Structure of the thesis

This thesis follows the Scandinavian model, comprising thematically linked, peer-reviewed journal papers. Chapters 2-7 of this thesis correspond to a specific segment of the research, i.e., a published or accepted paper. Integrating these studies ensures that appropriate and complementary methodologies address each research question and objective, and finally answer the stated hypotheses. The chapters are arranged logically to reflect a progression from analysis of crash outcomes using secondary data to exploring behavioral aspects based on primary data, including surveys and naturalistic sources. Findings from crash records, survey data, and naturalistic riding observations, i.e., conclusions from every chapter, are further systematically discussed and compared in Chapter 8 to enable cross-validation of results and enhance the overall conclusions' robustness and depth.

Figure 1-6 provides a detailed visual mapping of the thesis structure, highlighting how each chapter contributes to specific research objectives and questions while indicating the type of data used. Also, it shows which phase of the doctoral research framework is related to each part of the thesis. This thesis's chapters are briefly described in the continuation.

Chapter 2 uses historical crash data to investigate key factors influencing injury severity in single-vehicle motorcycle crashes. It emphasizes environmental and behavioral contributors and aligns with Objectives 1 and RQs 1 and 2.

Chapter 3 focuses on horizontal curve sections and examines how road safety barriers affect the severity of motorcyclist injuries, contributing to Objective 1 and RQ2.

Chapter 4 employs speed monitoring data to explore predictors of speeding on rural roads, specifically focusing on road geometry and environmental factors (Objective 2; RQ3).

Chapter 5 presents a psychometric evaluation of a modified Motorcyclist Behavior Questionnaire (MRBQ) in the Croatian context, addressing the methodological foundation for subsequent behavioral analysis (Objective 2; RQ4).

Chapter 6 further analyzes self-reported behaviors and crash involvement among motorcyclists, linking behavioral profiles with road safety outcomes, and contributes to Objectives 2, 3 and 4 and RQs 3 and 4.

Chapter 7 introduces naturalistic riding data collected via smartphone technology. It analyzes observed rider behavior in real-world conditions, addressing Objectives 4 and 5 and answering RQ5.

Finally, Chapter 8 synthesizes the findings across all empirical chapters, discusses the broader implications for motorcycle safety, and provides conclusions and recommendations (Objective 6).

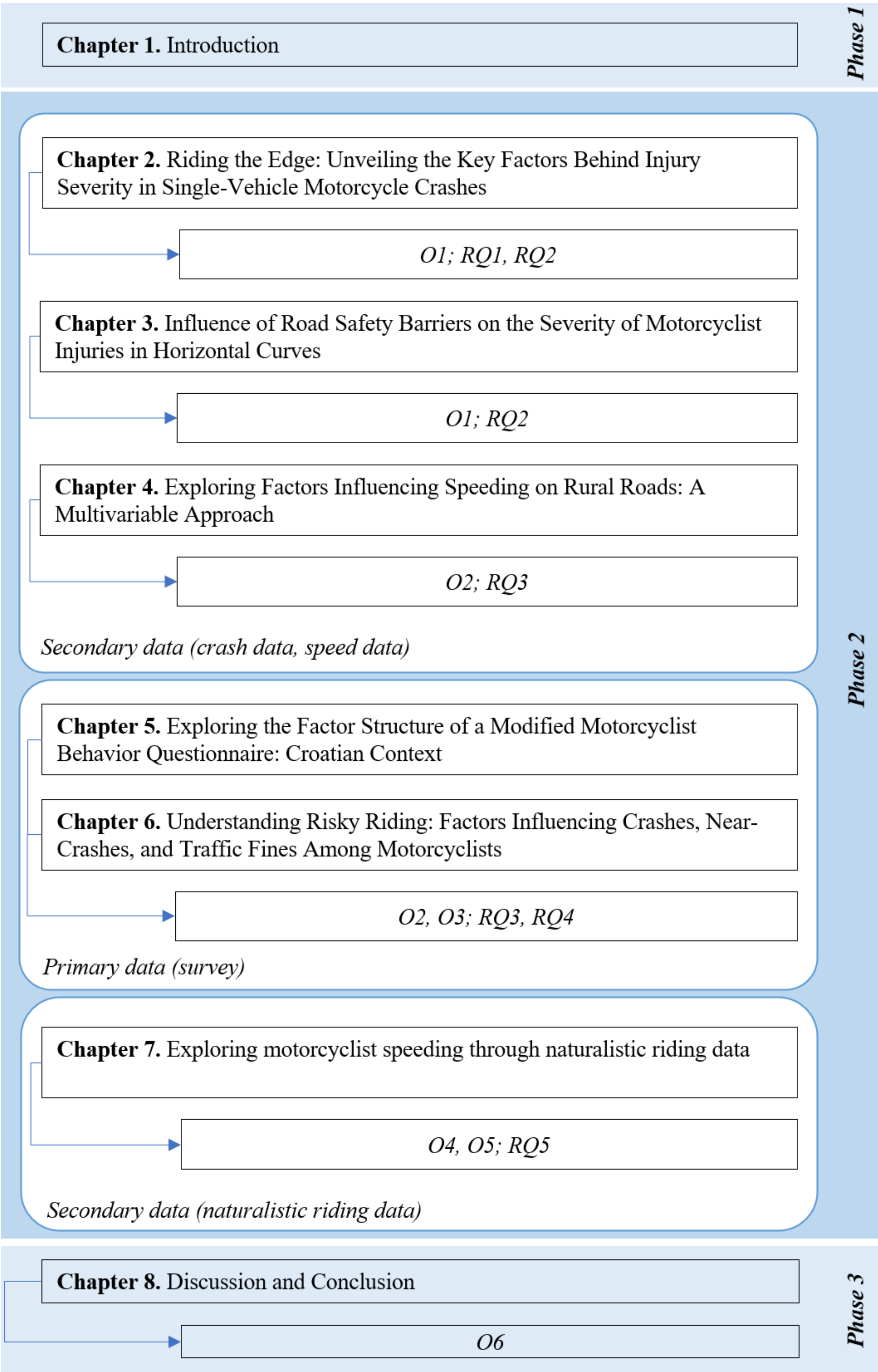


Figure 1-6. Structure of the doctoral thesis

Chapter 2.

Riding the edge: unveiling the key factors behind injury severity in single-vehicle motorcycle crashes

This chapter is based on the following journal article (published):

Ferko, M., Babić, D., & Pirdavani, A. (2025). Riding the Edge – Unveiling the Key Factors behind Injury Severity in Single-Vehicle Motorcycle Crashes. *Promet - Traffic&Transportation*, *37*(4), 834–852. https://doi.org/10.7307/ptt.v37i4.1091

ABSTRACT

Motorcyclists are among the most vulnerable road users, with single-vehicle crashes often resulting in severe or fatal injuries. Although some earlier studies focus on motorcyclists, crash statistics show significant space for motorcyclist safety improvement. This study examines the factors influencing crash severity by analyzing police-reported crash data in the Republic of Croatia from 2017 to 2022, incorporating rider characteristics, roadway and environmental conditions, and crash circumstances. A data-driven approach was applied to assess the relative importance of these factors in determining single-vehicle motorcycle crash injury severity. This study utilized two different modeling approaches – multinomial logistic regression and random forest modeling to investigate the factors influencing crash severity. The results highlight that rider age, road type, speed conditions, and alcohol consumption significantly influence crash outcomes. Older riders and crashes occurring on county and local roads were more likely to result in severe or fatal injuries. At the same time, inappropriate speed and collisions with roadside objects further increased the likelihood of fatal outcomes. The findings suggest the necessity of targeted interventions, including enhanced speed management, infrastructure improvements, stricter enforcement of alcohol regulations, and advanced rider safety programs. To complement this research, future research should integrate more detailed behavioral and vehicle-specific data to refine injury severity predictions. This study provides valuable insights for policymakers and transportation safety professionals seeking to mitigate the severity of motorcycle crashes and enhance overall road safety.

KEYWORDS

Motorcycle; crash severity; single-vehicle crash; safety.

2.1. Introduction

In road traffic, about 1.19 million people are killed each year worldwide, and half of those killed fall into the category of vulnerable road users, i.e., pedestrians, cyclists, and motorcyclists (WHO, 2023b). Motorcycle crashes tend to lead to more severe injuries and fatalities compared to crashes that involve other types of motor vehicles, mainly because motorcyclists lack physical protection in a crash event (Elliot et al., 2003). Additionally, motorcyclists suffer specific injuries in crashes depending on the type of collision (Petit et al., 2020). From 2010 to 2019, motorcycle fatalities decreased by 14% in the European Union, while overall road fatalities fell by 23%, leading to a slight increase in the proportion of motorcycle-related deaths (Slootmans, 2023b). A particularly worrying fact is that motorcyclists account for 30% of total road fatalities in Croatia (Ministry of the Interior of the Republic of Croatia, 2024). According to the European Commission, the proportion of motorcycle crashes on rural roads in the EU was 54% in 2020, compared with 39% on urban roads (Slootmans, 2021).

Single-vehicle crashes, a type of road crash in which only one vehicle and no other road user is involved, have a higher fatality rate compared to other types of motorcycle crashes (Pervez et al., 2022). Those crashes can occur due to the rider losing control, falling during a turn, or sudden motorcycle deceleration. Generally, motorcycles have a higher power-to-weight ratio than cars and are capable of very high speeds, which results in a high risk of severe injury (Lin et al., 2022). In addition, pavement quality and infrastructural elements, such as longitudinal ridging or grooving of the road surface and raised road markings, can produce steering instability for motorcycles (Elliot et al., 2003). Also, research confirms that the presence of motorcycles can raise the likelihood of injury crashes by approximately 30% and nearly double the probability of fatal crashes (Afshar et al., 2022).

When analyzing motorcycle crash data, considerable efforts have been made to improve road infrastructure safety. Road authorities and road designers need prediction tools to analyze the potential safety issues, identify safety improvements, and estimate the potential effect of these improvements. Possible interventions include designing safer infrastructure, incorporating road safety features, improving post-crash care, and improving driver/rider behavior. Therefore, road crash prediction models and, more broadly, analytical or explanatory approaches that identify key risk factors serve as valuable tools for understanding the frequency and severity of crashes. Unlike relying solely on descriptive statistics, these models enable exploring more profound, underlying relationships between variables. Generally, several modeling procedures have been applied in the literature to estimate the severity of motorcyclists' injuries. Crash severity models explore the relationship between crash severity injury and contributory factors such as driver behavior, vehicle characteristics, roadway geometry, and road-environmental conditions.

The European Commission has also recognized the importance of researching motorcycle crashes (Aarts et al., n.d.). Their study team suggests further research into injury causation mechanisms (including pre-injury events and differences between fatal and non-fatal injuries), the influence of travel patterns and risk factors identified, practical measures for reducing severe injuries and preventing fatalities, and a policy benchmarking review. To our knowledge, there is a limited number of similar studies in Europe, and, as stated earlier, motorcyclist safety is a significant concern, especially in the southern parts of this region. Before conducting the analysis, extensive research of the existing literature was carried out to familiarize with previous research and to learn which approaches and data were used by other authors. This study aims to explore which factors and to what extent influence the severity of single-vehicle motorcycle crashes. For that purpose, a crash dataset from Croatia is utilized, and two modeling approaches are used to investigate the factors influencing the crash severity of motorcyclists.

2.2. Literature review

To comprehend the context of similar research, we did an extensive literature review, focusing on previous findings and methods for revealing crash severity influencing factors. To fully understand the mechanism of reducing the severity of motorcycle crashes, there is a need to identify key factors that influence the crash severity.

2.2.1. Key factors influencing single-vehicle motorcycle crash severity

A combination of rider characteristics, environmental conditions, road infrastructure, and crash circumstances influences the severity of single-vehicle motorcycle crashes. Speeding has been identified as the most critical factor, with studies showing that unadjusted speed is the primary cause of over half of all fatal single-vehicle motorcycle crashes (Savolainen & Mannering, 2007b; Tollazzi et al., 2025). Research also found that motorcyclist violations, including speeding, overtaking, and U-turns, increase fatal injuries in single-vehicle crashes (Pervez et al., 2022). Another study showed that behavioral factors such as speeding, alcohol consumption (even within legal limits), and helmet non-use further exacerbate risks, with helmet non-use increasing the likelihood of fatality by 5.58 times (Wang, 2022). Blood alcohol content (BAC) above 0.2 g/L significantly increased the risk of severe injuries, with nighttime and weekend crashes further heightening fatality likelihood (Santos et al., 2024).

Rider characteristics, such as age and experience, are significant predictors of crash severity. Crashes involving young motorcyclists tend to have a lower risk of fatal injuries compared to older motorcyclists (Pervez et al., 2022). Studies consistently show that older riders face a higher risk of fatal injuries, i.e., they are more likely to sustain fatal injuries compared to younger riders (Farid & Ksaibati, 2021; Seyfi et al., 2023; Wei, F., et al., 2021). Some research shows that pillion passengers cause a lower chance of fatal crashes (Pervez et al., 2022), but others deny it (Seyfi et al., 2023).

Collisions with fixed objects such as trees, poles, or traffic devices present the highest fatality risks, with a likelihood of fatality up to 12.28 times greater (Wang, 2022). The probability of the fatal outcome increased by 12.2% and 19.2% in the case of a collision between a motorcycle and fixed objects (Sivasankaran et al., 2021). Moreover, the study showed an increased probability of fatal outcomes of 9.5% in run-off-road crashes. Significant risk factors include crash type, road width, terrain, road alignment, and collision point, with fixed-object collisions being the most critical (Zulherman et al., 2024). Further, higher fatality risks are associated with non-urban roads, curved segments, and high-speed limits (>60 km/h) (Zulherman et al., 2024). In the study on single-vehicle motorcycle crashes in Japan, fixed-object collisions accounted for the majority of fatalities, with a fatality rate four times higher than self-skidding crashes (Zulherman et al., 2022). Fatal crashes frequently occurred on car-only roads with segments 9–19.5 meters wide, curves, and dry road surfaces (Zulherman et al., 2022). Additionally, motorcycle-barrier crashes were found to be at risk of incurring severe injuries (Shaheed & Gkritza, 2014). Higher road standards increase the probability of severe injuries and fatalities for motorcycle-involved crashes (Quddus et al., 2002). Further, rider ejection, two-way roads with no physical separation, single vehicle, curve-aligned roadways are associated with a higher likelihood of fatal crashes (Das et al., 2018). Non-urban roads and roads without speed regulations also show higher fatality risks (Tollazzi et al., 2025; Zulherman et al., 2022). High-speed roads (over 50 mph) are associated with a greater probability of fatal crashes (Savolainen & Mannering, 2007b).

Some temporal and visibility effects have also been noted. Due to increased driving risk during adverse weather conditions, many studies have been dedicated to the investigation of weather effects on the crash occurrence of motor vehicles. The influence of rain was not a strong indicator of motorcyclist crash probability, indicating that the occurrence of rain decreased the possibility of crashes (Cheng et al., 2017). The good weather was statistically significant and related to severe injury crashes (Pai & Saleh, 2008). Also, the probability of fatal/severe injury increases for crashes occurring during dry weather conditions, in the early morning hours or late afternoon and/or early evening hours, and on weekdays (Waseem et al., 2019). Environmental factors such as dark conditions without street lighting significantly elevate the risk of fatal/serious injuries (Wei et al., 2021). Riding at night, speeding, alcohol consumption, and falling asleep are critical contributors to severe crashes, exacerbated by reduced visibility and challenging road curvature (Wisutwattanasak et al., 2024). Conversely, daytime crashes were influenced by speeding, with holidays and peak traffic hours slightly reducing severity due to slower traffic speeds.

In summary, the most influential factors contributing to severe and fatal injuries in single-vehicle motorcycle crashes include speeding, collisions with fixed objects, non-urban road environments, nighttime and weekend riding, alcohol consumption, helmet non-use, older rider age, and high-speed roadway conditions.

2.2.2. Statistical approaches to crash severity analysis

This subsection summarizes statistical and machine learning models used in crash severity analysis. Also, attention is paid to the use of variables and datasets. In crash severity modeling, various statistical approaches have been investigated, such as binary and multinomial logit models, nested logit models, and mixed and ordered probit models, and more advanced approaches like machine learning methods have been used. The data used in modeling motorcycle crash severity typically includes many details relating to the crash occurrence, including the number of vehicles involved, the age of crash victims, weather conditions, types of vehicles involved, and crash type (e.g., run-off-road, head-on, side collision, etc.). Those details can be integrated into statistical models, such as discrete choice models, the most commonly used tools to analyze injury severity (Anarkooli et al., 2017). Since the dependent variable (i.e., crash severity) usually has multiple outcome categories (e.g., fatal, different injury levels, and property damage), using logit and probit models to model the crash severity is standard practice (Abdulhafedh, 2017). Motorcycle crash data could lack some factors that are not observable or relevant and are not reported in crash data. Such information can include the size and speed of the motorcycle, rider experience, and training. To address the problem of unobserved heterogeneity, studies on crash injury severity analysis have used mixed logit models, latent-class models with random parameters, latent-class models, and bivariate/multivariate models with heterogeneity in means and variances. Random parameters (mixed logit) and finite mixture (latent class) methods can accommodate individual unobserved heterogeneity by allowing parameters to differ across observations (Shaheed & Gkritza, 2014).

Pervez et al. (2022) performed a random parameter logit model with heterogeneity in means and variances to identify the key factors influencing the injury severity of single-vehicle motorcycle crashes. The study was performed in Pakistan, and crash data were extracted from a crash injury research project during a one-year period. The variables for the model analysis were chosen using two criteria: characteristics that have been studied previously in the literature and variables based on the local environment. Consequently, variables were categorized into four main categories: temporal, motorcyclist, roadway, and crash characteristics. Similarly, Seyfi et al. (2023) used a random parameter (mixed) logit model (RPL) to evaluate the severity of injuries in motorcycle crashes. A total of 10,897 non-intersection motorcycle crash data from the beginning of 2009 to November 2020 in the State of Victoria, Australia, was analyzed in this study.

A study conducted by Wang (2022) utilized binary logit and mixed logit models to analyze factors influencing motorcyclist fatalities in single-motorcycle (SM), motorcycle-motorcycle (MM), and motorcycle-vehicle (MV) crashes.

Farid & Ksaibati (2021) modeled the severities of motorcycle crashes in Wyoming that occurred from 2008 to 2017 using random parameters. They implemented binary logistic regression and mixed binary logistic regression modeling structures. The mixed binary logistic regression model exhibited a better fit than the binary logistic regression model according to the AIC (a measure to assess model fit) results. Shaheed & Gkritza (2014) used a latent class multinomial logit model to investigate the factors that affect crash severity outcomes in 3644 single-vehicle motorcycle crashes from Iowa, USA, from the 2001-2008 period.

Quddus et al. (2002) conducted an analysis of motorcycle injury and vehicle damage severity using ordered probit models to explain how variations in the characteristics of the roadway, the rider, environmental factors, and the motorcycle can lead to variations in different levels of injury severity and damage to the motorcycle. An extensive database of 27,570 motorcycle crashes in Singapore was extracted from police reports over 9 years. The study included two variables: the severity of motorcycle crash injuries (three categorical levels: fatal, seriously injured, and slightly injured) and the severity of damage to the motorcycle (four categorical levels: total wreck, extensive damage, slight damage, and no damage).

The probability of a fatal outcome in motorcycle and fixed object crashes was also proven by Sivasankaran et al. (2021) in studying potential risk factors contributing to the severity of single-vehicle motorcycle crashes with an ordered logit model. The dataset consisted of 16,542 single-vehicle motorcycle crashes from 2009-2017 in Tamil Nadu, India.

Cheng et al. (2017) used alternative Bayesian multivariate crash frequency models and weather data to predict motorcycle crash severity. They observed motorcycle crashes in San Francisco (2008-2013) and categorized them into four levels of severity: fatal, serious injury, other visible injury, and complaint of pain. Five models were developed using a Full Bayesian formulation accounting for correlations commonly seen in crash data and then compared for fitness and performance. Wei et al. (2021) applied a Full Bayesian Spatial Random Parameters Logit Model to analyze rural single-vehicle crash severity across passenger cars, motorcycles, pickups, and trucks, utilizing data from 29,525 crashes in Shandong Province, China (2015–2020). Crash severity was categorized into three levels (no injury, slight injury, and fatal/serious injuries), focusing on fatal/serious outcomes.

Another approach is to apply deep learning to other aspects of transportation engineering and transportation safety analysis. Das et al. (2018) employed a deep learning technique to analyze 5 years of single-vehicle crashes in Louisiana. The study contributes to the existing injury severity modeling literature by developing a deep learning framework called DeepScooter to predict motorcycle-involved crash severities. The severity of crashes is recorded as five injury levels (commonly known as the KABCO injury scale).

Some researchers used machine learning techniques to evaluate motorcycle injury severity (Rezapour et al., 2020, 2021). The study adopted random forest, support vector machine, multivariate adaptive regression splines, and binary logistic regression techniques to predict injury severity outcomes of crashes (Rezapour et al., 2020). Although all the models perform similarly in predicting motorcycle crashes, the random forest model was the best-fit model according to the misclassification rate and AUC (area under the curve) measure. Later, they used a random forest model to identify the factors influencing motorcycle crash injury severity. A study in Japan applied a Deep Q-learning Network-based Imbalanced Classification (DQNIC) model to predict fatal single-vehicle motorcycle crashes using data from 2019–2022 (Zulherman et al., 2024). Wisutwattanasak et al. (2024) used the XGBoost-SHAP algorithm to analyze single-vehicle motorcycle crashes in Thailand under daytime and nighttime conditions, revealing key factors influencing crash severity.

Santos et al. (2024) conducted a study using data from Portugal (2010–2019). They applied machine learning techniques to analyze factors influencing motorcycle crash injury severity, identifying alcohol consumption, road type, and helmet use as key contributors.

Among seven machine learning models evaluated, random forest (RF) and logistic regression (LR) developed with a balanced dataset outperformed others in predicting fatalities.

2.2.3. Conclusions based on literature review

The reviewed studies highlight the complexity of methodologies used to analyze the severity of single-vehicle motorcycle crashes. Various statistical and machine learning approaches have been applied, including logit models (binary, multinomial, and mixed logit), ordered probit models, and deep learning techniques. While traditional statistical models, such as multinomial logit and probit models, provide interpretable relationships between predictor variables and crash severity, machine learning methods, including random forest, XGBoost, and deep learning algorithms, offer enhanced predictive performance by capturing complex interactions. The diversity of methodologies underscores the ongoing need to balance interpretability and predictive accuracy in crash severity modeling. However, the existing research is still relatively modest, especially in Europe.

Regarding contributing factors, the findings consistently highlight key variables that influence crash severity. Speeding, alcohol consumption, road curvature, and collisions with fixed objects are among the most critical determinants of severe and fatal motorcycle crashes. Nighttime riding, road surface conditions, and rider demographics (such as older age groups) have been frequently associated with increased crash severity. Still, a gap concerning the role of road design and infrastructure in crash outcomes could be noted. Differences in study findings suggest further research to explore context-specific risk factors and their interactions.

The research problem in this study extends beyond the general understanding that motorcyclists are vulnerable road users. While motorcycle crashes have been widely studied, the focus has primarily been on multi-vehicle crashes. Single-vehicle motorcycle crashes present distinct risk factors and severity patterns that require dedicated investigation. Although similar research questions have been previously investigated, our study produces a novel analysis with insights comparable to other studies, utilizing an uninvestigated crash dataset. Specifically, the study seeks to answer the following research questions:

1. Which factors significantly influence injury severity in single-vehicle motorcycle crashes?
2. Do influencing factors differ worldwide?
3. How do traditional statistical models (e.g., MLR) compare with machine learning models (e.g., RF) in predicting crash severity outcomes?

2.3. Methodology

The methodology section outlines this study's research design, data collection, and analysis procedures. It explains the statistical models and techniques applied to identify the significant factors influencing crash severity, ensuring a comprehensive and systematic approach to the analysis.

2.3.1. Research data

The data used in this study comprises police (Ministry of the Interior, Republic of Croatia) records of road crashes involving a single motorcycle (single-vehicle crashes) from 2017 to 2022 (except for 2020 because of an incomplete dataset). In the mentioned period, 7676 crashes involving motorcycles were recorded. After that, multi-vehicle crashes and crashes with an unknown GPS location/road type were filtered out, and a total of 2170 single-vehicle crashes were analyzed in this study. Data with incorrect/unrecorded GPS coordinates were excluded to avoid misclassifying the road type. The data describe crashes that occurred on the Croatian road network, which consists of motorways (primary roads), state and county roads (primary and secondary roads), lower-ranking roads (local and uncategorized), and urban roads/streets. It should be noted that all roads except motorways and urban roads are predominantly in rural areas. The dataset includes fundamental information on environmental conditions (road surface condition, weather, part of the year, visibility), rider characteristics (citizenship, gender, alcohol intoxication, age), infrastructure-related factors (road type, road characteristics, speed limit), and crash related data information (crash type, crash circumstance, crash outcome severity) relevant to each crash. The list of used variables is shown in Table 2-1 and Table 2-2. This comprehensive data provides a basis for examining the key determinants and patterns associated with motorcycle single-vehicle crashes.

2.3.2. Analysis methods

Following a review of previous research, random forest (RF) and multinomial logistic regression (MLR) methods were selected for further analysis. Although RF and MLR are well-known methods and have been proven helpful for this type of research, we did not find a reference where they were used on a single-vehicle motorcycle crash dataset to compare their efficacy. The selection of (RF) and (MLR) was also influenced by the study objectives, the nature of the dataset, and the inherent differences between these two modeling approaches. RF was chosen for its ability to handle non-linear relationships, detect complex interactions among variables, and rank feature importance, making it helpful in identifying key predictors of crash severity. Meanwhile, MLR was selected due to its interpretability and ability to estimate the likelihood of each crash severity level while controlling for multiple factors. All statistical analyses were conducted using SPSS (version 29.0) and R (version 4.3.3).

Multinomial logistic regression (MLR) is a widely used statistical method for modeling categorical dependent variables with more than two outcomes. Unlike binary logistic regression, which deals with two categories, MLR extends the approach by estimating the probability of an outcome falling into one of several possible categories relative to a reference category (El-Habil, 2012; Upton, 2016). It estimates a set of regression coefficients for each category, quantifying how predictor variables influence the likelihood of each outcome. This makes it particularly suitable for analyzing crash severity, where the response variable can take multiple levels, such as no injury, mild injury, or severe/fatal injury. The model's coefficients are interpreted through odds ratios, which indicate how changes in predictor variables affect the probability of a crash, resulting in a particular severity level. This robust method accommodates continuous and categorical predictors, making it suitable for complex real-world problems (Abdillah et al., 2020). The advantages of MLR are its ability to handle categorical and continuous predictors simultaneously and its high level of interpretability compared to many machine learning models.

Random forest enhances the decision tree approach by employing an ensemble method that generates multiple decision trees (Breiman, 2001; Sarker & Salah, 2019). A decision tree is a supervised learning technique primarily used for classification, though it can also be applied to regression. It begins with a root node representing the first decision point, where the dataset is split based on the feature that best separates the data into distinct classes. Each subsequent split leads to another decision node, further refining the classification or a terminal node that assigns a final class prediction. The process of dividing the data into binary partitions is known as recursive partitioning. Unlike traditional decision trees, random forest constructs multiple trees, with each tree trained on a random subset of features rather than using the entire dataset. The final classification outcome is determined through majority voting across all trees, ensuring greater robustness and reducing overfitting (Dutta et al., 2021; Liu et al., 2024). The number of predictor variables randomly selected at each node when constructing individual decision trees (mtry) is a key hyperparameter that controls the diversity of the trees in the ensemble (Louppe et al., 2013; Nembrini et al., 2018; Sikdar et al., 2025). A smaller number increases randomness, reducing tree correlation and improving generalization, but may lead to weaker individual trees.

On the other hand, a larger mtry number allows trees to be more similar to each other, potentially improving accuracy but increasing the risk of overfitting. The Gini index, or impurity, measures how well a decision tree node separates the classes (Louppe et al., 2013; Nembrini et al., 2018; Sikdar et al., 2025). It quantifies the probability that a randomly chosen element in a node would be incorrectly classified if randomly labeled based on the distribution of class labels. In a graphical representation, the mean decrease in Gini measures how important each variable is in doing splits during the decision tree construction process within the random forest model. In other words, a greater mean decrease in Gini indicates that the variable plays a stronger role in classification.

To evaluate model performance, receiver operating characteristic (ROC) curves were generated for both, with the area under the curve (AUC) calculated as a performance metric. The AUC quantifies a classifier’s ability to distinguish between classes, ranging from 0.5 (random chance) to 1.0 (perfect classification). Since the AUC considers the full range of classification thresholds, it is a reliable measure of model effectiveness. The AUC is computed by summing the areas of successive trapezoids under the ROC curve, providing a comprehensive assessment of classifier performance (Melo, 2013).

2.4. Results

The descriptive analysis provides an overview of road and infrastructure characteristics, circumstantial factors, and rider characteristics related to motorcycle crashes (Table 2-1). Most crashes occurred on state roads (39.6%), with 50.8% on curved road sections and 55.6% in areas with a 50 km/h speed limit. Dry and clean surfaces were predominant (85.3%), and clear weather was reported in 58.3% of cases. Regarding circumstantial factors, crashes were more frequent between April and September (78.1%) and during the day (70.6%). Run-off-road crashes (59.6%) were the most common, and inappropriate speed (69.3%) was the leading contributing factor. Nearly half of all crashes (46.5%) resulted in death or severe injuries. Rider characteristics showed that the vast majority of motorcyclists involved were male (95.9%), and 23.0% had alcohol in their system at the time of the crash.

Table 2-1. Descriptive statistics of categorical variables

Variable	Description	Code	Sample (N)	Percentage (%)
Road type	Motorway	1	57	2.63%
	State road	2	859	39.59%
	County road	3	395	18.20%
	Local road	4	167	7.70%
	Uncategorized	5	504	23.23%
	Urban street	6	188	8.66%
Road characteristics	Curve	17	1102	50.78%
	Road stretch	18	668	30.78%
	Other	23	46	2.12%
	Intersection	41	275	12.67%
	Other intersection	42	20	0.92%
	Road object	43	18	0.83%
	Railway crossing	44	8	0.37%
	Pedestrian/bicycle-related	47	33	1.52%
Speed limit (km/h)	<= 30	1	155	7.14%
	40	2	303	13.96%
	50	3	1207	55.62%
	60	4	189	8.71%
	>= 70	5	316	14.56%
Road surface condition	Dry – clean surface	1	1851	85.30%
	Dry – sand, gravel on the surface	2	90	4.15%
	Wet surface	3	196	9.03%
	Other conditions	4	33	1.52%
Weather conditions	Clear	1	1265	58.29%
	Cloudy	2	312	14.38%
	Rain	3	84	3.87%
	Other conditions	4	509	23.46%
Part of the year	April - September	1	1694	78.06%
	October - March	2	476	21.94%
Part of the day	Day	1	1531	70.55%
	Night	2	573	26.41%
	Dusk	3	51	2.35%
	Dawn	4	15	0.69%
Crash type	Run-off-road	1	1293	59.59%
	Hitting an object on the road/a roadside object	2	279	12.86%
	Other crash types	3	598	27.56%
Crash circumstances	Inappropriate speed	1	1503	69.26%
	Late hazard detection/Sudden braking	2	119	5.48%
	Other circumstances	3	548	25.25%
Crash severity*	No injuries	0	330	15.21%
	Mild injuries	1	832	38.34%
	Death or severe injuries	2	1008	46.45%
Citizen of Croatia	Yes	1	1744	80.37%
	No	2	425	19.59%
	Unknown	3	1	0.05%
Gender	Male	1	2082	95.94%
	Female	2	88	4.06%
Alcohol in blood	No	0	1671	77.00%
	Yes	1	499	23.00%

** Crash severity – dependent variable*

The descriptive statistics for rider age indicate that the dataset includes 2170 motorcyclists aged 14 to 86 (Table 2-2). The mean age is 39.13 years, with a standard deviation of 14.66, suggesting a relatively broad age distribution. The skewness value of 0.395 indicates a slight positive skew, meaning that the age distribution has a longer tail toward older riders. The kurtosis value of -0.643 suggests a relatively flat distribution compared to a normal distribution. These statistics highlight the presence of younger and older motorcyclists in the dataset, concentrating on middle-aged riders.

Table 2-2. Descriptive statistics of riders' age

	N	Min	Max	Mean	Std. Dev.	Variance	Skewness	Kurtosis
Rider age (yrs.)	2170	14	86	39.13	14.661	214.932	0.395	-0.643

The following sections examine the explanatory value of individual independent variables for different crash outcomes using RF and MLR. While RF will highlight variable importance and capture complex, non-linear relationships, MLR will provide interpretable estimates of how specific factors influence the crash severity levels. Rather than focusing solely on predictive accuracy, this analysis aims to enhance the understanding of key risk factors and their relative contributions to crash outcomes and offer valuable insights for road safety improvements.

2.4.1. Random Forest (RF)

An RF classification model was developed to gain insight into the importance of independent variables and predict crash severity using a dataset of motorcyclist-involved crashes. The model was trained on 1,100 trees with three variables randomly selected at each split (mtry = 3). A feature importance analysis was conducted to further interpret the model's decision-making process. Figure 2-1 illustrates the variable importance rankings from the RF model, measured by the mean decrease in the Gini index. Rider age is the most influential predictor, indicating that a rider's age substantially contributes to the model's ability to distinguish crash severity outcomes. Road type and speed limit are closely followed, underscoring the importance of roadway conditions and regulatory factors. Other notable predictors include road characteristics, weather conditions, and crash type, while gender appears to have the lowest relative importance among the examined variables.

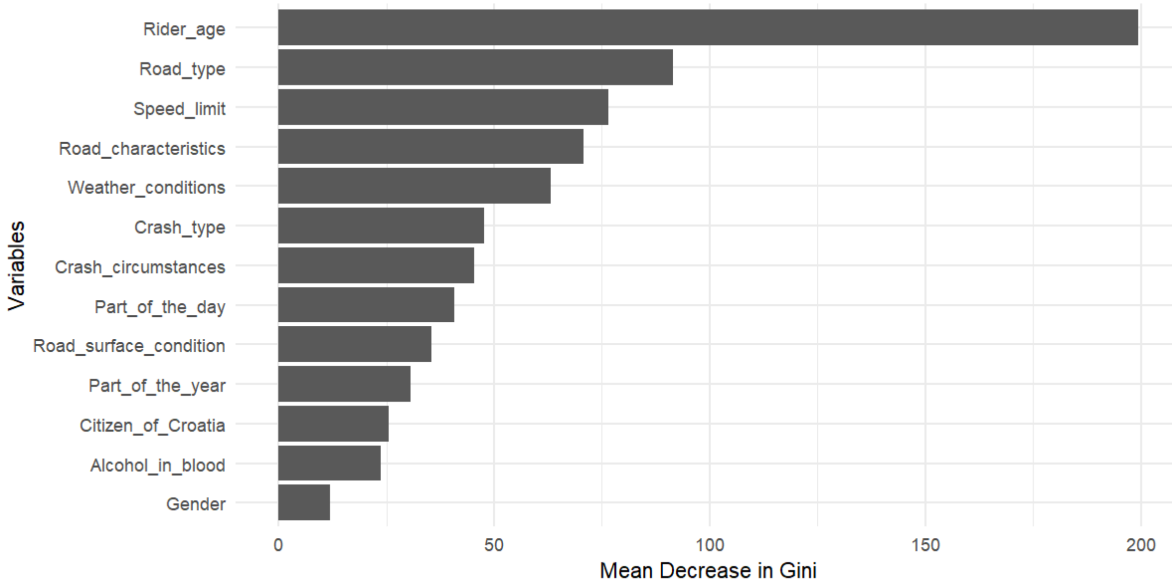


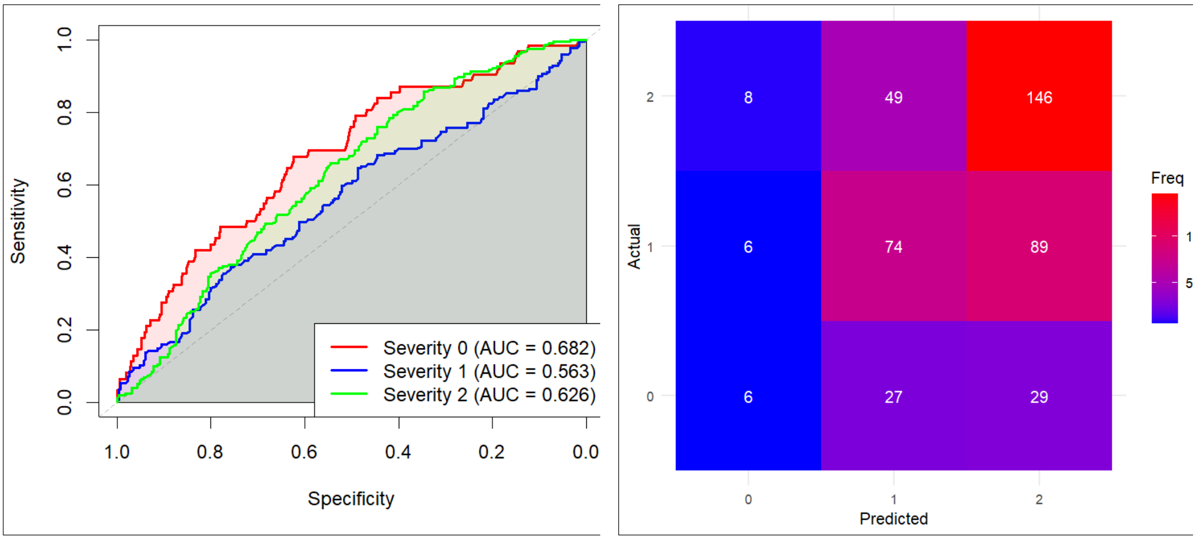
Figure 2-1. Variable importance according to the random forest model

Table 2-3 presents the performance metrics for predicting crash severity outcomes. The model demonstrates the highest sensitivity for the death or severe injury category (0.724), indicating its relatively strong ability to identify severe crashes. However, sensitivity is considerably lower for no injuries (0.113), suggesting the model struggles to correctly classify cases where no injuries occur. Mild injuries fall in between, with a sensitivity of 0.444, reflecting moderate recognition of this category. In terms of specificity, the model performs best for no injuries (0.968), effectively excluding cases that do not belong to this category. Precision, which measures the proportion of correctly predicted cases within each category, is highest for severe injuries (0.557) and lowest for no injuries (0.368), suggesting that predictions for the no-injury category include a higher number of false positives. The F1-score balances sensitivity and precision and follows a similar trend, with the best performance observed for death or severe injury (0.630). The model's overall accuracy is 0.528, meaning that the model correctly classifies cases 52.8% of the time. While the model effectively captures patterns related to severe or fatal injuries, its performance in distinguishing no-injury cases indicates room for improvement.

Table 2-3. Performance metrics of the random forest model for injury severity outcomes

Outcome (dependent variable)	Sensitivity	Specificity	Precision	F1-Score	Accuracy
0 – No injuries	0.113	0.968	0.368	0.173	0.528
1 – Mild injuries	0.444	0.713	0.497	0.469	0.528
2 – Death or severe injury	0.724	0.494	0.557	0.630	0.528

Figure 2-2 presents a) the Receiver Operating Characteristic (ROC) curves and b) the confusion matrix from the random forest model for each crash severity category. The Areas Under the Curve (AUCs) indicate moderate classification performance, with values of 0.682 for no injuries, 0.563 for mild injuries, and 0.626 for severe or fatal injuries. These results suggest that the model is relatively better at distinguishing no-injury cases, while its ability to classify mild injuries is notably weaker. In the confusion matrix, the diagonal elements represent correctly classified cases, whereas off-diagonal elements indicate misclassifications. The color intensity reflects misclassification frequency, with darker shades indicating higher counts. While the model captures general patterns in crash severity classification, further improvements might enhance its ability to better distinguish between mild and severe injury outcomes.



a) b)

Figure 2-2. a) ROC curves and b) confusion matrix for the random forest model

2.4.2. Multinomial logistic regression (MLR)

The results of the model fitting criteria indicate that the final multinomial logistic regression model provides a significantly better fit than the intercept-only model, as evidenced by the reduction in -2 Log Likelihood (from 4358.017 to 4085.802) and the significant likelihood ratio test ($\chi^2 = 272.215$, df = 70, $p < 0.001$). The goodness-of-fit tests further support the adequacy of the model, with both the Pearson ($\chi^2 = 4285.248$, df = 4178, p = 0.121) and Deviance ($\chi^2 = 4061.529$, df = 4178, p = 0.900) tests yielding non-significant results, indicating that the model does not show significant lack of fit. The pseudo-R-square values suggest that the model explains a modest proportion of the variance in the dependent variable (Cox and

Snell $R^2 = 0.118$, Nagelkerke $R^2 = 0.136$, McFadden $R^2 = 0.062$), highlighting that while the model provides meaningful insights, additional factors may influence the outcome. Nonetheless, the significant improvement over the null model and the acceptable fit statistics supports the model's suitability for analyzing the relationship between predictor variables and crash severity outcomes.

Several factors, including road type, alcohol consumption, gender, rider age, nationality, crash circumstances, crash type, and road surface conditions, are significantly associated with the outcome variable (Table 2-4). Road characteristics are borderline significant, meaning they may still contribute meaningfully but do not reach the conventional 0.05 threshold. These findings suggest that these factors should be carefully considered when analyzing crash risks and their severity. At the same time, other variables, such as part of the day and weather conditions, appear less influential in this specific model.

Table 2-4. Likelihood ratio tests for predictors in multinomial logistic regression

Variable	Chi-Square	df	Sig.
Road type	36.726	10	<0.001
Part of the day	4.743	6	0.577
Alcohol in blood	7.183	2	0.028
Gender	11.174	2	0.004
Rider age	14.612	2	<0.001
Citizen of Croatia	21.632	4	<0.001
Road characteristics	23.608	14	0.051
Road surface condition	16.239	6	0.013
Weather conditions	5.543	6	0.476
Crash circumstances	35.054	4	<0.001
Crash type	25.640	4	<0.001
Part of the year	3.158	2	0.206
Speed limit	7.095	8	0.526

Table 2-5 presents the multinomial logistic regression results for predictors of crash severity, with death or severe injuries as the reference category. For clarity of results, only those parameters that showed statistical significance ($p <= 0.05$) are shown in the table. Each coefficient (B) and odds ratio (Exp(B)) describe how a predictor variable affects the likelihood of experiencing either no injuries or mild injuries compared to death or severe injuries.

Several comparisons to the reference road type show strong negative associations in the no injuries category. For instance, crashes on a county road have a coefficient of -1.240 ($p < 0.001$; Exp(B) = 0.289), suggesting about a 71% reduction in the odds of no injuries compared to severe/fatal injuries on that road type. A similar pattern appears for mild injuries, albeit with slightly smaller effect sizes (e.g., state road: -0.629, $p = 0.002$; Exp(B) = 0.533).

Negative coefficients dominate the no injuries category among all road characteristics (e.g., curves, intersections, road objects). For example, encountering a road object yields a coefficient of −3.227 ($p = 0.011$; Exp(B) = 0.040), indicating that crashes involving a road object are associated with a 96% lower chance of no injuries than severe or fatal injuries. Inappropriate speed negatively affects the odds of no injuries (-0.561, $p < 0.001$; Exp(B) = 0.571), confirming that higher speeds increase the risk of severe or fatal injuries. Conversely, late hazard detection/sudden braking is positively associated with no-injury crashes (1.016, $p = 0.001$; Exp(B) = 2.761), meaning that such circumstances increase the odds of experiencing no injuries nearly threefold compared to severe injuries. Run-off-road crashes have negative coefficients in both the no injuries (−0.730, $p < 0.001$; Exp(B) = 0.482) and mild injuries (-0.300, $p = 0.016$; Exp(B) = 0.741) categories, indicating a higher likelihood of severe outcomes when a crash involves leaving the roadway.

For no injuries, male riders have a positive coefficient (1.341, $p = 0.007$; Exp(B) = 3.824), suggesting that males are nearly four times more likely to experience no injuries rather than severe injuries compared to females. Additionally, the absence of alcohol in the rider's blood increases the odds of no injuries (0.428, $p = 0.024$; Exp(B) = 1.535) and mild injuries (0.260, $p = 0.041$; Exp(B) = 1.297), reinforcing the protective effect of sobriety in reducing severe crash outcomes.

For no injuries, the coefficient for rider age is -0.017 ($p < 0.001$), with an odds ratio of 0.983, indicating that each additional year of age reduces the odds of experiencing no injuries rather than severe injuries by approximately 1.7%. For mild injuries, the coefficient is -0.009 ($p = 0.009$), with an odds ratio of 0.991, reflecting a 0.9% decrease in the odds of mild injuries for each additional year of age.

Older age, hazardous road characteristics (e.g., curves, intersections, road objects), and inappropriate speed increase the likelihood of severe or fatal injuries. On the other hand, late hazard detection, male gender, and the absence of alcohol were shown to increase the likelihood of less severe crash outcomes.

Table 2-5. Multinomial logistic regression parameter estimates for crash injury severity

Crash severity	Variable	B	Std. Error	Wald	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
							Lower Bound	Upper Bound
0 – No injuries	Rider age	-0.017	0.005	12.325	0.000	0.983	0.973	0.992
	Road type = State road	-1.016	0.251	16.412	0.000	0.362	0.221	0.592
	Road type = County road	-1.240	0.282	19.382	0.000	0.289	0.167	0.503
	Road type = Local road	-1.127	0.343	10.816	0.001	0.324	0.166	0.634
	Road type = Uncategorized	-0.683	0.249	7.503	0.006	0.505	0.310	0.823
	Road characteristics = Curve	-1.490	0.528	7.962	0.005	0.225	0.080	0.635
	Road characteristics = Road stretch	-1.242	0.525	5.609	0.018	0.289	0.103	0.807
	Road characteristics = Other	-1.464	0.663	4.872	0.027	0.231	0.063	0.849
	Road characteristics = Intersection	-1.114	0.540	4.260	0.039	0.328	0.114	0.945
	Road characteristics = Other intersection	-2.760	1.182	5.452	0.020	0.063	0.006	0.642
	Road characteristics = Road object	-3.227	1.267	6.480	0.011	0.040	0.003	0.476
	Crash circumstances = Inappropriate speed	-0.561	0.159	12.378	0.000	0.571	0.418	0.780
	Crash circumstances = Late hazard detection/Sudden braking	1.016	0.302	11.303	0.001	2.761	1.527	4.992
	Crash type = Run-off-road	-0.730	0.169	18.681	0.000	0.482	0.346	0.671
	Gender = Male	1.341	0.495	7.358	0.007	3.824	1.451	10.081
	Alcohol in blood = No	0.428	0.190	5.078	0.024	1.535	1.057	2.227
1 – Mild injuries	Rider age	-0.009	0.003	6.743	0.009	0.991	0.984	0.998
	Road type = State road	-0.629	0.205	9.362	0.002	0.533	0.357	0.798
	Road type = County road	-0.538	0.217	6.166	0.013	0.584	0.382	0.893
	Road type = Local road	-0.690	0.258	7.146	0.008	0.501	0.302	0.832
	Road characteristics = Curve	-0.982	0.483	4.143	0.042	0.374	0.145	0.964
	Crash type = Run-off-road	-0.300	0.125	5.782	0.016	0.741	0.580	0.946
	Alcohol in blood = No	0.260	0.128	4.163	0.041	1.297	1.010	1.665

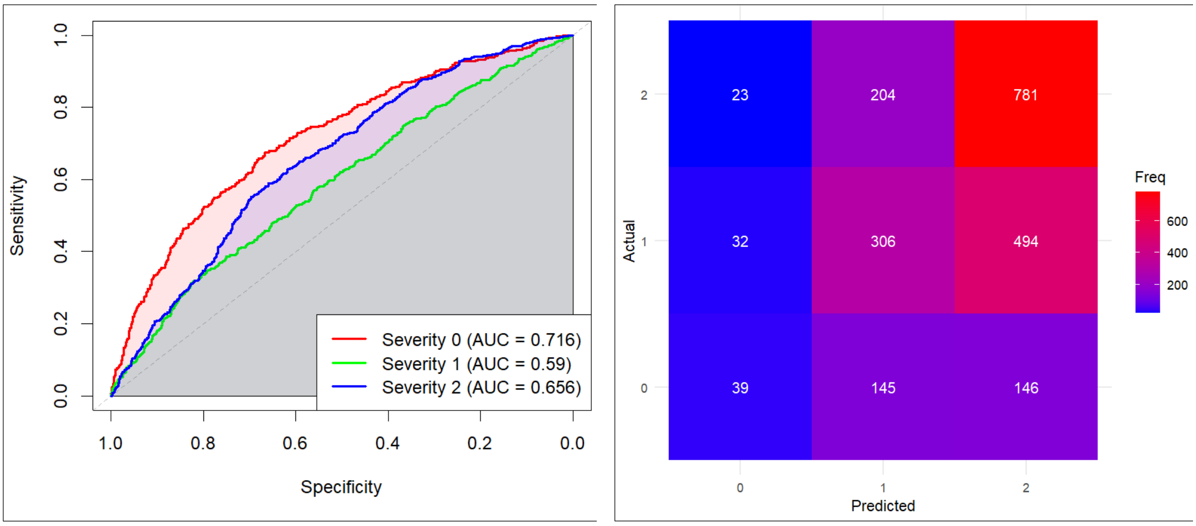
The reference category is 2 – Death or severe injuries.

Table 2-6 summarizes the performance metrics of the MLR model for predicting injury severity outcomes (no injuries, mild injuries, and death or severe injury). The model displayed its most substantial sensitivity for the most severe category, suggesting greater effectiveness at detecting cases resulting in severe outcomes. In contrast, sensitivity for mild injuries was more limited and especially low for cases with no injuries. Specificity was highest for no injuries, indicating strong performance excluding non-injury cases. This metric decreased for mild injuries and declined further for the most severe category, implying that some cases classified as severe may belong to other groups. A similar trend emerged for precision, which was comparatively higher for severe outcomes and lower for mild and no injuries. F1-scores, capturing the balance between sensitivity and precision, were also most significant for the most severe category, somewhat lower for mild injuries, and lowest for no injuries, aligning with the overall classification pattern.

Table 2-6. Performance metrics of the multinomial logistic regression model for injury severity outcomes

Outcome (dependent variable)	Sensitivity	Specificity	Precision	F1-Score	Accuracy
0 – No injuries	0.118	0.970	0.415	0.184	0.519
1 – Mild injuries	0.368	0.739	0.467	0.412	0.519
2 – Death or severe injury	0.775	0.449	0.550	0.643	0.519

Figure 2-3 illustrates the ROC curves for the three crash severity categories under the multinomial logistic regression model. The model demonstrates a fair level of discrimination for no injuries (AUC = 0.716) and a moderate ability to distinguish death or severe injury (AUC = 0.656) from other outcomes. In contrast, it performs relatively poorly in differentiating mild injuries from the other two categories (AUC = 0.590). This pattern suggests that while the model is most effective at identifying no-injury cases and can moderately discriminate severe outcomes, it struggles to classify mild injuries accurately. The trade-off between sensitivity and specificity is most favorable for the no-injury category, as indicated by the red curve lying furthest from the diagonal.



a) b)

Figure 2-3. a) ROC curves and b) confusion matrix for the multinomial logistic regression model

2.5. Discussion

This study explored the factors influencing the severity of single-vehicle motorcycle crashes using two distinct modeling approaches: random forest (RF) classification and multinomial logistic regression (MLR). The findings provide insights into the key predictors of crash severity and their relative contributions to injury outcomes.

2.5.1. Comparison of modeling approaches

The RF model effectively identified the most influential variables affecting crash severity. The mean decrease in the Gini index highlighted rider age, road type, and speed limit as the strongest predictors. This aligns with previous research indicating that older riders face a higher risk of severe crashes due to decreased reaction time and physical vulnerability (Nunn, 2011; Pai & Saleh, 2007; Wang, 2022). At the same time, roadway and speed conditions significantly influence crash outcomes. However, the random forest model exhibited moderate classification accuracy, with misclassification rates highest for mild injuries, suggesting that while it effectively captures complex interactions, its ability to distinguish between injury levels precisely remains limited. Conversely, the MLR model allowed an interpretable assessment of how individual factors influence crash severity. Several variables, including road type, alcohol consumption, gender, rider age, crash type, and speed limit, significantly impacted injury severity. The model better predicted deaths and severe crashes than distinguishing mild injuries from no injuries. The ROC analysis confirmed this pattern, with higher AUC values for no and severe/fatal injuries but a lower value for mild injuries, indicating difficulties differentiating intermediate severity cases. It has to be noted that some similar studies that used machine learning methods showed more favorable results but utilized a bigger dataset (Santos et al., 2024; Wahab & Jiang, 2020).

While RF provides robust variable importance rankings and captures non-linear relationships, MLR offers clearer interpretability regarding the direction and magnitude of predictor effects. Considering both models in a complementary way strengthens the reliability of findings by balancing interpretability and predictive performance. MLR helps explain how individual factors contribute to different injury severity levels, while RF detects complex interactions that traditional parametric models may overlook. MLR is well-suited for policy discussions because it provides statistical significance levels and effect estimates, making it easier to communicate results to policymakers. On the other hand, RF is valuable for identifying the most influential variables, even in non-linearity and interactions. The conclusions are similar to comparable studies' findings, saying that RF outperformed LR in terms of predictive ability, while LR provided stronger interpretability of individual risk factors (Santos et al., 2024; Wahab & Jiang, 2020).

2.5.2. Key factors

This study confirms the importance of rider age, road infrastructure, speed limits, and alcohol consumption in determining crash severity, findings that are consistent with prior studies on motorcycle safety.

Literature shows that younger riders tend to behave riskily and more carelessly and are more likely to be involved in crashes (Abdul Basit et al., 2022; Chang & Yeh, 2007; Liu et al., 2009). On the other hand, our findings revealed that older motorcyclists exhibited a higher likelihood of severe injuries, which is a trend observed in other studies (Champahom, 2023; Seyfi et al., 2023; Wang et al., 2023; Wei et al., 2021). Older riders are more likely to experience fatal or severe injuries, possibly due to reduced reaction time and increased physical vulnerability. This reinforces the need for targeted safety measures for aging riders, including training programs focused on hazard perception and reaction time, and promoting the usage of quality and certified personal safety equipment.

The findings also indicate that riders who are not under the influence are less likely to sustain severe or fatal injuries, i.e., the absence of alcohol in a rider's organism reduces the likelihood of death and severe injuries. This is a trend consistent with other authors' research confirming that alcohol in motorcyclists' blood might lead to severe or fatal crashes (Santos et al., 2024; Seyfi et al., 2023; Shankar & Mannering, 1996; Wang, 2022). Further, research confirms that road users' skills are significantly impaired by alcohol in the blood (Vu et al., 2020). Intoxicated riders exhibited slower response times and allowed greater margins for error, resulting in more frequent performance mistakes during tasks (Creaser et al., 2009). These results highlight the continued importance of alcohol enforcement measures, such as random breath testing and public awareness campaigns, to reduce crash severity outcomes.

Contrary to some previous studies (Champahom et al., 2023), male riders were found to have higher odds of no injuries than death or severe injuries, possibly due to greater physical resilience. However, it should be added that only 4% of the sample was female, which may have influenced this outcome. This is similar to results from Pakistan and Taiwan, where male motorcyclists were overrepresented in crashes but had slightly lower fatality rates than expected (Lin et al., 2022; Waseem et al., 2019).

This study shows that weather, season, and visibility conditions do not influence the severity of the observed motorcycle crashes. This is somewhat unexpected and contrary to earlier findings (Pervez et al., 2022; Se et al., 2021; F. Wei et al., 2021; Wisutwattanasak et al., 2024). Generally, motorcyclists tend to ride during optimal weather and visibility conditions (i.e., warm, dry, daytime), which might explain why no association was found between crash severity and those factors.

Crashes on county and local roads were more likely to result in severe injuries, which aligns with earlier studies, where non-urban roads were associated with more fatal crashes (Pervez et al., 2022; Tollazzi et al., 2025), as well as riskier behavior (He et al., 2012). Additionally, crashes occurring at curves or involving road objects increased the likelihood of severe outcomes significantly, further supporting previous findings on the dangers of high-speed cornering and roadside hazards (Blackman & Haworth, 2013; Waseem et al., 2019; Wei et al., 2021; Zulherman et al., 2022). It is expected that crashes with more serious consequences can occur on lower-ranked roads, given that they are generally less well-maintained, have less police control, and route elements may not fully comply with road design rules.

Inappropriate speed was identified as a major risk factor, significantly increasing the likelihood of severe injuries (Shankar & Mannering, 1996). This is consistent with previous research, which also highlighted fixed-object collisions and high-speed crashes as critical contributors to fatal injuries (Pervez et al., 2022; Sivasankaran et al., 2021; Zulherman et al., 2024). The current study further confirms that run-off-road crashes are particularly hazardous, in line with previous research (Ferko et al., 2022). Although speeding was recognized as an influencing factor, posted speed limits did not significantly impact crash severity outcomes. However, some studies indicate that the posted speed limit is positively associated with severe and fatal crash outcomes (Zahid et al., 2024).

One potential explanation for this discrepancy is the distinction between posted limits and actual rider behavior. The concept of inappropriate speed reflects context-specific riding that is too fast for road or traffic conditions rather than exceeding a legal threshold. Riders may exceed safe speeds even within legal limits, particularly on seemingly low-risk rural roads or during favorable weather, which could explain why the speed limit variable lacked significance. On the other hand, research shows that motorcyclists tend to overspeed more than other vehicle groups (Broughton et al., 2009). The lower the speed limit, the greater the speed excess (i.e., the amount by which the speed is exceeded) (Ferko et al., 2024). Considering the aforementioned and the vulnerability of motorcyclists, it is justified to conclude that speed significantly impacts crash outcomes, that is, the severity of the consequences.

These findings underscore the need for enforcement strategies and rider education campaigns beyond numerical limits, emphasizing speed adaptation based on real-time conditions. When discussing educational strategies to improve motorcycle safety, it is essential to emphasize the importance of practical, skills-based training and not only theoretical instruction. Participation in certified motorcycle safety programs, particularly those incorporating controlled environments such as closed-course driving ranges, offers substantial benefits beyond the general goal of crash avoidance. For example, riders can practice appropriate responses to common hazards such as unexpected curves, loose gravel, road surface irregularities, or sudden changes in pavement conditions. In addition to enhancing hazard perception and crash prevention, these programs should teach motorcyclists how to respond if a crash or near-crash situation becomes unavoidable. Learning how to react under pressure (such as managing panic, controlling the motorcycle during loss of traction, or assuming a safer body posture during impact) can significantly reduce the severity of injuries. Structured training also enables riders to evaluate their skill levels in a safe and supportive environment, fostering self-awareness and encouraging more adaptive riding behavior. A key component is the emphasis on situational awareness and the ability to adjust speed and positioning in response to rapidly changing road and traffic conditions. Literature confirms that training programs result in riders having fewer crashes and less severe motorcycle crashes (McDavid et al., 1989; Rowden et al., 2010; Rowden & Watson, 2008).

Although the findings are broadly consistent with previous research, the detected differences justify the assumption of regional influence on traffic safety. Furthermore, this study contributes to the growing body of research on motorcycle crash severity by employing both RF and MLR to analyze the key factors influencing injury outcomes in single-vehicle motorcycle crashes.

In summary, the identified risk factors, such as rider age, alcohol consumption, inappropriate speed, road type, and crash configuration, directly influence motorcycle crash severity by affecting both the likelihood of losing control and the rider's physical vulnerability upon impact. These factors shape the dynamics of crash occurrence and outcomes, either by increasing exposure to high-risk scenarios or reducing the rider's capacity to avoid or withstand a severe collision. Encouraging proactive and reactive riding competencies, such as educational interventions, contributes meaningfully to reducing motorcycle crash severity and potentially the occurrence. Furthermore, improving road design and maintenance levels and adjusting law enforcement could also contribute significantly to a more motorcyclist-friendly environment.

Additionally, infrastructure design should support appropriate speed behavior through explicit road signaling and geometry that encourages safe speeds.

2.5.3. Limitations and future research

While this study provides valuable insights, several limitations should be considered. Firstly, the study relies on police-reported crash data, which may contain errors or lack details on rider behavior, helmet use, and motorcycle condition. These factors could further influence injury severity. However, police databases remain one of the most comprehensive and widely used sources for crash analysis. Furthermore, a more extensive dataset might be beneficial for greater accuracy and robustness of prediction models. Finally, the study focuses on single-vehicle motorcycle crashes in Croatia, which may limit the generalizability of the results. Therefore, expanding the dataset and international comparisons could enhance the robustness of the findings. Future research could integrate hospital data, naturalistic riding data, or survey-based insights to complement the current findings. Although our current analysis focused exclusively on single-vehicle crashes, we acknowledge the value of comparing these with multi-vehicle crashes, especially in cases where the motorcyclist is at fault. Therefore, future research is planned to address this topic.

Regardless of the acknowledged limitations, the findings from our study provide valuable insight into what direction to take to reduce the severity of single-vehicle motorcycle crashes, especially when it comes to fatalities or severe injuries.

2.6. Conclusions

This study investigated the factors influencing the severity of single-vehicle motorcycle crashes using multinomial logistic regression and random forest classification. The findings highlight the significant role of rider demographics, road infrastructure, environmental conditions, and crash circumstances in determining injury severity. The random forest model identified rider age, road type, and speed limit as the most influential predictors of crash severity, emphasizing the importance of roadway conditions and rider behavior. Meanwhile, multinomial logistic regression provided interpretable insights, revealing that older riders, crashes on county and local roads, inappropriate speed, and collisions with roadside objects significantly increase the likelihood of severe injuries or fatalities. Additionally, the study confirmed that the absence of alcohol consumption is strongly associated with less severe crash outcomes, reinforcing the need for stricter enforcement of impaired riding laws. Both models exhibited moderate classification performance, with higher predictive accuracy for severe and fatal crashes than for mild injuries. Despite this, the key variables identified were statistically significant in explaining crash severity, as indicated by MLR likelihood ratio tests, where road type ($p < 0.001$), rider age ($p < 0.001$), alcohol in the blood ($p = 0.028$), gender ($p = 0.004$), crash circumstances ($p < 0.001$), and crash type ($p < 0.001$) were all strong predictors.

The findings of this study have important practical implications for road safety and policy development. Enhanced speed management through stricter enforcement, automated speed control, and improved road design can be crucial in reducing the severity of motorcycle crashes, particularly those resulting in fatal injuries. Infrastructure improvements on high-risk roads, especially county and local roads, should prioritize enhanced signaling and improved pavement conditions to mitigate crash risks. Given the increased vulnerability of older riders, targeted safety campaigns focusing on hazard perception and advanced riding techniques could help reduce the likelihood of severe crash consequences in this demographic. Furthermore, alcohol enforcement measures, including random breath testing and awareness campaigns, remain critical for addressing high-risk crashes associated with impaired riding. Additionally, run-off-road crash prevention strategies should be implemented, incorporating better roadside design, horizontal signaling, and motorcyclist-friendly safety barriers to minimize the severity of crashes occurring on curves or involving fixed objects. These findings underscore the need for comprehensive, data-driven interventions to improve motorcycle safety and reduce crash severity on various road types.

In conclusion, this study underscores the need for multifaceted interventions to enhance motorcycle safety. By integrating data-driven policy measures, improved infrastructure, and rider education, policymakers can reduce the severity of motorcycle crashes and enhance road safety for motorcyclists.

Chapter 3.

Influence of road safety barriers on the severity of motorcyclist injuries in horizontal curves

This chapter is based on the following journal article (published):

Ferko, M., Babić, D., Babić, D., Pirdavani, A., Ševrović, M., Jakovljević, M., & Luburić, G. (2022). Influence of Road Safety Barriers on the Severity of Motorcyclist Injuries in Horizontal Curves. *Sustainability*, *14*(22), 14790. https://doi.org/10.3390/su142214790

ABSTRACT

Motorcyclist safety remains a significant problem, and the overall safety of motorcyclists has been improved at a much slower rate in the last decade compared to passenger and commercial vehicles. Because motorcyclists are not protected by the vehicle frame, fatalities or severe injuries are often related to hitting a roadside object or safety barrier. The main objective of this study is to investigate relations between the presence and type of road safety barriers and the consequences of motorcycle crashes on rural roads. For this purpose, we analyzed Croatian rural road-crash data from 2015–2019, tested several factors as single predictors, and combined them using binary logistic regression. The results show that run-off-road crashes and nighttime driving are significant risk factors. There was no significant positive impact of the presence of safety barriers on the crash consequences due to the unsuitability of the barriers for motorcyclists, which proves the fact that the functionality of existing safety barriers should be upgraded. The results of this study could be further used by researchers, road designers, and experts to improve road infrastructure safety on rural roads.

KEYWORDS

Motorcyclist; safety barriers; crash; horizontal curve.

3.1. Introduction

Road safety is a significant social problem, given that around 1.35 million people die yearly in road crashes (the 8th leading cause of death for people of all ages), with millions suffering severe injuries (WHO, 2018). More than half of road fatalities are amongst pedestrians, cyclists, and powered two-wheelers (PTW), i.e., vulnerable road users (VRU). When it comes to PTWs, these are divided into motorcycles and mopeds. Motorcycles are two- or three-wheeled motor vehicles with an engine size up to 125 ccs or a maximum speed exceeding 45 km/h, while mopeds are two- or three-wheeled motor vehicles with an engine size of a maximum of 50 ccs and a maximum speed that does not exceed 45 km/h (Nuyttens, 2020). Due to their economic advantages (fuel efficiency/cost of ownership), flexibility in maneuvering and parking, and ecological aspects (less emissions than cars), PTW is widespread. It extends from recreational and leisure to commercial activities (Lin & Kraus, 2009; L. Wei et al., 2021).

Although motorcycles have many advantages, there are also downsides, primarily related to safety. The biggest safety issue concerning motorcycles is that these are single-track low-weight vehicles with powerful engines capable of higher acceleration and a higher top speed than most other vehicles. Moreover, motorcyclists do not have vehicle shell protection compared to other vehicles, and the motorcycle's balance highly depends on the rider's skill. Due to a relatively small contact area between the road surface and the motorcycle (tires), any loss of friction between the front or rear tire and the road surface, for example, when turning or negotiating a curve, is likely to have a significant negative impact on the handling. In addition, their relatively small size makes them less detectable and predictable to car drivers, while their low weight is a disadvantage in collisions with other vehicles that are heavier.

The information above suggests that road crashes involving motorcyclists often can have severe consequences. The crash statistics support this, as 15.5% of road fatalities in the EU involve motorcyclists (Nuyttens, 2020). The situation is even worse in developing countries, and the statistics vary from 20% to 70%, depending on the country and region (Arévalo-Támara et al., 2020; Kitamura et al., 2018).

Moreover, in the EU, the relative proportion of motorcycle fatalities within the total number of road fatalities increased slightly from 14.3% in 2010 to 15.5% in 2018 (Nuyttens, 2020). In addition, costs per fatality/injured motorcyclist are significantly higher than those for passenger vehicle drivers (Bambach et al., 2015).

For motorcyclists, the highest number of road fatalities occurs on rural roads, with a noticeable increase from 53% in 2010 to 57% in 2018 in the European Union (EU27) (Nuyttens, 2020). Data from Great Britain's Department for Transport show similar trends where more than 65% of all motorcyclist fatalities occurred on rural roads in 2016-2019 (Department for Transport, n.d.). In general, rural roads represent roads with changing geometry, which are often not maintained timely and properly, impacting the safety of motorcyclists.

Hazardous sections of rural roads from motorcyclists' perspectives are curves. This is mainly because motorcycles require certain riding skills, and riders can easily lose control over the motorcycle when steering and navigating through curves (Kronprasert et al., 2021). Moreover, in horizontal curves, a motorcyclist's roadway perception and visibility are degraded (Cafiso et al., 2012). This is especially evident on rural roads (Montella et al., 2020). Studies show that the crash frequency increases as the horizontal curve radius decreases (Schneider et al., 2010; Xin et al., 2017). In other words, motorcyclists are more prone to steering errors in horizontal curves than in other road sections, and depending on the terrain configuration, their visibility is often significantly reduced.

Standard safety measures, which are often implemented in curves, are road safety barriers. Road safety barriers are part of the road restraint systems (RRS) intended to prevent the vehicle from leaving the roadway and protect traffic from the opposite direction (Roque & Cardoso, 2013). Considering strength and deflection, the most common classification of road safety barriers concerns flexible (e.g., cable/wire-rope barriers, weak post W-beam barriers), semi-rigid (e.g., strong post or blocked-out W-beam barriers, blocked-out three-beam barriers), and rigid barriers (e.g., concrete barriers) (Nitinbhai, 2015). Although conventional road safety barriers perform well for occupants of passenger cars and trucks, their effects on other road user groups, especially motorcyclists, usually result in more severe injuries (Bambach et al., 2011; Tan et al., 2008).

When investigating the motorcyclist injury type and severity following the impact against a road safety barrier, there are two types of pre-crash configuration: sliding crash and upright posture crash (Grzebieta et al., 2013). The results of the study conducted by Grzebieta et al. (2013), where both sliding and upright crash configurations were evenly represented, show that the thorax region had the highest incidence of injury and maximum injury in fatal motorcycle-to-barrier crashes. The second highest was the head region. According to Roque & Cardoso (2013), the upper and lower extremities were the most injured body regions in all motorcycle crashes. Motorcyclists involved in road safety barrier crashes were 2.15 times more likely to suffer a severe injury to the thoracic region than motorcyclists not engaged in that type of crash (Roque & Cardoso, 2013).

According to the research review by Gabauer (2016), motorcycle-to-barrier crashes cause more severe injuries and an increased fatality risk compared to crashes involving only an impact with the ground. Those mentioned above were also concluded in a study conducted in Wyoming. It was found that barrier crashes were at risk of being more severe than all other single motorcycle crashes (Farid & Ksaibati, 2021). Of course, the impact speed and angle in motorcycle-to-barrier crashes greatly influence the level of injuries. Higher impact speed will increase the likelihood and severity of head, neck, chest, and femur injuries (Bambach et al., 2011; Daniello & Gabler, 2011, 2012). Moreover, Daniello & Gabler (2012) noted that various road safety barrier designs might influence the risk of injuries. However, because of the lack of detail in their dataset, a more exclusive correlation could not be determined. Nevertheless, it was found that steel W-beam safety barriers are not always considered fully satisfactory for motorcyclists' safety, especially when there's only one (upper) W-beam without the additional motorcycle protection system (MPS).

Furthermore, other studies found that injury risk is slightly increased for W-beam metal barriers due to the steel stiffness of the barrier posts and lack of absorption of the kinetic energy from the motorcycle during the crash (Gabauer, 2016; Tan et al., 2008). Impact angle also has a significant effect; however, this effect differs depending on the type of road safety barrier. For concrete barriers, low impact angles usually do not cause severe injuries to motorcyclists due to the sliding of the rider to the concrete barrier and the impact energy absorption, even for the high-velocity impact (Daniello & Gabler, 2012). On the other hand, for more perpendicular angles, the absence of the direct impact of the rider and concrete barrier results in decreased femur and pelvis injuries. However, low energy absorbing capability in high impact angles causes high head injury levels as an outcome of the secondary impact on the road (Daniello & Gabler, 2012). In addition, the results of the study conducted by Daniello & Gabler (2011) show that 40.1% of people involved in motorcycle crashes with W-beam barriers were dead or severely injured. This was almost the same as those involved in a motorcycle crash with a cable barrier (40.4%). In comparison, a lower percentage of fatalities or seriously injured (36.5%) occurred in motorcycle-concrete barrier crashes (Daniello & Gabler, 2011).

From the above, it is evident that road crashes involving motorcyclists are a significant problem, given the frequency and severity of the consequences and the lack of research focused on current road infrastructure safety practices. Namely, most of the studies were focused on investigating how different types of safety barriers affect the types of injuries of motorcyclists, as well as their severity when crashing into them. However, the scientific and expert studies were mainly conducted in the USA and Australia, where the road geometry and safety barrier standards and practices are different compared to Europe. Therefore, the main motivation for this study is to investigate how traditional approach to safety barriers, which is based on characteristics of cars and not motorcycles, impacts the severity of motorcycle crashes on typical European two-way rural roads, which are due to the changing road geometry and limited maintenance budget, highlighted as most challenging for motorcyclists. The main research question is whether the presence of such traditional safety barriers has any positive effect on reducing the severity of motorcycle crashes compared to when safety barriers are not present. For this study, we used a Croatian dataset to analyze and identify trends in frequency, location, causes, and consequences of motorcycle crashes and investigate possible impact of presence of road safety barriers on motorcyclist safety, i.e., injury severity. Besides the aforementioned, the second hypothesis of this study is that higher speed and smaller curve radius correlate with more severe motorcyclist injuries regardless of the presence of road safety barriers.

Although the analysis is done on a Croatian dataset, the results apply to other countries with similar geographical and climatic characteristics and road features.

3.2. Materials and methods

3.2.1. Data collection

Data on run-off-road crashes on Croatian state roads from January 2015 to December 2019 were examined to achieve defined objectives. According to the 2018 public road classification, the network of state roads in the periods above was approximately 7175 km long. These are secondary-level roads, mostly two-lane two-way roads in rural areas (average lane width 3.2 m), with some sections passing through the urban areas. The data related to the crashes, crash participants, and vehicles were collected by the police, i.e., the Croatian Ministry of the Interior, for research made available to the authors. In reports, crash consequences are divided into material damage, mild injuries, severe injuries, and fatalities.

For this study, only crashes on rural roads, i.e., outside the urban area, were considered. Several filters have been set to exclude the influence of other factors. First, only crashes that involved the motorcyclist as one of the participants were selected. After that, crashes that, according to available data, were described as run-off-road crashes were singled out. Furthermore, to investigate the impact of road safety barriers on the safety of motorcyclists, only those crashes in which the motorcycle was the only involved vehicle were segregated.

Finally, since road safety barriers on selected roads are generally installed in horizontal curves where run-of-road crashes are most common due to centrifugal force, crashes that occurred in horizontal curves have been singled out.

The next step was to examine each crash's location and determine if a road barrier was present at the crash site and which type of road barrier it was (steel W-beam or concrete safety barrier). In addition, the following data were recorded: curve radius, speed limit, crash consequences, time of the day, and the presence of road markings. The barrier type was determined by examining the crash location or using Google Street View, a method used in some earlier studies (Daniello et al., 2013; Gabauer, 2016). It has to be noted that the examined road safety barriers were not equipped with any type of MPS. Horizontal curve radii for the location of analyzed crashes were measured based on the road axis using the official Croatian Roads Ltd. GIS website for each horizontal curve.

3.2.2. Data analysis

Descriptive statistics were used to describe the current safety state of roads involving motorcycles and select factors for further analysis. Besides that, the binary logistic regression method was used to test different predictors, i.e., their significance in predicting motorcyclist crash consequences. Generally, binary logistic regression is a useful tool for interpreting the influence of one or more independent input variables on the dependent variable, which is categorical, with two possible outputs. The approach has been applied in several studies, which modelled the impact of crash 20(Al-Ghamdi, 2002; Joni et al., 2020; Santos et al., 2017; Shakya & Marsani, 2017).

In this case, the occurrence of crashes with severe or fatal consequences was used as the dependent variable (two possible outcomes: crash outcome was severe or fatal consequence or crash outcome was not severe or fatal consequence), with several independent variables used as potential predictors of the likelihood of crash occurrence. The strength of association between variables was measured using Cramer's φ coefficient, and its level of statistical significance was determined using the chi-square test. Since the outcome variable takes two possible values, its conditional distribution is based on a binomial probability distribution and a logit transformation, with regression coefficients representing the change in the logit associated with a one-unit change in the predictor. In order to ease the interpretation, regression coefficients were transformed into odds ratios, i.e., ratios of the odds outcome when a variable is present to the odds when it is absent, associated with a one-unit increase in the predictor (Hosmer & Lemeshow, 2000).

SPSS software (Statistical Package for the Social Sciences), version 24, was used to run the analyses conducted in this study.

3.3. Results

According to the observed dataset (described in subchapter 2.1), 29,403 crashes occurred, regardless of the type of vehicles involved. One or more motorcycles were involved in 1693 crashes, accounting for 5.8% of the total number of crashes. The share of motorcyclists involved in crashes that ended in fatalities and serious injuries was 44.9%. This fact has once again confirmed that motorcyclists are vulnerable road users and that further efforts are needed to improve their safety. In the continuation of this chapter, the analysis (descriptive statistics and prediction) of only those crashes that involved motorcyclists is presented. The number of crashes used in the further analysis is described in Table 3-1.

Table 3-1. Number of observed crashes

Crash type	Number of cases
All crashes where one or more motorcyclists were involved	1693
Single-vehicle motorcycle crashes	558
Single-vehicle motorcycle crashes in curves	371
Single-vehicle run-off-road motorcycle crashes	383
Single-vehicle run-off-road motorcycle crashes in curves	289

3.3.1. Descriptive analysis

3.3.1.1. Single- and multi-vehicle motorcycle crashes

As mentioned above, almost half of the 1693 crashes involving motorcycle(s) resulted in fatalities or severe injuries (44.9%), 37.9% resulted in mild injuries, and only 17.1% resulted in material damage. Most crashes involving motorcycles occurred on curved road sections (38%), followed by straight road sections (33.1%) and different kinds of intersections (25.5%). When looking at the type of crash in which at least one motorcycle was involved, the largest share relates to run-off-road crashes and accounts for more than a quarter of all crashes involving motorcycles (25.9%). Regarding the number of vehicles that took part in a crash, the highest percentage (55.4%) was for two-vehicle crashes (of which at least one was a motorcycle), while single motorcycle crashes accounted for 36.3% of all crashes.

3.3.1.2. Single-vehicle motorcycle crashes

For further analysis, 558 single-vehicle motorcycle crashes with sufficient data were analyzed. Crashes that lacked some of the data, such as GPS coordinates, road characteristics, etc., were excluded from the analysis. More than half of all analyzed crashes resulted in fatalities or severe injuries, and 66.5% of all single-vehicle motorcycle crashes occurred in curves (Table 3-2). Due to fewer crashes at sections other than curves and straight road segments, all other road sections were merged into one category named "Other" (e.g., bridge, tunnel, intersection, etc.).

Table 3-2. Consequences and road characteristics of single-vehicle motorcycle crashes (n_{crash} = 558)

	n	(%)
Severe injuries or fatalities		
No	260	(46.6)
Yes	298	(53.4)
Total	558	(100.0)
Road characteristics		
Curve	371	(66.5)
Straight road	119	(21.3)
Other	68	(12.2)
Total	558	(100.0)

Other variables observed were the types and circumstances of single-vehicle motorcycle crashes. According to the available data, the most significant share (68.6%) was run-off-road crashes (Table 3-3). The main crash circumstance was inappropriate speed (75.2%), while 82.8% of the crashes occurred during the daytime.

Table 3-3. Type of crash and crash circumstances (n_{crash} = 558)

	n	(%)
Type of crash – merged categories		
Run-off-road	383	(68.6)
Collision with fixed objects	36	(6.5)
Pedestrian strike or animal run	39	(7.0)
Other	100	(17.9)
Total	558	(100.0)
Inappropriate speed		
No	138	(24.8)
Yes	419	(75.2)
Total	557	(100.0)
Visibility conditions		
Daytime	462	(82.8)
Nighttime (9:01 PM till 7.00 AM)	96	(17.2)
Total	558	(100.0)

3.3.1.3. Single-vehicle run-off-road motorcycle crashes in horizontal curves

Because 66.5% of all single motorcycle crashes occurred in the horizontal curves, those crashes were selected to investigate the influence of road barriers on motorcyclist safety. As stated earlier, due to the specific characteristics of motorcycles, steering and navigating through the horizontal curve represents the most challenging driving task for motorcyclists. Hence, only single-vehicle crashes were observed to exclude the potential influence of other vehicles. Severe injuries or fatalities were the most common outcomes of these crashes, while a road barrier was present in 40.5% of the crashes (Table 3-4). The total number of crashes here refers to single-vehicle and run-off-road crashes in the curves.

Table 3-4. Crash consequences of single-vehicle run-off-road motorcycle crashes and the presence of a road barrier in horizontal curves (n_{crash} = 289)

	n	(%)
Crash consequences		
Material damage	31	(10.7)
Mild injuries	89	(30.8)
Severe injuries	142	(49.1)
Fatalities	27	(9.3)
Total	289	(100.0)
Road barrier		
No	172	(59.5)
Yes	117	(40.5)
Total	289	(100.0)

An additional variable was created for more detailed analysis to indicate the type of barrier when it was present on crash sites (Table 3-5). The analysis showed that most barriers were made of steel (35.9%). It must be noted here that all steel W-beam barriers were grouped together, regardless of whether they had a distance spacer. A similar approach was used with concrete barriers. After merging all concrete barriers ("New Jersey" style barriers and concrete walls), it was concluded that such barriers existed only in 3.5% of the crashes.

Table 3-5. Road barrier type (n_{crash} = 289)

Road barrier and type	n	(%)
No barrier	172	(59.5)
Steel W-beam safety barrier	102	(35.3)
Concrete safety barrier	10	(3.5)
No data about barrier type	5	(1.7)
Total	289	(100.0)

Moreover, some extra road characteristics at the crash locations were noted, which are shown in Table 3-6. In only 13.8% of curves, no edge road markings were present, while the centerline was present in almost 99% of the situations.

Table 3-6. Road characteristics (n_{crash} = 289)

	n	(%)
Edge lines		
No	40	(13.8)
Yes	249	(86.2)
Total	289	(100.0)
Centerline		
No	4	(1.4)
Yes	285	(98.6)
Total	289	(100.0)
More than two lanes		
No	264	(91.3)
Yes	25	(8.7)
Total	289	(100.0)

As in previous cases, the most common crash circumstance noted in the database was the inappropriate speed (91% of crashes). In observed curve-located crashes, the speed limit ranged from 30 to 90 km/h, with a mean of 53.1 (SD = 13.09), and the most frequent was 50 km/h. For further analysis, the speed limit was categorized as 50 km/h or below and above 50 km/h. Regarding curve radius, a mean value was 164.83 m (SD = 230.71, Max = 2400, Min = 19), and the categorization of radii used in the analysis is shown in Table 3-7. For two crashes, it was impossible to determine the radius; therefore, the number of observed crashes is 287. The curve radii presented in Table 3-7 were determined due to the relatively small crash sample and the speed–radius ratio used in the Croatian Rulebook (Croatian Ministry of Maritime Affairs Transport and Communications, 2001).

Table 3-7. Speed limit and curve radius (n_{crash} = 287)

	n	(%)
Speed limit above 50 km/h		
No	171	(59.2)
Yes	118	(40.8)
Total	289	(100.0)
Curve radius (m)		
≤ 74 m	93	(32.4)
75-174 m	118	(41.1)
175-349 m	49	(17.1)
≥ 350 m	27	(9.4)
Total	287	(100.0)

3.3.2. Statistical analysis

Of the individual circumstances that preceded the motorcycle-involving crashes, the most prominent is excessive or unadjusted speed, which was the case in 38.7% of the crashes, followed by the disregard of rights-of-way (17.0%). Regarding the visibility conditions, 89.1% of the crashes occurred during the daytime.

When each predictor was analyzed separately, statistically significant risk factors for severe crash consequences were curve, as well as run-off-road crashes, single-vehicle crashes, inappropriate speed, and nighttime driving. In an analysis that considered all predictors simultaneously (i.e., controlling for their inter-relations), run-off-road and single-vehicle crashes were no longer significant risk factors of severe crash consequences. This analysis indicated curve crashes, inappropriate speed, and nighttime driving as significant risk factors (Table 3-8).

Table 3-8. Prediction of severe injuries or fatalities – all types of motorcyclist crashes (n_{crash} = 1693)

	Severe injuries or fatalities									
	No		Yes		Single predictor			All predictors		
Predictor	*n*	(%)	*n*	(%)	*OR*	[95% CI]	*p*	*OR*	[95% CI]	*P*
Curve										
No	642	(61.2)	407	(38.8)	1			1		
Yes	290	(45.0)	354	(55.0)	**1.93**	**[1.58, 2.35]**	**< 0.001**	**1.33**	**[1.05, 1.69]**	**0.018**
Run-off-road										
No	753	(60.0)	501	(40.0)	1			1		
Yes	179	(40.8)	260	(59.2)	**2.18**	**[1.75, 2.72]**	**< 0.001**	1.36	[0.98, 1.91]	0.069
Single vehicle										
No	655	(60.8)	423	(39.2)	1			1		
Yes	277	(45.0)	338	(55.0)	**1.89**	**[1.55, 2.31]**	**< 0.001**	0.94	[0.69, 1.29]	0.719
Inappropriate speed										
No	653	(63.2)	380	(36.8)	1			1		
Yes	275	(42.1)	378	(57.9)	**2.36**	**[1.93, 2.89]**	**< 0.001**	**1.78**	**[1.37, 2.31]**	**< 0.001**
Nighttime										
No	856	(56.8)	652	(43.2)	1			1		
Yes	76	(41.1)	109	(58.9)	**1.88**	**[1.38, 2.57]**	**< 0.001**	**1.72**	**[1.25, 2.37]**	**0.001**

Note. OR = odds ratio, 95% CI = 95% confidence interval for odds ratio, p = level of statistical significance.

Table 3-9 describes shares of road characteristics associated with single-vehicle motorcyclist crash consequences. Although most single-vehicle motorcycle crashes occurred on curved road sections, further analysis using the Cramer's φ coefficient showed no statistically significant association between road characteristics and crash consequences ($\varphi = 0.07$, $\chi^2(6) = 2.34$, $p = 0.886$).

Table 3-9. Association between crash consequences and road characteristics (n_{crash} = 558)

Road characteristics	Material damage n	(%)	Mild injuries n	(%)	Severe injuries n	(%)	Fatalities n	(%)	Total n	(%)
Curve	44	(11.9)	123	(33.2)	171	(46.1)	33	(8.9)	371	(100.0)
Straight road	14	(11.8)	46	(38.7)	51	(42.9)	8	(6.7)	119	(100.0)
Other	7	(10.3)	26	(38.2)	31	(45.6)	4	(5.9)	68	(100.0)
Total	65		195		253		45		558	

As stated, to identify risk factors for crashes resulting in severe consequences (i.e., severe injuries or fatalities), the prediction of severe consequences was made using binary logistic regression. Analyses at the level of each predictor separately (i.e., without considering its relationship with other predictors) indicated that statistically significant risk factors for severe crash consequences were run-off-road crashes, inappropriate speed, and nighttime driving. When all predictors were considered simultaneously, inappropriate speed was no longer a significant predictor of severe injuries or fatalities. At the same time, run-off-road crashes and nighttime driving remained significant risk factors (Table 3-10).

Table 3-10. Prediction of severe injuries or fatalities of single-vehicle motorcyclist crashes (n_{crash} = 558)

Predictor	Severe injuries or fatalities: No *n*	(%)	Yes *n*	(%)	Single predictor *OR*	[95% CI]	*p*	All predictors *OR*	[95% CI]	*p*
Curve										
no	93	(49.7)	94	(50.3)	1			1		
yes	167	(45.0)	204	(55.0)	1.21	[0.85, 1.72]	0.292	0.96	[0.65, 1.42]	0.832
Run-off-road										
no	101	(57.7)	74	(42.3)	1			1		
yes	159	(41.5)	224	(58.5)	1.92	[1.34, 2.76]	< 0.001	1.76	[1.18, 2.62]	0.005
Inappropriate speed										
no	77	(55.8)	61	(44.2)	1			1		
yes	182	(43.4)	237	(56.6)	1.64	[1.12, 2.42]	0.012	1.36	[0.88, 2.09]	0.169
Nighttime										
no	226	(48.9)	236	(51.1)	1			1		
yes	34	(35.4)	62	(64.6)	1.75	[1.11, 2.76]	0.017	1.73	[1.09, 2,75]	0.021

Note. OR = odds ratio, 95% CI = 95% confidence interval for odds ratio, p = level of statistical significance.

Most crashes in total and those that resulted in severe or fatal consequences occurred when there was no safety barrier on the road. Similarly, in the analyzed dataset, 59.5% of all crashes occurred in locations with no road safety barrier. On the other hand, when we look at the ratio between the number of crashes with severe and fatal consequences and the total number of crashes in horizontal curves when safety barriers were and were not present, the ratio above is almost equal. Furthermore, using Cramer's φ coefficient and χ^2 test, the impact of the presence of the road barrier on crash consequences was tested. The initial results show no statistically significant association ($\varphi = 0.11$, $\chi^2(3) = 3.53$, $p = 0.317$) between the presence/non-presence of a road barrier and crash consequences (Table 3-11).

Table 3-11. Association between crash consequences and the presence of a road barrier ($n_{crash} = 289$)

Road barrier present	Material damage		Mild injuries		Severe injuries		Fatalities		Total	
	n	(%)	n	(%)	n	(%)	n	(%)	n	(%)
No	15	(8.7)	59	(34.3)	83	(48.3)	15	(8.7)	172	(100.0)
Yes	16	(13.7)	30	(25.6)	59	(50.4)	12	(10.3)	117	(100.0)
Total	31		89		142		27		289	

The type of road safety barrier and other factors were considered predictors of severe injuries and fatalities. However, none of the factors came out as a statistically significant predictor in single-vehicle motorcyclist crashes in curves. There was no significant impact of road safety barriers on the crash consequences regardless of the driving speed, curve radii or the presence of road markings (Table 3-12). Nevertheless, the division of the curve radius to less than 250 m vs 250 m and above is marginally statistically significant in interaction with the presence of a safety barrier, indicating that repeating the analysis with a larger crash sample could show some significance.

Table 3-12. Prediction of severe injuries or fatalities in single-vehicle run-off-road motorcyclist crashes in curves ($n_{crash} = 289$)

	Severe injuries or fatalities									
	No		Yes		Single predictor			All predictors		
Predictor	*n*	(%)	*n*	(%)	*OR*	[95% CI]	*p*	*OR*	[95% CI]	*p*
Road barrier and type										
no barrier	74	(43.0)	98	(57.0)	1			1		
Steel W-beam safety barrier	38	(37.3)	64	(62.7)	1.27	[0.77, 2.10]	0.348	1.32	[0.76, 2.27]	0.323
Concrete safety barrier	6	(60.0)	4	(40.0)	0.50	[0.14, 1.85]	0.301	0.48	[0.13, 1.84]	0.286
Inappropriate speed										
no	13	(50.0)	13	(50.0)	1			1		
yes	107	(40.7)	156	(59.3)	1.46	[0.65, 3.27]	0.360	1.27	[0.54, 3.02]	0.586
Nighttime										
no	102	(42.1)	140	(57.9)	1			1		
yes	18	(38.3)	29	(61.7)	1.17	[0.62, 2.23]	0.624	1.23	[0.61, 2.48]	0.560
Speed limit above 50 km/h										
no	69	(40.4)	102	(59.6)	1			1		
yes	51	(43.2)	67	(56.8)	0.89	[0.55, 1.43]	0.627	0.72	[0.42, 1.22]	0.221
Curve radius (m)										
≤ 74 m	41	(44.1)	52	(55.9)	1			1		
75-174 m	47	(39.8)	71	(60.2)	1.19	[0.69, 2.07]	0.534	1.23	[0.67, 2.23]	0.506
175-349 m	17	(34.7)	32	(65.3)	1.48	[0.73, 3.04]	0.280	1.91	[0.81, 4.51]	0.138

Predictor	Severe injuries or fatalities: No n	(%)	Yes n	(%)	Single predictor OR	[95% CI]	p	All predictors OR	[95% CI]	p
≥ 350 m	13	(48.1)	14	(51.9)	0.85	[0.36, 2.00]	0.709	1.03	[0.39, 2.73]	0.951
Edge lines										
yes	101	(40.6)	148	(59.4)	1			1		
no	19	(47.5)	21	(52.5)	0.75	[0.39, 1.47]	0.409	0.84	[0.41, 1.71]	0.622
More than 2 lanes										
no	108	(40.9)	156	(59.1)	1			1		
yes	12	(48.0)	13	(52.0)	0.75	[0.33, 1.71]	0.493	0.62	[0.25, 1.58]	0.317

Note. OR = odds ratio, 95% CI = 95% confidence interval, p = level of statistical significance

3.4. Discussion

As predicted in the beginning, the analysis highlighted curves as one of the most dangerous and demanding road sections concerning motorcycle crashes and the severity of their consequences, given that 38% of crashes involving motorcycles occurred on curved road sections. This is also consistent with previous studies that indicated that horizontal curves are spots where the frequency of motorcyclist crashes is the highest 1(Berg et al., 2005) and where consequences are most severe (Gabauer, 2016). One of the reasons for such statistics is related to the characteristics of the motorcycle. Namely, motorcycles are most commonly single-track vehicles with a small contact area between the road surface and tyres and, as such, require a particular riding skill, especially when driving and navigating through horizontal curves (Kronprasert et al., 2021). Moreover, an additional problem for motorcyclists in horizontal curves is related to the perception and visibility of the environment (Cafiso et al., 2012). Finally, motorcycles do not offer riders physical protection when crashes happen.

Further support for the above-mentioned is that most of the analyzed crashes were run-off-road (25.9%), meaning that motorcycle stability issues in riding are significant. Riding mistakes are often caused by either inappropriate speed (riding above the speed limit) or speed unadjusted to conditions on the specific road sections, such as curves, which leads to losing control over the motorcycle. Overall, the analysis indicated that 38.7% of motorcycle crashes are related to speeding (inappropriate or unadjusted speed), according to the police reports from the crash sites. Several studies analyzed in recent literature reviews highlighted that speed is one of the main contributing factors to motorcycle-related road crashes (Lin & Kraus, 2009; Vlahogianni et al., 2012; Yousif et al., 2020). Moreover, our analysis shows that more than half of single motorcycle crashes resulted in fatalities or severe injuries. This is primarily due to the inappropriate riding speed since speeding significantly affects the injury severity, since motorcycles do not provide physical protection to the rider (Savolainen & Mannering, 2007b).

Even though our analysis showed that 66.5% of single motorcycle crashes occurred in curves, further analysis showed no statistically significant correlation between road characteristics (curved or straight section) and the crash consequences. However, this finding should be taken with caution as it may result from a limited and uneven sample size. Namely, Vlahogianni et al. (2012), in their literature review, concluded that the radius and length of each horizontal curve significantly influence the frequency and severity of motorcycle crashes. Furthermore, Gabauer & Li (2015) have highlighted the horizontal curve radius of 249.94 m (820 ft) or less as a significant predictor of motorcycle-to-barrier crashes. Besides that, they found that approximately 40% and 73% of curves with motorcycle-to-barrier crashes have a radius less than 318.2 m (1044 ft) and 853.4 m (2800 ft), respectively. In other words, small and medium radius curves were found to be more likely to be where motorcycle-to-barrier crashes occur. It has to be noted that when we analyzed curves with radii less than 250 m vs 250 m and above, the effect was marginal in interaction with the presence of a road safety barrier. This is also, to some extent, consistent with the literature suggesting that smaller radii indicate higher crash frequency (Bíl et al., 2019; Leskovšek et al., 2016). Therefore, a deeper investigation that includes a larger sample should be conducted.

Since the main goal of this paper was to investigate the potential impact of road safety barriers on motorcyclist safety, the focus was therefore brought to single-vehicle crashes. This was done to exclude the potential impact of other vehicles. The analysis of all motorcycle crashes showed that most of them occur in curves. In addition, curves are the most common location for road safety barrier installation on rural roads. Like before, severe injuries and fatalities made the most significant share of these crashes' consequences (more than 58%), and an inappropriate speed was the most common circumstance, according to the police reports.

Given that none of the road safety barriers were motorcyclist-friendly, i.e., equipped with MPS, the initial testing results were as expected, i.e., the initial hypothesis was confirmed. The results showed no statistically significant relation between crash consequences and the presence of road safety barriers or the barrier type. Further analysis also included other variables, such as curve radius, number of lanes, non-compliance with speed limits, time of day, and presence of edge road markings. All these factors, combined with the road barrier type, were considered possible predictors in predicting fatalities and severe injuries. However, after the analysis, none of the factors were significant predictors.

Suppose we focus on the primary goal of this manuscript. In that case, we can see that implemented road safety barriers designed primarily for cars did not significantly benefit motorcyclists when they crashed compared to the situation where there were no barriers at all.

Moreover, no statistically significant differences between individual types of barriers were found. The most common barrier type in this study are steel W-beam barriers, which have several issues concerning motorcyclists. The major issue is related to the fact that such barriers have exposed poles that a motorcyclist may hit when sliding on the pavement after losing control of the motorcycle, which may cause extremely severe injuries or a fatality (Brandimarti et al., 2011). Another issue may occur when motorcyclists slide under the barrier beam with their bodies, hitting the beam with their head or sliding entirely under it and falling into a chasm or hitting another fixed object. Therefore, some studies indicate that concrete safety barriers are more favorable for motorcyclists since they do not have exposed barrier posts and cannot slide under them (Daniello & Gabler, 2011; Nordqvist et al., 2015). However, this study could not make a more detailed comparison between steel W-beam and concrete barriers due to the relatively small and uneven sample size.

Overall, the findings indicate no statistical difference in the consequences of motorcycle crashes where road safety barriers without MPS were or were not present. This further supports the finding by Bambach et al. (2015), highlighting that appropriate road safety barriers should be placed in the proper places (Simpson et al., 2015). Proper design and placement of road safety barriers provide an additional safety layer during motorcycle crashes. This may significantly reduce the risk of fatal and severe injuries compared to situations where motorcyclists hit trees, poles, or other objects due to a lack of barriers next to the road (Bambach et al., 2013). In other words, although safety barriers unadjusted to motorcyclists can be dangerous objects, they still protect from other fixed roadside objects like trees or poles (Bambach et al., 2011). This is also in accordance with our findings, since, although no positive impact of barriers was detected, no negative impact was detected either. Therefore, the development and implementation of MPS are imperative, especially in horizontal curves (FEMA, 2012), to accomplish a noticeable positive impact on crash consequence severity. According to Nordqvist et al. (2015), a positive effect is gained using continuous MPS when a motorcyclist collides with a barrier both in upright and sliding positions. Good practices in EU countries with similar road characteristics and geometry, such as Slovenia (Šraml et al., 2012) or Austria (Winkelbauer et al., 2017; Winkelbauer & Brunner, 2019), present additional proof that such thinking can bring significant benefits. Nevertheless, further before-and-after and cost-benefit analyses are recommended to confirm the efficiency of MPS and its types.

Although the study provided valuable results, it has certain limitations that must be considered. First, the analysis should be conducted on a bigger sample to ensure more reliable results. Since this analysis was performed on a relatively small crash sample, within which different types of safety barriers are represented unevenly, the results should be interpreted cautiously. Another limitation is the crash database that was used, which has inevitable shortcomings, mainly related to the quality and accuracy of the data. The quality and level of detail of data collected through police crash examination and reports differ from country to country, and sometimes within the country, since it can depend on the subjective observation of the police officer, which ultimately complicates the comparison between similar studies (Amoros et al., 2006; Güss et al., 2020). Furthermore, additional variables could be identified as a part of better data collection, including the length of the curve arc, transverse slope, longitudinal inclination, skid resistance, AADT, etc. Motorcyclist characteristics such as age, gender, or riding experience could also be included in the analysis. Finally, it is recommended that the impact of road elements on the consequences of crashes be investigated, as well as how motorcyclists perceive certain aspects of road infrastructure, to effectively prevent motorcyclist crashes and reduce their number.

Nevertheless, the significance of the results is manifested in the fact that there is no positive impact of the currently implemented safety barriers on the safety of motorcyclists. It also opens opportunities for future research comparing the consequences of crashes involving motorcyclists hitting motorcyclist-friendly barriers, since the installation of such barriers is in progress in Croatia. One of our goals for future research projects is to conduct a before-and-after analysis to determine the extent to which motorcyclist-friendly safety barriers and possibly other safety-enhancing solutions reduce the severity of motorcyclist crashes.

Another recommendation for road authorities and crash investigators arising from this study is using uniform crash report forms, which would enable the collection of more precise and detailed information, including location and road equipment specifications. In this way, very valuable information could be obtained for further research, leading to the improvement of the safety of motorcyclists. More detailed crash reports could be used to determine the most useful safety barriers and set up the MPS evaluation criteria (Hill et al., 2008; Silvestri-Dobrovolny et al., 2021). Also, this could enable comparative analyses from different countries, i.e., areas with different geographical and cultural characteristics, to make sure that the best practices are used.

3.5. Conclusions

Motorcyclist safety is one of the most significant issues in road traffic, considering the severity of crash consequences and fatality rate. The specifics of riding a motorcycle differ from those of other motorized vehicles, so some parts of the road are more demanding for motorcyclists. This paper aimed to analyze Croatian road crash statistics related to motorcycles and investigate the impact of road safety barriers on the severity of motorcyclists' injuries. For that purpose, a crash dataset of all crashes on the Croatian secondary road network (state rural roads) from January 2015 to December 2019 was analyzed.

Overall, horizontal curves on rural roads stand out as one of the riskiest situations for motorcyclists. The most common crash type is run-off-road, primarily resulting in motorcyclists hitting fixed roadside objects. After analyzing crashes and road characteristics, no significant impact of road safety barriers on the crash consequences was found. Since the most common road safety barrier was steel W-beam barriers without any MPS, the results indicate that, from the perspective of motorcycle crash consequences, it is the same whether those barriers were present or not. The results of this study indicate a need for enhancing motorcyclist safety, especially in tourist countries like Croatia, and that one solution indeed lies in implementing appropriate road safety barriers while considering the specific characteristics of different road users.

As said, no positive impact of existing road safety barriers without MPS on mitigating the severity of motorcyclist crashes has been proven. Hence, this remains an incentive for experts in the field of road safety and road authorities to implement error-forgiving solutions for motorcyclists, which is also a recommendation given as one of the conclusions of the thorough literature review from 2022 (Abdulwahid et al., 2022). Recognizable road design and the forgiveness of the environment are some of the safe system principles aimed at eliminating road deaths. Improving road restraint systems is certainly one way to achieve sustainable road safety. Furthermore, focusing on the specific road crashes helps detect possible intervention options. However, achieving the set goals in practice will not be possible without further scientific research.

Chapter 4.

Exploring factors influencing speeding on rural roads: a multivariable approach

This chapter is based on the following journal article (published):

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ABSTRACT

Speeding is one of the main contributing factors to road crashes and their severity; therefore, this study aims to investigate the complex dynamics of speeding and uses a multivariable analysis framework to explore the diverse factors contributing to exceeding vehicle speeds on rural roads. The analysis encompasses diverse measured variables from Croatia's secondary road network, including time of day and supplementary data such as average summer daily traffic, roadside characteristics, and settlement location. Measuring locations had varying speed limits ranging from 50 km/h to 90 km/h, with traffic volumes from very low to very high. In this study, modeling of influencing factors on speeding was carried out using conventional and more advanced methods with speeding as a binary dependent variable. Although all models showed accuracy above 74%, their sensitivity (predicting positive cases) was greater than their specificity (predicting negative cases). The most significant factors across the models included the speed limit, distance to the nearest intersection, roadway width, and traffic load. The findings highlight the relationship between the variables and speeding cases, providing valuable insights for policymakers and law enforcement in developing measures to improve road safety by determining locations where speeding is expected and planning further measures to reduce the frequency of speeding vehicles.

KEYWORDS

Road safety; speeding; prediction modeling; rural roads; spot measurements.

4.1. Introduction

Speeding is known as one of the most common driving violations and one of the leading causes of road crashes, especially those with severe consequences. According to the European Commission, speeding refers to driving at excessive (exceeding the legal speed limit) or inappropriate speed (driving too fast for the traffic situation, infrastructure, weather conditions, and/or other special circumstances) (Van den Berghe, 2021). In the context of this study, we used the first part of the definition, which refers to the speed limit.

Among the EU countries that monitor levels of speed compliance on urban roads, between 35% and 75% of observed vehicle speeds are above the speed limit, while this share on rural non-motorway roads is between 9% and 63%. When looking at fatalities, in the EU, 37% of fatalities occur on urban roads and 55% on rural non-motorway roads. The majority of the countries with a significantly lower road crash death rate compared to the EU average (50 deaths per million inhabitants) prescribed a 70 or 80 km/h speed limit on rural roads (Adminaité-Fodor & Jost, 2019). Additionally, high speed has been recognized as a factor that increases the probability of a crash and increases injury severity (Aarts & van Schagen, 2006; Islam & Mannering, 2021). A random parameter assessment showed no significant effect of increased speed on the average number of crashes; however, while the model results did not clearly link temporal shifts in parameters to the speed increase, the rise in rollover crash probability in single-vehicle incidents suggests higher speeds may have contributed to more severe injuries in those crashes (Alnawmasi & Mannering, 2022). Similarly, higher mean speeds are linked to an increased frequency of severe crashes, while lower speeds are associated with more property damage-only crashes (Nassiri & Mohammadpour, 2023).

Speed management is a crucial component of the Safe System approach, with addressing unsafe speeds being the first step to improving a transport system that fails to protect people (International Transport Forum, 2022b). Previous research states that operating speed is one of the main factors affecting traffic safety (Vertlberg et al., 2024). Some studies primarily focused on drivers' behavior and selected speeds, exploring the relation of road safety with speeds. Different driving styles can be distinguished depending on the category of aggressiveness when driving (from non-aggressive to very aggressive), which means that parameters like speed, acceleration, and braking will differ from driver to driver (Constantinescu et al., 2010). Various factors can influence the speed chosen by a driver on different road sections. Some of the factors mentioned are the psychophysical state of the driver, personal preference, social pressure, vehicle characteristics, and environmental factors like weather and road characteristics (Eboli et al., 2017). Further, depending on the part of the road, drivers may misestimate the speed of movement (Ju & Wallraven, 2023). Hence, it can be concluded that regardless of the statutory speed limit, not all drivers will comply with it.

Obeying the set speed limits depends on various factors. Hence, the main objective of this study is to identify these factors. In this research, the emphasis is on linking the main characteristics of the location and type of vehicle with the extent of non-compliance with legal speed limits. Time of day and average summer daily traffic (ASDT) are also considered. To optimally manage speeds, it is necessary to gain insight into the characteristics of traffic flow and operating speeds, both day and nighttime. Furthermore, the aim is to determine which modeling approach fits the objective the best and to point out what factors contribute to or influence the drivers' speeding.

4.2. Literature background

Many of the previous studies were based on a behavioral approach. A multilevel logistic regression was utilized on GPS-based data to explore driving behaviors, including speeding (Familar et al., 2011). The data were supplemented with drivers' demographics and self-reported speeding behavior, emphasizing the impact of speed zones on speeding behavior. In some studies, a driver behavior questionnaire (DBQ) and the theory of planned behavior model (TPB) were utilized (Atombo et al., 2016). Regression techniques were applied, and the results show that the components of TPB and DBQ variables can predict drivers' intentions for speeding and overtaking violations. However, it was found that speeding was a more frequent violation than overtaking. A self-assessment questionnaire was used as a data collection tool to investigate speeding behavior in low-visibility conditions (Zhang et al., 2018). The authors employed structural equation modeling to explore the predictors influencing speed choice under reduced visibility, highlighting driving ability as one of the main factors. In residential areas, critical predictors of speeding intention included affective attitude, descriptive and personal norms, perceived behavioral control, habits, and residential street characteristics (Alizadeh et al., 2023). Intention emerged as the sole direct predictor of speeding behavior, with street specifications and facilities significantly influencing it.

The speeding problem among young drivers was recognized, and a qualitative analysis was performed by conducting a focus group experiment including 60 young drivers (Truelove et al., 2022). Findings revealed that the following factors influence the prevention of speeding: legal consequences, fear of injury, and speed awareness monitors. Factors perceived to contribute to violating speed restrictions included perceiving it is safe to do so, a perceived norm to speed, emotions, and unintentional speeding.

Factors influencing speeding behavior among Indian long-haul truck drivers were explored using data collected through individual interviews and a questionnaire (Shandhana Rashmi & Marisamynathan, 2024). Further analysis of predicting speeding behavior included conventional modeling (binary logit approach) and more advanced machine learning algorithms (Decision Tree, Random Forest, Adaptive Boosting, and Extreme Gradient Boosting), with random forest showing the best performance. The obtained results from the variable importance plot showed that the eight important factors influencing speeding behavior are pressured delivery of goods, sleeping and driving duration per day, age and size of the truck, monthly income, driving experience, and the driver’s age.

In addition to using self-reported data from questionnaires and focus groups, some studies utilized naturalistic driving data. Safe, unsafe, and safe but potentially dangerous behaviors were identified based on continuous speed data obtained from smartphone-equipped vehicles on tangent and curve road sections (Eboli et al., 2017). The findings indicate that with increasing age and driving experience, behavior tends to be safe, or drivers tend to drive at low speeds, which can be dangerous for road traffic; however, if the driver lacks habit, the behavior tends to be unsafe. Thus, young people with low driving experience are more inclined toward unsafe driving behavior in terms of speeding. In another study, speeding behavior was examined using naturalistic driving data gathered from field experiments on typical two-lane mountainous rural highways in five provinces of China (Yu et al., 2019). A speeding prediction model was developed using random forest, achieving an accuracy of over 85%. Logistic regression was also used to investigate factors influencing speeding behavior, with an accuracy of around 70%. The speeding prediction model identified current acceleration and driving speed as the most critical variables. Visual environment parameters, such as visual curve length in the “near scene” and visual curve curvature in the “middle scene”, are followed in importance. Additionally, drivers’ age and driving experience significantly affected speeding behavior, and different roadside landscapes were found to lead to distinct speeding behaviors. Speed modeling utilizing data from smartphone sensors was conducted using linear regression to establish models for various road types and times of day, and a general model was developed (Tselentis et al., 2020). Similarly, naturalistic data from smartphones were used to create an overall model applicable to all road environments, along with separate models for urban and rural roads (Kontaxi et al., 2023). The study found that trip distance and mobile phone use while driving were statistically significant factors positively correlated with speeding.

Another approach to examining speeding involves collecting spot speed data and utilizing distinct modeling methods, focusing more on infrastructure characteristics. For instance, the investigation of operating speeds on curved rural road sections was carried out using regression models and artificial neural networks (ANNs) (Semeida, 2014). In the initial analysis, regression models were employed to study the relationship between V_{85} and horizontal alignment as well as roadway factors, with separate predictive models proposed for cars and trucks. The subsequent ANN analysis revealed better predictive performance. The curve radius was the most influential variable affecting V_{85} for cars, while for trucks, it was the median width. Curve radius emerged as the most significant factor for the car ANN model, followed by median width. For the truck ANN model, the median width was the most influential variable, with the deflection angle coming next. In another study, a Beta regression model was employed to analyze the proportion of speeding using probe speed data, incorporating a grouped random parameter modeling structure to account for varying effects of speed management strategies and other road attributes across different road types (urban and suburban arterials) (Cai et al., 2021). A fixed beta model was also developed for comparison. The results indicated that the grouped random parameter model outperformed the fixed beta model, offering better insights into how road features and other factors influence speeding on various road types. Seven variables were significant in both models: AADT, daily transit frequency, asphalt pavement, an indication of low-speed limits, outer shoulder width, and the number of lanes.

In a recent study, speeding frequency was examined using roadside observational surveys along with spatial and temporal attributes of selected locations (Khaddar et al., 2023). A random parameter negative binomial model was developed to analyze speeding behavior, incorporating unobserved heterogeneity across speeding locations, accounting for temporal, road geometric, and built environment factors. The findings highlight significant variability in speeding behavior at different locations. Based on the results, the authors suggest that implementing temporary speed-calming measures during non-peak hours and weekends could be effective. Additionally, the use of speed humps, rumble strips, or enhanced law enforcement and developing well-connected roads with frequent intersections and traffic signals could also serve as a strategy to discourage speeding. Another study employed a negative binomial statistical model to analyze data from traffic cameras, considering both temporal and environmental factors (Kutela et al., 2024). The model revealed the significance and likelihood of speeding tendencies by incorporating variables such as year, month, number of lanes, dwelling unit types, school-related factors, and open green space. The results indicated that aggregating speeding data tends to underestimate the influence of these factors. For instance, the impact of posted speed limits was found to be up to twice as significant in disaggregated models compared with aggregated ones. Additionally, speeding violations in summer months were about 25% higher in aggregated models than 40% in disaggregated models. Camera enforcement was associated with a 25% reduction in speeding over four years. Built environment factors showed varied effects, with one-unit dwellings linked to increased speeding, whereas proximity to schools was associated with a speed decrease.

Further, it is also possible to investigate speed data in artificial environments, such as driving simulators. A mathematical model for an intelligent speeding prediction system was developed, categorizing inputs into three types: model inputs and related in-vehicle technology, a mathematical model along with a data processing module, and warning messages combined with a human–machine interface (Zhao et al., 2013). The system was tested using a driving simulator, and experimental data were utilized to validate models predicting intentional and unintentional speeding, showing no statistically significant time difference between the modeled and experimental results. A study involving a driving simulator investigated drivers' speed compliance behavior in urban and rural environments, employing a Generalized Linear Model with speed difference as the dependent variable and driving environments and driver attributes as predictors (Yadav & Velaga, 2021). The results indicated better speed compliance in urban settings compared with rural ones. Additionally, drivers' age was positively correlated with speed compliance. Male drivers exhibited lower speed compliance than female drivers, while those with postgraduate or graduate education demonstrated better compliance than those with only secondary education. Driving experience negatively impacted speed compliance, and drivers with prior crash history showed better compliance. Factors such as vehicle type and preferred driving time did not significantly affect speed compliance. Another study used a driving simulator and numerical analysis to examine road infrastructure design and operating speeds for establishing credible speed limits on Italian roads (Montella et al., 2024). The research concluded that increasing speed limits, combined with safety countermeasures, could lead to a 23% reduction in crashes.

Previous studies on speeding behavior have employed various methodologies to explore its influencing factors and to develop predictive models. Behavioral approaches have highlighted how intentions and self-reported behavior can predict speeding, including drivers' demographics, self-assessment questionnaires, driver behavior questionnaires (DBQ), and the theory of planned behavior (TPB). Legal consequences, fear of injury, and speed awareness monitors were found to be influential in preventing speeding, while factors such as perceived safety, norms, emotions, and unintentional speeding contributed to speeding violations. Several studies utilized naturalistic driving data to analyze speeding behavior. For instance, based on these data, prediction models with high accuracy highlight acceleration, driving speed, trip distance, mobile phone, and visual environment parameters as significant predictors. Studies employed several techniques, such as regression models, random forests, and artificial neural networks, revealing different infrastructural factors influencing operating speeds. The results showed that factors differ on urban and rural roads.

A limited number of studies have focused on spot speed measurement data, which is essential for capturing real-time speeding behavior at specific locations. This gap is particularly significant in rural road environments, where unique challenges such as varying road conditions, limited enforcement, and distinct driving behaviors, compared with urban areas, complicate speed management. The diversity of speeding behaviors across different locations, influenced by cultural, environmental, and infrastructural factors, underscores the need for targeted research in rural settings. Although some research has addressed infrastructure characteristics, a more comprehensive analysis that integrates traffic flow, road design, and speed management is necessary to develop effective interventions for reducing speeding.

4.3. Methodology

4.3.1. Data collection

Raw data for this paper are based on two years of data collection (for July) and were collected through traffic counters installed on state roads (secondary roads) in the Republic of Croatia. Road authorities use them to control the amount and the heterogeneity of traffic and gain insight into the operating speed at a particular location. Stationary traffic counters with electromagnetic inductive loops were installed in characteristic places (tangent road parts on regularly maintained pavement and with the appropriate lane width) on two-way, two-lane roads. The type of these counters, QLD-6CX nano (vehicle detection accuracy > 99.9%, vehicle classification precision ~97%, speed measurement error: at 50 km/h < 2.8% and at 160 km/h < 8%), can measure the times of individual vehicles passing through the measuring point and their current speeds (Prometis Ltd., 2019), and which is why they are placed on the road parts where free traffic flow is expected. The counter has a built-in software solution for recognizing and eliminating double-counting of vehicles that pass through the counter by occupying two lanes simultaneously. The vehicle is counted in the lane corresponding to the movement’s direction.

Selecting tangent road sections for measuring and assessing speeding is justified since the highest and most uniform speeds are expected on these sections (Malaghan et al., 2021).

Moreover, significant acceleration is expected on the tangents following the curve and deceleration on the tangents preceding the curve (Figueroa Medina & Tarko, 2007). The white central line and edge road markings were painted at all measuring locations, emphasizing road alignment. Since no law enforcement cameras are installed at the measuring locations, nor are there regular police patrols, drivers know they cannot be fined based on the counters installed on the roadway. This is another factor that speaks in favor of freely choosing the speed of movement.

Most measuring points on Croatian state roads meet the requirements for speed measurement, allowing drivers to choose their speed freely based on subjective assessments of road conditions and speed limits. Free traffic flow is defined as vehicle movement in one direction, on straight roads, outside intersections, with dry pavement and no speed-restricting factors, where vehicles are far enough apart to drive independently. Ideally, vehicle speeds in free flow should be measured in dry conditions, but the current system cannot guarantee this; however, the impact of wet roadways is minimized by analyzing speed data from July and August (Prometis Ltd., 2019), which is in accordance with the previous study that showed speeding is most likely to occur in summer months (Kutela et al., 2024).

Data for this research were collected from 20 traffic counters on 15 distinct Croatian state roads, considering five different speed limits. The traffic counters are located on the roads referred to as rural since they are outside the urban area, although some pass through small, non-urban settlements. After filtering out empty rows and rows with unclassified vehicles, the sample consisted of 4,623,852 unique records. After rejecting irregular records and considering that an error could have occurred with the counter, speed was not observed as a continuous variable. Still, the dependent variable was set as “Speeding,” distinguishing cases in which the amount of overspeed was >0 km/h as “Yes” and all other cases as “No.”

In addition to speeding, additional data were collected through the field inspection and from road authorities: roadside state, whether the location is inside the settlement, posted speed limit, whether overtaking was allowed, the width of the roadway, the distance to the nearest intersection, and the average summer daily traffic (ASDT). The last two were considered especially important, assuming they indicate the characteristic of the traffic flow (i.e., where there is higher traffic and the intersection is close, the speed might decrease). In addition, the roadside was considered, given the presumption that unsafe roadside elements could impact the severity of crash injuries (Dumitrascu, 2024). Based on the above, the measurement locations were carefully chosen to encompass a variety of conditions, such as different speed limits, varying traffic loads, distances to the nearest intersection, and other traffic and infrastructure characteristics.

4.3.2. Data analysis

After the previous research examination, several methods were selected to find the best-fitting model to explain each independent variable's importance. All statistical analyses were performed using the statistical software SPSS (version 29.0) and R (version 4.3.3).

Since the primary focus was on understanding the factors influencing the decision to speed rather than the degree of speeding, we treated speeding as a binary variable. This approach aligns with legal standards, where any speed above the limit constitutes a violation. While different levels of speeding may have distinct implications, binary classification provides clear interpretability, making it valuable for policymakers and practitioners. It also helps mitigate the impact of measurement inaccuracies in spot speed data.

The aim was to use conventional binary logistic regression since "Speeding" was set as the dependent/outcome variable with a binary result (1 – speeding occurred; 0 – speeding did not occur); however, given the extensive data sample available in this study, the potential for utilizing some of the machine learning algorithms was noticed.

Regression analysis is a technique used to predict the relationship between a dependent (outcome) variable and one or more independent (predictor) variables using a mathematical equation called a model (Faizi & Alvi, 2023; Fritz & Berger, 2015; Mostoufi & Constantinides, 2023). Since the proposed dependent variable is categorical, logistic regression was preferable over linear regression.

Artificial neural networks mimic the functioning of the human brain through a vast network of interconnected processing nodes. They excel at recognizing patterns. A usual neural network comprises numerous simple, interconnected processing elements known as neurons (Maceiras et al., 2024; Sarker, 2021). Each neuron generates a series of real-valued activations for the target outcome. The mathematical model of an artificial neuron includes inputs (Xi), weights (w), bias (b), a summation function (Σ), an activation function (f), and the corresponding output signal (y), as shown in Figure 4-1.

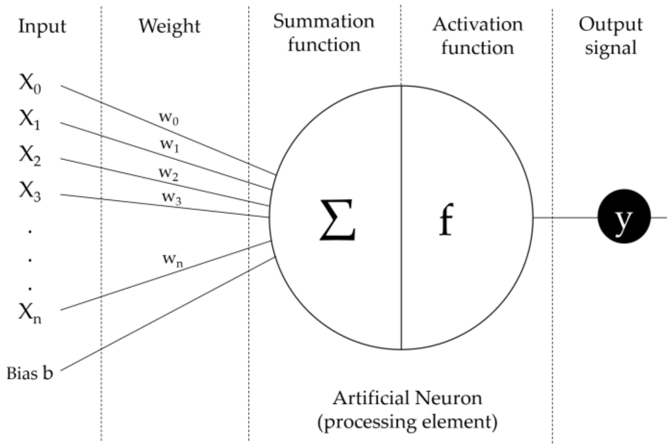

Figure 4-1. Scheme an artificial neuron mathematical model (Sarker, 2021)

For this paper, a Multi-layer Perceptron (MLP) was used. The Multi-layer Perceptron (MLP) is a supervised learning approach and a feedforward artificial neural network (Sarker, 2021; Udurume et al., 2024; Van Efferen & Ali-Eldin, 2017). A typical MLP is a fully connected network comprising an input layer that receives input data, an output layer that makes a decision or prediction about the input signal, and one or more hidden layers between these two that serve as the network's computational engine. The output of an MLP network is determined using various activation functions, also known as transfer functions, such as ReLU (Rectified Linear Unit), Tanh, Sigmoid, and Softmax. An MLP maintains the structure of a single layer but includes one or more hidden layers, with all nodes connecting between layers. The network trains itself using an algorithm called backpropagation.

Random forest extends a decision tree approach by using an ensemble method that constructs multiple decision trees (Breiman, 2001; Sarker & Salah, 2019). A decision tree is a supervised learning technique primarily employed for classification tasks, though it can also be used for regression. It starts with a root node representing the initial decision point for splitting the dataset based on a single feature that best separates data into distinct classes. Each split leads to a new decision node, which applies another feature to refine the data into more homogeneous groups or a terminal node that provides the final class prediction. This method of dividing data into binary partitions is known as recursive partitioning. Instead of utilizing all features to build each tree, a random subset of features is used for each decision tree in the forest. Each tree then predicts a class outcome, and the final prediction is determined by a majority vote among all the trees (Liu et al., 2024). Thus, a random forest model predicts values or categories by aggregating the results from numerous decision trees (Dutta et al., 2021).

The receiver operating characteristic (ROC) curves were generated for the neural network and random forest models, with the calculation of the area under the curve (AUC). The

AUC is a scalar value that assesses the overall performance of a binary classifier. The AUC ranges from 0.5 to 1.0, where 0.5 indicates the performance of a random classifier, and 1.0 corresponds to a perfect classifier with zero classification error. AUC is a robust measure for evaluating score classifiers as it accounts for the entire ROC curve, incorporating all possible classification thresholds. The AUC is calculated by summing the areas of successive trapezoids under the ROC curve (Melo, 2013).

Among other tree-growing algorithms, Chi-square Automatic Interaction Detector (CHAID) was employed as one of the modeling approaches. CHAID accommodates nominal, ordinal, and continuous data, with continuous predictors being categorized into groups with approximately equal numbers of observations (Azam et al., 2019; Milanović & Stamenković, 2016; Onoja et al., 2018; Song & Lu, 2015). After identifying the target (dependent variable), which is the decision or classification tree’s root, CHAID divides the root into two or more categories, referred to as parent nodes, and further splits these nodes into child nodes. CHAID analysis constructs a predictive model or tree to identify how variables interact to explain the outcome of a given dependent variable.

4.4. Results

4.4.1. Variables’ description

Given that the research aims to determine the influencing factors on speeding, the dependent variable is binary (the vehicle exceeded or did not exceed the speed limit). Of the recorded vehicles, 57.7% drove faster than permitted at a particular measuring location (Table 4-1).

Table 4-1. Description of the dependent variable

Dependent Variable		Description	Frequency	Cumulative Percent	Mean	St. Dev.
Speeding	(0)	No	1,956,378	42.3	0.58	0.494
	(1)	Yes	2,667,474	100		
		Total	4,623,852			

Before conducting further analysis, a Variance Inflation Factor (VIF) was investigated to check the multicollinearity between independent variables. Since all considered variables’ VIFs were <3, all of them were included, as shown below.

Seven categorical variables were included in the further analysis. Table 4-2 shows the characteristics and frequencies of each categorical variable, with their encoding values.

Table 4-2. Description of the categorical explanatory variables included in the analysis

Variable	Description		Frequency	Cumulative Percent	Mean	St. Dev.
Vehicle group	(0)	Motorcycles	85,351	1.8	1.2	0.613
	(1)	Passenger cars with or without trailer	3,915,205	86.5		
	(2)	Vans with or without trailer	284,847	92.7		
	(3)	Cargo vehicles	300,090	99.2		
	(4)	Buses	38,359	100		
Roadside state	(1)	Shoulder/Maintained	3,034,433	65.6	1.66	1.228
	(2)	No shoulder/Not maintained	1,094,420	89.3		
	(5)	Open drain canal	494,999	100		
In settlement	(0)	No	2,374,668	51.4	0.49	0.5
	(1)	Yes	2,249,184	100		
Overtaking allowed	(0)	No	2,991,094	64.7	0.35	0.478
	(1)	Yes	1,632,758	100		
Day of the week	(1)	Monday	771,045	16.7	3.96	2.065
	(2)	Tuesday	696,168	31.7		
	(3)	Wednesday	553,363	43.7		
	(4)	Thursday	565,909	55.9		
	(5)	Friday	643,012	69.8		
	(6)	Saturday	750,335	86.1		
	(7)	Sunday	644,020	100		
Part of the day	(1)	Daytime	3,792,118	82.0	1.35	0.815
	(2)	Twilight	314,927	88.8		
	(3)	Nighttime	268,968	94.6		
	(4)	Dawn	247,839	100		
Speed limit		50	1,324,261	28.6	65.81	14.454
		60	1,499,306	61.1		
		70	321,978	68.0		
		80	745,813	84.2		
		90	732,494	100		

Table 4-3 describes the continuous variables, where “Width across the roadway” implies the overall width of traffic lanes and nearby roadside, and “Average Summer Daily Traffic” (ASDT) implies average traffic in summer months (July and August). Finally, “Distance to the closest intersection” considers the distance to the intersection nearest to the measuring point.

Table 4-3. Description of the continuous variables included in the analysis

	Mean	Std. Dev.	Min.	Max.
Width across the roadway (m)	6.868	0.534	5.00	8.00
Average Summer Daily Traffic – ASDT (vehicles)	10,577.51	10,577.51	2,867.00	21,562.00
Distance to the closest intersection (m)	215.720	149.19	85.00	850.00

The variables were chosen based on their potential relevance and availability. The variables depicting the state of the infrastructure are “In settlement,” “Speed limit,” “Roadside state,” and “Width across the roadway.” The variable “Roadside state” was included to capture the physical condition and characteristics of the roadside environment, potentially influencing driver behavior and safety outcomes. A well-maintained shoulder with drainage channels, curbs, and sand covering (Shoulder/Maintained) typically enhances safety. In contrast, roads lacking a shoulder or having poorly maintained edges, such as grassy areas without barriers or curbs (No shoulder/Not maintained), may increase risk and uncertainty for drivers. Similarly, an open water canal may represent certain risks and influence driving behavior.

Furthermore, "Distance to the closest intersection," ASDT, and "Overtaking allowed" are assumed to describe the traffic flow characteristics. More precisely, "Overtaking allowed" (Yes or No) refers to road sections where overtaking is legally permitted and the center line is dashed. "Day of the week" and "Part of the day" describe the time component that could influence the speed selection. "Vehicle group" is a variable that clarifies the observed vehicles' technical characteristics, assuming that the vehicles with the most favorable power/mass ratio (motorcycles) will also be the fastest, i.e., the most likely to overspeed.

4.4.2. Descriptive statistics on speeding

The vehicles were automatically classified into ten groups based on length; however, due to the minor vehicle frequency in some groups, in further analysis, the vehicles were finally sorted into five groups (Table 4-4). As stated in Table 4-1, 57.7% (N = 2,667,852) of vehicle speed records were above the legal speed limit; therefore, speeding was only compared between vehicles that were above the speed limit. The test of homogeneity of variances confirmed that the variances among the groups are significantly different. Hence, the significance of differences in the means between the presented vehicle groups was tested using the Welch test, which confirmed statistically significant differences in the amount of speeding among the groups at the 0.05 level.

Table 4-4. Descriptives on the amount of speeding by vehicle groups (km/h)

Vehicle Group	N	Mean	Std. Dev.	Std. Error
Motorcycles	58,237	24.11	19.41	0.08
Passenger cars with or without trailer	2,289,814	13.22	10.985	0.007
Vans with or without trailer	158,203	13.15	11.16	0.028
Cargo vehicles	142,664	11.39	8.836	0.023
Buses	18,556	10.03	7.616	0.056
Total	2,667,474	13.34	11.252	0.007

Based on the Games–Howell post hoc test results, passenger cars, and vans are the only groups with insignificant mean differences in speeding. Motorcycles proved to be the fastest form of travel. The average amount of speeding is more than 10 km/h higher for motorcycles than for other vehicle groups. The results are presented in Table 4-5.

Table 4-5. Multiple comparisons on the speeding mean difference

(I) Vehicle Group	(J) Vehicle Group	Mean Difference (I-J)	Std. Error	Sig.
Motorcycles	Passenger cars with or without trailer	10.884 *	0.081	<0.001
	Vans with or without trailer	10.959 *	0.085	<0.001
	Cargo vehicles	12.717 *	0.084	<0.001
	Buses	14.083 *	0.098	<0.001
Passenger cars with or without trailer	Vans with or without trailer	0.075	0.029	0.072
	Cargo vehicles	1.833 *	0.024	<0.001
	Buses	3.199 *	0.056	<0.001
Vans with or without trailer	Cargo vehicles	1.757 *	0.037	<0.001
	Buses	3.124 *	0.063	<0.001
Cargo vehicles	Buses	1.367 *	0.061	<0.001

**The mean difference is significant at the 0.05 level.*

4.4.3. Binary Logit Model

Binary logistic regression with the enter method was employed to examine the relevant variables in predicting the occurrence of speeding. The Nagelkerke R Square of 0.380 suggests that the model explains approximately 38% of the variance in the dependent variable (e.g., speeding). At the same time, the Cox and Snell R Square is slightly lower (0.283), indicating a reasonable but not perfect fit. Table 4-6 illustrates the classification of correctly and incorrectly predicted values (with a cut-off value of 0.5). The model performs very well in predicting “Yes” cases with a high sensitivity of 89.3% (the model’s ability to identify speeding cases correctly), while that is not the case for negative outcomes with a specificity of 55.0% (i.e., the model’s accuracy in identifying non-speeding cases).

Table 4-6. Classification table (binary logistic regression)

Observed		Predicted		
		Speeding		Percentage Correct
		No	Yes	
Speeding	No	1,075,436	880,942	55.0%
	Yes	284,357	2,383,117	89.3%
Overall Percentage				74.8%

The model indicates that all factors significantly influence speeding, with speed limits being the most impactful factor, while ASDT has no meaningful impact on the likelihood of speeding (Table 4-7). The negative coefficients indicate a strong inverse relationship between the speed limit and the likelihood of speeding, with higher speed limits strongly predicting the outcome “No.” Further, as expected, greater distances to intersections increase the odds of speeding (B = 0.003, Exp(B) = 1.003), while locations within settlements have significantly lower odds of speeding compared with those outside settlements (B = -1.148, Exp(B) = 0.317). The width of the roadway has a negative association with speeding, indicating that wider roadways are associated with lower speeding odds (B = -0.295, Exp(B) = 0.744), while allowed overtaking increases the odds of speeding (B = 0.296, Exp(B) = 1.345). The odds of speeding vary by day of the week and the time of the day, with the highest odds observed on Sundays (B = 0.330, Exp(B) = 1.392) and during dawn (B = 0.937, Exp(B) = 2.552). Motorcyclists are significantly more likely to speed than other vehicle types, with passenger cars, vans, buses, and cargo vehicles all exhibiting lower odds.

Table 4-7. Regression coefficients, odds ratios, and confidence intervals for variables predicting speeding likelihood

Variables in the Equation	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
ASDT	0.000	0.000	372.296	1	<0.000	1.000	1.000	1.000
Distance to the closest intersection	0.003	0.000	50,940.542	1	<0.000	1.003	1.003	1.003
Width across the roadway	−0.295	0.003	9260.942	1	<0.000	0.744	0.740	0.749
Shoulder/Maintained			42,580.405	2	<0.000			
No shoulder/Not maintained	0.853	0.007	15,876.513	1	<0.000	2.347	2.316	2.379
Open drain canal	1.753	0.009	42,173.050	1	<0.000	5.772	5.677	5.870
In settlement (Yes)	−1.148	0.004	73,416.343	1	<0.000	0.317	0.315	0.320
Speed limit (50 km/h)			712,758.350	4	<0.000			
Speed limit (60 km/h)	−0.247	0.006	1636.172	1	<0.000	0.781	0.772	0.791
Speed limit (70 km/h)	−2.832	0.009	107,559.285	1	<0.000	0.059	0.058	0.060
Speed limit (80 km/h)	−2.556	0.005	219,753.026	1	<0.000	0.078	0.077	0.078
Speed limit (90 km/h)	−4.578	0.006	582,896.093	1	<0.000	0.010	0.010	0.010
Overtaking allowed (Yes)	0.296	0.004	5063.941	1	<0.000	1.345	1.334	1.356
Monday			7726.487	6	<0.000			
Tuesday	0.070	0.004	315.058	1	<0.000	1.073	1.065	1.081
Wednesday	0.039	0.004	86.571	1	<0.000	1.040	1.032	1.049
Thursday	0.067	0.004	257.313	1	<0.000	1.070	1.061	1.079
Friday	0.042	0.004	106.092	1	<0.000	1.043	1.034	1.051
Saturday	0.067	0.004	290.725	1	<0.000	1.069	1.061	1.077
Sunday	0.330	0.004	6397.624	1	<0.000	1.392	1.380	1.403
Daytime			36,411.946	3	<0.000			
Twilight	0.102	0.004	526.301	1	<0.000	1.107	1.098	1.117
Nighttime	0.498	0.005	10,173.651	1	<0.000	1.645	1.629	1.661
Dawn	0.937	0.006	28,154.951	1	<0.000	2.552	2.524	2.580
Motorcycles			11,493.604	4	<0.000			
Passenger cars with or without trailer	−0.644	0.009	5134.531	1	<0.000	0.525	0.516	0.535
Vans with or without trailer	−0.683	0.010	4710.769	1	<0.000	0.505	0.495	0.515
Cargo vehicles	−1.004	0.010	10,115.399	1	<0.000	0.366	0.359	0.374
Buses	−0.670	0.015	1971.906	1	<0.000	0.511	0.497	0.527
Constant	3.909	0.027	21,414.320	1	<0.000	49.848		

4.4.4. Neural Network Model

The initial dataset is divided into a training set (70%) and a test set (30%) to perform neural network modeling. The input layer comprises 31 units (excluding the bias unit), while the hidden layer contains 10. The hyperbolic tangent activation function was used for the hidden layer, while the Sigmoid function was used for the output layer, with the sum of squares used as the error function. Batch was used as a type of training, with maximum training epochs computed automatically. The model's performance is evaluated using classification metrics on both the training and testing datasets (Table 4-8).

The model demonstrated an overall accuracy of 76.8% on these training data, indicating that it effectively learned the patterns in these data. The overall accuracy of these testing data was 76.6%, slightly lower than the accuracy of the training data. This suggests the model generalizes well to unseen data and does not suffer from overfitting. Sensitivity, with 85.0% for the training set and 83.6% for the testing set, reflects the model's strong performance in detecting instances of speeding. Specificity was comparatively lower, at 65.6% for the training set and 67.1% for the testing set. A model with two hidden layers was created for control, but the performance was not better than the initial one-hidden-layer model. The factor that proved to be the most influential is the speed limit, followed by the distance to the closest intersection, roadway width, ASDT, and vehicle group.

Table 4-8. Classification table (neural network)

		Predicted		
Sample	Observed	No	Yes	Percent Correct
Training	No	899,402	470,605	65.6%
	Yes	279,665	1,587,025	85.0%
	Overall Percent			76.8%
Testing	No	393,561	192,810	67.1%
	Yes	131,495	669,289	83.6%
	Overall Percent			76.6%

The AUC for the neural network model was 0.840 for both training and testing datasets, indicating that the model has good discriminative ability (Figure 4-2). An AUC of 0.840 means an 84% chance that the model will correctly distinguish between a randomly chosen positive instance (speeding) and a randomly chosen negative instance (no speeding). These results further support the effectiveness of the neural network model in predicting speeding.

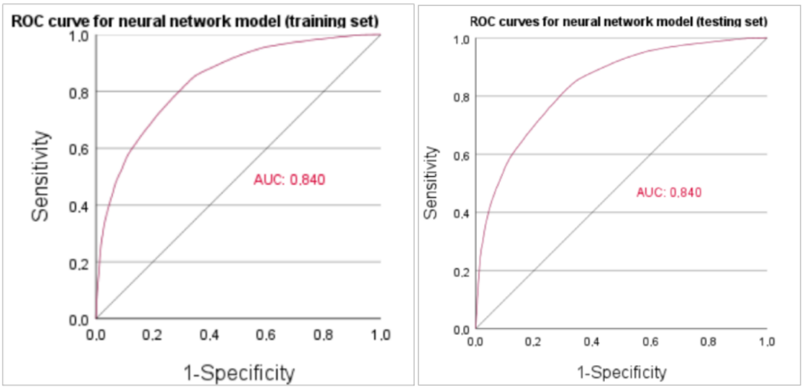

Figure 4-2. ROC curves for training and testing a one-hidden-layer neural network model

4.4.5. Chi-Squared Automatic Interaction Detector (CHAID)

The Chi-squared Automatic Interaction Detector (CHAID) model was employed to analyze factors influencing speeding behavior. The model, validated through a split sample approach (70% training set, 30% test set), identified six significant predictors of speeding: distance to the closest intersection, ASDT, vehicle group, time of the day, day of the week, and width across the roadway. With tree depth of 3 and 160 nodes, including 115 terminal nodes, the model provides detailed insights into how these factors influence speeding behaviors across different contexts.

The risk estimates for speeding obtained from the CHAID model are 0.231 and 0.232, with a standard error of 0.000 for both datasets. These estimates reflect the stability and consistency of the model's predictions across training and test datasets. In classification results for speeding, the training dataset shows an overall correct prediction percentage of 76.9% (Table 4-9). The sensitivity was high, with values of 85.2% for both the training and testing sets. This suggests that the model is robust in detecting speeding cases. The specificity was lower, with 65.5% on the training set and 65.3% on the testing set, indicating that the model has a moderate error rate in classifying non-speeding instances. These metrics indicate the model's effectiveness in classifying instances of speeding based on the specified variables and the CHAID growing method.

Table 4-9. Classification table for the CHAID model

Sample	Observed	Predicted		
		No	Yes	Percent Correct
Training	No	896,729	473,294	65.5%
	Yes	275,399	1,590,846	85.2%
	Overall Percent			76.9%
Testing	No	383,166	203,189	65.3%
	Yes	118,407	682,822	85.2%
	Overall Percent			76.8%

The CHAID model demonstrates predictive solid performance, as evidenced by AUC values of 0.838 for the training set and 0.839 for the testing set (Figure 4-3). These AUC values indicate that the model can discriminate between speeding and non-speeding cases, performing consistently well on both the training and testing datasets. The close similarity in AUC values suggests that the model generalizes effectively to new data, maintaining its accuracy and robustness outside the initial training environment.

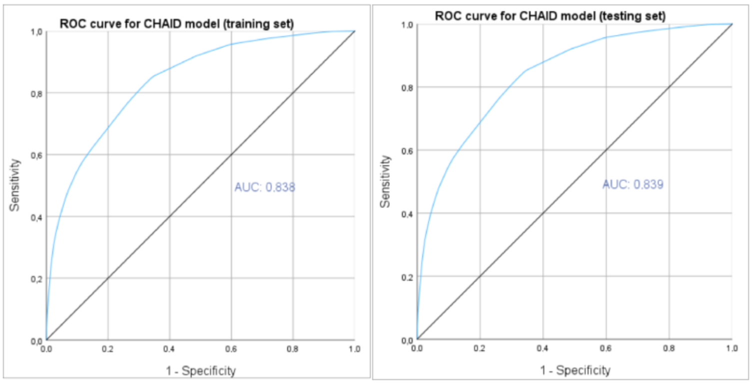

Figure 4-3. ROC curves for training and testing of the CHAID model

4.4.6. Random Forest Model

The random forest model trained in this study is capable of predicting speeding behavior appropriately. Using a dataset of 3,236,697 observations (70% training set, 30% test set), the model comprising 500 trees achieved an out-of-bag (OOB) prediction error (Brier score) of 0.1597. On the training set, the model achieved an accuracy of 76.8% (95% CI: 76.74–76.83%), with a sensitivity of 84.4% and a specificity of 66.35%. On the test set, the model maintained a similar accuracy of 76.8% (95% CI: 76.73–76.87%), with a sensitivity of 84.5% and a specificity of 66.3%. The results are presented in Table 4-10. These metrics demonstrate the model's consistency and robustness across different datasets. Regarding predictors' importance, the ones with the highest importance are speed limit, distance to the closest intersection, ASDT, and roadway width.

Table 4-10. Classification table for the random forest model

Sample	Observed	Predicted		
		No	Yes	Percent Correct
Training	No	908,674	290,506	66.4%
	Yes	460,791	1,576,726	84.4%
	Overall Percent			76.8%
Testing	No	389,311	124,255	66.3%
	Yes	197,602	675,987	84.5%
	Overall Percent			76.8%

The random forest model demonstrated strong discriminative power, achieving an AUC of approximately 0.840 and 0.841 for the training and the testing dataset, respectively (Figure 4-4). This high AUC indicates excellent performance in distinguishing between speeding and non-speeding instances.

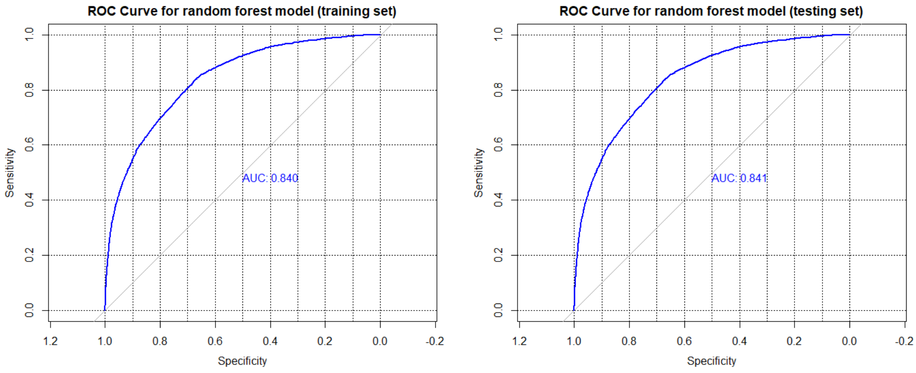

Figure 4-4. ROC curves for training and testing the random forest model

4.5. Discussion

4.5.1. Average values of speeding concerning vehicle groups

The classification of vehicles into five groups, based on length, was a pragmatic approach to ensure sufficient sample sizes of each group for meaningful analysis. This consolidation likely enhanced the robustness of subsequent statistical tests by mitigating the issue of minor vehicle frequency, which could lead to unreliable estimates and conclusions. Given that the specified groups of vehicles differ significantly in their driving-dynamic characteristics, the amounts of speeding for them were observed before analyzing the factors influencing speeding. Furthermore, the groups were compared with the basic assumption that the highest speeding was recorded among motorcyclists.

With a mean speeding amount of 24.11 km/h, motorcycles are the fastest vehicles, significantly surpassing other vehicle groups by more than 10 km/h. This result indicates a higher propensity for speeding among motorcyclists, highlighting them as a critical category. Further, as expected, passenger cars and vans showed similar speeding behavior, with mean speeds of 13.22 km/h and 13.15 km/h, respectively. Finally, cargo vehicles and buses exhibit the lowest speeding amounts, with means of 11.39 km/h and 10.03 km/h, respectively. This may reflect the professional nature of drivers in these categories or inherent vehicle characteristics that limit speed.

Earlier studies confirmed that motorcyclists are more likely to exceed the posted speed limit compared to passenger cars and other motor vehicles (Baldock et al., 2010; Jevtić et al., 2015; Kontaxi et al., 2021; Walton & Buchanan, 2012). Furthermore, the results of our study are consistent with previous research, stating that motorcyclists are more likely to speed on rural roads due to motorcycle maneuverability and riders' enjoying fast riding (Broughton et al., 2009). Some studies point out that there is also a significant difference in the speeding between different types of motorcycles (e.g., sports and enduro), which can be an implication for future research (Jevtić et al., 2015).

4.5.2. Speeding prediction models

This study applied several modeling techniques to examine the factors influencing speeding behavior and evaluate their predictive performance. The methods compared include binary logistic regression, neural network, CHAID classification tree, and random forest. Each model has distinct characteristics, strengths, and limitations, as discussed below.

All models showed a more accurate prediction of "Yes" cases, with a sensitivity greater than 84%. All approaches showed decent results when observing the models' accuracy (>74%).

Table 4-11 compares the performance of four classification models across six key metrics: sensitivity, specificity, accuracy, precision, F1-Score, and Cohen's Kappa. The binary logistic model exhibits the highest sensitivity at 89.30%, demonstrating strong performance in identifying true positive cases (e.g., identifying "Yes" instances); however, this is paired with the lowest specificity (55.00%), indicating weaker performance in correctly identifying true negative cases (e.g., identifying "No" instances). On the other hand, the machine learning models show a more balanced performance. Sensitivities for the neural network, CHAID tree, and random forest models hover around 85%, while specificities range from 65.41% to 66.14%. In terms of accuracy, all three machine learning models perform similarly, with the CHAID tree model achieving the highest accuracy at 76.85%, followed closely by the neural network (76.82%) and random forest (76.78%).

Table 4-11. Summary of models' performance

Model	Sensitivity	Specificity	Accuracy	Precision	F1-Score	Cohen's Kappa	The most significant factors
Binary logistic	89.30%	55.00%	74.80%	73.04%	80.36%	0.459	Speed limit, distance to intersection, roadway width, roadside state, etc.
Neural network	85.02%	65.65%	76.82%	77.13%	80.88%	0.517	Speed limit, distance to intersection, roadway width, ASDT, vehicle group
CHAID tree	85.25%	65.41%	76.85%	77.05%	80.94%	0.516	Distance to intersection, ASDT, vehicle group, time of the day, day of the week, roadway width

Random forest	84.59%	66.14%	76.78%	77.31%	80.78%	0.516	Speed limit, distance to intersection, ASDT, roadway width, roadside state

Precision and F1-Score further confirm the balanced performance of the machine learning models, with the random forest model showing the highest precision (77.31%) and the CHAID tree model achieving the best F1-Score (80.94%). Cohen’s Kappa values, which measure overall agreement between predicted and observed classifications, are also higher for the machine learning models, with the neural network model slightly outperforming the others (0.517), suggesting a better overall predictive quality compared with the binary logistic model (0.459).

Several aspects can explain the similar performance across the models. First, the data quality and structure likely offer transparent relationships between variables, making it easier for simpler models, such as logistic regression, to perform well. Moreover, the complexity of the problem may not demand highly sophisticated models, so machine learning methods such as neural networks or decision trees do not provide significantly better results. Furthermore, without extensive hyperparameter tuning, the more complex models may not fully exploit their potential, resulting in only marginally better performances than more straightforward approaches. Last, the large sample size and the absence of all potential causal parameters in the dataset can influence the models’ similar performance. A large dataset often provides enough information for different models to achieve stable and consistent predictions, reducing variability in performance. This can lead to even simpler models capturing essential patterns effectively. Additionally, while the models’ performance is satisfying, there is a potential for including some more causal factors. Above all, the similarity of results between training and test sets generally indicates a good model performance and generalizability. The abovementioned explains why the models display similar sensitivity, specificity, and overall accuracy levels.

The table reveals that, while speed limit and distance to the closest intersection are consistently significant predictors across multiple models, the importance of other factors such as ASDT, roadway width, and time-related variables varies depending on the model used. These variations suggest that the choice of model should align with the specific needs of the analysis, whether prioritizing simplicity or a more comprehensive, multifactorial approach; therefore, it will be essential for the authorities to evaluate these models against their specific datasets to determine the most suitable one for implementation.

The association between speeding and several explanatory variables was constructed with several modeling approaches, which aligns with the previous research. Given that the performance of all models is similar, binary logistic regression is the basis for further discussion, showing strong sensitivity (89.30%). By utilizing binary logistic regression, the findings are interpretable (outputs in the form of odds ratios (Exp(B), previously shown in Table 4-7), statistically sound, and actionable, contributing meaningfully to the understanding of speeding behavior and its underlying determinants.

Higher speed limits are significantly associated with lower odds of speeding. This implies that as speed limits increase, drivers are less likely to exceed them. This trend may be attributed to factors such as enforcement practices and adjustments in driver behavior. In addition, it might imply that drivers feel bored or too slow at lower speeds, or even think that posted speed limits do not comply with the road design. The difference between the road design and the posted speed limit can also lead to speeding (Garber & Gadiraju, 1989). Roadway characteristics substantially impact speed selection behavior, leading drivers who usually tend to drive fast to increase their speeds more than slower drivers when opportunities to drive faster are present (Gupta et al., 2023; Mahmud et al., 2021). Another study shows that drivers justify speeding by saying the speed limits are too low, the road conditions allow higher speeds, or it is a habit (Alonso et al., 2013). Kutela et al. (2024) concluded that the analysis of speed limits reveals an increase in the likelihood of speeding as the speed limits increase; however, the design difference should be taken into account. Similarly, Cai et al. (2021) confirmed that drivers are more likely to exceed the speed limit when the speed limit is low. Other studies also confirmed that speeding is more likely to occur on low-speed limit roads (Perez et al., 2021), concluding that drivers choose their operating speed based on the other drivers' speed (Zhao et al., 2019); therefore, the speed distribution should serve as the foundation for determining suggested speed limits, with the final recommended value considering roadway type, context, safety performance, and other relevant characteristics (Fitzpatrick et al., 2021).

Research shows that a wider shoulder is associated with higher speeds, while narrower lanes encourage a speed reduction (Cai et al., 2021). Contrary to expectations, this study revealed that a wider roadway is associated with a lower likelihood of speeding; however, this must be considered cautiously since the difference between road width was relatively small (St. Dev. = 0.534 m). Interestingly, the roadside without a well-maintained shoulder and safety barrier is a more significant indicator of speeding than where the shoulder has a curb and/or a safety barrier. That may indicate that, in addition to the safety function, protective barriers and curbs impact the drivers' perception, i.e., drivers are more careful not to hit the roadside object.

Similar to previous research, increased traffic can be connected to reduced speed (Lobo et al., 2018; Olmez et al., 2021). The fact that the importance of variables such as distance to the closest intersection and ASDT has been shown indicates that traffic flow characteristics influence speed selection. In other words, the influence of other vehicles and increased drivers' caution when approaching or passing through an intersection is possible. This is consistent with previous studies showing that the least "smooth driving" is expected in urban areas (i.e., cities) (Jurecki & Stańczyk, 2021). Since the increased share of speeding vehicles is expected outside urban areas, the selection of measurement locations in this research is justified when discussing factors potentially affecting speeding. Further, it can be expected that speeding will occur outside the settlements, even in rural areas, as well as on road sections where overtaking is allowed, which this study confirmed.

Weekends, notably Sundays, show increased odds of speeding, particularly in combination with nighttime and dawn driving, which is associated with a higher likelihood of speeding. The finding is particularly worrying since crashes, especially single-crashes, often occur during nighttime, at weekends, and under low traffic volume (Høye, 2020). On the other hand, some research shows that it is more likely that speeding will occur during evening and midday weekend hours (Heydari et al., 2020). This difference may indicate that it is necessary to consider the geographical and cultural components when modeling speeding behavior or discussing transportation in general, since the dynamics of people's lives and habits can vary.

The analysis within our research indicated significant differences in speeding behavior across various vehicle groups. The results suggest motorcycle riders are more likely to be involved in speeding incidents than all other drivers. Specifically, as vehicle type changes from motorcycles to other groups, the likelihood of speeding decreases significantly. This expected result underscores the distinct driving behaviors and speed compliance levels associated with different vehicle types, highlighting motorcycles as a more prominent risk group for speeding-related incidents. Previous studies confirm that motorcycle riders are more prone to speeding than other drive(Broughton et al., 2009). The above is particularly worrying, considering that research shows that excessive speed significantly affects the occurrence of severe injuries and fatalities among motorcyclists (Islam & Brown, 2017; Shaheed et al., 2013).

While most of this study's findings align with previous research, which confirms the role of factors such as speed limits in influencing speeding behavior, there were also some notable variations. These diverse indicators suggest that geographical and sociological aspects may play a significant role in shaping speeding tendencies. For example, the analysis revealed that temporal factors, such as the day of the week and time of day, significantly affect speeding likelihood. This indicates that drivers' behavior might be influenced by social or cultural norms tied to specific times, such as weekend driving habits or nighttime driving patterns. This variation could also indicate regional differences in driving culture, law enforcement practices, or public awareness of road safety, which more standardized driver behavior models might need to capture fully.

4.5.3. Limitations and future implications

This paper provides valuable insights into the factors influencing speeding behavior and choosing the appropriate modeling approach; however, several limitations should be acknowledged. This study did not account for individual driver characteristics such as age, gender, driving experience, or driving history. This means that only the vehicle and road characteristics were taken into account; however, this information can be unavailable to road authorities since they do not know the drivers' characteristics when posting speed limits. Still, according to some researchers, driver attitude and other driver features strongly correlate with obeying speed limits (Etika et al., 2020; Liu et al., 2020). The problem is solved to some extent by using groups of vehicles since a specific group of drivers is often associated with some typical behavior in the literature.

Further, the speed measurements were point-based, capturing speed at specific locations rather than over a continuous stretch of road. This method may not fully represent the overall driving behavior and could miss variations in speed between measurement points.

Finally, the dataset in this study represents summer measurements only. Although this ensures uniform measurement conditions, future research could include data from other seasons when conditions differ (e.g., snow, fog, etc.). On the other hand, favorable weather conditions are one of the prerequisites for free traffic flow, which is a vital assumption when inspecting speeding.

According to the presented results, the focus of future research could be more specific, for example, more detailed monitoring and data collection on motorcyclists' movements (e.g., naturalistic data collection). Furthermore, it could be fruitful to separately observe weekends as a perilous period from the point of view of driving speed. Another potential approach is to observe speeding by class, based on the amount of speeding, and to observe cases inside and outside the settlement separately since the results show a higher possibility of speeding outside the inhabited settlement; however, the sample size presented in this study is one of its key advantages, enhancing the reliability and generalizability of the findings, as it reduces the likelihood of sampling bias and increases the precision of estimates. Furthermore, the sample size allows for detecting subtle relationships between the predictors and the likelihood of speeding and for a more granular analysis of subgroups, such as different vehicle types. In this context, the presented research is a base point for directing further examination, employing a more analytical approach.

Based on everything presented, there is a significant potential for further expansion of individual models so that they can ultimately be applied. By applying the results of those models, road authorities and law enforcement offices could precisely predict locations for the implementation of traffic calming measures or the installation of speed cameras. This can contribute to lower costs and increased traffic safety.

4.5.4. Conclusions

This study aimed to identify the key factors influencing speeding behavior on Croatian state roads using various statistical and machine-learning methods. By analyzing data collected from traffic counters on rural roads over two years, the research explored the impact of vehicle type, road characteristics, time of day, and other variables on speeding occurrences. Among the models, the random forest demonstrated superior performance, achieving an accuracy of 76.8% and a robust discriminative power, indicating its effectiveness in predicting speeding behavior; however, binary logistic regression could be one of the most useful models because of its favorable interpretability. The findings consistently highlighted the speed limit as the most significant predictor of speeding, with lower speed limits strongly associated with increased speeding likelihood. The distance to the closest intersection and the width of the roadway also emerged as influential factors. Vehicle type, time of day, and day of the week further contributed to speeding behavior, with motorcycles exhibiting the highest average speeding and speeding more likely to occur during nighttime and weekends.

This study uniquely contributes to road safety research by comprehensively analyzing speeding factors on rural roads in Croatia, a region underrepresented in previous studies. Combining traditional and advanced modeling techniques offers a more robust analytical approach and examines a distinctive set of factors, including some rarely explored in this context. These insights provide practical recommendations for targeted interventions, enhancing the understanding of speeding behavior in specific geographical and infrastructural settings. Overall, this research contributes valuable insights into the multifaceted factors influencing speeding behavior, thereby supporting the development of targeted interventions and policies aimed at enhancing road safety. Some general suggestions for road authorities can be provided:

- Utilize intelligent transportation systems (ITS). Implement advanced traffic management systems that leverage real-time data and analytics to optimize traffic flow and enhance enforcement measures, such as strategically placed speed cameras.
- Focus on eco-friendly road design. Implement road-narrowing techniques at transition zones, such as residential areas and intersections, to effectively reduce vehicle speeds. By designing roadways that physically guide drivers to slow down, these measures enhance safety while also promoting eco-friendly practices through the use of sustainable materials and designs that minimize environmental impact.
- Enhance road visibility and safety. Improve the visibility and frequency of speed limit signs by incorporating digital displays that adapt to real-time conditions, ensuring drivers are consistently informed of speed regulations. Additionally, perceptual road markings should be utilized to create a visual narrowing effect, which can psychologically encourage drivers to reduce their speed. This combination of advanced signage and perceptual techniques not only enhances visibility but also significantly improves safety by promoting more cautious driving behavior in critical areas.
- Data-driven speed limit adjustments. Regularly review and establish realistic speed limits based on comprehensive analyses of road types, traffic volumes, and crash histories, ensuring that limits are both safe and enforceable.
- Tech-enhanced educational campaigns. Initiate campaigns that leverage digital platforms to inform drivers about the significance of adhering to speed limits and the dangers linked to speeding, thereby promoting a culture of safety on the roads.

Further, based on the results presented in this study, some more specific and applicable suggestions for road authorities, policymakers, and law enforcement can be proposed:

- Speed limit review. Conduct a thorough revision of posted speed limits by analyzing operational speeds at critical locations, assessing the current condition of the infrastructure, and considering additional contextual factors such as land use, pedestrian activity, and road geometry. This approach helps ensure that speed limits are appropriate for the environment and encourages safer driving behavior.
- Road safety equipment installation. Strategically install appropriate road safety equipment, such as crash barriers and guardrails, in high-risk areas to reduce the severity of crashes. These physical measures not only protect drivers but also act as visual cues, encouraging speed reduction and caution in known crash-prone zones.

- Increased police presence. Implement more frequent and targeted police patrols, especially during high-risk periods such as weekends and holidays when speeding and dangerous driving behaviors are more prevalent. A visible law enforcement presence is a deterrent to speeding and reckless driving.
- Improved intersection marking. Ensure consistent and timely installation of highly visible and uniformed road markings at intersections to warn drivers clearly. This can significantly enhance driver awareness and reduce the likelihood of speeding in these complex traffic zones, minimizing potential collisions.
- Motorcycle safety focus. Pay special attention to areas with high motorcycle traffic by identifying potential hazards and launching targeted safety campaigns. Educate motorcyclists and other road users about safe practices and implement infrastructure improvements to enhance motorcycle safety.
- Traffic surveillance enhancement. Install traffic monitoring cameras at locations where errant drivers, particularly motorcyclists, are frequently observed. These cameras help enforce traffic laws in cases where it is challenging for police to apprehend offenders, such as motorcyclists fleeing from officers or concealing license plates.
- Crash and speeding monitoring. Continuously track and analyze data related to traffic crashes caused by speeding, including the severity of injuries and fatalities. This ongoing evaluation can inform future road safety measures and adjustments to enforcement strategies, helping to reduce the incidence of speed-related crashes over time.

Implementing measures that address the identified factors, such as integrating advanced road design improvements and stricter enforcement of speed limits, can significantly reduce speeding incidents and associated risks. Through a comprehensive approach that combines enforcement, innovative design, and technology, we can create safer road environments that minimize the dangers of speeding.

Chapter 5.

Exploring the factor structure of a modified motorcyclist behavior questionnaire: Croatian context

This chapter is based on the following journal article (published):

Ferko, M., Pirdavani, A., & Babić, D. (2023). Exploring the Factor Structure of a Modified Motorcyclist Behavior Questionnaire: Croatian Context. *Transportation Research Procedia*, *73*, 250-256. https://doi.org/10.1016/j.trpro.2023.11.915

ABSTRACT

Road crashes, particularly those involving vulnerable road users, such as motorcyclists, are a major public concern worldwide, especially on rural roads. To understand the factors contributing to the heightened risk experienced by motorcyclists, a survey was conducted among motorcycle riders. The Motorcycle Rider Behavior Questionnaire (MRBQ), a widely used self-report instrument, was employed to gather insights into motorcyclists' perspectives, behaviors, and attitudes regarding road safety. This study focused on the factor structure of the MRBQ within the context of Croatia. Principal component analysis (PCA) with varimax rotation was performed to examine the underlying factors of motorcyclist behavior. Five distinct factors were identified: violations (e.g., speeding and reckless riding), errors (e.g., risky maneuvers and inattention), stunts (e.g., wheelie), safety equipment (e.g., use of protective gear), and substance use (e.g., riding under influence). These factors explained 40.44% of the variance among the analyzed items. These findings contribute to the understanding of motorcycle rider behavior patterns. Future research will explore the relationship between these factors and motorcyclists' involvement in risky situations and crashes.

KEYWORDS

Motorcycle; motorcyclist safety; rider; behavior questionnaire.

5.1. Introduction

Road crashes pose a significant global public health concern, resulting in approximately 1.3 million of fatalities each year, according to the WHO's report (WHO, 2018). Vulnerable road users, including pedestrians, cyclists, and motorcyclists, account for a substantial proportion of these fatalities. According to the Global Status Report on Road Safety (WHO, 2018), motorcyclists account for approximately 23% of global road traffic deaths. In the European Union (EU27) alone, motorcyclists accounted for 16% of all road fatalities in 2019. While the number of motorcycle fatalities exhibited a reduction of 14% between 2010 and 2019, the overall decrease in total road fatalities was 23%. Consequently, the relative proportion of motorcycle fatalities among the total number of road fatalities increased from 14% in 2010 to 16% in 2019. Analysis of the data revealed that rural roads consistently recorded the highest number of motorcycle road fatalities, followed by urban roads and motorways. Specifically, road stretches accounted for the majority of motorcycle fatalities (71%), with fewer incidents occurring at junctions (19%) or roundabouts (2%), as listed in *Facts and Figures – Motorcyclists and Moped Riders – 2021* (Slootmans, 2021). These statistics emphasize the urgent need for comprehensive research and evidence-based strategies to improve the road safety of motorcyclists and reduce their vulnerability to different types of road sections.

Road safety is a multidimensional concern that requires scientific examination and targeted interventions to address the distinctive risks faced by motorcyclists. With their inherent vulnerability and exposure to various environmental and traffic factors, motorcyclists experience higher crash rates and injury severity than other road users. To address this critical issue, this study aimed to investigate the factors contributing to the heightened risk experienced by motorcyclists. By conducting a survey among motorcyclists, this research seeks to gather valuable insights into their perspectives, behaviors, and attitudes regarding road safety. Numerous studies have shown that examining rider behavior and factors that affect their decision-making is necessary to determine the directions of interventions and strategies that can be used to improve the safety of motorcyclists.

The motorcycle rider behavior questionnaire (MRBQ) has become a common self-report instrument for investigating the factors influencing motorcyclist safety and risk-taking tendencies on the road. Its development followed the driver behavior questionnaire, a widely used instrument for investigating driving behaviors in four-wheeled vehicles utilized by Reason et al. (1990). The authors categorized deviant car driving behaviors based on a system of errors and violations, defining errors as "failure of planned actions to achieve their intended consequences" and violations as "deliberate deviations from those practices believed necessary to maintain the safe operation of a potentially hazardous system". Further, errors were divided into slips and errors ("the unwitting deviation of action from intention") and mistakes ("the departure of planned actions from some satisfactory path towards a desired goal"). After a principal component analysis with varimax rotation and a scree plot applied to the 43 MRBQ items, Elliott et al. (2007) concluded that the data were best fitted by a 5-factor solution, indicating that there were five main behavior types supporting the MRBQ. A similar approach has been used over the past 15 years by other authors worldwide. Some of the researchers used the same questionnaire items, like Özkan et al., (2012), Sakashita et al. (2014), and Stephens et al. (2017), but some authors have added additional items, for instance, Motevalian et al. (2011) and Setoodehzadeh et al. (2021).

This paper represents the first phase of wider research that deals with the behavior and perception of motorcyclists in Europe. For this reason, only an MRBQ part of the survey will be analyzed. In future phases, a connection between self-assessed behavior and involvement in risky situations and crashes will be investigated. The objective of this paper is to examine and analyze the factor structure of the MRBQ specifically within the context of Croatia, where the questionnaire was administered. By exploring the underlying factors and dimensions of motorcyclist behavior as captured by the MRBQ, this research aims to contribute to the understanding of motorcycle rider behavior patterns. The findings will shed light on the psychometric properties and structure of the MRBQ instrument when applied to a sample of motorcyclists from Croatia, providing valuable insights into the factors influencing motorcycle rider behavior and facilitating targeted interventions for enhancing road safety in the region.

5.2. Methodology

A questionnaire specifically designed for motorcycle riders was developed to gain insights into further research on motorcycle rider safety. An online survey was conducted to collect data from the participants. Additionally, principal component analysis (PCA) was performed to examine the underlying factors of the questionnaire items.

5.2.1. Questionnaire design

This study was based on a questionnaire consisting of four major sections: sociodemographic characteristics, Motorcycle Rider Behavior Questionnaire (MRBQ), road perception, and past crash involvement. The present article focuses on the analysis of the section pertaining to motorcycle rider behavior (MRBQ). The MRBQ was developed based on a study conducted by Elliott et al. (2007), which incorporated 40 questions of 43 questions used in the original MRBQ. An additional 15 new items were added to expand the original questionnaire and to gain new insights. The questionnaire was originally composed in English and translated into Croatian for the purposes of research conducted in Croatia. All questionnaire items were formulated as declarative statements, and respondents rated their agreement with each statement on a Likert scale ranging from one to six.

5.2.2. Participants and data collection

The inclusion criteria for participant selection required that individuals be of legal age and possess a valid motorcycle driver's license. These criteria ensured that participants had the necessary legal qualifications and experience to engage in motorcycle riding activities, thus enabling them to provide valuable insights into motorcycle rider behavior and perceptions.

The data used in this paper were collected in Croatia between January and May 2023. Participants were recruited from various motorcycle clubs and online platforms, utilizing link sharing as a means of participation. The recruitment strategy aimed to obtain a diverse and representative sample of motorcycle riders in Croatia. Each participant received a unique link to access and complete the questionnaire, which had an average completion time of 33,84 minutes (SD = 126,14). The use of a unique link for participation allowed the management of participant responses, ensuring data integrity and privacy.

The sample consisted of 906 participants who answered all the questions regarding their riding behavior. Among them, 125 (13.8%) were female, 775 (85.5%) were male, and six (0.7%) preferred not to declare their gender. After excluding three participants with invalid responses, the ages of the participants ranged from 18 to 75 years, with a mean of 37.44 years (SD = 11.04).

5.2.3. Data analysis

Principal component analysis (PCA) with varimax rotation was conducted to examine the structure of different types of motorcycle rider behavior. Prior to analysis, the number of factors that best explained the data structure was explored using several criteria. Principal component analysis (PCA) is a widely used statistical technique used to examine the underlying structure of a dataset. According to various researchers, like Campos et al. (2020) and Watkins (2018), it aims to reduce the dimensionality of the data while preserving as much information as possible by transforming the original variables into a new set of uncorrelated variables called principal components. Varimax rotation is a rotation method applied to the principal components obtained from the PCA. Rotation helps to obtain a simpler and more interpretable factor structure by maximizing the variance of squared loadings within each factor while minimizing correlations between factors. The final factor structure was assessed based on the item loadings. Each item was evaluated to determine its factor membership by examining the loading values. Factor loading represents the strength of the relationship between a questionnaire item and a factor. Items with higher loadings for a particular factor indicated a stronger association with that factor. A factor loading close to 1 indicates a strong positive relationship, a factor loading close to -1 indicates a strong negative relationship, and factor loadings close to 0 suggest a weak or negligible relationship. Item loading values of 0.3 were used as a cut-off point.

5.3. Results and discussion

Questionnaire responses were collected from a sample of participants who were asked to rate their driving behaviors on a 6-point Likert scale, which is commonly used in similar studies made by Elliott et al. (2007), Motevalian et al. (2011), Sakashita et al. (2014) and Uttra et al. (2020). To analyze the data, PCA was performed to identify the underlying factors that explain the patterns of responses across the questionnaire items.

Parallel analysis indicated that there are seven components that can be extracted from the data. However, the eigenvalues of the sixth and seventh factors were very close to those of the simulated data and the Velicer MAP criteria indicated six factors. In the seven-factor solution, only two items were loaded on one of the factors, and in the six-factor solution sixth factor was not interpretable; therefore, results were obtained for the five-factor solution. The total variance of the items included in the analysis explained by the five factors was 40.44%. In the rotated solution, the variances explained by the first, second, third, fourth, and fifth factors were 13.38%, 8.82%, 7.69%, 6.16%, and 4.39%, respectively.

The loadings for these five factors are listed in Table 5-1. Each of the factors had several items loaded on it, making them stable. In the case of the first three factors, there were items that loaded highly only on them, but there were also items with relatively high cross-loadings. According to the obtained item loadings, 12 items were loaded onto Factor 1, 12 items were loaded onto Factor 2, five onto Factor 3, four onto Factor 4, and five onto Factor 5. Nine analyzed factors loaded onto two or more factors, while there were six items without high loadings on any of the extracted factors. The fourth and fifth factors had a clear structure, with items that loaded highly only on each of them.

Table 5-1. Factor loadings from principal components analysis with varimax rotation

Questionnaire item	1	2	3	4	5
Q25_2 Exceeding the speed limit on a country/rural road/outside the urban area.	**0.82**	0.10	-0.02	-0.04	-0.15
Q25_1 Exceeding the speed limit on a motorway/highway.	**0.80**	0.06	0.07	0.01	-0.09
Q25_3 Exceeding the speed limit on an urban/city road/residential area.	**0.76**	0.08	-0.06	-0.12	-0.01
Q25_5 Opening up the throttle and "going for it" on rural/country roads.	**0.74**	0.11	0.21	-0.09	0.05
Q25_4 Disregarding the speed limit late at night or in the early hours of the morning.	**0.74**	0.09	0.04	-0.12	0.05
Q22_6* Start overtaking a slower vehicle in front, even though this is prohibited.	**0.70**	0.13	0.20	-0.05	0.08
Q22_7* Start overtaking a slower queue of three or more vehicles in front.	**0.66**	0.08	0.21	0.02	0.15
Q24_5* Overtaking another vehicle at a short distance/slalom riding.	**0.58**	0.10	**0.48**	-0.06	0.15
Q22_10* Turning onto the main road from a side road without stopping at the "Stop" sign.	**0.52**	0.22	0.05	-0.14	0.10
Q25_6* Disregarding the speed limit during rainy conditions.	**0.52**	0.11	0.12	0.00	0.20
Q22_9* Merging from a side road onto the main road while seeing vehicles approaching on the lane I am merging to.	**0.47**	0.18	0.03	-0.08	0.26
Q24_7 Ride between two lanes of fast-moving traffic.	**0.46**	0.10	**0.31**	-0.01	**0.31**
Q22_8 Attempt to overtake someone that you had not noticed to be signaling a right turn.	**0.46**	0.20	0.11	-0.03	0.19
Q24_6 Race away from traffic lights with the intention of beating the driver/rider next to you.	**0.45**	0.17	**0.32**	-0.09	0.14
Q23_7 Riding so close to the vehicle in front that it would be difficult to stop in an emergency.	**0.44**	**0.35**	0.24	-0.03	0.10
Q22_1* Not maintaining a sufficient safety distance between vehicles.	**0.40**	0.14	0.19	-0.01	0.09
Q23_5 Slipping on a wet road, manhole covers, road markings, etc.	**0.32**	0.29	**0.32**	0.07	-0.06
Q22_3* Not using direction indicators (so-called blinkers) when turning or changing lanes.	0.28	0.23	0.19	-0.15	0.11
Q23_6 Changing gear around a curve/corner.	0.18	0.15	0.10	0.12	0.14
Q22_20 Not notice someone stepping out from behind a parked vehicle until it is nearly too late.	0.11	**0.68**	-0.03	0.00	0.08
Q22_19 Fail to notice that pedestrians are crossing when turning into a side street from a main road.	0.14	**0.65**	-0.04	-0.03	0.06
Q22_14 Distracted or pre-occupied, you belatedly realize that the vehicle in front has slowed and you have to brake hard to avoid a collision.	0.17	**0.62**	0.06	-0.09	0.03
Q22_21 Not notice a pedestrian waiting to cross at a zebra crossing, or a pelican crossing that has just turned red.	0.22	**0.60**	0.04	-0.11	-0.05
Q22_15 When riding at the same speed as other traffic, you find it difficult to stop in time when a traffic light has turned against you.	0.03	**0.58**	-0.02	-0.03	0.04
Q23_2 Run wide when going round a corner.	0.14	**0.54**	0.12	-0.02	-0.03
Q22_11 Pull out on to a main road in front of a vehicle that you had not noticed, or whose speed you have misjudged.	0.21	**0.54**	0.09	-0.07	0.23
Q22_13 Queuing to turn left on a main road, you pay such close attention to the main traffic that you nearly hit the vehicle in front.	0.05	**0.49**	0.11	0.03	0.06
Q23_3 Having difficulty controlling the motorcycle while riding at high speed (e.g., steering wobble).	0.04	**0.49**	0.21	-0.01	0.13
Q22_12 Miss "Give Way" signs and narrowly avoid colliding with traffic having the right of way.	0.14	**0.47**	0.06	-0.04	0.28
Q23_8* Braking too quickly on a slippery road.	0.19	**0.45**	0.23	-0.04	0.11
Q23_1 Riding so fast into a curve that I feel like I might lose control.	**0.36**	**0.44**	**0.40**	0.00	-0.06
Q22_2 Fail to notice or anticipate that another vehicle might pull out in front of you and have difficulty stopping.	0.02	**0.42**	0.09	-0.08	0.11
Q23_4 Riding so fast into a curve/corner that I have to brake or throttle-back round it.	**0.33**	**0.37**	0.23	0.00	-0.03

Questionnaire item	1	2	3	4	5
Q22_5* Not using mirrors to check the vehicles surrounding me while riding or turning.	0.04	0.29	0.20	-0.11	0.11
Q26_10 Have trouble with your visor or goggles fogging up.	0.01	0.19	-0.03	-0.09	-0.04
Q24_3 Pulling away too quickly, and my front wheel coming off the road (lifts).	0.27	0.06	**0.82**	-0.07	0.09
Q24_1 Attempting to or actually doing a wheelie (a trick or maneuver whereby a bicycle or motorcycle is ridden for a short distance with the front wheel raised off the ground).	0.19	0.02	**0.80**	-0.09	0.05
Q24_2 Intentionally doing a wheel spin.	0.19	0.09	**0.71**	-0.16	0.10
Q24_4* Braking too rapidly with the front brake, and my rear wheel going up in the air.	0.07	0.12	**0.71**	0.05	0.14
Q24_8 Get involved in unofficial “races” with other riders or drivers.	**0.42**	0.15	**0.52**	-0.10	0.20
Q23_9 Unintentionally doing a wheel spin.	0.14	0.24	**0.51**	-0.01	-0.11
Q26_11 Use dipped headlights on your motorcycle.	0.12	0.00	-0.17	0.15	-0.15
Q26_3 Wear protective trousers (leather or non-leather).	-0.11	-0.05	-0.01	**0.80**	0.01
Q26_4 Wear riding shoes/boots.	-0.05	-0.11	0.00	**0.76**	0.01
Q26_2 Wear a protective jacket (leather or non-leather).	0.00	-0.09	-0.13	**0.70**	-0.12
Q26_5 Wear motorcyclist gloves.	0.00	-0.07	-0.14	**0.61**	-0.10
Q26_6 Wear body armor to protect elbows, knees, shoulders, etc.	-0.10	-0.11	0.09	**0.60**	0.03
Q26_8 Wear bright/fluorescent or reflective markings /strips on your clothing or helmet.	-0.26	0.00	-0.01	**0.51**	-0.06
Q26_7 Wear fluorescent clothing/helmet or reflective vest/clothing/helmet.	-0.29	0.03	-0.01	**0.48**	-0.08
Q26_1* Wear a protective helmet.	0.10	0.02	-0.10	**0.34**	-0.20
Q26_9 Wear no protective clothing.	-0.03	0.13	0.02	-0.19	0.03
Q22_18 Ride when you suspect you might be over the legal limit for alcohol.	0.25	0.13	0.01	-0.05	**0.79**
Q22_16* Immediately before driving a motorcycle, I consumed alcohol. Hence, I drove under the influence of alcohol.	0.23	0.10	-0.03	-0.10	**0.78**
Q22_17* I consumed light/heavy drugs, strong medicaments, or other intoxicants and drove under the influence of drugs and strong medicaments.	0.05	0.13	0.14	-0.16	**0.47**
Q22_4* Going through a red light.	0.15	0.18	0.18	-0.17	**0.40**

Note: Loadings greater than 0.30 are typed in bold.
** - new questionnaire items*

Items associated with the first factor refer mainly to speeding and reckless riding, that is, deliberate disregard for riding that would be considered safe. This factor is consistent with the previously defined “Violations”. The highest loadings within Factor 1 are associated with items that are related to exceeding speed limits under various road conditions. Twelve items loaded on Factor 2 mainly represented risky maneuvers, inattention, and the distraction of riders, and well represent situations that can be characterized as “Errors”. Items with high positive loadings in Factor 3 include maneuvers with a motorcycle, which can be labeled as “Stunts,” for example, wheelie. There are five items with loadings clearly related to the third factor. As mentioned earlier, the fourth and fifth factors had a clear structure according to the analysis performed. Factor 4 relates to the use of protective motorcycle gear, including helmets, jackets, gloves, and additional protective equipment, so it can be labeled as “Safety equipment”. Items with high positive loadings in Factor 5 are associated with risky behaviors such as riding under the influence of alcohol, drugs, or medications. However, one of the items (Q22_4) could not be related to substance misuse.

The five factors accounted for a total variance of 40.44% among the analyzed items, which is a percentage comparable to previous studies: Elliott et al. (2007), Motevalian et al. (2011), and Trung Bui et al. (2020). Further, Motevalian et al. (2011) in a Persian version of the MRBQ showed a six-factor, while Hosseinpourfeizi et al. (2018) developed a shortened version of the MRBQ which included 23 questionnaire items showed a three-factor structure. The study from Vietnam by Trung Bui et al. (2020), which utilized 43 items from the original MRBQ, revealed a four-factor structure, with six items displaying low weights that were not associated with any factor, while one item exhibited loading across multiple factors, which is similar to results obtained from a study from Nigeria executed by Sunday (2010). On the other hand, a 43-item MRBQ adapted to the Indian context by Sumit et al. (2021) revealed a five-factor structure, similar to the one in the original questionnaire.

The results presented in this paper are in line with previous research, although they do exhibit slight variations, which was anticipated considering that the existing literature emphasizes the existence of differences among motorcyclists depending on the region under study.

In future research, the identified factors will continue to provide valuable insights into the structure of motorcycle rider behavior, shedding light on the distinct dimensions that influence rider actions and choices. According to the presented values, the final structure of the questionnaire (without items that do not belong to any factor and without items that showed high cross-loadings) contains a total of 41 items in five factors. Of these, 12 are new and 29 items are from the original MRBQ. The refinement process focuses on the most relevant questionnaire items that demonstrate strong associations with the underlying factors. By omitting items with low loading values, the precision and validity of the questionnaire can be improved, thereby facilitating a clearer understanding of motorcycle rider behavior. The next step in the research will involve investigating the relationship between the obtained factors and motorcyclists' self-reported risky situations, such as involvement in crashes and penalties for traffic violations.

5.4. Conclusion

In conclusion, this study examined the factors influencing motorcycle rider behavior with the aim of enhancing the road safety of motorcyclists. The analysis of data collected from a sample of motorcycle riders in Croatia revealed a five-factor structure of motorcycle rider behavior, similar to the original motorcycle rider behavior questionnaire (MRBQ). The factors identified could be grouped as “Violations” representing deliberate disregard for safe riding practices; “Errors” encompassing risky maneuvers, inattention, and distractions; “Stunts” related to motorcycle maneuvers such as wheelies; “Safety equipment” reflecting the use of protective gear; and “Substances misuse” associated with riding under the influence of alcohol, drugs, or medications.

These findings contribute to the existing body of research on motorcycle rider behavior by providing insights specific to the Croatian context. The results align with those of previous studies, demonstrating both consistency and slight variations in the factor structure of motorcycle rider behavior across different regions.

The identification of these factors offers valuable insights into the dimensions that influence rider actions and choices. By refining the questionnaire based on the omitting items with low loading values or cross-values, the precision and validity of the MRBQ could be enhanced, facilitating a clearer assessment of motorcycle rider behavior. In future research, the relationship between the identified factors and motorcyclists’ self-reported risky situations, such as involvement in crashes and traffic violations, will be explored. This will provide further evidence of the impact of motorcycle rider behavior on road safety outcomes. Overall, this study contributes to the broader goal of reducing the vulnerability of motorcyclists and improving their road safety. By addressing the distinct risks faced by motorcyclists and understanding the factors that influence their behavior, evidence-based interventions can be developed to promote safer riding practices and ultimately reduce motorcycle-related injuries and fatalities.

Chapter 6.

Understanding risky riding: factors influencing crashes, near-crashes, and traffic fines among motorcyclists

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ABSTRACT

Motorcyclists are one of the most vulnerable road user groups, with crash rates and fatalities consistently exceeding those of other vehicle users. This study investigates the behavioral and perceptual factors influencing motorcycle crashes, near-crashes, and traffic fines in Croatia using an extended version of the Motorcycle Rider Behavior Questionnaire (MRBQ). The survey, conducted among 842 Croatian motorcyclists, explored risky behaviors, protective practices, and perceptions of road infrastructure. Principal Component Analysis (PCA) identified a five-factor structure of rider behavior: Violations, Errors, Stunts, Personal Protective Equipment (PPE), and Intoxication. Errors emerged as the strongest predictor of crash and near-crash involvement, while violations and stunts significantly predicted traffic fines. Analyses revealed that younger riders exhibited higher rates of risky behaviors, including speeding and stunts. In comparison, older riders and those with children demonstrated safer riding patterns and greater PPE use. Riders' perceptions of road infrastructure, particularly inadequate road markings and surface conditions, also highlighted safety concerns. The findings emphasize the need for targeted interventions: advanced rider training focusing on control errors, strict enforcement against violations and substance use, infrastructure improvements, and incentive programs for PPE adoption. Addressing these factors through evidence-based strategies can reduce motorcyclist crash risks and promote safer riding behaviors.

KEYWORDS

Motorcyclists; risky behavior; MRBQ; road infrastructure; traffic safety

6.1. Introduction

Motorcyclist road safety remains a critical focus within traffic safety research worldwide, as motorcyclists are disproportionately represented in fatal and severe crash statistics compared to other road users, i.e., they are about 9 to 30 times more likely to be killed in traffic compared to a car driver (Slootmans, 2023b). Motorcyclists are especially at risk due to vehicle instability, limited protection, and higher crash injury severity than other vehicle types. Given the vulnerability of motorcyclists in crashes, research into behavioral and environmental factors can help inform targeted interventions aimed at reducing crash involvement and enhancing rider safety.

Although all powered two-wheeler riders are considered vulnerable road users, the crash data reveals distinct trends in moped and motorcycle crashes in the European Union (EU). Namely, the number of moped-related crashes in the EU steadily decreased up to 45% between 2010 and 2019, while motorcycle fatalities decreased only by 14% (Slootmans, 2023b). Moreover, although the number of motorcycle-related fatalities declined by 16.5% between 2012 and 2022, the total number of road fatalities decreased even further, by 22% during the same period. As a result, the relative share of motorcycle-related fatalities within the overall road fatality count has slightly increased and accounts for around 19% of all road fatalities in the European Union (Slootmans et al., 2024). Regarding motorcyclist safety in Croatia, the share of motorcycle-related crashes in the total number of crashes increased from 3.53% to 4.40% in the 2013-2023 period (Ministry of the Interior of the Republic of Croatia, 2024). Fatalities among motorcyclists fluctuated in the mentioned period, with significant increases observed in some years. Notably, between 2018 and 2022, the share was 19%-23%, while in 2023, motorcycle-related fatalities accounted for 30.7% of all road crash fatalities in Croatia, indicating a substantial rise. Although official data for 2024 have not yet been published, preliminary analysis shows that motorcyclist fatalities account for 1/3 of all road deaths. This percentage shows that the share of motorcycle-related fatalities is significantly above the EU average and highlights motorcyclists as particularly vulnerable. The challenging road network, the influx of seasonal riders, and informal rider communication about the police check-out or camera locations (e.g., via social media or apps) present unique behavioral and enforcement challenges. These contextual specifics highlight the need for a focused study on Croatian motorcyclists to inform behavior- and infrastructure-based interventions. Furthermore, it is a worrying fact that research shows that riders are more prone to traffic violations than drivers and, at the same time, less concerned about the risk of a road crash (Cordellieri et al., 2019).

Despite these concerning trends, research on motorcyclist safety in the EU remains notably scarce. This gap highlights the urgent need for targeted studies to better understand the unique risks motorcyclists face, which could inform policies and interventions to reduce crash rates and improve safety outcomes for this high-risk group. Given the unique risks associated with motorcyclists and the limited research on this topic in Croatia, as well as in the EU, a survey was conducted to capture data specific to motorcyclist behavior, including measures from the Motorcycle Rider Behavior Questionnaire (MRBQ). The MRBQ is a validated instrument widely used in traffic safety research to examine riding behaviors and their relationship to crash involvement. This survey approach enables a comprehensive understanding of the behavioral factors contributing to increased risk among motorcyclists, paving the way for evidence-based strategies to improve road safety for this vulnerable group.

6.1.1. Previous research review

6.1.1.1. Background on the MRBQ and risk contributing factors

The Motorcycle Rider Behavior Questionnaire (MRBQ), initially developed by Elliott et al. (2007), has become an essential tool for assessing motorcyclist behaviors correlating with increased crash risks. Inspired by the Driver Behavior Questionnaire (DBQ) (Reason et al., 1990), the MRBQ enables the measurement of specific rider behaviors that predict crashes, including errors, violations, and usage of safety equipment (Elliott et al., 2007). The MRBQ originally consisted of five behavioral categories: traffic errors, control errors, speed violations, stunts, and safety equipment usage. These factors capture different dimensions of rider behavior, with traffic errors representing lapses in situational awareness, control errors reflecting mishandling of the motorcycle, speed violations and stunts as intentional risk-taking behaviors, and safety equipment use indicating protective practices.

The validity of the MRBQ has been tested across various regions and demographic groups, demonstrating consistent reliability and adaptability across cultures, though with modifications to factor structures in some cases. For instance, in Iran, a modified, shortened MRBQ showed strong reliability and interchangeability with the full version, supporting its use for assessing rider behavior in regions with limited resources (Hosseinpourfeizi et al., 2018).

Due to regional variations in riding behaviors and crash contexts, the MRBQ has been adapted in different countries. In Brazil, a Portuguese-translated version was validated to reflect local behaviors, particularly to address high rates of motorcycle crashes in urban areas with intensive use for commercial activities such as deliveries (Coelho et al., 2012). Similarly, in

Colombia, where motorcycle taxis are common, adaptations of the MRBQ showed that frequent speed violations and stunts are strongly associated with crash risk (Ospina-Mateus et al., 2021).

In Thailand, the MRBQ has also been adapted to capture culturally specific factors affecting rider safety, with findings indicating high rates of control errors and low usage of safety equipment among riders (Uttra et al., 2020). Research in Thailand has also highlighted how risk perception influences behavior, with younger riders often underestimating their vulnerability (Hongsranagon et al., 2011). Another adapted-version MRBQ study from Thailand investigated risky motorcycle riding behaviors among middle-aged and older adults (> 35 years) and identified four behavioral dimensions: speed violations, control errors, traffic errors, and safety (Sunmud et al., 2024). Riders with 1–3 years of experience were significantly more likely to report crash involvement. However, no statistically significant differences were found in traffic violations by age group, nor were age and crash involvement significantly correlated. In Vietnam, research on app-based motorcycle taxi riders indicated that lifestyle factors such as smoking and alcohol consumption strongly correlate with risky behaviors, including riding without helmets and speeding (Nguyen-Phuoc et al., 2020). This study revealed that lifestyle choices impact riding behaviors and risk-taking tendencies, particularly among motorcyclists in high-demand roles like ride-hailing. Recently, a validation of the MRBQ was also performed in Indonesia (Setyowati et al., 2024b).

In studies focused on both novice and experienced riders in Australia, the MRBQ was used to assess various risky behaviors across rider demographics. Novice riders were more likely to engage in control errors, while experienced riders showed higher incidences of speed violations (Stephens et al., 2017). These findings highlighted the need for targeted interventions based on rider experience levels. Additionally, studies demonstrated that combining control and traffic errors in the MRBQ offered better predictive validity for crash involvement among new riders, suggesting that factor configurations may need adjustment for different populations (Sakashita et al., 2014).

Research on young motorcyclists in New Zealand used the MRBQ to assess risky behaviors and protective attitudes (Reeder et al., 1996). The study found that while most young riders supported helmet use, compliance with other protective gear was lower, and many engaged in behaviors like speeding and drinking while riding. The study highlighted significant peer influences on riding behavior, underscoring the need for peer-focused safety initiatives.

The MRBQ's findings have also been integrated with psychological models, such as the Theory of Planned Behavior (TPB) and the Health Belief Model (HBM). Studies indicate that variables like perceived control and cues to action from these models significantly correlate with MRBQ factors such as speed violations and safety equipment use (Özkan et al., 2012). For example, stunts and speed violations are closely associated with a low sense of control. At the same time, using safety equipment is often linked to high perceived behavioral control and awareness of risks. Özkan et al. (2012) reported that speed violations significantly predicted traffic offenses, while traffic and control errors, although theoretically relevant, did not show strong associations with crashes. Annual mileage positively predicted all crash and offense outcomes, while age was negatively associated, supporting findings from Elliott et al. (2007).

Recent systematic reviews confirmed the predictive and informative potential of the MRBQ, with an implication for researchers to enhance the predictive(Chouhan et al., 2023; Krishnakishore & Othayoth, 2022).

Beyond the MRBQ, other survey-based tools are employed to capture self-reported data on specific behaviors, attitudes, and experiences of motorcyclists, e.g., focus groups or interviews (Huth et al., 2014; Sumit et al., 2022), behavioral observations and on-road studies (Bartolozzi et al., 2023), motorcycle simulator studies (Kovácsová et al., 2020; Vu et al., 2020), and other forms of self-report surveys and questionnaires (Chen & Chen, 2011; Esmaeli et al., 2022; Goh et al., 2020; Suteja et al., 2018). Additionally, motorcyclist behavior cross-cultural research was conducted, comparing riders from two countries (Lee et al., 2015) or more countries (ESRA) (Ziakopoulos et al., 2021).

Cloninger's psychobiological model of personality was applied to explore the relationship between temperament, character traits, and motorcycle crash involvement (Romero et al., 2019). The findings showed that high scores in novelty seeking and low scores in harm avoidance were significantly associated with a range of risky behaviors, including speeding, substance use, and disregard for traffic rules. Moreover, these traits were linked to more severe crash consequences, such as fractures and hospitalization. Riders who used motorcycles for work exhibited even higher risk-oriented personality profiles. The study also found that low self-directedness and cooperativeness were common among riders, which may impair behavioral regulation and reduce accountability. These results spotlight the role of psychological predispositions in shaping rider behavior.

Sensation-seeking is one of the commonly reported personal traits among motorcyclists. Among adolescents, sensation-seeking and weak parental norms predicted violations, and at the same time, lower risk perception was linked to more frequent risky behavior (Falco et al., 2013). The most commonly reported behavior among university students suggests control errors and thrill-seeking/stunt-like behavior (Setyowati et al., 2024a). The wheelie-related behaviors appear to be recreational or adventure-driven, not always related to substance use, which also indicates sensation-seeking motivations. The same study shows that gender, licensing status, and riding frequency were not significantly related to risky behavior. In a Taiwanese study, riders were classified into sensation-seeking, amiable, and impatient profiles (Wong et al., 2010). Sensation-seekers were aware of traffic but felt comfortable with unsafe behaviors, while impatient riders had poor awareness and low confidence but still sought utility from risk. The authors also reported that sensation-seekers have fewer but potentially more severe crashes due to extreme behaviors. Personality traits (e.g., normlessness, aggression, sensation-seeking) predict risky riding, while intention and attitudes are strong mediators of behavior.

A study in which an extended TPB was applied revealed that risky behaviors such as bending traffic rules, pushing limits, and performing stunts were strongly predicted by sensation seeking, positive attitudes toward risk, and peer influence (Tunnicliff et al., 2012). The concept of self-identity as a risky rider and specific subjective norms (i.e., expectations from fellow riders) also significantly influenced the intention to engage in dangerous behavior. In contrast, intentions to ride safely were mainly influenced by perceived behavioral control, suggesting that confidence in one's riding ability is a key driver of safer choices. Notably, the variance explained in models predicting risky behaviors was higher than that for safe behaviors, indicating that risky intentions are more psychologically and socially reinforced.

A systematic review of 22 African studies identified multiple rider-related and environmental factors associated with motorcycle crash involvement (Konlan & Hayford, 2022). The most frequent behavioral contributors included alcohol and drug use, speeding, riding at night, carrying multiple passengers, and lack of helmet use. Crashes were more prevalent among younger riders, those with limited riding experience, and individuals without formal training or valid licenses. Poor knowledge of traffic rules and low compliance with safety regulations further elevated the risk. In addition, road infrastructure deficiencies, such as potholes, inadequate signage, and slippery surfaces, were frequently reported as external crash-contributing factors.

Although it is reasonable to assume that traffic fines discourage illegal behavior, some findings show the opposite. Perceived crash risk deters behavior more than perceived traffic fines risk, as many motorcyclists continue risky riding despite being aware of fines (Truong et al., 2018). At the same time, behaviors like drunk riding and red-light violations were strongly associated with increased crash exposure. Furthermore, crashes are often caused by violations and poor road knowledge (Bolbol & Zalat, 2018). Commercial pressure, lack of rest, and poor enforcement contribute to speeding and phone use, leading to the conclusion that occupational exposure significantly increases crash risk (Nguyen-Phuoc et al., 2020).

Based on the literature review, it has to be noted that most offenses like mobile phone use, riding without a helmet, smoking, and not having a valid license are mostly observed outside the EU area (e.g., Taiwan, Egypt, Vietnam, etc.). On the other hand, speeding is the main issue in Europe. Further, in some areas, questions about alcohol usage are not relevant due to very low endorsement. The above points out that, apart from infrastructure conditions and vehicles, riding culture differs worldwide, and that is an additional motivation for focused research on motorcyclist safety.

6.1.1.2. Methods and variable selection

The most commonly used statistical methods for examining the underlying factor structure of a questionnaire are explanatory factor analysis (EFA) (Chakraborty & Maitra, 2024; Stephens et al., 2017), principal component analysis (PCA) (Özkan et al., 2012; Sunday & Akintola, 2010; Vandael Schreurs et al., 2023), and structural equation modeling (SEM) (Naderpour et al., 2023).

The use of MRBQ data in conjunction with structural equation modeling (SEM) and artificial neural networks (ANN) further demonstrates the potential of the MRBQ to enhance predictive models for motorcycle crash risk. In Iranian studies, for example, integrating MRBQ with SEM-ANN frameworks yielded higher accuracy in predicting motorcyclist injuries (Hasanzadeh et al., 2020). By integrating the MRBQ with SEM, latent constructs influencing crash risk could be identified, while the use of ANN allowed for the detection of complex, non-linear interactions that traditional models may fail to capture, thereby enhancing predictive accuracy.

Based on the examined literature, riders' risky behavior was most often investigated through crash risk. Depending on the research, the crash risk was observed through active and passive crash involvement (Chakraborty & Maitra, 2024; Özkan et al., 2012) and self-reported crash, near-crash, and traffic offenses (Stephens et al., 2017; Vandael Schreurs et al., 2023).

The connection between the dependent variable (crash risk or risky behavior) was most commonly inspected using generalized linear modeling (Elliott et al., 2007), Poisson regression models (Chakraborty & Maitra, 2024), negative binomial regression (Trung Bui et al., 2020), and logistic regression models (Stephens et al., 2017; Vandael Schreurs et al., 2023).

6.1.2. Objectives and hypotheses

The primary objective of this study was to examine the behavioral factors associated with motorcycle crash risk in Croatia, a country where motorcyclist safety remains a significant concern. For that purpose, an existing questionnaire was employed, with the addition of new items designed to capture further nuances in rider behavior. This approach allowed for exploring the underlying structure of rider behavior specific to Croatian motorcyclists while also enabling comparisons with findings from other countries. Through this study, we aim to provide a comprehensive understanding of the factors influencing crash risk, which could inform future interventions to improve motorcyclist safety. Croatia’s road conditions, enforcement practices, and cultural attitudes toward motorcycling may reveal distinct behavioral trends. Aspects such as seasonal tourism and varying road quality could impact motorcyclist behavior uniquely compared to other countries. Therefore, adapting the MRBQ to account for these conditions and getting insight into their habits and crash involvement may yield valuable insights into crash risks.

It is hypothesized that specific behavioral factors representing risky behavior identified in the questionnaire will significantly correlate with increased crash risk. We expected that certain factors, similar to those observed in studies from other countries, would emerge as influential in the Croatian context, highlighting behaviors that contribute to higher crash risk among motorcyclists. Additionally, through factors regarding the perception of infrastructural elements and the safety of motorcyclists, the connection between crash involvement and the experience of infrastructure will be sought.

Based on the existing literature and the current state of motorcyclist safety in Croatia, several research questions were formulated to guide this study:

1. Can the MRBQ be an effective tool for predicting risky behaviors among Croatian motorcyclists, and will it include additional items to enhance its predictive capability?
2. How does the factor structure of the MRBQ derived from Croatian data compare to findings from previous studies in other contexts?
3. Can attitudes toward deficiencies in road infrastructure reveal additional behavioral characteristics among motorcyclists in Croatia?
4. Will some behavioral or demographic rider characteristics be significantly associated with risky outcomes?

In summary, this research enhances our understanding by providing additional insights compared to previous studies utilizing the MRBQ. The main contribution of our research is in an up-to-date perspective while respecting existing knowledge. More precisely, some new MRBQ items were added to update the survey and include the behaviors observed among motorcyclists recently. Additionally, a part of the survey investigating the perception of infrastructure flaws contributing to crashes was created. To our knowledge, there are only a limited number of studies in the EU dealing with the mentioned problem, meaning that this study contributes greatly to motorcyclist safety.

6.2. Methodology

The research methodology consists of several key stages: survey design, participant recruitment, and survey administration, as well as data processing and analysis. The research methodology is described in detail in the following subsections.

6.2.1. Survey design

The survey was designed to investigate factors influencing crashes, near-crashes, and traffic fines among motorcycle riders. It included questions on rider demographics, experience, and habits, gathering essential information such as age, gender, riding experience, average annual kilometers traveled, and general riding practices to provide context for behavioral patterns.

The Motorcycle Rider Behavior Questionnaire (MRBQ) was a central survey component. Initially developed in English, it was subsequently translated into Croatian to accommodate the study's participant base. From the original 43 MRBQ items, 40 were adopted either unchanged or slightly modified for contextual relevance. Three items were excluded, and 15 new items were introduced to address this research's pertinent attributes. Considering that more than 20 years have passed since the initial MRBQ, we added items to investigate the influence of additional specific actions during riding. Furthermore, additional questions were asked regarding the specificity of motorcycling in Croatia, where alcohol abuse, side collisions, speeding, and dangerous maneuvers on the roads are repeatedly reported by the police. This approach ensured the questionnaire was comprehensive and tailored to the study's objectives and aligned with other studies (Chakraborty & Maitra, 2024). The additional 15 questions were carefully reviewed by traffic psychology experts and experienced motorcycle riders to ensure their clarity, relevance, and alignment with current risky riding practices observed in Croatia.

All MRBQ items are displayed in Appendix 1, where all new items are marked with a star. Another section of the survey explored riders' perception of road infrastructure. Specifically, 11 items assessed the extent to which participants believed that certain road infrastructure elements contributed to motorcycle crashes. This provided insights into riders' subjective evaluations of external risk factors. The list of these items is shown in Appendix 2.

By introducing the additional MRBQ items and road infrastructure items, this study broadens up the previous literature findings and brings new knowledge to the field.

Behavioral assessments and opinions were measured using a 6-point Likert scale, where responses ranged from 1 (indicating disagreement or least frequent behavior) to 6 (indicating complete agreement or most frequent behavior). This scale allowed for a nuanced exploration of behaviors' frequency and the participants' beliefs' strengths and was commonly used in previous research (Elliott et al., 2007; Rowe et al., 2015; Sakashita et al., 2014; Uttra et al., 2020; Vandael Schreurs et al., 2023).

The final section of the survey focused on participants' involvement in crashes and near-crashes, as well as their history of receiving traffic fines issued by law enforcement. This section covered three years, offering a temporal perspective on risky behaviors and their consequences, and in line with earlier studies (Chakraborty & Maitra, 2024; Özkan et al., 2012).

6.2.2. Participants and data collection

Data for this study were collected in Croatia from 9th January to 31st May 2023 through the survey created in Qualtrics. The survey was open to participants between January and May, before the peak summer riding season started, when recreational motorcycling and traffic volumes were highest, to reduce potential seasonal bias and overrepresentation of atypical riding behavior. This approach also allowed us to capture the full last three years and allowed participants to reflect on their riding behavior from previous riding seasons, reducing potential recall bias. Surveying before the peak summer riding period ensured that responses were based on experiences from comparable and complete riding seasons rather than being influenced by current seasonal riding patterns.

To avoid seasonal bias and ensure a more representative assessment of rider behavior, the MRBQ survey was conducted during the mentioned period. In Croatia, motorcycle usage and crash involvement increase substantially during the summer months (June–August), driven by favorable weather, recreational riding, tourism, and motorcycle events. These seasonal factors can lead to atypical or riskier riding patterns that may not reflect riders' routine behavior. By collecting data prior to the peak season, we aimed to capture more stable, everyday riding habits and reduce the potential influence of recent crash experiences on self-reported responses. Additionally, national crash statistics and traffic monitoring data support this approach: motorcycle-involving crashes rise sharply after May, and the Average Summer Daily Traffic (ASDT) for motorcycles exceeds the Average Annual Daily Traffic (AADT), indicating increased exposure during summer. This timing also allows for early-season insights that can inform timely safety interventions.

Participants were recruited through various motorcycle clubs and online platforms, with unique links shared to facilitate participation. When distributing the survey link, careful consideration was given to the geographical diversity of Croatia. To ensure broad territorial representation, outreach efforts targeted motorcycle clubs and individual riders across all major regions of the country, including the northern and southern coastal areas, as well as the central and eastern regions. While a formal random sampling strategy was not employed, the survey was widely disseminated through multiple online platforms and established networks within the motorcycling community. This approach was intended to capture a diverse cross-section of riders and mitigate potential regional bias in the responses.

The inclusion criteria for participant selection required individuals of legal age and possessing a valid motorcycle driver's license. These criteria ensured that participants had the necessary legal qualifications and practical motorcycle riding experience, enabling them to provide valuable insights into rider behavior and perceptions. The correctness of these criteria was based on the respondents' honesty, and it was additionally verified through the difference in the respondents' age and the year of issuance of their license.

Upon initiating the survey, each respondent was automatically assigned a unique response ID, preventing duplicate entries and ensuring data integrity. Additional control mechanisms were implemented to enhance reliability further, including cross-checking demographic information and analyzing response patterns to identify inconsistencies or repeated submissions. To minimize the risk of repeated participation, we conducted multiple verification steps beyond the use of unique response IDs. In addition to filtering incomplete and inconsistent responses, we applied custom R scripts using various combinations of demographic and behavioral variables (e.g., year of birth, gender, engine capacity, riding frequency, and psychometric scores) to identify potentially duplicate cases. Suspected duplicates were further checked using the IP address. No confirmed duplications were found, enhancing our confidence in the uniqueness of the responses in the final sample (N = 842). The Ethics Committees of Hasselt University (SMEC) and the University of Zagreb – Ethical Committee of the Faculty of Transport and Traffic Sciences approved the study's conduct.

To ensure the relevance of the potential risky situations' predicting factors, participants who had not ridden a motorcycle in the past three years were excluded from the sample. A period of three years was taken as a reference, given that motorcycle riding is seasonal and that a shorter period might not provide sufficiently representative data.

However, not all variables contain the maximum number of responses for several reasons. Firstly, some participants did not fully complete the survey, resulting in missing data for certain variables. Secondly, errors in open-ended responses, such as unrealistic entries (e.g., “20001” instead of a valid year), contributed to the exclusion of specific data points. Finally, some responses were excluded due to inconsistencies; for example, a rider reported in one question that he had ridden a motorcycle in the last three years, but in another question, he stated the opposite, etc. These issues are typical in survey-based research and necessitate careful data cleaning to ensure the reliability of the analyses. After data cleaning and filtering from the initial 1380 records, the sample observed in this study consisted of 842 valid responses, as shown in Figure 6-1.

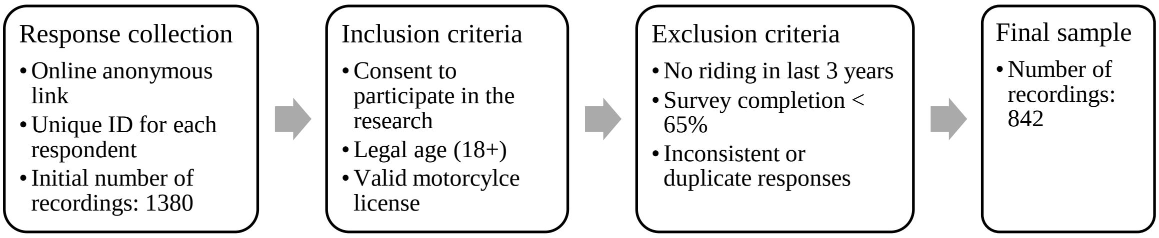

Figure 6-1. Workflow illustrating sampling procedure

6.2.3. Data analysis

Post-processing and statistical analysis were performed using MS Office Excel and SPSS, version 29.0. A principal component analysis (PCA) with varimax rotation and Kaiser normalization was conducted to examine the structure of various motorcycle rider behaviors. PCA is a widely used statistical method for exploring the underlying structure of a dataset by reducing its dimensionality while preserving as much information as possible (Hind et al., 2023; Pearson, 1901). This is achieved by transforming the original variables into a new set of uncorrelated variables, known as principal components (Campos et al., 2020; Watkins, 2018). Varimax rotation, applied to the principal components, helps create a simpler and more interpretable factor structure by maximizing the variance of squared loadings within each factor while minimizing correlations between factors. The eigenvalue criterion and a scree plot were utilized to determine the optimal number of factors for analysis. The eigenvalue represents the variance explained by each factor, with values greater than 1 often used as a threshold for retaining factors (Piedmont, 2014). The scree plot, a graphical representation of eigenvalues plotted against the number of factors, helps visualize the “elbow point,” where the curve begins to level off, indicating the most appropriate number of factors to retain (K. Lee & Ashton, 2007).

The final factor structure (i.e., belonging of individual items to a particular factor) was evaluated based on the loadings of each item (Hind et al., 2023). Items were assigned to factors by examining their loading values, representing the strength of the association between an item and a factor. A loading value of 0.30 was set as the cut-off point for item inclusion in each factor (Hind et al., 2023). Cronbach's alpha was calculated to assess the internal consistency of the scales, ensuring that the items reliably measured their respective constructs (Cronbach, 1951). The threshold of acceptance was set to 0.70, indicating adequate internal consistency (Hind et al., 2023). The composite scale score for each factor was calculated by averaging the responses to the items associated with specific factors (Chakraborty & Maitra, 2024). This arithmetic mean represents the overall score for the factor based on the participant's responses. The summary of a procedure applied to the MRBQ and road infrastructure items is shown in Figure 6-2.

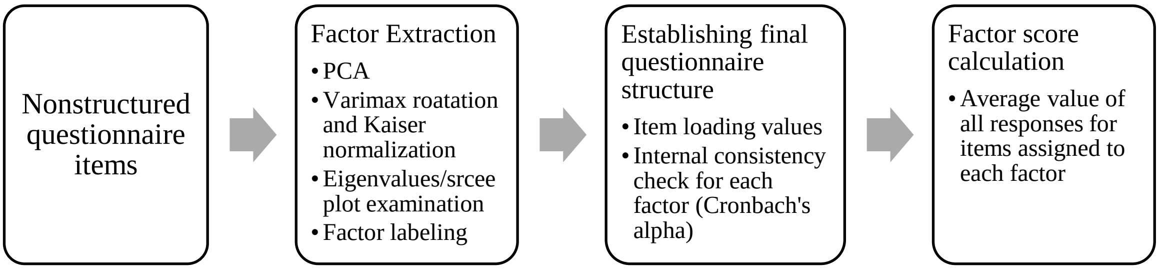

Figure 6-2. Workflow for factor structure development

Further, several correlation analyses were conducted to examine the relationships between the variables. Spearman's rank correlation was chosen due to the nature of the data (Zar, 2005). Specifically, many of the variables in the dataset, including those derived from the MRBQ, were ordinal or non-normally distributed. This method allowed for identifying both monotonic relationships and possible associations between riders' behaviors, demographic characteristics, and the frequency of crashes, near-crashes, and traffic fines. The number of responses (N) for each item may vary for several reasons. Not all participants responded to every question; in some cases, participants may have left certain items unanswered. Additionally, there could have been errors in data entry for items that allowed open-ended answers. If an open-ended response's meaning needed to be clarified, it was excluded from the analysis to maintain data quality and integrity. Missing responses were treated as missing values rather than being substituted with average values. The decision not to replace missing data with averages was made to avoid potential bias or misrepresentation of the underlying data distribution (Kalpourtzi et al., 2024). Imputing missing values with averages can lead to inflated correlations and artificial relationships between variables, especially in non-normally distributed data. Finally, logistic regression models were employed to assess the influence of behavioral and demographic factors on crash or near-crash risk and traffic offenses (Bangdiwala, 2018). This approach allowed for the evaluation of the relationship between predictor variables and the likelihood of involvement in risky driving outcomes, i.e., crashes or fine offenses (Vandael Schreurs et al., 2023). Before including variables in the model, multicollinearity was tested using variance inflation factors (VIFs), with a value of 5 set as a threshold for variable exclusion, as recommended in the literature (James et al., 2021).

6.3. Results

6.3.1. Sample description

The study sample comprised 842 respondents, but not all variables included responses from all participants. Missing data arose due to incomplete survey submissions, errors in open-ended responses, and inconsistencies in answers (e.g., conflicting statements about recent motorcycle use). This is why the response frequency does not always sum up to 842. The demographic characteristics of the respondents show that the majority were male (84.9%), while females constituted 14.4% of the sample (Table 6-1). Regarding employment, most participants reported working full-time (84.7%), with smaller proportions being students (5.2%), retired (3.2%), or unemployed (1.9%). Educational levels varied, with 61.5% having a high school education and 37.5% holding higher education degrees (Bachelor’s, Master’s, or Ph.D.). Regarding marital status, 47.9% were married, 24.5% were in relationships, and 20% were single. Lastly, 53.6% of participants reported having children.

Table 6-1. Socio-demographic characteristics of the sample

Variable description		Frequency	Percent
Gender	Female	121	14.4
	Male	715	84.9
	Not stated	6	0.7
Employment status	Full-time	713	84.7
	Half-time	17	2
	Unemployed	16	1.9
	Student	44	5.2
	Retired	27	3.2
	Other	25	3
Education level	Elementary school/primary education	6	0.7
	High school /secondary occupation	518	61.5
	Bachelor’s degree	152	18.1
	Master’s degree	138	16.4

	Variable description	Frequency	Percent
	Ph.D.	25	3
	Other	3	0.4
Marital status	Single	168	20
	Married	403	47.9
	In a relationship	206	24.5
	Divorced	52	6.2
	Widow/widower	3	0.4
	Other	10	1.2
Having children	Yes	451	53.6
	No	391	46.4

The average participant age is 38.12 years (S.D. = 10.65), indicating a relatively broad range of ages in the sample (Table 6-2). On average, participants have held their motorcycle license for 12.94 years (S.D. = 10.84), reflecting varying experience levels. Participants' mean annual distance ridden is 8805.23 km (S.D. = 9133.39), showcasing substantial variability in riding habits.

Table 6-2. Descriptive statistics for participant riding characteristics

	N		Mean	Min	Max	Std. Dev.
	Valid	Missing				
Participant age (yrs.)	839	3	38.12	18	69	10.65
Motorcycle license age (yrs.)	837	5	12.94	0	50	10.84
Average km/year	841	1	8805.23	100	150,000	9133.39

Among the surveyed participants, 98% owned a motorcycle (Table 6-3). Regarding motorcycle types, the most commonly used were Standard/Naked models (26.2%), followed by Touring/Sport-Touring (25%) and Enduro/Dual Sport/Adventure (17.5%). Sport motorcycles accounted for 17.4%, while Cruiser/Custom-Chopper models represented 9.8%. Smaller proportions owned Motocross/Off-road/Supermoto (1.4%) or scooters (1.1%). Motorcycle engine capacities varied, with the majority riding motorcycles in the 501–1000 cm^3 range (68.3%), followed by 1001–1500 cm^3 (20.2%) and 126–500 cm^3 (7.5%). Motorcycles with engines larger than 1500 cm^3 were the least common (2.6%).

Table 6-3. Motorcycle ownership and vehicle-related characteristics

	Variable description	Frequency	Percent
Own motorcycle	Yes	825	98.0
	No	17	2.0
Motorcycle type	Sport	146	17.4
	Standard/Naked	220	26.2
	Touring/Sport-Touring	210	25
	Enduro/Dual sport/Adventure	147	17.5
	Motocross/Off-road/Supermoto	12	1.4
	Cruiser/Custom-cruiser/Chopper	82	9.8

Variable description		Frequency	Percent
	Light motorcycle – Scooter (50-125 cm3)	9	1.1
	Other	15	1.8
Motorcycle engine capacity	50-125 cm^3	12	1.4
	126-500 cm^3	63	7.5
	501-1000 cm^3	572	68.3
	1001-1500 cm^3	169	20.2
	> 1500 cm^3	22	2.6

Most participants (75.9%) reported riding a moped before transitioning to motorcycles, while 70.7% rode a motorcycle before obtaining a license (Table 6-4). Regarding maintenance habits, 83% of participants agreed or strongly agreed with regularly checking the motorcycle's state before long rides, showing responsible behavior. However, 29% slightly agreed they were better than other riders, and 19.9% agreed or strongly agreed, indicating a mixed self-perception of skills among riders.

Table 6-4. Participants' riding habits

Variable description		Frequency	Percent
Rode moped before motorcycle	Yes	639	75.9
	No	201	23.9
	Can't recall	2	0.2
Rode motorcycle before license	Yes	595	70.7
	No	239	28.4
	Can't recall	8	1
Always checking state of motorcycle before long rides	Strongly disagree	12	1.4
	Disagree	14	1.7
	Slightly disagree	40	4.8
	Slightly agree	77	9.1
	Agree	298	35.4
	Strongly agree	401	47.6
Being better than other riders	Strongly disagree	34	4
	Disagree	204	24.2
	Slightly disagree	193	22.9
	Slightly agree	244	29
	Agree	126	15
	Strongly agree	41	4.9

6.3.2. Crash involvement and traffic fines

As a part of the survey, participants reported their involvement in crashes and near-crashes over the past three years, including single-vehicle and multi-vehicle incidents, depicted in Table 6-5. Due to the previously mentioned reasons (errors when filling out the survey), the sum of all responses is not always equal, i.e., it is not 842. Most had no single-vehicle (79.6%) or multi-vehicle (87.4%) crashes. However, 17.3% experienced one single-vehicle crash, and 11.1% reported one multi-vehicle crash. Near-crashes were more common, with 54.7% having no single-vehicle near crashes but 33.6% reporting three or more multi-vehicle near-crashes. A portion of participants (5.8%) reported leaving a crash site without noticing the relevant emergency services. The results indicate that while crashes are infrequent, near crashes are relatively common, particularly involving multiple vehicles.

Table 6-5. Participants self-reported involvement in crashes, near-crashes, and traffic violations over the past three years

Variable		Frequency	Percent
Single-vehicle crash	None	585	79.6
	One	127	17.3
	Two	17	2.3
	Three or more	6	0.8
Multi-vehicle crash	None	641	87.4
	One	81	11.1
	Two	10	1.4
	Three or more	1	0.1
Single-vehicle near crash	None	399	54.7
	One	148	20.3
	Two	65	8.9
	Three or more	118	16.2
Multi-vehicle near crash	None	213	29.2
	One	181	24.8
	Two	91	12.5
	Three or more	245	33.6
Ran of the crash site	None	688	94.2
	One	33	4.5
	Two	8	1.1
	Three or more	1	0.1
Fined as motorcycle rider	No	602	83.4
	Yes	120	16.6

6.3.3. MRBQ factor structure

An initial PCA on all 55 MRBQ items without a predefined number of factors suggested 14 components. However, this resulted in higher cross-loadings, factors with fewer items, and low loading of individual items. Furthermore, determining the number of factors according to eigenvalue > 1 suggested seven components, with more cross-loadings and unclear grouping of items. Then, the scree plot was analyzed (Figure 6-3), based on which the number of factors was finally defined (eigenvalues ∼ 2 and higher).

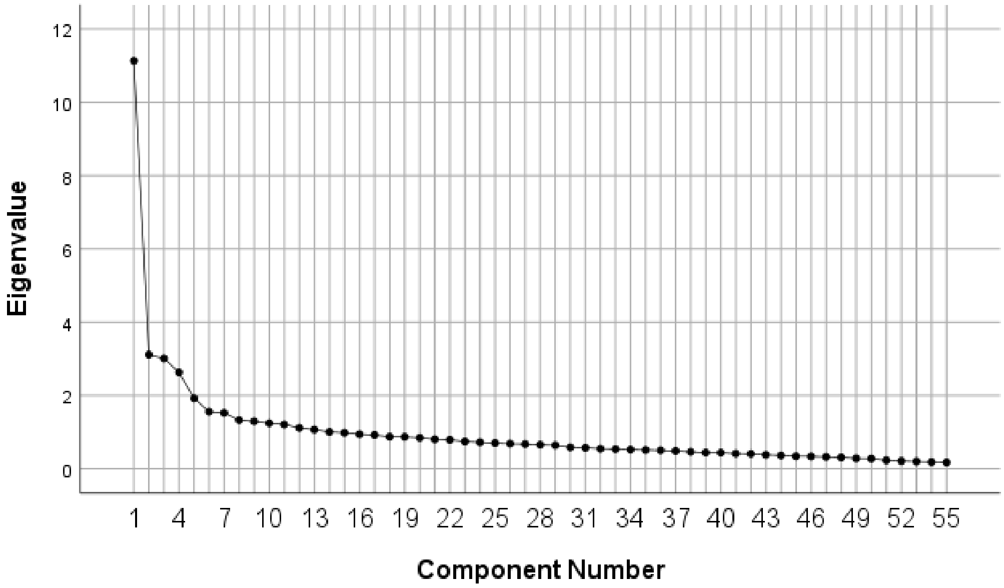

Figure 6-3. Scree plot on initial 55 MRBQ items

The solution with five components (factors) showed a clear and interpretable structure. Appendix 1 shows all the items before the omission of some components, which were later omitted for the sake of a clean structure and improved internal consistency. After excluding items with cross-loadings and loading values < 0.30 (Trung Bui et al., 2020), 43 items were included in further analysis. Then, one more item was omitted after the reliability analysis (Cronbach's Alpha < 0.7), making the final structure of 42 items. Table 6-6 shows the final 42-item structure, where values > 0.3 are bolded, depending on their assigned component (factor). The components are distinct, and the items show strong loadings, indicating better clarity in each factor's representation. The items load more clearly onto specific factors, creating clearer constructs. According to the type or topic of the items that were grouped into factors, the factors were named as follows: (1) Violations; 12 items – relate to intentional and conscious violations in traffic, for example, speeding; (2) Errors; 14 items – refer to errors during riding, e.g., control error or too late detection of danger; (3) Stunts; 5 items – performance of stunts (e.g., wheelie) while riding; (4) Personal protective equipment (PPE); 8 items – using protective clothing, footwear, and helmet; (5) Intoxication; 3 items – riding under the influence of substances such as alcohol. After rotation, these five factors cumulatively account for 43.37% of the total variance, with Factor 1 contributing 13.70%, Factor 2 contributing 10.29%, Factor 3 contributing 7.71%, Factor 4 contributing 7.61%, and Factor 5 contributing 5.06%. The rotation improved the interpretability of the factors by redistributing the explained variance more evenly across the components, highlighting their distinct contributions to the overall data structure.

Table 6-6. Five-factor structure with 42 questionnaire items from the extended MRBQ based on the rotated component matrix, with bolded significant loadings (> 0.30)

Code	Item	Violations 1	Errors 2	Stunts 3	PPE 4	Intoxication 5
Q22_1*	Not maintaining a sufficient safety distance between vehicles.	**0.37**	0.16	0.24	0.02	0.10
Q22_2	Fail to notice or anticipate that another vehicle might pull out in front of you and have difficulty stopping.	0.00	**0.39**	0.06	-0.09	0.14
Q22_5*	Not using mirrors to check the vehicles surrounding me while riding or turning.	0.04	**0.31**	0.20	-0.10	0.07
Q22_6*	Start overtaking a slower vehicle in front, even though this is prohibited.	**0.70**	0.14	0.20	-0.05	0.13
Q22_7*	Start overtaking a slower queue of three or more vehicles in front.	**0.66**	0.11	0.22	0.03	0.16
Q22_8	Attempt to overtake someone that you had not noticed to be signaling a right turn.	**0.43**	0.21	0.14	0.00	0.22
Q22_9*	Merging from a side road onto the main road while seeing vehicles approaching on the lane I am merging to.	**0.46**	0.19	0.04	-0.07	0.27
Q22_10*	Turning onto the main road from a side road without stopping at the „Stop“ sign.	**0.53**	0.22	0.10	-0.13	0.14
Q22_11	Pull out on to a main road in front of a vehicle that you had not noticed, or whose speed you have misjudged.	0.18	**0.56**	0.11	-0.05	0.18
Q22_12	Miss „Give Way“ signs and narrowly avoid colliding with traffic having the right of way.	0.12	**0.50**	0.07	-0.03	0.12
Q22_13	Queuing to turn left on a main road, you pay such close attention to the main traffic that you nearly hit the vehicle in front.	0.05	**0.48**	0.09	0.00	-0.01
Q22_14	Distracted or pre-occupied, you belatedly realize that the vehicle in front has slowed and you have to brake hard to avoid a collision.	0.18	**0.60**	0.09	-0.10	0.01
Q22_15	When riding at the same speed as other traffic, you find it difficult to stop in time when a traffic light has turned against you.	0.01	**0.62**	-0.05	-0.07	0.13
Q22_16*	Immediately before driving a motorcycle, I consumed alcohol. Hence, I drove under the influence of alcohol.	0.17	0.10	-0.04	-0.05	**0.83**
Q22_17*	Immediately before driving a motorcycle, I consumed light/heavy drugs, strong medicaments, or other intoxicants and drove under the influence of drugs and strong medicaments.	0.04	0.06	0.16	-0.17	**0.50**
Q22_18	Ride when you suspect you might be over the legal limit for alcohol.	0.19	0.12	-0.01	0.00	**0.83**
Q22_19	Fail to notice that pedestrians are crossing when turning into a side street from a main road.	0.10	**0.67**	-0.09	-0.01	-0.03
Q22_20	Not notice someone stepping out from behind a parked vehicle until it is nearly too late.	0.09	**0.69**	-0.07	0.02	-0.02
Q22_21	Not notice a pedestrian waiting to cross at a zebra crossing, or a pelican crossing that has just turned red.	0.21	**0.61**	0.02	-0.10	-0.13
Q23_2	Run wide when going around a corner.	0.14	**0.50**	0.09	0.02	0.05
Q23_3	Having difficulty controlling the motorcycle while riding at high speed (e.g., steering wobble).	0.03	**0.48**	0.21	-0.02	0.11
Q23_4	Riding so fast into a curve/corner that I have to brake or throttle-back round it.	0.28	**0.35**	0.22	-0.04	0.08
Q23_8*	Braking too quickly on a slippery road.	0.18	**0.44**	0.21	-0.05	0.01
Q23_9	Unintentionally doing a wheel spin.	0.14	0.28	**0.50**	-0.02	-0.08
Q24_1	Attempting to or actually doing a wheelie (a trick or maneuver whereby a bicycle or motorcycle is ridden for a short distance with the front wheel raised off the ground).	0.19	0.03	**0.82**	-0.08	0.02
Q24_2	Intentionally doing a wheel spin.	0.18	0.12	**0.72**	-0.14	0.13
Q24_3	Pulling away too quickly, and my front wheel coming off the road (lifts).	0.24	0.07	**0.84**	-0.07	0.10
Q24_4*	Braking too rapidly with the front brake, and my rear wheel going up in the air.	0.06	0.13	**0.72**	0.09	0.07

Code	Item	Violations 1	Errors 2	Stunts 3	PPE 4	Intoxication 5
Q25_1	Exceeding the speed limit on a motorway/highway.	**0.82**	0.07	0.07	0.01	-0.06
Q25_2	Exceeding the speed limit on a country/rural road/outside the urban area.	**0.84**	0.08	-0.01	-0.05	-0.12
Q25_3	Exceeding the speed limit on an urban/city road/residential area.	**0.77**	0.08	-0.05	-0.13	-0.02
Q25_4	Disregarding the speed limit late at night or in the early hours of the morning.	**0.74**	0.10	0.05	-0.13	0.03
Q25_5	Opening up the throttle and „going for it“ on rural/country roads.	**0.74**	0.12	0.20	-0.09	0.10
Q25_6*	Disregarding the speed limit during rainy conditions.	**0.51**	0.13	0.11	0.01	0.13
Q26_1*	Wear a protective helmet.	0.15	-0.03	-0.05	**0.37**	-0.10
Q26_2	Wear a protective jacket (leather or non-leather).	0.01	-0.08	-0.12	**0.69**	-0.01
Q26_3	Wear protective trousers (leather or non-leather).	-0.12	-0.03	-0.02	**0.80**	0.02
Q26_4	Wear riding shoes/boots.	-0.06	-0.08	-0.01	**0.76**	-0.01
Q26_5	Wear motorcyclist gloves.	0.00	-0.05	-0.14	**0.61**	0.01
Q26_6	Wear body armor to protect elbows, knees, shoulders, etc.	-0.09	-0.08	0.11	**0.59**	-0.01
Q26_7	Wear fluorescent clothing/helmet or reflective vest/clothing/helmet.	-0.25	0.00	0.01	**0.45**	-0.23
Q26_8	Wear bright/fluorescent or reflective markings /strips on your clothing or helmet.	-0.23	-0.04	0.03	**0.49**	-0.21

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.
Rotation converged in 5 iterations.
** - questionnaire items added to the original MRBQ (Elliott et al., 2007)*

Table 6-7 presents the reliability analysis of five components from the MRBQ. The reliability of each component is measured using Cronbach’s Alpha, which indicates the internal consistency or reliability of the items within each component. Overall, the components show good to excellent internal consistency, with Cronbach’s Alpha values ranging from 0.748 to 0.891, suggesting that the MRBQ is reliable for assessing various motorcycle rider behaviors.

After determining the factors and items loading to each factor, factor scores for each identified component were calculated as the average of the items with significant loadings on the respective factor. Further, the statistics of factor scores were established (Table 6-7). The factor scores provide insight into participants’ behaviors and perceptions. Violations had a mean of 2.891, indicating moderate engagement in intentional risk-taking like speeding. Errors, with a mean of 1.634, were less frequent, reflecting lower levels of unintentional mistakes. Stunts showed a mean of 1.610, suggesting that extremely risky behaviors are less common but vary among individuals. Conversely, PPE usage (mean = 4.393) reflected high adherence to safety gear usage. Lastly, intoxication (mean = 1.335) was infrequent but concerning for a subset of riders.

Table 6-7. Reliability analysis of MRBQ factors and MRBQ factor score descriptive statistics

Factor		Questionnaire		Factor scores					
		No. of items	Cronbach's Alpha	N	Min	Max	Mean	Std. Er.	Std. Dev.
1	Violations	12	0.891	842	1	5.67	2.891	0.03187	0.92468
2	Errors	14	0.787	842	1	3.64	1.634	0.01543	0.44763
3	Stunts	5	0.831	814	1	5.2	1.610	0.02862	0.81646
4	PPE	8	0.748	765	1	6	4.393	0.03225	0.89196
5	Intoxication	3	0.749	842	1	6	1.335	0.02207	0.64049

6.3.4. Road infrastructure items factor structure

This survey section aimed to understand motorcyclists' perceptions of how specific infrastructure shortcomings might contribute to the likelihood of a crash. The listed items focus on damaged or poorly maintained road surfaces, inadequate road markings, and challenging road alignments. By evaluating the riders' responses, the analysis seeks to identify perceived high-risk conditions in the infrastructure that could influence crash risks.

The number of factors was determined using the scree plot (Figure 6-4), which clearly shows that only three components have eigenvalues greater than 1, suggesting that these three factors explain the most variance and should be retained for further analysis.

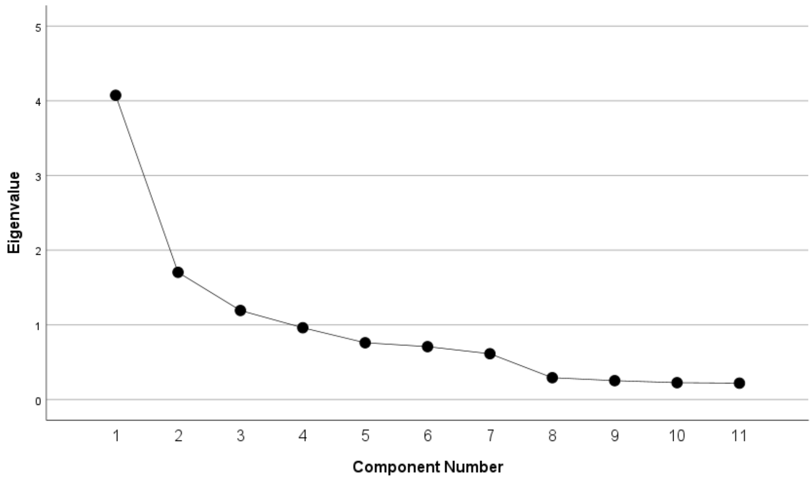

Figure 6-4. Scree plot on initial 11 infrastructure perception items

Out of the initial 11 questionnaire items (Appendix 2), nine were shown to contribute significantly to factors based on the loadings and reliability analysis. Table 6-8 presents the final nine-factor structure loadings from a PCA with Varimax rotation, examining how specific road-related items align with three identified factors: (1) Road markings, (2) Road alignments, and (3) Road surface. Factor 1 relates to road markings and includes items related to missing or poorly visible markings. Further, the second factor emphasizes crash risks related to the characteristics of curves and straight stretches. Finally, Factor 3 is related to the quality of the road surface and captures issues like pavement distress or slipperiness. The three components explain 73.09% of the total variance after rotation. Precisely, Factor 1 accounted for 27.68%, Factor 2 for 22.84%, and Factor 3 for 22.58% of the variance, respectively.

Table 6-8. Three-factor structure with nine questionnaire items related to the perception of infrastructure deficiencies (Rotated Component Matrix)

Code	Item	Road markings 1	Road alignment 2	Road surface 3
Q27_1	How likely do you think a motorcyclist will crash due to damaged pavement (ruts, holes, cracks, etc.).?	0.19	-0.04	**0.88**
Q27_2	How likely do you think a motorcyclist will crash due to poorly maintained pavement (numerous patches, bituminous fillings, smoothed surfaces, etc.)?	0.23	0.00	**0.88**
Q27_3	How likely do you think a motorcyclist will crash due to a roadway missing a centerline?	**0.86**	0.20	0.18
Q27_4	How likely do you think a motorcyclist will crash due to a road missing edge lines?	**0.89**	0.22	0.11
Q27_5	How likely do you think a motorcyclist will crash due to poorly visible road markings?	**0.86**	0.18	0.17
Q27_6	How likely do you think a motorcyclist will crash due to a slippery road surface (damp, wet, icy, etc.)?	0.01	0.30	**0.63**
Q27_7	How likely do you think a motorcyclist will crash due to consecutive curves in the opposite direction (e.g., left and right turns in a row)?	0.25	**0.83**	0.10
Q27_8	How likely do you think a motorcyclist will crash due to consecutive same-direction curves (e.g., two right turns in a row)?	0.26	**0.83**	-0.01
Q27_10	How likely do you think a motorcyclist will crash due to a long straight stretch of road where it is possible to reach high speeds?	0.08	**0.68**	0.10

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.
Rotation converged in 5 iterations.

The reliability analysis of the three factors demonstrates solid internal consistency (Cronbach’s Alpha > 0.70). Road markings, in particular, show excellent reliability with a high value, while road surface and road alignment exhibit acceptable reliabilities (Table 6-9). These results validate the structure of the survey, ensuring the items effectively capture riders’ perceptions of how infrastructure shortcomings influence crash likelihood.

The factor scores for the extracted components provide an overview of how participants perceived specific infrastructure issues. The mean score for the Road markings factor was 2.891, indicating moderate concern. The Road alignment factor had a lower mean of 1.634, reflecting less perceived risk. Lastly, Road surface showed a mean of 1.610, suggesting that participants rated this factor as less impactful than markings but with some variability.

Table 6-9. Reliability analysis of road infrastructure-related factors and descriptive statistics of factor scores

	Factor	Questionnaire: No. of items	Questionnaire: Cronbach's Alpha	Factor scores: N	Min	Max	Mean	Std. Er.	Std. Dev.
1	Road markings	3	0.894	736	1	5.67	2.891	0.03187	0.92468
2	Road alignment	3	0.737	736	1	3.64	1.634	0.01543	0.44763
3	Road surface	3	0.752	736	1	5.20	1.610	0.02862	0.81646

6.3.5. Correlation investigation

A correlation analysis was conducted to identify meaningful relationships among variables in this study. This approach was essential to explore the associations between behavioral, demographic, and exposure variables and key outcomes. The analysis serves multiple purposes: it aids in understanding underlying patterns in the data, investigates the relationship between individual variables, informs subsequent model-building by highlighting potential predictors, and evaluates potential issues of multicollinearity that could affect the robustness of regression models. Before testing the correlation, the nature of the data was investigated to determine the optimal correlation test. Both Kolmogorov-Smirnov and Shapiro-Wilk tests showed significant p-values for the selected variables ($p < 0.05$), indicating that the tested variables deviate from a normal distribution. Therefore, for correlation examination, Spearman 2-tailed tests were used. Several noteworthy patterns emerged, highlighting the interplay between risky behaviors, safety practices, and crash involvement (Table 6-10).

Risk-taking behaviors, including violations, errors, and stunts, were moderately and positively correlated. These behaviors are also significantly associated with adverse outcomes (crash and near-crash involvement). Among the three, stunts demonstrated the strongest association with both crash ($\rho = 0.160$, $p < 0.001$) and near-crash involvement ($\rho = 0.182$, $p < 0.001$), indicating its role as a particularly hazardous behavior. Being fined as a motorcycle rider was positively associated with risky behaviors, including violations and stunts, as well as near-crash involvement.

The use of PPE showed a negative correlation with violations, errors, and stunts. These findings suggest that riders engaging in safer behaviors are less likely to participate in risky activities. Also, PPE usage correlated positively with rider age and having children, but negatively with crash involvement.

Age was inversely related to violations, errors, and stunts, indicating that younger and less experienced riders are more likely to engage in risk-taking behaviors. However, age was positively associated with crash involvement. Average yearly mileage was correlated positively with crash situations and fines, confirming that greater exposure can lead to a greater chance of error or risky situations. Furthermore, having children was shown to be negatively related to risky behavior, as well as participation in crashes, which potentially confirms that riders who have children are more cautious than others.

When it comes to the factors that represent the extent to which infrastructural elements are the cause of motorcycle crashes, it can be noticed that riders with less experience tend to blame the infrastructure more (Table 6-11). Blaming road elements for crash occurrence also significantly correlates with errors. On the other hand, blaming road infrastructure for crashes did not correlate with crash or near-crash involvement. However, a slightly significant negative association was observed for traffic fines, meaning that more responsible riders potentially pay more attention to motorcycle steering, regardless of the condition of the infrastructure.

The correlation analysis revealed several significant associations between riders' self-assessment of their riding ability and various behaviors and outcomes (Table 6-12). Notably, a positive correlation was found between riders' assessment of their ability compared to other riders and their involvement in stunts ($r = 0.183$, $p < 0.01$) and violations ($r = 0.083$, $p < 0.05$), suggesting that riders who considered themselves better than others were more likely to engage in risky behaviors. Additionally, a significant, albeit weaker, correlation was observed with intoxication ($r = 0.070$, $p < 0.05$). However, no significant correlations were found between self-assessment and crash involvement, near-crash involvement, or fines.

Table 6-10. Correlation analysis between MRBQ factors and rider-, vehicle- and crash-related variables

	Errors	Stunts	PPE	Intoxication	Rider age	License age	Average km/year	Motorcycle engine capacity	Having children	Crash involvement	Near crash involvement	Fined as a motorcycle rider
Violations	**0.419****	**0.417****	**-0.261****	**0.282****	**-0.208****	-0.026	**0.193****	0.052	**-0.184****	**0.122****	**0.169****	**0.184****
Errors	1,000	**0.339****	**-0.201****	**0.187****	**-0.182****	**-0.095****	0.014	-0.041	**-0.104****	**0.156****	**0.190****	**0.118****
Stunts		1,000	**-0.144****	**0.188****	**-0.290****	-0.034	**0.159****	-0.009	**-0.192****	**0.160****	**0.182****	**0.172****
PPE			1,000	**-0.201****	**0.271****	**0.169****	**0.103****	**0.160****	**0.154****	-0.006	**-0.091***	-0.001
Intoxication				1,000	0.038	**0.107****	**0.101****	**0.098****	0.020	**0.093***	**0.090***	**0.104****
Rider age					1,000	0.668**	-0.062	**0.258****	**0.634****	**-0.171****	**-0.180****	-0.029
License age						1,000	-0.012	**0.282****	**0.451****	**-0.079***	-0.064	-0.014
Average km/year							1,000	**0.122****	**-0.095****	**0.159****	**0.132****	**0.175****
Motorcycle engine capacity								1,000	0.198**	**-0.125****	-0.028	0.070
Having children									1,000	**-0.092***	**-0.096****	-0.036
Crash involvement										1,000	**0.147****	**0.099****
Near crash involvement											1,000	**0.130****

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

Table 6-11. Correlation analysis between road infrastructure perception factors and rider-, vehicle- and crash-related variables

	Violations	Errors	Stunts	PPE	Intoxication	Age	License age	Average km/year	Having children	Motorcycle engine capacity	Crash involvement	Near crash involvement	Fined as a motorcycle rider
Road markings	-0.044	**0.137****	0.026	0.059	0.018	0.046	0.029	-0.053	0.042	0.036	-0.038	0.047	**-0.074***
Road alignment	-0.053	**0.144****	**-0.081***	-0.001	-0.027	-0.062	**-0.101****	**-0.126****	-0.056	-0.012	0.019	0.043	**-0.081***
Road surface	0.048	**0.111****	**0.110****	-0.045	-0.071	**-0.152****	**-0.114****	-0.040	**-0.095****	**-0.092***	0.037	0.060	-0.040

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

Table 6-12. Correlation analysis between self-assessed riding abilities and MRBQ factors and self-reported crash-related variables

	Violations	Errors	Stunts	PPE	Intoxication	Crash involvement	Near crash involvement	Fined as a motorcycle rider
Assessment of own riding ability compared to other riders	**0.083***	-0.024	**0.183****	-0.003	**0.070***	0.002	-0.003	0.011

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

6.3.6. Predicting risky behavior

Before proceeding with the analysis, collinearity diagnostics were conducted to ensure the absence of multicollinearity among the predictor variables. Variance Inflation Factor (VIF) values were calculated, with all values being less than 3, indicating no significant multicollinearity issues.

A binary logistic regression examined the relationship between MRBQ factors and some rider characteristics with crash involvement, near-crash involvement, and traffic fines. The final model included eight predictors: violations, errors, stunts, personal protective equipment usage (PPE), intoxication, average kilometers ridden per year, age, and license age. Table 6-13 presents the results of the analysis, further discussed in the subsections below.

Table 6-13. Binary logistic regression results for crash involvement, near-crash involvement, and traffic fines

	B	S.E.	Wald	Sig.	Exp(B)	95% C.I. for EXP(B)	
Crash involvement							
R^2 = 0.117; Hosmer and Lemeshow p = 0.553							
						Lower	Upper
Violations	0.006	0.112	0.003	0.954	1.006	0.808	1.253
Errors	0.620	0.215	8.346	0.004	1.859	1.221	2.831
Stunts	0.198	0.114	3.020	0.082	1.219	0.975	1.523
PPE	0.144	0.111	1.684	0.194	1.155	0.929	1.435
Intoxication	0.166	0.139	1.429	0.232	1.180	0.899	1.548
Average km/year	0.000	0.000	7.044	0.008	1.000	1.000	1.000
Rider age	-0.042	0.013	10.117	0.001	0.959	0.934	0.984
License age	0.015	0.012	1.497	0.221	1.015	0.991	1.040
Near-crash involvement							
R^2 = 0.133; Hosmer and Lemeshow p = 0.436							
	B	S.E.	Wald	Sig.	Exp(B)	95% C.I. for EXP(B)	
						Lower	Upper
Violations	0.101	0.123	0.664	0.415	1.106	0.868	1.409
Errors	0.846	0.269	9.913	0.002	2.331	1.376	3.947
Stunts	0.167	0.157	1.120	0.290	1.181	0.868	1.608
PPE	-0.155	0.116	1.793	0.181	0.857	0.683	1.074
Intoxication	0.101	0.189	0.286	0.593	1.106	0.764	1.603
Average km/year	0.000	0.000	7.058	0.008	1.000	1.000	1.000
Rider age	-0.036	0.012	8.589	0.003	0.965	0.942	0.988
License age	0.009	0.011	0.768	0.381	1.009	0.988	1.031
Traffic fines							
R^2 = 0.100; Hosmer and Lemeshow p = 0.236							
	B	S.E.	Wald	Sig.	Exp(B)	95% C.I. for EXP(B)	
						Lower	Upper
Violations	0.356	0.133	7.214	0.007	1.428	1.101	1.852
Errors	0.273	0.247	1.227	0.268	1.314	0.810	2.131
Stunts	0.290	0.131	4.859	0.028	1.336	1.033	1.729
PPE	0.120	0.134	0.799	0.371	1.127	0.867	1.466
Intoxication	0.002	0.162	0.000	0.992	1.002	0.729	1.376
Average km/year	0.000	0.000	10.123	0.001	1.000	1.000	1.000
Rider age	0.020	0.015	1.832	0.176	1.020	0.991	1.050
License age	-0.013	0.014	0.889	0.346	0.987	0.961	1.014

6.3.6.1. Crash involvement

A crash involvement was set as a dependable variable, as we wanted to examine whether there is a relationship between riding behaviors, demographic characteristics, and being involved in a crash. The model was statistically significant (χ^2 (8) = 61.286, p < 0.001), indicating that the predictors collectively distinguished between riders involved in crashes and those who were not. The Hosmer-Lemeshow test supported a good model fit (χ^2 (8) = 6.852, p = 0.553), and the Nagelkerke R^2 value of 0.117 suggested modest explanatory power. The model's classification accuracy was 75.1%, with solid sensitivity in predicting non-crash involvement (96.9%).

Among the predictors, errors (B = 0.620, S.E. = 0.215, p = 0.004) significantly increased the odds of crash involvement, with an odds ratio (OR) of 1.859, suggesting that for every unit increase in the error score, the odds of being involved in a crash nearly double. Similarly, average kilometers ridden per year (B = 0.000, S.E. < 0.001, p = 0.008, OR = 1.000) was positively associated with crash involvement. Age (B = -0.042, S.E. = 0.013, p = 0.001) was inversely related to crash involvement (OR = 0.959), indicating that older riders are less likely to be involved in crashes. Other predictors, including violations, stunts, PPE use, intoxication, and license age, were not significantly associated with crash involvement (p > 0.05).

6.3.6.2. Near-crash involvement

The logistic regression analysis assessed the relationship between riding behaviors, demographic characteristics, and near-crash involvement. The model was statistically significant (χ^2 (8) = 67.02, p < 0.001), indicating that the included predictors collectively contributed to explaining near-crash involvement. The Nagelkerke R^2 value of 0.133 suggests the model explained approximately 13.3% of the variance in near-crash involvement, reflecting a moderate effect size for the predictors. The Hosmer-Lemeshow goodness-of-fit test (χ^2 (8) = 7.98, p = 0.436) indicated that the model fit the data well, with no evidence of significant deviation between observed and predicted values. Classification accuracy for the model was 75.9%. The model performed exceptionally well in predicting near-crash involvement, correctly classifying 98.0% of cases.

Among the predictors, errors emerged as a significant factor (B = 0.846, p = 0.002, OR = 2.33). Age is also significantly associated with near-crash involvement (B = -0.036, p = 0.003, OR = 0.965). The negative coefficient suggests that older riders were less likely to be involved in near-crash incidents, with each additional year of age associated with a 3.5% reduction in the odds of involvement. This finding may reflect greater riding experience, improved judgment, or more cautious riding behavior among older motorcyclists. Other predictors were not statistically significant in this model. Although average yearly mileage approached significance, the effect size (OR = 1.000) was negligible, suggesting minimal practical impact despite statistical significance.

6.3.6.3. Traffic fines

The binary logistic regression model investigating the factors associated with being fined as a motorcycle rider was statistically significant ($\chi^2 = 43.821$, df = 8, $p < 0.001$). This suggests that the independent variables included in the model are collectively predictive of the likelihood of being fined. The model's fit was also confirmed by the Hosmer-Lemeshow Test ($\chi^2 = 10.433$, $p = 0.236$), indicating no significant deviations between observed and predicted values. The Nagelkerke R^2 value of 0.100 shows that the predictor variables in the model can explain approximately 10% of the variability in the likelihood of being fined. The classification indicates an overall accuracy of 83.8%, with a high rate of correct predictions for those not fined (99.5%).

The factors violations (B = 0.356, p = 0.007, Exp(B) = 1.428) and stunts (B = 0.290, p = 0.028, Exp(B) = 1.336) were statistically significant predictors, increasing the odds of being fined as a motorcycle rider by 42.8% and 33.6%, respectively. The variable average km/year (B = 0.000, p = 0.001, Exp(B) = 1.000) also showed significance, indicating a slight increase in the likelihood of being fined with higher annual mileage, although the effect was minimal. Other factors were not significant predictors of being fined.

6.4. Discussion

6.4.1. MRBQ findings

The five factors identified in this study explained 43.37% of the variance among the analyzed items, a percentage consistent with previous research (Elliott et al., 2007; Ospina-Mateus et al., 2021; Özkan et al., 2012; Trung Bui et al., 2020). The internal consistency among MRBQ factors in this study was from 0.748 to 0.891, which is consistent with previous research that showed 0.82-0.89 (Trung Bui et al., 2020) or 0.660-0.847 (Vandael Schreurs et al., 2023).

Regarding the number of revealed factors, a six-factor structure was identified using a Persian version of the MRBQ (Motevalian et al., 2011). A three-factor structure was found in a shortened version of the MRBQ with 23 items (Hosseinpourfeizi et al., 2018), while the full 43-item MRBQ conducted in Vietnam revealed a four-factor structure (Trung Bui et al., 2020), similar to what was earlier discovered among the Nigerian riders (Sunday & Akintola, 2010), Indian riders (Chouhan et al., 2021), and Australian novice riders (Sakashita et al., 2014). More recent studies that utilized the MRBQ discovered a five-factor structure (Stephens et al., 2017; Sumit et al., 2021; Vandael Schreurs et al., 2023), which is in line with our findings. Apart from the research being conducted in different parts of the world, the number of detected factors may vary because Likert scales of different ranges were used or because the items differ to a greater or lesser extent. Nevertheless, although the factor structure and items loaded according to a particular factor may differ, most research captured similar conclusions and similar behavior patterns.

In our case, „Violations" relate to deliberately undertaking risky actions (such as dangerous overtaking, merging, and riding above the speed limit in various conditions), similar to the fourth factor „Deliberate violations" in (Chakraborty & Maitra, 2024). Very similar in the context of items, the authors in some studies named the factor „Speed violations" (Elliott et al., 2007; Vandael Schreurs et al., 2023). Some research also reported „Speed violations", „Traffic violations," and „Safety violations" (Z. Yu et al., 2023).

Our second established factor was named „Errors," and it describes both traffic and control errors, i.e., actions that were a product of carelessness, distraction, inexperience, and the like. Most of the previous studies separated those factors into „Traffic errors" and „Control errors" (Elliott et al., 2007; Motevalian et al., 2011; Özkan et al., 2012; Stephens et al., 2017). On the other hand, there are some studies that recognized the factor „Traffic errors" (Sakashita et al., 2014; Topolšek & Dragan, 2016) or just „Errors" (Sunday, 2010).

The recognition of „Stunts" as one of the factors was constant throughout all of the literature (Elliott et al., 2007; Motevalian et al., 2011; Vandael Schreurs et al., 2023), which is in line with our findings. Then, a recent study did not establish either „Stunts" or „Safety equipment" (Chakraborty & Maitra, 2024). Some differences were noted in naming the latter, e.g., „Protective gear" (Stephens et al., 2017), while we named it „Personal protective equipment". In a study from Slovenia, besides „Safety equipment," two factors stood out regarding rider protection: „Helmet" and „Clothing" (Topolšek & Dragan, 2016).

What distinguishes our research from previous ones is the detection of the factor „Intoxication", i.e., items related to driving under the influence of alcohol or drugs. As pointed out in the introductory part, in Croatia, there are more reports of unlicensed riding as well as riding under the influence of alcohol, which was proven by capturing this factor.

The differentiation between deliberate and unintentional behaviors reflects Reason's (1990) Generic Error Modeling System, in which violations derive from motivational factors (e.g., thrill-seeking), while errors arise from perceptual or decision-making failures. This further emphasizes the need for multifaceted behavioral interventions targeting cognition and motivation.

One of the questions we wanted to answer was whether the items added to the original MRBQ would capture the characteristic behavior of motorcyclists. Out of a total of 55 MRBQ items that were initially set in the survey, the final structure contains 42 items. Moreover, according to the loading values, 12 out of 15 additional items belonged to one of the defined factors. This confirms that the assumptions about the specific actions of motorcyclists in Croatia were justified and opens up the potential for updating the original MRBQ items.

As discussed before, in an earlier study (Vandael Schreurs et al., 2023), grouping questionnaire items into factors varies slightly depending on the authors' choice, the number and variety of items, and the region where the research was conducted. The observation that similar studies conducted across diverse regions of the world have produced comparable, though not entirely congruent findings, underscores the nuanced interplay of regional, cultural, and contextual influences on motorcycle rider behavior. While the MRBQ serves as a robust tool for identifying universal dimensions of rider behavior, these differences highlight the importance of considering localized factors that can significantly modulate behavioral outcomes. For instance, regional variations in road infrastructure quality, enforcement of traffic laws, and access to safety education may contribute to divergent risk profiles. Cultural attitudes toward risk-taking, authority, and individual responsibility further shape how riders perceive and engage with their environments. Economic conditions, urban versus rural riding contexts, and the prevalence of motorcycles as primary transport modes also introduce variability in rider behaviors and crash risks.

6.4.2. Behavior characteristics' investigation based on descriptive statistics and correlations

In order to gain better insight into the motorcyclists as a specific road user group, we investigated some specific questions, like habits, experiences, attitudes, and self-perceptions of motorcyclists. The majority of participants (75.9%) reported having ridden a moped before transitioning to motorcycles. This prevalence suggests that mopeds often serve as a gateway vehicle, allowing riders to gain preliminary experience with motorized two-wheelers before advancing to motorcycles. Early exposure to riding a motorcycle, especially prior to obtaining a license (reported by 70.7% of participants), raises important considerations regarding the informal acquisition of riding skills. This is particularly worrying since motorcycles are much more prevalent in traffic in Croatia than mopeds. While this early experience may foster technical familiarity and confidence, it also introduces potential risks of developing unsafe habits without proper training or regulatory oversight. These findings align with research reporting unlicensed motorcycle riding among teenagers (Karimiankakolaki et al., 2024; Nguyen et al., 2023; Yeh et al., 2008; Yeh & Chang, 2009). Interestingly, prior riding experience can be linked to later risky driving behavior (Yousaf & Wu, 2023).

Motorcyclists' habits regarding pre-ride safety checks varied widely, with 82% of respondents agreeing or strongly agreeing that they consistently checked the state of their motorcycle before long rides. This strong commitment to vehicle maintenance is a positive behavioral indicator, demonstrating awareness of mechanical reliability as a critical factor in safety. However, 7.9% of riders who disagreed or strongly disagreed with this practice represent a subset of riders who may be at heightened risk due to neglect of this precautionary behavior.

Participants were asked to evaluate their riding ability compared to others, with responses showing a broad distribution. A significant proportion (29%) slightly agreed they were better than other riders, while 19.9% expressed stronger agreement. On the other hand, about half (51.1%) of respondents expressed disagreement or slight disagreement. Riders with overconfidence in their skills may engage in riskier behaviors, underestimating potential hazards or overestimating their skills. Conversely, those who rate their ability conservatively may adopt safer riding practices but could also experience reduced confidence in their decision-making during critical moments. Overconfidence has been linked to higher violations and stunt-related behavior rates, indicating a need for targeted messaging to recalibrate riders' perceptions of their capabilities. Previous studies have found that some novice riders tend to display overconfidence in their riding skills (Liu et al., 2009). Younger riders exhibited stronger positive correlations with violations, errors, and stunts, suggesting that age plays a significant role in riskier behaviors. This aligns with previous research indicating that younger drivers and riders often engage in more reckless driving due to inexperience, sensation-seeking tendencies, and lower perceived risks (Abdul Basit et al., 2022; Chang & Yeh, 2007). A significant negative correlation was revealed between age and crash and near-crash involvement, suggesting that younger riders are likelier to be involved in crashes. This is consistent with previous research, which has found that older riders crashed less often, received better performance evaluations, and approached hazards at more appropriate speeds (Liu et al., 2009). Additionally, stronger motorcycle engines correlated with lower crash involvement, possibly because older and more experienced riders usually prefer high-capacity engines. On the other hand, an important finding in the literature was the lack of correlation between both years of riding experience and self-assessed overall riding skill with braking performance, such as adequate deceleration (Huertas-Leyva et al., 2019). This suggests a need for further examination of riding skills to create advanced and needs-tailored training (Savolainen & Mannering, 2007a). From the results and literature examination, it can be concluded that riders' age is a more significant factor than the riding experience itself (Chouhan et al., 2023).

The correlations to having children revealed notable patterns in motorcyclists' behavior and safety outcomes. Riders with children are less likely to engage in violations, errors, and stunts. This suggests that parenthood may encourage safer riding habits, e.g., using PPE, possibly due to the increased sense of responsibility and risk aversion. Furthermore, having children shows a negative correlation with both crash and near-crash involvement, indicating a potential mitigating effect against high-risk behaviors that lead to crashes. The effects of parenthood on riding behavior have rarely been reported in previous studies, highlighting the novelty of these findings in the context of motorcycle safety research. Addressing this gap could provide valuable insights for targeted interventions and safety programs tailored to demographic characteristics.

With a mean of 2.891, violations represent a deliberate disregard for traffic laws. These behaviors, such as speeding or overtaking dangerously, are risk-oriented and closely linked to enforcement outcomes like fines. Errors, which refer to unintentional mistakes during riding, had the lowest mean score (1.634). These behaviors, such as failing to check blind spots or misjudging distances, are often tied to skill deficiencies or lapses in attention. Their strong connection to crashes and near-crashes reinforces the importance of improving riders' cognitive and perceptual skills through advanced training programs. The factor of stunts, with a moderate mean (1.610) and high reliability (0.831), captures high-risk thrill-seeking behaviors like wheelies or racing on public roads. While less frequent, their presence indicates a subset of riders prioritizing excitement over safety, necessitating targeted campaigns to discourage such behaviors. Earlier research points out that sensation-seeking and aggression were strongly linked to riding errors, excessive speeding, and, particularly, the performance of stunts (Antoniazzi & Klein, 2019). Furthermore, motorcyclists' unsafe behavior is not always due to a poor perception of the involved risks (Kiwango et al., 2020). Using personal protective equipment showed a higher mean (4.393), reflecting consistent use of protective gear. Higher scores suggest substantial compliance with safety norms among the surveyed riders, although room for improvement exists. With the lowest mean (1.335), intoxication indicates infrequent but high-risk behavior involving alcohol or drugs while riding. Alcohol and drug use, as well as non-use of PPE, were noted as influential factors on road crashes in another research (Konlan & Hayford, 2022; Liu et al., 2023).

6.4.3. Predicting risky outcomes

Overall, the findings from this study align with the assumptions and are generally in line with the previous research. In our study, involvement in risky outcomes, or risky behavior, is represented by involvement in crashes, near-crash situations, and getting fined by the police (self-reported by the survey participants). The results in this study align with theoretical frameworks that differentiate between deliberate (violations and stunts) and unintentional (errors) behaviors in influencing risky outcomes. Errors were more closely linked to crashes and near-crashes, while violations and stunts predominantly explained traffic fines. More detailed explanations and discussions are provided below.

Earlier research from Australia confirmed that human errors are a primary contributor to motorcyclist single- and multi-vehicle crashes (T. Allen et al., 2017). Most earlier studies confirmed error-related factors as predictors of crash involvement (Chouhan et al., 2021; Elliott et al., 2007; Sakashita et al., 2014; Trung Bui et al., 2020), which is in line with our results. On the contrary, a Flemish study did not show that relationship (Vandael Schreurs et al., 2023), indicating a more careful motorcyclist society. Contrary to previous research, in our study, violation-related factors were not a significant predictor of crash involvement (Chouhan et al., 2023; Elliott et al., 2007; Sakashita et al., 2014). As for near-crash involvement, our models showed a similar situation; that is, „Errors” are the only MRBQ factor predicting this outcome. The finding is in accordance with previous research, showing that error-related factors significantly predict near-crashes (Ospina-Mateus et al., 2021; Sakashita et al., 2014; Vandael Schreurs et al., 2023).

When it comes to predicting situations where a motorcyclist will be fined, „Violations” and „Stunts” arise as significant predictors. This result is somewhat expected, given that those factors represent deliberate rule violations or potentially dangerous actions. It is also in line with existing literature, where most commonly speeding violations were linked to traffic fines (Özkan et al., 2012; Stephens et al., 2017; Trung Bui et al., 2020; Vandael Schreurs et al., 2023), as well as stunts (Özkan et al., 2012; Sumit et al., 2021). Contrary to our result, several studies have linked error-related factors to traffic fine prediction (Ospina-Mateus et al., 2021; Trung Bui et al., 2020).

The use of personal protective equipment (PPE) did not emerge as a significant predictor in this analysis, possibly because PPE impacts crash outcome and injury severity rather than the likelihood of crash occurrence or fines (de Rome et al., 2011; Kim et al., 2015). On the other hand, safety equipment was a significant predictor of crashes in some studies (Sumit et al., 2021; Trung Bui et al., 2020). The protective role of age across crash and near-crash predicting models highlights the value of experience and maturity in mitigating risky outcomes. The latter is in line with previous research, stating that the riding style should align with the rider's skills and experience (Bartolozzi et al., 2023; Huth et al., 2014).

The finding that average yearly mileage significantly predicted crash involvement, near-crash involvement, and traffic fines across all models highlights the complex relationship between riding exposure and risk. Greater exposure through increased mileage inherently elevates the probability of encountering hazardous situations, not solely due to motorcyclists' traits or riding behaviors but also due to the dynamic and often unpredictable interactions with other road users. Motorcyclists who accumulate higher annual mileage are subjected to a greater number of variables, such as road conditions, traffic density, and the behaviors of other drivers (Romero et al., 2019). Additionally, frequent riders may exhibit behavioral adaptations, such as risk compensation, where increased riding familiarity results in reduced caution, offsetting experience benefits.

While the explained variance (R^2) for all models was modest, it is similar to previous literature (Vandael Schreurs et al., 2023). These findings still provide valuable and actionable insights for interventions. Addressing errors through rider education and advanced training could significantly reduce crash risk, while enforcement efforts should target violations and stunts to deter deliberate risk-taking.

The relationships between the behavioral factors and the observed outcomes reveal important patterns in how different types of risk interact. Our regression models and correlation analyses show that these factors do not operate in isolation but tend to co-occur in meaningful ways. For instance, Violations, Errors, and Stunts are moderately correlated, suggesting that riders who engage in one form of risky behavior are more likely to engage in others. These interconnected patterns underscore the cumulative risk posed by clusters of risky behaviors. Conversely, PPE usage showed a consistent negative correlation with all risk-prone behaviors, highlighting its role as a key protective factor and indicator of safety-conscious riding. While Intoxication was not a frequently reported behavior, it was still positively correlated with Errors and Stunts, suggesting that substance use may amplify already existing behavioral risks. These findings emphasize the importance of addressing multiple risky behaviors simultaneously in intervention strategies rather than tackling them in isolation. For example, motivating riders not to drink alcohol and ride afterward may also indirectly reduce the likelihood of engaging in other high-risk behaviors. This holistic understanding of rider behavior patterns provides a more comprehensive framework for improving motorcyclist safety.

6.4.4. Road infrastructure perception

Previous research shows that road type (Oltaye et al., 2021), road design (Le & Nurhidayati, 2016), or road surface (Tamakloe et al., 2022) can influence motorcycle crash occurrence or outcomes (Abdul Manan et al., 2018). Moreover, road design influences motorcyclists' behavior, such as speeding or helmet usage (Sukor et al., 2017). Since motorcyclists often state that the road infrastructure is the main culprit for crashes, part of the survey referred to individual infrastructure elements. More precisely, we asked them to what extent they think some defect, such as faulty signaling or road alignment, is to blame for the crash.

On average, irregularities in road markings were deemed the most problematic (mean = 2.891), followed by road alignment (mean = 1.634) and road surface (mean = 1.610). These differences suggest that motorcyclists prioritize certain aspects of road infrastructure over others when attributing crash responsibility. For instance, faded or unclear road markings may have a more immediate and visible impact on rider navigation than subtler alignment flaws or surface conditions. This is in line with expectations, considering that motorcyclists rely more on horizontal road marking, which at the same time announces the road alignment (Lobjois et al., 2016). Road markings dedicated exclusively to motorcyclists have also proven to be an effective means of increasing motorcyclist safety (Stedmon et al., 2021). On the other hand, studies report that the condition of the road surface, including poor maintenance, is a critical situation leading to safety risks (Huth et al., 2014).

Another novel contribution of our study is the integration of riders' perceptions of road infrastructure as possible external factors influencing motorcyclist behavior. This dimension has been underreported in prior research. Perceived problems with road markings were positively associated with rider errors and negatively associated with being fined as a motorcycle rider, suggesting that riders who notice or are affected by inadequate road markings may struggle with judgment during navigation, leading to more errors. However, they are less likely to receive fines. This could reflect compensatory cautious behavior in poorly marked areas or lower enforcement in such conditions. Perceptions of faulty road alignment were positively correlated with errors but negatively associated with stunts, license age, and average kilometers ridden per year. These findings indicate that riders who identify alignment issues are more error-prone but may be less experienced. Concerns about road surface conditions correlated significantly with errors and stunts while showing negative correlations with age, license age, and having children. These relationships suggest that younger and less experienced riders, or those without family responsibilities, are more likely to attribute crashes to surface conditions.

Given that no correlation was found between blaming road infrastructure and risky outcomes, it can be concluded that the state of infrastructure in Europe is not critical. On the other hand, riders are aware of infrastructure defects that can lead to crashes, and in the vast majority of cases, they adjust their riding to the road conditions. This emphasizes the need to investigate the riders' behavior and discover mechanisms to help motorcyclists ride more safely. Together with the MRBQ findings, these discoveries enhance the survey relevance and provide evidence-based directions for both behavioral interventions and road safety policy in under-studied regions like Croatia.

6.4.5. Research limitations and future perspective

While this study provides valuable insights into motorcycle rider behavior and associated crash risks, several limitations should be acknowledged. The survey was conducted prior to the identified high-risk season to optimize participant availability and maximize response rates, as peak periods often coincide with holidays that may reduce participation. Additionally, the survey questions were designed to capture rider behaviors and perceptions over extended periods, often spanning the past three years, rather than focusing solely on a specific seasonal window. Therefore, the results reflect general risk tendencies that are applicable throughout the year, not restricted to the pre-high-risk season. Although the survey was not conducted during the high-risk period, the timing was appropriate and still captures general rider behavior, including habitual risk attitudes that are relevant throughout the year. This provides a stable baseline for understanding rider behavior. Future research is planned to explore specific behavioral differences during high-risk periods to complement and extend these findings.

Further, the reliance on self-reported data through the MRBQ introduces potential biases, such as social desirability bias and recall errors. Participants may underreport risky behaviors or overestimate safety practices. Then, environmental and external variables, such as weather and enforcement intensity, were not fully explored, which could further influence motorcyclist behavior and crash involvement. Finally, although infrastructure perception was assessed, the objective condition of road infrastructure was not directly measured or correlated with crash rates.

Given the study's findings and limitations, future research directions are proposed. To better understand causality, longitudinal studies tracking riders over time are essential. Additionally, experimental studies using simulators or on-road observations could complement self-reported behaviors. Utilizing telematics, GPS data, and sensor-based tools could provide objective data on rider behaviors, speed, and braking patterns, enhancing the reliability of findings. Also, studies combining subjective infrastructure perceptions with objective road condition assessments can offer a comprehensive understanding of environmental risks influencing motorcycle crashes. Given variations in riding behaviors across regions, comparative studies with neighboring countries or within Europe could provide broader insights into cultural and regulatory impacts on motorcyclist safety. Furthermore, a comparative analysis between riders and drivers could provide valuable information, especially in determining the fault in multi-vehicle road crashes.

6.5. Conclusions and practical recommendations

This study was based on a motorcyclist-targeted survey consisting of four main parts. The main focus was on MRBQ results, alongside demographics, road infrastructure perception, and self-reported data on crashes, near-crashes, and police fines. The findings are broadly consistent with previous research, with some novelties such as introducing new MRBQ items and insight into road infrastructure perception. The most important predictors of crash and near-crash involvement were errors, average yearly mileage, and rider age. Regarding traffic fines, violations, and stunts stood out as significant predictors, as did average yearly mileage. When it comes to road infrastructure flaws, road markings were shown as the most important indicator of crash possibility, according to participants' responses. Some practical recommendations to improve motorcyclist safety were established based on the findings obtained, the discussion of the results, and a comparison with other relevant studies.

Motorcyclist training programs and behavioral interventions are critical in mitigating crash and near-crash involvement, as evidenced by the significant role of errors in these events. Emphasizing proper cornering techniques, effective braking, and hazard perception within advanced riding courses can enhance novice and experienced riders' skills. Younger riders, who are more prone to violations and stunt-related behaviors, would particularly benefit from educational campaigns focusing on the consequences of risky actions such as speeding and intoxication. Structured interventions, including behavioral feedback and mentorship initiatives through motorcycle clubs, can further address hazardous behaviors. Establishing more safe-riding courses and periodic skill assessments for motorcyclists would ensure ongoing improvement in riding abilities and promote safer riding practices.

Law enforcement campaigns are equally essential, particularly in targeting deliberate violations such as speeding, unsafe overtaking, and stunts, which have been associated with higher rates of fines and crashes. Increased enforcement in high-risk areas, such as rural and high-speed roads, through police presence and automated traffic monitoring systems can act as deterrents. Complementary media campaigns addressing violations and overconfidence, especially among young and high-risk groups, would reinforce the importance of compliance. Enhanced alcohol and drug testing at motorcycling events and popular routes and incentives for PPE use, such as tax benefits or subsidies for high-quality gear, would further strengthen safety measures.

Infrastructure improvements also play a pivotal role in reducing motorcycling risks. Maintenance of road surfaces, particularly in areas with reported deficiencies like damaged pavement or poor visibility of markings, should be prioritized. Enhancing road markings can improve rider visibility and predictability of road conditions. Addressing alignment issues on roads with high crash prevalence, especially in rural areas with consecutive curves, would further create a safer riding environment. These combined efforts across training, enforcement, and infrastructure provide a comprehensive strategy to improve motorcycling safety.

By addressing the limitations and adopting the proposed recommendations, researchers, policymakers, traffic safety agencies, and motorcyclist advocacy groups can collaborate to enhance road safety, reduce crashes, and ultimately protect one of the most vulnerable road users – motorcyclists. Policymakers and safety agencies can implement evidence-based interventions by focusing on error reduction, targeting deliberate risky behaviors, improving road conditions, and promoting protective behaviors. These strategies address both behavioral and environmental factors highlighted in this study, paving the way for enhanced motorcyclist safety.

Chapter 7.

Exploring motorcyclist speeding through naturalistic riding data

This chapter is based on the following journal article (accepted for publication):

Ferko, M., Babić, D., Brijs, T., & Pirdavani, A. Exploring motorcyclist speeding through naturalistic riding data. (2025). *Transportation Research Procedia*.

ABSTRACT

Motorcyclists represent a vulnerable group of road users, often exhibiting elevated crash severity risk due to speeding and limited physical protection. This study explores speeding behavior among motorcyclists using smartphone-based naturalistic data, a relatively novel approach in motorcycle safety research. The aim of the study was to examine which factors influence rider speeding behavior. A total of 1,853 trips (36,169.3 km) from 19 participants were recorded via a phone application capable of detecting speeding and other riding dynamics in real-world traffic conditions. Linear regression was applied to investigate the effect of several potential predictors, including road type, average speed, speed over the limit, indicators of aggressive maneuvers (acceleration, braking), and contextual variables (daytime, weekend). The model explained 72% of the variance in speeding behavior, with the percentage of trip duration spent speeding as a dependent variable. Key predictors included the average speed over the limit, which was strongly positively associated with the observed outcome, and the proportion of motorway driving, displaying a negative association. Harsh accelerations also had a significant positive effect, while factors such as daylight and weekends did not yield significant effects. Findings highlight the potential of smartphone-based data collection for monitoring speeding in naturalistic settings. While several limitations were acknowledged, this study offers a valuable starting point for broader applications of mobile sensing in road safety, with potential implications for tailored feedback, rider coaching, and intelligent transport systems.

KEYWORDS

Motorcyclists; speeding; naturalistic; smartphone; behavior; safety; regression.

7.1. Introduction

7.1.1. Context and motivation

WHO (2023a) reported that, globally, 30% of reported road deaths are related to powered two-wheeler (PTW) riders. According to a report by Slootmans et al. (2024), PTW fatalities accounted for 18.8% of all road deaths in the European Union (EU). While PTW fatalities in the EU declined by 16.5% between 2012 and 2022, all road fatalities dropped significantly (22%). Consequently, the relative share of PTW fatalities has slightly increased over the past decade. When looking at the type of fatal crashes, 37% of motorcyclist fatalities are the outcome of a single-vehicle crash. Additionally, according to Slootmans (2023), motorcyclists are estimated to be between 9 and 30 times more likely to die in traffic crashes compared to car drivers.

(Van den Berghe, 2021) stated that an estimated 10 to 15% of all road crashes and 30% of fatal injury crashes directly result from excessive or inappropriate speed. According to researchers Temmerman & Roynard (2016), excessive speed is a prevalent issue among motorcyclists, even more so than car drivers. On roads with speed limits ranging from 50 to 90 km/h, the average free-flow speed of motorcyclists was significantly higher than that of car drivers. Mannering & Grodsky (1995) found that 70% of motorcyclists tend to exceed the posted speed limits and intend to repeat such behavior in the future. According to Chorlton et al. (2012), motorcyclists' intention to engage in high-speed riding on rural roads can be explained by a combination of factors, including past behavior, attitudes, control beliefs, age, normative beliefs, anticipated regret, self-identity, behavioral beliefs, and training status.

7.1.2. Literature background on naturalistic data studies

Naturalistic data are collected in real traffic conditions without interfering with driver or rider behavior, as described by van Schagen and Sagberg (2012). These datasets are typically recorded using various tools, such as cameras (onboard, traffic, etc.) or sensors, according to Dingus et al. (2016) and Silva et al. (2022). Data collection can involve a single instrumented vehicle, as shown by Halim et al. (2025), or multiple vehicles equipped individually, as shown by Khairul Alhapiz Ibrahim et al. (2019). Outay et al. (2023) used a post-driving questionnaire filled out by the participants to deepen the observational data. A recent systematic review by Alam et al. (2023) found that naturalistic data are increasingly utilized for examining a wide range of driver behaviors, including distraction, fatigue, risk perception, and responses to safety-critical events. Further, naturalistic methods have become especially valuable for studying risk-related behaviors, such as speeding, distraction, and sudden maneuvers.

Prior studies by Tselentis et al. (2020) and Tselentis et al. (2021) have shown that smartphone-based platforms can effectively capture safety-related behaviors such as harsh braking, speeding, and phone use in naturalistic settings. Based on six linear regression models, Tselentis et al. (2020) concluded that the most influential factors in determining a driver's average speed are the total distance traveled, the frequency of harsh driving events, and the deceleration rate.

Winkelbauer et al. (2019) utilized naturalistic GPS and sensor data from the UDRIVE project to analyze time headway and following distances under real-world conditions. Their findings showed that motorcycles are typically followed more closely than other vehicles and that headway decreases as speed increases. Balsa-Barreiro et al. (2023) point out that applying GPS mapping is one of the advantages of conducting naturalistic studies.

Aupetit et al. (2015) conducted a naturalistic study of motorcyclists commuting in the Paris region. Using video-equipped motorcycles and follow-up self-confrontation interviews, the authors revealed that perceptual activities play a key role in rider behavior, particularly anticipating risk and efforts to enhance visual conspicuity in dense urban traffic. Naude et al. (2022) showed that motorcycles were more often exposed to medium and high positive acceleration and braking levels, though car drivers tended to brake more intensely overall. Furthermore, Halim, Sartika, et al. (2025) equipped an electric motorcycle with sensors and cameras to collect data about speed, throttle position, brake and horn activation, turn signal usage, and motorcycle tilt.

McCall et al. (2014) examined the influence of environmental conditions on motorcyclist behavior using data from a large-scale naturalistic riding study. Findings revealed that cold temperatures and precipitation significantly impacted rider behavior, notably reducing riding frequency and influencing speed profiles. Furthermore, naturalistic studies can support assessing driving ability affected by aging, according to Knoefel et al. (2018).

Based on the above, naturalistic studies offer valuable insights into real-world driving and riding. While commonly applied to car drivers, their use in motorcycle research remains limited, especially with smartphone-based data. Smartphones provide a low-cost, scalable, and unobtrusive way to record riding metrics such as speed, acceleration, and phone use.

7.1.3. Paper objectives and contribution

The main objective of this study is to explore how unobtrusively collected smartphone-based data can be used to quantify motorcyclist speeding behavior under real-world traffic conditions. Using continuous metrics (speed, speeding, harsh events, travel time, and distance) and other variables (road type, rider age, weekend/daylight ride) from naturally occurring motorcycle trips, this work provides a data-driven approach to analyzing speed-related riding patterns without experimental influence. The central aim of the study is to explore what influences rider speeding, observed through the percentage of travel time spent above the speed limit. Furthermore, the study relies on driving characteristics and environmental data in relation to speeding, without including personal traits or subjective opinion. The conceptual framework assumes that features such as road type, temporal context, and riding dynamics influence speeding behavior.

This paper makes several contributions to the literature. First, it demonstrates the value of using smartphone applications to gather large-scale behavioral data in a motorcycling context, a relatively underexplored area compared to car driving. Second, the analysis focuses on a log-transformed dependent variable representing the percentage of time spent speeding, allowing for more precise modeling of skewed data distribution. It sets the groundwork for future research incorporating broader contextual and behavioral variables. This research presents a scalable and cost-effective methodological foundation for understanding and eventually influencing risky motorcyclist behavior.

7.2. Methods

7.2.1. Participants and data collection

This study uses data from participants' motorcycle trips collected through a smartphone application, TOECAN, developed under the Horizon 2020 i-DREAMS project. Each recorded trip includes GPS traces, average and over speed, acceleration and deceleration events, time-stamped start and end points, and behavioral indicators such as time spent speeding. The data were collected passively, with no instructions or constraints imposed on the participants.

The Ethical Committee of the Faculty of Transport and Traffic Sciences, University of Zagreb, approved the data collection. The research was introduced through public presentations at relevant events and gatherings, as well as mutual invitations between motorcyclists. Participants joined voluntarily, and the inclusion criteria required participants to be of legal age, to hold a valid motorcycle driving license, and to own a mobile phone device compatible with the data collection app. In the *Participant Information Sheet and Consent to Participate in the Research*, participants were informed about the app used, the handling of their data, and data storage. After receiving detailed information about the study, all participants provided informed consent prior to participation. They were invited to install the monitoring application on their smartphones upon consent. The recruitment process did not target specific riding profiles, and participation was open to all eligible individuals, ensuring a degree of randomness and diversity in the sample.

A total of 19 motorcyclists (16 male, 3 female) participated in the data collection. Table 7-1 shows the basic demographic characteristics of the study participants. The average age of participants was 45.2 years (SD = 12.9), ranging from 18 to 64 years, indicating a fairly broad age distribution. The average number of years holding a motorcycle license was 16.7 years (SD = 13.7). However, at the same time, the wide variance (186.8) and range (1–43 years) indicate that the sample included both novice and highly experienced motorcyclists. These aspects suggest a heterogeneous group regarding riding experience, which supports the generalizability of the findings across different rider profiles. However, we aimed to achieve a distribution of participants that was as similar as possible to the actual population of motorcycle riders in Croatia.

The total amount of recorded rides was 1853 (36,169.3 km) in the 15th March-21st May 2025 period. Based on the proportion of distance traveled in different road contexts, trips were performed as follows: 0% ridden on motorway (n = 1468; 79.2%), 1–50% ridden on motorway (n = 224; 12.1%), and more than 50% of the trip ridden on motorway (n = 161; 8.7%).

Table 7-1. Participants' description

	N	Min.	Max.	Mean	Std. Dev.	Variance
Participant age	19	18	64	45.19	12.903	166.477
Driving license age (motorcycle)	19	1	43	16.72	13.667	186.785

7.2.2. Data analysis

The primary outcome variable analyzed in this study was the percentage of riding time spent speeding, computed for each trip as the share of time a rider exceeded the posted speed limit. This measure captures both the prevalence and duration of speeding behavior in a continuous, scalable way. However, the variable displayed a highly right-skewed distribution with a large proportion of zero values, indicating that many trips involved no speeding. A logarithmic transformation (base-10 logarithm) was applied to address this skewness and ensure the assumptions of linear regression were satisfied. This transformation compressed extreme values and normalized the residual distribution, making the outcome suitable for further parametric modeling.

A multiple linear regression model was applied using the log-transformed percentage of riding time spent speeding as the dependent variable (DV) to investigate the factors associated with motorcyclists' speeding behavior. The potential independent variables (IVs) included trip duration and distance, percentage of trip distance driven on motorways, average trip speed, average speed over the limit, number of harsh braking and acceleration events, daylight condition (day/night), and weekend indicator (weekend/no weekend). These variables describe riding characteristics, road context, and temporal perspective.

Before running the regression, multicollinearity was assessed using Variance Inflation Factors (VIF), with 5 as an acceptance threshold. All analyses were conducted in SPSS (version 29.0), using the enter method for regression.

7.3. Results

7.3.1. Descriptive statistics of trip characteristics

For this study, 1853 trips (36,169.3 km) were recorded. Table 7-2 presents cumulative descriptive statistics for continuous variables across all motorcycle trips included in the dataset. The average trip distance was 19.52 km (SD = 34.15), with a skewed distribution, indicated by the wide range (0.5–422.8 km) and a median of only 7.5 km. Trip durations were generally short, averaging 0.35 hours (approximately 21 minutes), with a maximum of 4.35 hours.

On average, 9.96% of trip distances were traveled on motorways, but the median value was 0%, reflecting that most trips did not include motorway segments. The average speed across all trips was 47.78 km/h, while the average speed exceeding the speed limit was 11.79 km/h. Riders spent on average 6.79% of their riding time speeding, with considerable variability (SD = 10.39) and a maximum of 79%, again pointing to a skewed distribution of speeding behavior.

Regarding maneuver intensity, the average number of harsh brakes per trip was 1.68, and harsh accelerations were 1.43. However, both variables exhibited large standard deviations and medians close to 0 or 1, suggesting that a small number of trips accounted for the most extreme behaviors.

Table 7-2. Cumulative statistics (continuous variables)

Variable	Min.	Max.	Mean	Median	Std. Dev.	Variance
Distance (km)	0.50	422.80	19.52	7.50	34.153	1166.394
Duration (h)	0.02	4.35	0.35	0.24	0.407	0.166
Percentage of trip driven on motorway (%)	0.00	100.00	9.96	0.00	23.165	536.596
Average. speed of the trip (km/h)	15.00	138.00	47.78	43.00	19.190	368.239
Speeding (% of riding time)*	0	79.00	6.79	3.00	10.387	107.896
Average. speed over speed limit (km/h)	0	51.00	11.79	14.00	9.768	95.421
No. of harsh brakes	0	27.00	1.68	1.00	2.552	6.513
No. of harsh accelerations	0	36.00	1.43	0.00	3.762	14.150

** Dependent variable.*

Table 7-3 presents the distribution of the categorical variables included in the analysis. Most trips (95%) were completed during daylight, indicating a strong daytime riding pattern among participants. Additionally, 37.7% of trips occurred during the weekend, suggesting that a considerable proportion of riding was leisure-related or outside weekday commuting hours. These distributions provide important context for understanding the temporal characteristics of the sample and may influence riding behavior.

Table 7-3. Cumulative statistics (categorical variables)

Variable		Frequency	Percent	Variable		Frequency	Percent
Daylight	No	92	5.0	Weekend	No	1154	62.3
	Yes	1761	95.0		Yes	699	37.7

7.3.2. Explaining speeding behavior using linear regression

In order to quantify the factors contributing to speeding behavior, a linear regression model was developed. All variables from Table 7-2 and Table 7-3 were considered potential predictors in observing speeding behavior. However, a high degree of multicollinearity was identified between distance and duration (Pearson's r = 0.940), and the VIF for distance exceeded 10 in preliminary models. To reduce redundancy and maintain model stability, trip distance was excluded, and duration was retained as an exposure variable. Furthermore, the VIF value for average speed (km/h) exceeded 5; therefore, it was excluded from further analysis.

The final model included trip duration (h), percentage of trip distance on motorways (%), average speed over the limit (km/h), number of harsh braking and acceleration events, daylight indicator, and weekend indicator. All VIFs were well below the conventional threshold of 5, indicating no multicollinearity concerns.

The multiple linear regression model aimed to explain the natural logarithm of the percentage of riding time spent speeding (DV) based on several trip-level independent variables. The model was statistically significant ($F(7, 1845) = 684.35$, $p < 0.001$), indicating that the included predictors collectively explained a substantial proportion of the variance in the dependent variable. The model yielded an R^2 of 0.722, with an adjusted R^2 of 0.721, suggesting that the included variables accounted for approximately 72.1% of the variance.

The standard error of the estimate was 0.281, indicating a relatively good model fit given the log-transformation of the dependent variable. These findings reflect a robust model and confirm that the selected variables are jointly informative for understanding variation in speeding behavior.

Table 7-4 presents the multiple linear regression model's independent variables' coefficients. To support the interpretation of the results, the unstandardized regression coefficients from the log-transformed model were converted into approximate percentage changes in the original dependent variable. Given that the dependent variable was transformed using a base-10 logarithm, the transformation *(10^B – 1) × 100* was applied. This estimates the relative change in the percentage of riding time spent speeding for a one-unit increase in each predictor, shown in the last column in Table 7-4.

The results show that the average speed over the speed limit had the most substantial effect. Each additional kilometer per hour over the limit was associated with a 10.9% increase in the percentage of riding time spent speeding.

Additionally, each harsh acceleration was associated with an estimated 2.3% increase in speeding time, indicating that aggressive throttle behavior is closely linked to prolonged speeding. The percentage of trip distance driven on motorways showed a small but significant negative effect, with every 1-percentage-point increase associated with a 0.2% decrease in speeding duration.

Table 7-4. Regression coefficients

Independent variable	B	Std. Error	Beta	Sig.	VIF	Approx. % change in DV (original scale)
(Constant)	0.027	0.031		0.382		
Duration (h)	-0.015	0.021	-0.011	0.478	1.712	-3.4
Percentage of trip driven on motorway (%)	-0.001	0	-0.047	0.003	1.627	-0.2
Average. speed over speed limit (km/h)	0.045	0.001	0.832	<0.001	1.454	10.9
No. of harsh brakes	0.001	0.004	0.003	0.869	2.143	0.2
No. of harsh accelerations	0.010	0.002	0.068	<0.001	2.034	2.3

Independent variable	B	Std. Error	Beta	Sig.	VIF	Approx. % change in DV (original scale)
Daylight	0.002	0.03	0.001	0.952	1.002	0.5
Weekend	0.020	0.014	0.018	0.140	1.022	4.7

7.4. Discussion

7.4.1. Interpretation of key findings

Among the predictors, average speed over the speed limit emerged as the most influential variable (B = 0.045, $p < 0.001$), with a standardized coefficient ($\beta = 0.832$), indicating that higher overspeeding levels are strongly associated with greater speeding duration. This is consistent with an earlier study by Ferko et al. (2024), stating that higher speed limits are associated with a reduced likelihood of speeding.

The percentage of trip distance traveled on motorways was negatively associated with speeding (B = -0.001, $p = 0.003$), suggesting that motorway riding tends to reduce the time spent speeding, potentially reflecting stricter enforcement, safer infrastructure, or more consistent traffic flow on motorways. This can further be related to the research by Abdul Manan et al. (2017), indicating that motorcyclists are significantly more likely to ride at excessive speeds on roads without shoulders than on those with shoulders. Additionally, primary roads had nearly five times greater odds of motorcyclists exceeding the 85th percentile speed than expressways. According to Seefong et al. (2024), when the road design appears safe, riders may become more confident in their ability to manage higher speeds, which can encourage risk-taking behaviors like excessive speeding.

The number of harsh acceleration events was a significant positive predictor (B = 0.010, $p < 0.001$), indicating that trips with more aggressive acceleration are also characterized by greater speeding. In a similar study conducted by Kontaxi et al. (2021), statistically significant variables on the percentage of time spent speeding were trip duration, distance driven during risky hours, morning peak hours, and the number of harsh accelerations.

From the above, it can be concluded that speed control and management are of greater importance on rural roads (outside urban areas) that provide opportunities for „go-for-it“ riding, with relatively low speed limits, but also with low traffic. Broughton et al. (2009) confirmed that motorcycle riders are more likely to speed on rural roads, and speeding is also more likely in the daytime. Other potential predictors in this study (trip duration, number of harsh brakes, daylight conditions, and weekend trips) did not significantly contribute to explaining the variance in speeding ($p > 0.05$).

These effects highlight that both the amount of overspeeding and aggressive acceleration patterns are key contributors to extended periods of speeding, while motorway riding (potentially due to more stable speed environments and stricter enforcement, as well as high effect of other traffic and higher speed limits) has a modest mitigating influence.

7.4.2. Study's limitations and future research implications

This study provides novel insights into motorcyclist safety research, but several limitations should be acknowledged. The sample comprised 19 riders, which limits generalizability and statistical power, particularly for subgroup analysis. Nevertheless, despite a relatively small sample of riders, the study includes over 1800 trips (36,169.3 km), offering robust insight into naturalistic motorcycle riding behavior. Moreover, as participation was voluntary, it is possible that the participants were generally more safety-conscious and aware of road safety, for themselves and other road users, which may have also motivated them to participate in the study. This self-selection bias could mean the findings underestimate riskier behaviors in the broader riding population.

Additionally, rides were analyzed collectively rather than stratified by individual or rider subgroups, which limits the ability to identify within-participant patterns or differences across distinct behavioral profiles. The assumption of potential differences between groups of motorcyclists is in line with the conclusions by Eyssartier et al. (2017). Vehicle characteristics were also not available in the dataset; including factors such as engine power, motorcycle type, or safety features could have yielded further behavioral insights. Furthermore, contextual variables such as weather, traffic density, road geometry, or enforcement presence were not captured, all of which may influence speeding behavior.

Despite these limitations, this study represents a promising starting point for this behavioral traffic safety research type. Future analyses will benefit from resolving these limitations and incorporating additional variables such as ride-scoring metrics, mobile phone use during riding, and geographic context. Broadening the research will allow a more nuanced and comprehensive understanding of motorcyclist behavior in real-world traffic environments.

7.4.3. Conclusions

This study explored speeding among motorcyclists using smartphone-based naturalistic data, offering an innovative, minimally intrusive approach to understanding real-world riding dynamics. Using log-transformed speeding duration as the dependent variable allowed for better modeling of right-skewed data distribution and yielded a robust linear regression model with high explanatory power (adjusted $R^2 = 0.721$).

The results confirmed that average speed over the posted limit is the most influential predictor of speeding duration, followed by acceleration intensity. Furthermore, riders who rode more of their trips on motorways tended to spend less time speeding, suggesting that infrastructure type and traffic flow speed may moderate speeding behavior. Other predictors, such as trip duration, daylight, and weekend travel, showed non-significant effects.

From a practical standpoint, these findings provide an empirical basis for developing targeted behavioral feedback in smartphone-based safety applications. For example, by monitoring acceleration and over-speed metrics in real time, digital tools could offer riders actionable feedback to reduce risky behaviors. Additionally, the study supports the potential of leveraging mobile technologies for large-scale, low-cost road safety monitoring.

Despite its limitations, this study marks an important step toward integrating digital behavioral data into road safety research. As smartphone technologies and data processing capabilities continue to advance, the approach used here could be scaled and refined to support evidence-based interventions to improve motorcyclist safety.

Chapter 8.
Discussion and conclusion

This chapter begins by outlining the overall research design and summarizing the key findings. It then provides an in-depth discussion of the results, considering their scientific relevance and practical implications. Subsequently, the study's limitations are examined, and recommendations for future research are proposed. The chapter concludes by highlighting the research project's main contributions and final reflections.

8.1. Research overview

This section provides an overview of the research conducted within this doctoral study, structured around the published papers that form the core chapters of the thesis. Each paper targets specific objectives and research questions, contributing to a broader understanding of motorcycle safety on rural roads. The studies draw upon multiple datasets, ranging from national crash databases and speed monitoring records to structured surveys and naturalistic riding data, to address the multifaceted nature of motorcyclist risk.

Figure 8-1 provides a structured summary of the research framework adopted in this doctoral study. It outlines the six overarching research objectives, five guiding research questions, three core hypotheses, and the methodological approach to address them. The objectives range from identifying crash risk factors and analyzing rider behavior to assessing the applicability of naturalistic data. Corresponding research questions investigate the influence of infrastructure and behavior on crash outcomes and explore measurable behavioral differences among riders. The hypotheses are grounded in empirical modeling, behavioral analysis, and data integration strategies. The figure also summarizes the methodological orientation, combining a multi-method quantitative approach with primary and secondary data sources. This visual representation provides a comprehensive overview of the most important research setup.

Objectives

O1. To identify key factors influencing the severity of motorcycle crashes on rural roads and to assess how specific infrastructure affects motorcycle crash outcomes.

O2. To assess how specific infrastructure characteristics influence motorcycle rider behavior.

O3. To investigate the relationship between self-reported rider behavior, road perception, and crash history.

O4. To explore rider behavior and risk perception differences across road types and conditions.

O5. To demonstrate the naturalistic riding data's applicability and added value in rural safety research.

O6. To derive scientific and practical recommendations for improving motorcycle safety on rural roads.

Research questions

RQ1. What are the key factors influencing the occurrence and severity of motorcycle crashes on rural roads?

RQ2. How do infrastructure conditions – such as road geometry, signage, equipment, and road surface – affect motorcycle crash outcome?

RQ3. How do infrastructure conditions – such as road geometry, signage, equipment, and road surface – affect motorcycle rider behavior, particularly speed selection and visual attention?

RQ4. To what extent does rider behavior – measured through self-reports and observed data – correlate with crash involvement and perceived road risks in rural areas?

RQ5. Are there measurable differences in the behavior and perception of motorcyclists when riding on different road types or infrastructure conditions?

Hypotheses

H1. By integrating data on crashes, infrastructure conditions, traffic signaling and road equipment, and crash participants, it is possible to develop a model that identifies factors influencing the frequency and consequences of motorcycle crashes on rural roads.

H2. The state of road infrastructure, traffic signaling, and road equipment on rural roads influence motorcycle rider behavior in terms of speed, visual scanning of the environment, and perception of road elements.

H3. Conducting an extended questionnaire on motorcycle rider behavior can help determine the relationship between behavior patterns, road infrastructure conditions, and the occurrence of crashes.

Methodological approach

- Multi-method quantitative approach
  - Descriptive and correlation analysis
  - Various statistical methods
- Primary data
  - Survey
- Secondary data
  - Crash data, speed data, naturalistic riding data

Figure 8-1. Overview of research key points

To provide a structured summary of the research contributions, Table 8-1 outlines the key findings from each empirical chapter and shows how they address the stated research objectives (O1–O5) and research questions (RQ1–RQ5). This consolidated view presents unique insights based on different datasets and methodological approaches, collectively contributing to a comprehensive understanding of motorcyclist safety on rural roads. The section below synthesizes the core findings of each paper.

Table 8-1. Overview of key findings from each empirical chapter, and their correspondence to the study's research objectives and questions

Ch.	Key findings	Addressed
2	• Older rider age, inappropriate speed, and alcohol consumption were significantly associated with an increased likelihood of severe or fatal injury outcomes. • Crashes on county and local roads, as well as those on curves, at intersections, or involving fixed roadside objects, were more likely to result in severe or fatal injuries. • Run-off-road crashes had a notably higher probability of resulting in death or serious injury. • Male riders and sober riders were more likely to experience less severe outcomes. • Inappropriate speed (as a crash factor) strongly predicted crash severity. • The RF model identified rider age, road type, and speed conditions as the most influential variables. • The MLR model confirmed significant effects of road type, rider age, alcohol, crash type, and surface conditions.	*O1; RQ1, RQ2*
3	• Analyzed motorcyclist injury severity in crashes on horizontal curves with and without roadside barriers. • No statistically significant reduction in severe or fatal injuries was found associated with the presence of roadside barriers. • Identified steel W-beam barriers as the most commonly used type, yet they offer limited safety benefits for motorcyclists in the event of a crash. • Results emphasize implementing motorcycle protection systems (MPS) on curved rural road segments to mitigate crash consequences.	*O1; RQ2*
4	• Motorcycles were significantly more likely to exceed the speed limit than other vehicle types, confirming their distinct speeding patterns on rural roads. • Speed limit was identified as the most influential factor in predicting speeding behavior; lower posted limits were associated with a higher probability of speeding. • Temporal variables, such as time of day and day of the week, revealed that speeding was more frequent at night and during weekends.	*O2; RQ3*
5	• PCA with varimax rotation revealed a five-factor structure explaining 40.44% of the total variance. • The five behavioral dimensions identified were: violations (e.g., speeding, reckless riding, illegal overtaking), errors (e.g., inattention, misjudgments, failure to observe hazards), stunts (e.g., wheelies, racing from stoplights), safety equipment use (e.g., helmet and protective gear), substance use (e.g., riding under the influence of alcohol or drugs). • These findings were a foundation for future analysis of the relationship between behavior and crash involvement.	*O3; RQ4*

Ch.	Key findings	Addressed
6	• Errors were the only behavioral factor that significantly predicted both crash and near-crash involvement, highlighting unintentional mistakes as a primary safety concern among motorcyclists. • Violations and stunts were significant predictors of receiving traffic fines, emphasizing the role of deliberate risky behavior in enforcement outcomes. • PPE use was negatively correlated with risky behaviors (errors, violations, and stunts) and crash involvement, suggesting a protective effect of safety gear. • Younger age and higher annual mileage were associated with more frequent engagement in risky behaviors and a higher likelihood of crashes, near-crashes, and fines. • Riders with children showed fewer risky behaviors and lower crash involvement, indicating a possible moderating effect of personal responsibility. • Riders with higher self-assessed skill levels were likelier to perform stunts and violations, indicating a potential overconfidence effect. • Riders with less experience were more likely to blame infrastructure for crash involvement, although infrastructure perception was not significantly associated with crash or near-crash occurrences.	*O2, O3, O4; RQ3, RQ4*
7	• A higher share of motorway riding was associated with reduced speeding duration. • Greater average overspeed and harsher acceleration events significantly predicted longer speeding time. • The linear regression model explained 72.1% of the variance in speeding behavior, demonstrating the strong predictive power of trip-level indicators.	*O4, O5; RQ5*

The studies' findings are discussed in more detail in the following Discussion subsections.

8.2. Joint discussion

This section presents a synthesis of findings from the six empirical studies in the thesis. It discusses and outlines how they collectively contribute to a deeper understanding of motorcycle safety on rural roads. While each study is grounded in a specific dataset and methodological approach, their findings are interlinked and address the overarching research objectives and questions.

Collectively, the studies provide an integrated understanding of the factors influencing crash severity, speeding behavior, rider psychology, and interactions with road infrastructure. The discussion highlights individual contributions and the interconnections between the studies, offering a holistic interpretation of results relevant to road safety research and practice.

8.2.1. Determinants of motorcycle crash severity

Studies presented in Chapters 2 and 3 primarily relied on historical crash data to identify key determinants of motorcycle crash severity.

The second chapter presented the results of investigating the factors contributing to a severe or fatal crash outcome. This chapter examined the factors influencing motorcycle crash severity using a multinomial logistic regression model and a random forest classifier. The dependent variable had three ordered categories*:* no injuries, mild injuries, and death or severe injuries.

The study revealed that several rider-related and environmental factors significantly influence injury outcomes. Older rider age, alcohol consumption, inappropriate speed, and run-off-road crash types were consistently associated with an increased risk of severe or fatal injury. Context variables such as curve presence, local or county road classification, and surface conditions emerged as important risk enhancers. The random forest analysis highlighted rider age, road type, and speed-related variables as the most influential predictors.

Rider age was a significant predictor in both injury categories. However, the negative coefficients indicate that with increasing age, riders were more likely to experience severe or fatal injuries compared to no or mild injuries. This finding contrasts with some previous literature suggesting that older riders may be more cautious; however, it may reflect age-related physical vulnerability or slower reaction times that worsen outcomes in the event of a crash.

Behavioral factors like inappropriate speed dramatically increased the likelihood of severe or fatal outcomes. This aligns with the random forest model results, identifying speed-related circumstances as among the most important predictors.

Alcohol presence showed mixed effects. In the regression model, riding without alcohol in the blood was associated with higher odds of sustaining lower-severity injuries. This likely reflects the known impairing effects of alcohol on risk perception and reaction time. However, in the RF model, alcohol in blood showed a low influence.

State, county, and especially local roads were associated with significantly lower odds of no-injury outcomes, suggesting these lower-class roads carry a higher risk of serious or fatal crashes. This aligns with expectations, as local roads often have poorer infrastructure, reduced visibility, more challenging road alignment, or higher exposure to roadside hazards. Besides that, the presence of motorcyclists is the highest on those roads (compared to motorways or urban streets), since they often provide a unique experience of riding through nature, interesting tourist attractions, and the like.

Within road characteristics, particularly noteworthy were road objects such as bridges, tunnels, and underpasses. These were associated with higher crash severity, which may be explained by constrained space, reduced visibility, or lack of escape paths in emergencies. Similarly, other intersections, which include complex or non-standard designs, posed elevated risks. Their association with lower odds of avoiding injury suggests a need for design standardization or improved signalization in such locations.

Curves and road stretches also showed significantly higher odds of severe injuries, confirming findings from prior studies that indicate curvature and speed misjudgment as critical crash contributors.

Chapter 3 specifically addressed crashes occurring on horizontal curves, examining the role of roadside barriers. Although barriers generally offer a degree of protection, the findings demonstrated that their presence was not significantly associated with reduced injury severity among motorcyclists. This calls into question the effectiveness of conventional barrier designs (e.g., steel W-beam) for two-wheeled vehicles and underscores the need for motorcycle-friendly protection systems (MPS). The analysis reaffirms that curve geometry and roadside design are critical to rural road safety planning.

Chapters 2 and 3 confirm that both behavioral and infrastructure factors substantially shape crash outcomes. The interaction between rider characteristics and the road environment suggests that improvements in infrastructure alone may be insufficient without behavioral adaptations.

8.2.2. Speeding behavior and road geometry

Chapter 4 analyzed speeding behavior using vehicle-based speed monitoring data. Multiple analytical techniques, including BLR, CHAID, and ML models, were employed to capture complex interactions. A key finding was that motorcycles were significantly more likely to exceed speed limits than other vehicle types, reaffirming the importance of targeted enforcement and educational campaigns for motorcyclists. The analysis revealed that the likelihood of speeding increased on segments with lower posted speed limits and during nighttime and weekend periods, indicating a temporal dimension to risky behavior.

Geometric and environmental features, e.g., overtaking permission and riding outside the settlement, were also associated with elevated speeding risk. Interestingly, roads without built shoulders (e.g., drainage gutters, curbs, safety barriers, or rightly filled sand) were less prone to speeding than roadsides without built shoulders (e.g., where there is grass, no road safety barriers, no curbs, etc.). This may reflect a psychological effect on riders, as they may be more cautious in the former case because there are objects along the road that they could hit. In addition, although such roads are usually wider, side objects such as curbs and barriers can create the visual impression that the road is narrower than it actually is.

The results from Chapter 7, based on naturalistic riding data, are consistent with this, particularly in that motorway are associated with less speeding. In other words, rural roads provide more opportunities for prolonged speeding and speeds not adjusted to the infrastructure, which ultimately contributes to the likelihood of severe or fatal outcomes.

The linkage between observed speeding patterns and infrastructure characteristics reinforces the critical role of contextual road design in influencing rider behavior. These insights suggest that infrastructure countermeasures such as speed calming and intelligent signage could be more proactive in mitigating motorcyclist speeding. Nevertheless, further continuous research related to infrastructure can show which measures are the most favorable and effective in reducing motorcyclists’ speed of movement.

8.2.3. Behavioral dimensions and crash risk

Chapters 5 and 6 introduced a behavioral perspective, focusing on self-reported data collected through structured surveys.

Chapter 5 conducted a psychometric evaluation of a modified version of the Motorcyclist Behavior Questionnaire (MRBQ), conducted on a Croatian sample. Factor analysis identified five distinct behavioral domains: violations, errors, stunts, substance use, and protective equipment use. This validated structure served as a foundation for exploring behavioral profiles and assessing their relationship with safety outcomes. Chapter 6 expanded on this foundation by empirically linking these behavioral factors to crash, near-crash, and fine involvement. In relation to Chapter 5, in the study in Chapter 6, stricter criteria for the final sample were applied (e.g., all subjects who had not driven a motorcycle in the last three years were excluded). However, the final factor structure of the MRBQ remained the same (5 factors of the behavior pattern), which confirms the sound structure of the questionnaire itself.

A unique component of Chapter 6 was the inclusion of perceived infrastructure flaws. In addition to the MRBQ items, the survey included a dedicated section addressing riders’ perceptions of infrastructure-related crash risks. The analysis of infrastructure-related items resulted in a three-factor solution, capturing key dimensions of perceived infrastructural shortcomings: road markings (e.g., missing or poorly visible lines), road alignment (e.g., consecutive curves, long straight segments), and road surface conditions (e.g., damaged or slippery pavement). Participants rated deficiencies in road markings as the most influential crash factor related to infrastructure.

Initially, correlation analyses offered insight into the relationships between behavioral components, rider characteristics, and safety outcomes. Positive correlations were observed between self-reported (near-)crashes, traffic fines, and factors: violations, errors, stunts, and intoxication. Protective gear use showed negative correlations with crash and near-crash involvement and getting fined, supporting the view that PPE use is a marker of cautious riding. Rider age and having children were negatively correlated with risky behaviors, while rider exposure, measured in average yearly mileage, was positively correlated.

The correlation analysis revealed several statistically significant relationships between riders' perceptions of infrastructure-related risks and their self-reported behaviors.

Notably, errors were positively correlated with all three infrastructure perception components (i.e., road markings, road alignment, and road surface), suggesting that riders who report more unintentional mistakes also tend to perceive infrastructural elements as contributing to crash risk. This may suggest that riders are either more sensitive to infrastructural issues or that poor road conditions increase the likelihood of committing errors. Interestingly, stunt-prone riders perceive fewer issues with road alignment but more issues with road surface, possibly reflecting higher expectations due to their aggressive riding style. Riders who were fined report fewer problems with road design elements (road markings and alignment), which may suggest a cognitive disconnect between enforcement encounters and perceived environmental risks. Moreover, older riders, those with more experience, and riders with children tend to report fewer infrastructure issues, indicating greater riding adaptability or differing risk perceptions.

The analysis reveals that self-assessed riding ability, i.e., how riders perceive their skills compared to others, is modestly but significantly correlated with several behavioral indicators.

Riders who rate themselves as more skilled are slightly more likely to report violations and ride under the influence, implying reduced perceived vulnerability. Self-assessed higher ability is strongest among riders who engage in stunt-related behaviors. This is expected and suggests that perceived skill may foster overconfidence, potentially reinforcing high-risk actions. According to the results, riders with higher self-perceived ability are more likely to engage in risky behaviors. However, this confidence is not reflected in a reduced likelihood of crashes or fines, indicating a potential overconfidence bias in safety self-assessments.

Chapter 6 examined predictive relationships using binary logistic regression models based on the correlation findings. These models assessed whether the identified behavioral factors (extracted through PCA) could significantly predict the likelihood of motorcyclists being involved in crashes, near-crashes, or receiving traffic fines. Although the correlation analyses revealed several significant associations between behavioral traits and crash history, these relationships were not always sustained in the context of multivariable prediction.

The most notable and consistent predictor across models was errors, which significantly predicted both crash and near-crash involvement. This reinforces the idea that unintentional risky behaviors, such as lapses in attention or misjudgments in traffic situations, are especially consequential for rider safety. It is particularly relevant when compared to deliberate behaviors like stunts or violations, which, while correlated with risky outcomes, were more predictive of traffic fines than crash involvement.

This distinction between intentional and unintentional behaviors is important when designing intervention strategies. While violations and stunts may be targeted through enforcement and education, error-related crashes may require enhanced rider training, attention management techniques, or the implementation of human-centered infrastructure design.

Furthermore, while stunts and violations were strongly associated with receiving traffic fines, they were not significant predictors of crash or near-crash involvement in the adjusted models. This highlights a discrepancy between enforcement patterns and actual crash risk, potentially indicating that some high-risk behaviors (e.g., inattention or misjudgment) may go undetected by traditional enforcement mechanisms.

Personal protective equipment (PPE) use did not significantly predict crash or near-crash occurrence, despite being negatively correlated with risky behaviors in the bivariate analysis. This might suggest that PPE use serves more as a proxy for safety orientation rather than a direct mitigating factor for crash involvement, but it also might point out that PPE usage is more useful when investigating crash outcomes, rather than crash occurrence.

The demographic predictors also provided insightful contrasts. Younger age and higher annual mileage were associated with increased crash likelihood in the correlation analysis, but predictive power was not retained in all models. Interestingly, having children, which was negatively correlated with risky behaviors, did not significantly reduce crash odds in the prediction models. However, it did contribute to a safer behavioral profile, suggesting an indirect protective effect.

Based on Chapter 2 and Chapter 6, it can be concluded that younger riders are more inclined to participate in risky situations (crashes, near crashes, and traffic fines), while older riders are more inclined to more severe consequences when a crash occurs. This further implies the need for an adjusted safety strategy through targeted campaigns and practices.

These findings highlight the complexity of modeling crash involvement and reinforce the idea that not all risky behaviors are equal in their impact on safety outcomes. While some traits (e.g., errors) are directly and significantly associated with crash risk, others may be more relevant for understanding enforcement outcomes or general risk exposure. Importantly, these insights complement findings from earlier chapters based on crash and speed data, where inappropriate speed and road characteristics played a dominant role. By integrating behavioral and environmental variables, the study provides a more nuanced picture of how crashes occur and which rider traits or choices are most critical to address.

8.2.4. Data-driven understanding of rider behavior through naturalistic observation

The empirical study conducted in a real-world environment obtained smartphone-based naturalistic riding data to examine motorcyclist behavior, focusing on speeding. The study provided high-resolution behavioral insights under authentic traffic conditions by analyzing data from over 1800 trips covering more than 36,000 kilometers. Continuous, unobtrusively collected variables, such as average speed over the limit, acceleration events, and road context, enabled a robust understanding of riding characteristics.

A key contribution is demonstrating the added value of naturalistic data in motorcycle safety research, particularly in rural and mixed road contexts. The multiple linear regression model explained over 72% of the variance in speeding behavior and confirmed that average speed over the speed limit was the strongest predictor of prolonged speeding time. Although at first it seems logical, it can be expected that longer rides at high speeds increase the burden on the riders (physically and mentally) and that they have to slow down to increase their concentration.

Furthermore, harsher accelerations were positively associated with speeding duration, while motorway riding proportion had a modest mitigating effect. These results align with prior findings in the thesis that linked aggressive behaviors and infrastructure context to elevated risk levels. In other words, rural roads represent a greater challenge for motorcyclists, since they provide more opportunities for speeding (less traffic, slower traffic, interesting road configuration, etc.), and the infrastructure is often not advanced enough to mitigate severe crash consequences.

This study supports the idea that certain riding behaviors, like acceleration/braking events and speeding, can be captured through mobile sensors and used to develop safety-improving interventions. Compared to earlier chapters, which focused on self-reported or crash-based data, this naturalistic approach enables real-time behavioral profiling. It supports future applications in rider feedback and behavioral nudging systems. Additionally, the findings contribute to Objective 4 by highlighting how behavior varies with infrastructure type and Objective 5 by showcasing the utility of smartphone-based data in rural safety analysis.

8.2.5. Confirming hypotheses

The hypotheses proposed in this thesis were supported by the findings from the studies described in earlier chapters. Each hypothesis was tested using complementary methodological approaches.

H1 assumed that integrating crash data with road infrastructure characteristics and participant-level information would allow for the development of models identifying the key factors influencing the frequency and consequences of motorcycle crashes on rural roads. This hypothesis was addressed primarily through the work in Chapter 2. The results confirmed that crashes on lower-level roads (local, county), certain road parts (curves, intersections), inappropriate speed, run-off-road crashes, older riders, male riders, and alcohol consumption were factors that increase the likelihood of fatal or severe injury crash outcomes. Moreover, Chapter 3 refined this analysis by isolating single-vehicle crashes and emphasizing the role of infrastructure design (safety road barriers) in crash severity. These findings collectively confirm the hypothesis and demonstrate that when appropriately combined with crash and contextual data, infrastructure-related variables yield reliable explanatory models of motorcyclist crash risk.

H2 focused on the influence of infrastructure characteristics on rider behavior, particularly speed and perception. The second hypothesis was supported by self-reported data (Chapter 6) and naturalistic data (Chapter 7). In Chapter 6, riders who perceived road markings and alignment as deficient showed higher self-reported errors and stunt behaviors. Additionally, road surface quality perceptions correlated with various factors, rider age and motorcycle engine size. In Chapter 7, speeding behavior captured through a smartphone application was shown to vary depending on infrastructure type, with motorways being associated with shorter speeding durations. These findings support H2 by showing that infrastructure quality and context influence rider behavior.

H3 proposed that extended rider behavior questionnaires can be used to identify associations between behavioral patterns, infrastructure perception, and crash outcomes. The results from the MRBQ-based survey presented in Chapter 6 support this hypothesis. The factor analysis revealed that rider risky behavior has multiple dimensions, including violations, stunt performing, and riding under the influence. Also, errors and the use of personal protective equipment (PPE) were established as behavioral factors. Errors were shown as a significant predictor of crash and near-crash involvement, while violations and stunts were predictors of getting traffic fines. Using PPE correlated positively with rider experience and having children, and negatively with intoxication, indicating riders' responsibility. In addition, when combined with riders' perceptions of infrastructure quality, the MRBQ scores offered insight into the interaction between individual behaviors and environmental conditions. All of this highlights the value of self-reported behavioral data in understanding the broader context of motorcycle safety.

In conclusion, the work presented in this thesis confirms earlier established hypotheses. Infrastructure characteristics predict crash severity (H1) and shape rider behavior and how they perceive some infrastructure features (H2). Furthermore, well-constructed rider behavior questionnaires can capture the behavioral features contributing to crash involvement and interact meaningfully with infrastructure-related perceptions (H3). Using mixed methods (statistical modeling, survey analysis, and naturalistic observation) strengthens the conclusions and demonstrates the value of triangulated approaches in road safety research.

8.2.6. Recap of findings

The studies in this thesis complement each other not only in content but also in methodological approach. Crash data offered statistical insight into associations between observable crashes, road attributes, and injury outcomes. Speed data capture on-road behavior in real time, bridging the gap between environmental exposure and behavioral outcome. Survey data provided psychological depth and subjective perspectives, while naturalistic riding data adds objective, continuous measurements of behavior under real-world conditions.

This triangulation enables the validation of findings across data types. For instance, crash data and survey results pointed to inappropriate speed as a central issue. Moreover, while crash reports indicated that errors and environmental factors matter, survey data helped clarify which types of behaviors (e.g., misjudgments or distractions) drive those outcomes. The inclusion of naturalistic data grounds these observations in actual behavior, offering an opportunity to cross-validate self-reports and statistical models with real-world.

The integration of findings points to several overarching conclusions.

- Infrastructure and behavior are not independent but interact to shape risk: motorcyclists adapt their behavior based on road features, but not always in safe ways.
- Demographic and psychological diversity among riders necessitates tailored, data-informed safety strategies.
- Behavioral and naturalistic data must complement traditional data sources like police records to capture the complete picture of crash causation and prevention.

Apart from general observations, these conclusions from the presented studies can be further specified as listed below.

- Speed remains a central risk factor in rural motorcycling, linked to both crash severity and observed behavior. Infrastructure-based interventions must consider behavioral tendencies.
- Errors and inattention, rather than just deliberate violations, are significant contributors to motorcycle crashes, especially among younger or less experienced riders.
- Protective behaviors like PPE use correlate with reduced risk, suggesting that behavioral interventions could have tangible safety benefits.
- Road design and contextual factors, such as curves, road type, and roadside features, play a major role in shaping behavior and crash outcomes. Motorcycle-friendly design should be prioritized.
- Demographic and psychosocial diversity among riders requires targeted, nuanced safety policies rather than one-size-fits-all interventions.

Taken together, the findings from the presented studies offer a comprehensive, multi-level understanding of the determinants of motorcyclist safety on rural roads. They provide a strong foundation for evidence-based policy, infrastructure design, and behavioral intervention strategies to reduce motorcycle crash frequency and severity.

8.3. Theoretical and scientific contributions

This doctoral research contributes to the broader field of transportation safety and road user behavior through theoretical, methodological, and empirical advancements. By focusing on motorcyclist safety in rural settings, an area often overlooked in mainstream traffic safety research, this work bridges critical knowledge gaps and offers new insights into rider behavior, crash determinants, and the role of infrastructure.

8.3.1. Contributions to transportation safety research

This dissertation advances the transportation safety field by addressing motorcyclists' vulnerability on rural roads, employing a multifaceted, data-driven approach. Combining police crash data, roadside infrastructure information, behavioral survey responses, and smartphone-based natural road behavior data, this research provides a rich empirical foundation for understanding the determinants of motorcycle crashes and risky behavior.

These findings contribute to identifying some of the infrastructure-related risk factors, particularly in single-vehicle crashes, and offer evidence-based insights into the interaction of motorcyclist behavior with road conditions. Furthermore, the dissertation emphasizes the importance of assessing safety in context. Patterns revealed across methodological approaches support the validity of integrated analyses in road safety research. Importantly, using naturalistic data provides new insights into real-world road behavior and a scalable method for future monitoring and intervention design. The methodological triangulation used in the thesis sets a precedent for future safety research involving vulnerable road users.

8.3.2. Theoretical advancements in motorcyclist behavior modeling

This thesis contributes to the theoretical understanding of motorcyclist behavior by demonstrating how personal, situational, and infrastructural factors influence behavioral patterns. Applying an extended and context-tailored version of the Motorcycle Rider Behavior Questionnaire (MRBQ) identified five distinct behavioral dimensions: violations, errors, stunts, protective behavior (PPE), and intoxicated riding. These components were shown to correlate differently with crash history, near-crash experiences, and fines, offering a nuanced understanding of risk-taking profiles among riders.

Integrating behavioral self-assessment with infrastructure perception metrics revealed how motorcyclists' judgments of road markings, alignment, and surface quality relate to risky behaviors and safety outcomes. The dissertation also demonstrates the added value of combining traditional statistical and machine learning techniques to explore nonlinear relationships. These findings highlight the interplay between rider cognition, behavior, and the environmental features. This also provides a foundation for further research and theoretical development related to motorcyclist safety based on additional data collection and conclusions from the presented chapters.

8.4. Practical implications

The findings of this dissertation provide several practical implications for road safety practice, motorcycle safety policy, and infrastructure planning on rural roads.

First, specific infrastructure-related factors, such as poor road alignment, inadequate surface quality, and missing or unclear road markings, highlights the need for rural road design and maintenance improvements. Therefore, infrastructure audit protocols and maintenance prioritization systems should more explicitly account for motorcycle-specific vulnerabilities. For example, implementing motorcyclist-friendly infrastructure, especially on roads with a high proportion of motorcyclists and on curves, is a proposal to mitigate the consequences of crashes. This especially applies to safety barriers that are often not placed in adequate places or not equipped with motorcyclist protective systems. Adopting various infrastructural measures to influence speed reduction is also a proposal to mitigate the consequences and avoid crashes. Maintaining quality road markings (well visible and non-slippery), maintaining the road surface, and timely marking of road alignment can help combat errors that occur when riding.

Second, the behavioral profiles derived from the extended MRBQ and their association with crash, near-crash, and fine history suggest that behavioral interventions should be tailored to different rider types. For example, interventions aimed at high-risk riders could emphasize awareness of their behavior patterns, particularly concerning stunts, violations, or intoxicated riding. Overall, the results indicate that younger riders are more likely to be involved in risky situations (crashes, near-crashes, and traffic fines) and older riders tend to experience more severe consequences when a crash occurs. These discoveries accentuate the need for directed safety strategies, including targeted campaigns and interventions adapted to different rider age groups. In other words, awareness campaigns, knowledge of regulations, and infrastructure assessment are more necessary for younger drivers (who are more thrill-seeking and inexperienced). On the other hand, among all age groups, it is important to promote driving without the consumption of alcohol or other intoxicants, the use of high-quality and certified complete protective equipment, and safe driving training and schools. One of the recommendations is reevaluating driving schools and improving the conditions for learning to ride, both theoretically and practically.

Third, the demonstrated applicability of naturalistic riding data collected via smartphones opens opportunities for scalable, low-cost behavioral monitoring. These data can be the ground for feedback systems or rider coaching applications that promote safer riding through real-time analytics and behavioral scoring. The approach also shows the potential to conduct large-scale behavioral studies without expensive instrumentation or experimental setups.

Fourth, the predictive models developed using crash and behavioral data may support evidence-based decision-making by road authorities. These models can be integrated into GIS-based risk mapping tools, along with the other information they have (e.g., AADT, weather forecast, live information, or similar), to identify critical hotspots for motorcyclists and propose countermeasures such as speed moderation, better signage, or the deployment of passive safety devices.

To sum up, from a practical standpoint, the findings underline the importance of prioritizing road safety improvements on rural roads (local and county roads), especially by enhancing safety features and visibility around bridges, tunnels, and atypical intersections. Speeding behavior should be addressed through enforcement measures, safety awareness campaigns, and infrastructure design interventions. Continued efforts to combat alcohol-impaired riding remain essential. Finally, road safety strategies should be created so they reflect rider demographics, particularly riders with higher risk profiles. It should also be noted that the problem of motorcyclist safety should be approached from several directions, namely road management (engineering, road maintenance), law enforcement, raising social awareness, and research (in the area of vehicle development, rider equipment, road infrastructure equipment, motorcyclist behavior, and so on.

8.5. Limitations and future research directions

While the thesis provides a comprehensive, multi-perspective examination of motorcyclist safety with particular focus on rural roads, several limitations should be acknowledged. Recognized limitations certainly open up space for future research and raise future research questions.

First, data source limitations could affect the depth and granularity of analysis. Police-reported crash data, while official and structured, often lack contextual detail regarding rider behavior, precise environmental conditions, and vehicle dynamics at the time of the crash. Some relevant variables (e.g., road surface condition at the exact location, signage visibility, or exact time of crash) may be imprecisely recorded or missing altogether.

Second, the survey-based analyses, although extensive, relied on self-reported data. As such, they are subject to recall bias and social desirability bias, particularly concerning sensitive topics such as alcohol use, speeding, and aggressive riding. Therefore, the possibility remains that participants underreported certain behaviors.

Third, although highly valuable for understanding real-world behavior, the naturalistic riding data were collected from a relatively small sample of riders. This limits generalizability, especially considering the relatively short data collection period and concentration within specific regions or riding styles. The diversity of the riding population, in terms of age, experience, motorcycle type, and exposure to various road types, may not be fully captured.

Fourth, despite integrating infrastructure-related data, certain road features (e.g., pavement quality, roadside hazards, enforcement presence, lighting conditions) were not consistently available or quantifiable across all datasets. This may limit the precision of road design and infrastructure quality conclusions.

Fifth, due to the structure and nature of the different datasets, it was not always possible to establish direct causal relationships. Most analyses are correlational or explanatory in nature, and while multiple models and cross-validation strategies were used, causal inferences must be made with caution.

Further, limitations related to visual perception investigation must be pointed out, since it was not objectively measured, but examined through questionnaire items. Future studies should include more objective ways of investigating visual perception and attention, such as eye tracking or similar non-invasive methods.

Lastly, while the thesis incorporates multiple methodological approaches (e.g., logistic regression, CHAID, ML models, descriptive analysis), some trade-offs between complexity and interpretability must be made. For instance, machine learning models offer predictive power but may be less transparent in explaining underlying behavioral mechanisms than traditional statistical approaches. However, future research could utilize bigger datasets and therefore enhance advanced modeling approach and results.

Future research should aim to extend the scope and depth of motorcycle safety studies by integrating broader data sources, advanced technologies, and comparative regional insights. Expanding the naturalistic riding dataset in terms of both the number of participants and data collection duration, and adding more variables would enhance statistical power and allow for analysis across varying riding conditions, seasons, and rider profiles. Including a wider demographic and geographic range of riders would improve generalizability and support the development of efficient safety interventions. No less important, further research into riders' behavior and their motivations, as well as personality traits, can significantly contribute to a better understanding of the presented issues and to improving the state of motorcyclist safety.

Another opportunity lies in incorporating a geospatial dimension into crash severity and frequency analysis and behavioral analyses. Researchers can better understand location-specific risks by linking behavioral patterns with spatial features such as crash hotspots, elevation, and enforcement zones. This also opens the possibility of developing predictive geospatial models of risk and informing infrastructure planning and enforcement strategies.

Since the current research focuses primarily on single-vehicle motorcycle crashes, future studies should include multi-vehicle collisions involving motorcyclists. It can be assumed that these crashes involve another level of interactions between road users and may reveal additional risk factors related to visibility, communication, and vehicle dynamics that are not captured in single-vehicle events. Moreover, examining crash outcomes and specific injury types in detail would be noteworthy.

Further opportunities are related to comparing findings with those from neighboring or demographically similar countries. Cross-country or cross-regional comparative studies could help identify universal versus context-specific risk factors and assess the transferability of policy measures and infrastructure solutions. Such comparisons would also support alignment with broader EU road safety objectives.

There is substantial room for exploring the role of active and passive safety systems specifically designed for motorcyclists. Advanced rider assistance systems (ARAS), advanced warning technologies, smart helmets, and concepts such as motorcycle airbags and wearable protective equipment should be evaluated in real-world contexts. Although the development of these technologies has only gained momentum in recent years, they hold the potential to mitigate the consequences of crashes and support more responsive riding behavior.

Developing and testing new infrastructure solutions designed according to motorcyclists' needs is another promising direction. These may include motorcycle-specific lane treatments, improved road surface materials, and redesigned road furniture that minimizes injury risk.

From a methodological perspective, integrating machine learning and intelligent systems in predictive modeling can enhance the detection of high-risk practices and produce dynamic safety assessments. Real-time data processing and feedback systems, embedded in mobile applications or rider equipment, could be directed to assess their impact on behavior change and risk reduction.

Finally, aligning future research with evolving vehicle technology, such as electric motorcycles, shared mobility platforms, and connected vehicle environments, will be essential. These trends may influence exposure, risk perception, and behavior in ways not fully captured by current models and should be addressed in forthcoming research initiatives.

8.6. Conclusion

This doctoral thesis seeks to provide an in-depth, evidence-based understanding of motorcycle safety on rural roads by combining multiple methodological approaches and data sources. The thesis is structured around empirical studies, each contributing to a broader view of the risk factors associated with motorcycle crashes, rider behavior, and infrastructure conditions.

The first part of the thesis used official crash data to explore how road characteristics influence crash frequency and severity. These analyses highlighted the crucial role of road alignment, road edge characteristics, and visibility conditions. Using survey data, the second part examined rider behavior using validated instruments and comprehensive questionnaires. Links were revealed between risky driving behaviors and the likelihood of crashes, near-crashes, and traffic fines. Younger drivers were more frequently involved in these incidents, while older drivers suffered more serious consequences.

Finally, naturalistic riding data provided insight into behavior in real-life situations, confirming the importance of variables such as excessive speed, sudden acceleration, and road context. These results further supported the conclusions of the survey-based analyses, highlighting the added value of unobtrusive monitoring in road safety research.

Throughout the thesis, findings demonstrate that a combination of infrastructure deficiencies, behavioral patterns, and contextual factors influences motorcycle road safety on rural roads. The thesis highlights the need for developing and testing specified interventions, including infrastructure improvements, behavior-based campaigns, and the development of real-time feedback tools.

In conclusion, the thesis offers theoretical and practical contributions to road safety, especially for vulnerable road users. The multi-method structure of the thesis allowed for triangulation of results, strengthening the findings and providing a solid foundation for future research and policy development.

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Appendices

Appendix 1. Complete MRBQ with initial component loadings in a 5-factor structure

Rotated Component Matrix[a]

Item Code	Item	Component 1	2	3	4	5
Q22_1*	Not maintaining a sufficient safety distance between vehicles.	0.37	0.16	0.25	0.02	0.09
Q22_2	Fail to notice or anticipate that another vehicle might pull out in front of you and have difficulty stopping.	0.01	0.40	0.08	-0.08	0.13
Q22_3*	Not using direction indicators (so-called blinkers) when turning or changing lanes.	0.24	0.24	0.20	-0.13	0.09
Q22_4*	Going through a red light.	0.10	0.16	0.16	-0.18	0.34
Q22_5*	Not using mirrors to check the vehicles surrounding me while riding or turning.	0.03	0.31	0.18	-0.12	0.06
Q22_6*	Start overtaking a slower vehicle in front, even though this is prohibited.	0.70	0.13	0.22	-0.04	0.11
Q22_7*	Start overtaking a slower queue of three or more vehicles in front.	0.66	0.09	0.24	0.03	0.15
Q22_8	Attempt to overtake someone that you had not noticed to be signaling a right turn.	0.43	0.19	0.14	0.00	0.21
Q22_9*	Merging from a side road onto the main road while seeing vehicles approaching on the lane I am merging to.	0.46	0.18	0.05	-0.08	0.27
Q22_10*	Turning onto the main road from a side road without stopping at the “Stop” sign.	0.52	0.21	0.07	-0.14	0.11
Q22_11	Pull out on to a main road in front of a vehicle that you had not noticed, or whose speed you have misjudged.	0.18	0.55	0.10	-0.06	0.18
Q22_12	Miss “Give Way” signs and narrowly avoid colliding with traffic having the right of way.	0.12	0.48	0.04	-0.04	0.15
Q22_13	Queuing to turn left on a main road, you pay such close attention to the main traffic that you nearly hit the vehicle in front.	0.05	0.47	0.10	0.00	-0.01
Q22_14	Distracted or pre-occupied, you belatedly realize that the vehicle in front has slowed and you have to brake hard to avoid a collision.	0.18	0.60	0.11	-0.10	0.00
Q22_15	When riding at the same speed as other traffic, you find it difficult to stop in time when a traffic light has turned against you.	0.02	0.62	-0.03	-0.05	0.15
Q22_16*	Immediately before driving a motorcycle, I consumed alcohol. Hence, I drove under the influence of alcohol.	0.17	0.08	-0.04	-0.07	0.82
Q22_17*	Immediately before driving a motorcycle, I consumed light/heavy drugs, strong medicaments, or other intoxicants and drove under the influence of drugs and strong medicaments.	0.04	0.05	0.15	-0.19	0.49
Q22_18	Ride when you suspect you might be over the legal limit for alcohol.	0.19	0.10	0.00	-0.01	0.83
Q22_19	Fail to notice that pedestrians are crossing when turning into a side street from a main road.	0.11	0.65	-0.07	-0.01	-0.01

Q22_20	Not notice someone stepping out from behind a parked vehicle until it is nearly too late.	0.10	0.68	-0.06	0.03	0.01
Q22_21	Not notice a pedestrian waiting to cross at a zebra crossing, or a pelican crossing that has just turned red.	0.22	0.60	0.03	-0.09	-0.12
Q23_1	Riding so fast into a curve that I feel like I might lose control.	0.35	0.42	0.42	-0.02	0.02
Q23_2	Run wide when going around a corner.	0.15	0.51	0.14	0.04	0.03
Q23_3	Having difficulty controlling the motorcycle while riding at high speed (e.g., steering wobble).	0.04	0.47	0.25	-0.01	0.11
Q23_4	Riding so fast into a curve/corner that I have to brake or throttle-back round it.	0.29	0.35	0.27	-0.01	0.08
Q23_5	Slipping on a wet road, manhole covers, road markings, etc.	0.31	0.28	0.30	0.08	0.01
Q23_6	Changing gear around a curve/corner.	0.16	0.16	0.10	0.10	0.23
Q23_7	Riding so close to the vehicle in front that it would be difficult to stop in an emergency.	0.42	0.36	0.24	-0.01	0.10
Q23_8*	Braking too quickly on a slippery road.	0.20	0.43	0.23	-0.03	0.05
Q23_9	Unintentionally doing a wheel spin.	0.14	0.27	0.50	-0.01	-0.09
Q24_1	Attempting to or actually doing a wheelie (a trick or maneuver whereby a bicycle or motorcycle is ridden for a short distance with the front wheel raised off the ground).	0.17	0.01	0.79	-0.09	0.01
Q24_2	Intentionally doing a wheel spin.	0.17	0.10	0.70	-0.15	0.10
Q24_3	Pulling away too quickly, and my front wheel coming off the road (lifts).	0.23	0.05	0.82	-0.08	0.09
Q24_4*	Braking too rapidly with the front brake, and my rear wheel going up in the air.	0.04	0.11	0.69	0.07	0.08
Q24_5*	Overtaking another vehicle at a short distance/slalom riding.	0.55	0.12	0.50	-0.07	0.19
Q24_6	Race away from traffic lights with the intention of beating the driver/rider next to you.	0.42	0.18	0.34	-0.07	0.12
Q24_7	Ride between two lanes of fast-moving traffic.	0.41	0.09	0.34	0.01	0.28
Q24_8	Get involved in unofficial “races” with other riders or drivers.	0.40	0.16	0.54	-0.12	0.22
Q25_1	Exceeding the speed limit on a motorway/highway.	0.81	0.06	0.07	0.02	-0.07
Q25_2	Exceeding the speed limit on a country/rural road/outside the urban area.	0.83	0.08	-0.02	-0.03	-0.13
Q25_3	Exceeding the speed limit on an urban/city road/residential area.	0.77	0.07	-0.05	-0.11	-0.02
Q25_4	Disregarding the speed limit late at night or in the early hours of the morning.	0.74	0.09	0.04	-0.12	0.03
Q25_5	Opening up the throttle and “going for it” on rural/country roads.	0.74	0.11	0.21	-0.07	0.10
Q25_6*	Disregarding the speed limit during rainy conditions.	0.50	0.11	0.10	0.02	0.17
Q26_1*	Wear a protective helmet.	0.14	-0.02	-0.05	0.38	-0.11
Q26_2	Wear a protective jacket (leather or non-leather).	0.00	-0.09	-0.11	0.70	-0.01
Q26_3	Wear protective trousers (leather or non-leather).	-0.14	-0.04	-0.02	0.79	0.04
Q26_4	Wear riding shoes / boots.	-0.08	-0.09	-0.01	0.75	0.01
Q26_5	Wear motorcyclist gloves.	-0.01	-0.06	-0.12	0.61	0.01
Q26_6	Wear body armor to protect elbows, knees, shoulders, etc.	-0.11	-0.09	0.11	0.57	-0.01

Q26_7	Wear fluorescent clothing / helmet or reflective vest / clothing / helmet.	-0.27	0.00	-0.01	0.45	-0.18
Q26_8	Wear bright/fluorescent or reflective markings /strips on your clothing or helmet.	-0.25	-0.03	0.00	0.48	-0.16
Q26_9	Wear no protective clothing.	-0.03	0.14	0.02	-0.17	0.06
Q26_10	Have trouble with your visor or goggles fogging up.	0.00	0.20	-0.02	-0.11	-0.01
Q26_11	Use dipped headlights on your bike.	0.07	0.02	-0.13	0.15	0.03

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.
Rotation converged in 6 iterations.
** - questionnaire items added to the original MRBQ (Elliott et al., 2007)*

Appendix 2. Road perception questionnaire items

Rotated Component Matrix[a]

Item Code	Item	Component 1	Component 2	Component 3
Q27_1	How likely do you think a motorcyclist will crash due to damaged pavement (ruts, holes, cracks, etc.).?	0.216	-0.036	0.857
Q27_2	How likely do you think a motorcyclist will crash due to poorly maintained pavement (numerous patches, bituminous fillings, smoothed surfaces, etc.)?	0.250	0.001	0.851
Q27_3	How likely do you think a motorcyclist will crash due to a roadway missing a centerline?	0.858	0.196	0.156
Q27_4	How likely do you think a motorcyclist will crash due to a road missing edge lines?	0.884	0.213	0.086
Q27_5	How likely do you think a motorcyclist will crash due to poorly visible road markings?	0.859	0.192	0.160
Q27_6	How likely do you think a motorcyclist will crash due to a slippery road surface (damp, wet, icy, etc.)?	0.014	0.284	0.615
Q27_7	How likely do you think a motorcyclist will crash due to consecutive curves in the opposite direction (e.g., left and right turns in a row)?	0.242	0.821	0.081
Q27_8	How likely do you think a motorcyclist will crash due to consecutive same-direction curves (e.g., two right turns in a row)?	0.257	0.822	-0.024
Q27_9	How likely do you think a motorcyclist will crash due to insufficiently clear/visible/understandable traffic signs?	0.389	0.425	0.246
Q27_10	How likely do you think a motorcyclist will crash due to a long straight stretch of road where it is possible to reach high speeds?	0.066	0.689	0.110
Q27_11	How likely do you think that the consequences of a motorcyclist crashing will be more severe due to a safety barrier without an additional (lower) plate / beam?	0.017	0.042	0.373

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.
Rotation converged in 5 iterations.

Author's Biography

Marija Ferko (born June 25, 1991, in Novo mesto, Slovenia) specializes in road safety, traffic, and transport systems, particularly on vulnerable road users and motorcyclists. She earned her master's degree in Transport Engineering from the Faculty of Transport and Traffic Sciences, University of Zagreb, in 2017. As part of her doctoral research (conducted at University of Zagreb, Croatia, and Hasselt University, Belgium), she has explored multiple dimensions of motorcyclist safety using police crash data, survey-based behavioral models, and naturalistic smartphone data.

Marija has received multiple academic awards, including the Dean's Award for academic excellence and the University Rector's Award for scientific research.

She is the author and co-author of over 15 scientific publications, including papers in journals such as *Transportation Research Part F, Safety Science*, and *Sustainability*. Her work is regularly presented at international conferences. Her work has contributed to advancing the understanding of crash risk factors, injury severity predictors, and behavioral patterns among motorcyclists.

Besides scientific research, she has been employed as an engineer actively and has been involved in expert projects focused on improving the safety of road users and road signaling quality control.

She is a member of the *Croatian Association of Engineers of the Faculty of Transport and Traffic Sciences AMAC-FSC* and advocates for evidence-based traffic safety policy development.

List of Publications

List of publications included in this thesis

Ferko, M., Babić, D., & Pirdavani, A. (2025). Riding the Edge – Unveiling the Key Factors behind Injury Severity in Single-Vehicle Motorcycle Crashes. *Promet - Traffic&Transportation, 37*(4), 834–852. https://doi.org/10.7307/ptt.v37i4.1091

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Ferko, M., Pirdavani, A., & Babić, D. (2023). Exploring the Factor Structure of a Modified Motorcyclist Behavior Questionnaire: Croatian Context. *Transportation Research Procedia, 73*, 250-256. https://doi.org/10.1016/j.trpro.2023.11.915

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Ferko, M., Babić, D., Brijs, T., & Pirdavani, A. Exploring motorcyclist speeding through naturalistic riding data. (2025). *Transportation Research Procedia*. (Accepted for publication on July 10, 2025).

List of other author's publications

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Conference papers

Tkalčević Lakušić, V., Babić, D., Kosovec, B., & **Ferko, M.** (2025). Prometne nesreće i cestovna infrastruktura – kritične lokacije udara u stupove u Hrvatskoj. In Plenoria (Ed.), *CESTE 2025: Zbornik radova* (pp. 75–94). Plenoria.

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Novačko, L., & **Ferko, M**. (2016). Traffic flow management in emergency situations. In *Proceedings of the International Scientific Conference: Perspectives on Croatian 3PL Industry in Acquiring International Cargo Flows* (pp. 137–147). University of Zagreb, Faculty of Transport and Traffic Sciences.