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Article *in* Journal of Transportation Safety & Security · December 2024

DOI: 10.1080/19439962.2024.2435297

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Journal of Transportation Safety & Security

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/utss20

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JOURNAL OF TRANSPORTATION SAFETY & SECURITY
https://doi.org/10.1080/19439962.2024.2435297

Exploring the influence of rider age and experience on motorcycle crash risk: Evidence from a case-control study

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ABSTRACT

Motorcycling provides freedom and excitement, yet riders face a greater risk of crashes and injuries compared to other motorists. Understanding the factors contributing to motorcycle crash risk, especially rider age, experience, and training, is essential for developing effective safety measures. Using a unique and comprehensive matched case-control database of the Motorcycle Crash Causation Study, this study analyzes how the risk of crashing is influenced by riders' age, experience, and training levels while controlling for other factors, such as alcohol use by the rider. The data consist of 350 cases (crash-involved riders) and 700 controls (similarly at-risk non-crash-involved riders). Based on a conditional logit analysis accounting for the matched case-control structure of the data, "risk curves" are created to understand the relationships between rider age and crash risk. Results suggest that younger riders have a heightened risk, which is reduced with increasing age. Each additional year of a rider's age is associated with a 15.66% reduction in the odds of a crash, although a nonlinear specification is also examined. Each year of rider experience is associated with a 2.53% reduction in the odds of a crash, and recent participation in a training program is also associated with lower risk.

KEYWORDS

motorcycle rider; Motorcycle Crash Causation Study (MCCS); case-control design; crash risk; riding experience; blood alcohol concentration (BAC)

HIGHLIGHTS

- Understanding the factors contributing to motorcycle crash risk, particularly rider age, experience, training, and alcohol impairment, is crucial for enhancing road safety measures.
- Using a unique and comprehensive matched case-control database of the Motorcycle Crash Causation Study (MCCS), this study analyzes the association between crash risk and rider age, experience, and training level while controlling for other factors.

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Supplemental data for this article can be accessed online at https://doi.org/10.1080/19439962.2024.2435297.

- Conditional logit analysis is applied to account for the matched case-control design, creating "risk curves" that capture the nonlinear relationship between rider age and crash risk.
- Each additional year of rider age is associated with a 15.66% reduction in the odds of being involved in a crash. However, the relationship exhibits a U-shaped nonlinear pattern, highlighting a higher risk for both younger and older riders.
- Each additional year of rider experience is associated with a 2.53% reduction in the odds of a crash. Participation in recent motorcycle training programs and testing negative for alcohol consumption significantly lower crash risk, with sober riders having a 75.41% reduced likelihood of crash involvement.

1. Introduction

Motorcycles are one of the most convenient, affordable, and fuel-efficient modes of transportation. They offer a thrilling sense of freedom and the joy of exploration. In terms of parking and maneuvering, motorcycles are more appealing and flexible than regular motor vehicles, especially in densely populated areas (Lin & Kraus, 2009). However, motorcyclists are also more vulnerable to crashes and severe injuries than other motorists. Motorcycle crash injuries and fatalities are key public health concerns causing significant economic losses in the United States and globally. From 2002 to 2015, motorcycle-involved fatalities increased by 48%, while those related to passenger vehicles (cars and light trucks) decreased by 32% in the US (NHTSA, 2016). In addition to being a two-wheeled mode of transportation, motorcycles differ from other motor vehicles in terms of physical operation, weight, size, and operator (driver/rider) exposure. Several factors, including small size, powerful engines, and lack of adequate rider protection, make motorcycles more unstable and vulnerable to crashes (Adanu et al., 2023; Daniello et al., 2010; Wang et al., 2022). Riding a motorcycle is physically challenging, and riders' visibility and stability are affected by their direct exposure to weather conditions (Horswill & Helman, 2002). Furthermore, the availability of more powerful motorcycles and their increasing use for recreational purposes have increased the risk of motorcycle injuries and fatalities (Deasy et al., 2012). Beyond the loss of lives and the health care costs associated with injuries, motorcycle crashes put an extra burden on society through emergency response and insurance costs (Cholo et al., 2023; Derrick & Faucher, 2009). Understanding the factors contributing to motorcycle crash risk, especially rider age, experience, and training, is essential for developing effective safety measures. Rider characteristics such as gender, age, and experience may significantly influence rider behavior and attitudes. Past studies reveal that crash risk is higher for younger and inexperienced riders due to their propensity for risk-taking behavior and their attitudinal predispositions (Stanojević et al., 2020; Wali et al., 2018; Yeh & Chang, 2009). In contrast, experienced riders tend to have a lower crash risk (Fagnant & Kockelman, 2015; Haworth et al., 2000; Möller et al., 2020; Mullin et al., 2000). For instance, due to a lack of experience, the perception and decision-making capabilities of young riders are significantly affected; however, age-related decline in reaction times and physical abilities may increase the risk for older adults. Moreover, inexperienced riders may lack the skill to handle emergencies effectively, making them more susceptible to crashes. Motorcycle rider training has been identified as a significant factor in mitigating crash risk. The US Department of Transportation (USDOT) has made substantial efforts to improve training programs for motorcycle riders, particularly since the early 2000s. These efforts include the Motorcycle Safety Foundation's (MSF's) Basic Rider Course and Advanced Rider Course, developed under the National Agenda for Motorcycle Safety (NAMS) (Baer et al., 2005; NHTSA, 2000). These training programs were enhanced in 2010 through initiatives such as the Model National Standards for Entry-Level Motorcycle Rider Training and the Safe, Accountable, Flexible, Efficient Transportation Equity Act: A Legacy for Users (SAFETEA-LU) (Baer et al., 2010; Fischer, 2005; NHTSA, 2010).

A synthesis of past studies indicates that most of them focused on factors associated with motorcycle crash injury severity, including rider behavior; roadway, environmental, and lighting conditions; and rider characteristics such as helmet use, speed, and alcohol impairment (Adanu et al., 2023; Bambach et al., 2011; Cunto & Ferreira, 2017; Fagnant & Kockelman, 2015; Ijaz et al., 2022; Islam & Burton, 2020; Khattak et al., 2022; McKnight & Robinson, 1990; Möller et al., 2020; Ouyang et al., 2024; Savolainen & Mannering, 2007b; Shaheed et al., 2013; Shankar & Mannering, 1996; Wali et al., 2018; 2019; 2022; Wang et al., 2022; Wong et al., 1990). Alcohol impairment or drunk driving has been identified as a significant factor in various types of crashes, including those involving trucks, cars, and motorcycles across different road setups (Adeel et al., 2024; Soderstrom et al., 1990; Wali et al., 2018). Impairment and substance use are associated with an increased crash risk, with the effect being more pronounced for motorcycle riders. Motorcyclists with a positive blood alcohol concentration (BAC) are more likely to be at fault in a crash and less likely to wear helmets compared to those with a negative BAC (Li et al., 2017; Liu & Fan, 2021; Sarmiento et al., 2020). Although findings on the effectiveness of formal training are mixed (Fagnant & Kockelman, 2015; Ivers et al., 2016; McDavid et al., 1989; Savolainen & Mannering, 2007a), a few past studies suggest a lower crash risk for riders who recently participated in a motorcycle training program (Wali et al., 2018). Moreover, the use of personal protective equipment, a key factor in injury prevention in case of a crash, was more prevalent among trained motorcyclists (Daniello et al., 2009).

Compared to purely cross-sectional frameworks, a case-control study design is better suited to examine different groups retrospectively and identify factors that contribute to crashes. Furthermore, case-control designs can better identify the key risk factors involved in safety-critical events in an exposed group (e.g., crash-involved riders) and disentangle the marginal impacts of such risk factors by analyzing their prevalence in unexposed groups (e.g., non-crash-involved-riders). Yet very few studies have used a case-control framework to analyze the determinants of crash risk, mainly due to the difficulty of collecting such data (Haque et al., 2013; Möller et al., 2020; Wali et al., 2018). In the case-control framework, crash risk is computed while comparing cases (crash-involved riders) with controls (non-crash-involved riders) matched on temporal and spatial factors (Connor et al., 2001; Cummings et al., 2001; Haque et al., 2013; Haworth et al., 2000; Möller et al., 2020; Mullin et al., 2000; Wali et al., 2018; Yeh & Chang, 2009). While some past studies analyzed data on cases and controls to quantify crash risk, in most cases, their data were based on a limited sample size or traditional questionnaires containing subjective and unvalidated data.

Using the unique and comprehensive matched case-control database of the US Motorcycle Crash Causation Study (MCCS), this study examines how crash risk is influenced by riders' age, experience, and training level while controlling for other factors, such as alcohol use. This study assesses the relationships between these variables and motorcycle crash risk to identify promising countermeasures. The data used in this study consist of 350 cases (crash-involved riders) and 700 controls (similarly at-risk non-crash-involved riders). All the motorcycle crashes ($N = 350$) resulted in some type of injury. Based on a conditional logit analysis accounting for the matched case-control structure of the data, "risk curves" are created to understand the relationships between rider age and crash risk. The study also investigates how participation in motorcycle training programs and alcohol use influence riders' likelihood of being involved in a crash.

2. Methodology

2.1. Data source and study design

The study utilizes data from the Motorcycle Crash Causation Study (MCCS), a comprehensive data source funded by the US Department of Transportation (USDOT) and managed by the Federal Highway

Administration (FHWA) (FHWA, 2019; J. W. Nazemetz et al. 2019a). The MCCS is supported by a broad coalition of federal agencies, state departments of transportation, local police jurisdictions, and the motorcycle industry, all of which have a vested interest in improving motorcycle safety. The MCCS was led by Oklahoma State University through the Southern Plains Transportation Center, with collaboration from renowned motorcycle and crash data experts. The study employed the internationally recognized Organization for Economic Cooperation and Development (OECD) protocol for crash investigation, ensuring the depth and completeness of the data collected. The MCCS was approved by two institutional review boards (IRBs) that oversaw the research involving human subjects. A primary IRB provided approval during the pilot study, with a Certificate of Confidentiality issued by the National Institutes of Health (NIH) to protect sensitive data. During the main study, a sub-IRB reviewed the operations, ensuring compliance with data confidentiality and security protocols. The MCCS data did not include any personal identifiers, and all crash investigators and project personnel completed the required Human Subjects Protection training course before the data were collected (J. Nazemetz et al., 2019a). For detailed information about the MCCS data set, refer to Wali et al. (2018). To learn more about how to access the MCCS data, visit the FHWA's website at https://highways.dot.gov/research/safety/motorcycle-crash-causation-study/motorcycle-crash-causation-study.

The MCCS data include detailed information on 350 motorcycle crashes collected through on-scene investigations in Orange County, California, and interviews with 700 control riders. For each case (motorcycle crash), data on two controls were obtained, which were then matched with the case (regarded as "baseline") based on the day of the week, time of the day, roadway type, location (rural/urban), travel direction, and weather conditions (FHWA, 2019; J. W. Nazemetz et al., 2019a; Wali et al., 2018). In this study, a matched case-control framework using triplets (one crash-involved rider paired with two non-crash-involved riders) is employed to analyze the associations between key policy-sensitive factors—such as rider age, experience, motorcycle training level, and alcohol use—and crash risk, as shown in Figure 1.

The MCCS data include detailed information about crash sites and riders, capturing conditions and events before, during, and after the crashes (FHWA, 2019; J. W. Nazemetz et al., 2019a; Wali et al., 2018). In the MCCS data, rider information includes (but is not limited to) rider age, rider experience, hours of sleep before riding, alcohol use by the rider (checked by BAC), and training level based on training programs attended by the rider (none, basic, experienced, professional). The MCCS data also include comprehensive data on roadway conditions, traffic controls, and environmental

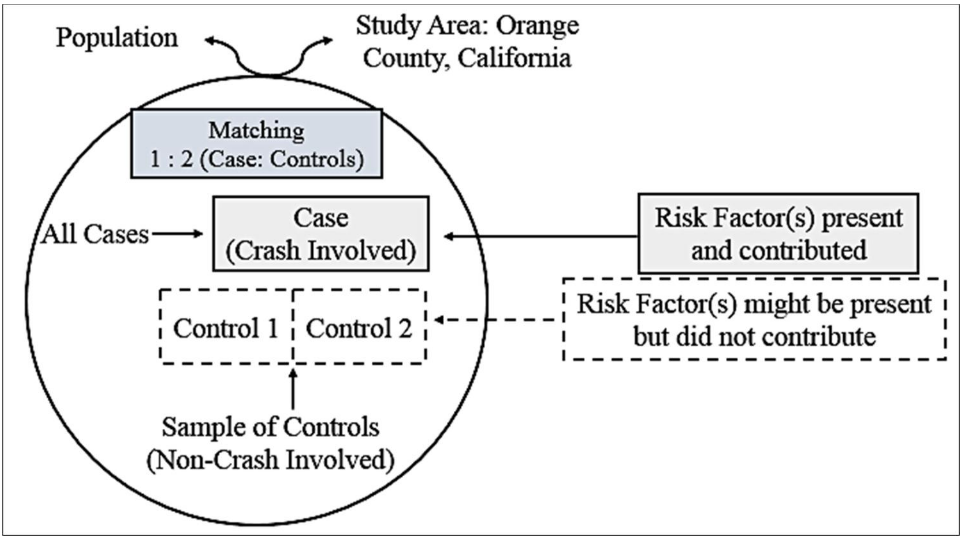

Figure 1. Matched case-control framework.
Note: The arrow indicates that it is a subsample for controls selected from a population in the study area and should not be considered the whole population of motorcyclists in the study area.

details that might have contributed to the occurrence of a crash (FHWA, 2019; Wali et al., 2018). It is worth mentioning that crash data based on police reports may exhibit subjectivity and biases, especially concerning injury information (Ahmad et al., 2019; Wali et al., 2018). The MCCS data provide a unique and objective source of in-depth injury information collected through rigorous post-crash evaluation protocols—linking information from police, hospitals, and interviews. This study utilizes the comprehensive MCCS data set and employs a matched case-control design to correlate the associations between key variables—such as rider age, rider experience, alcohol use, and training level—and the risk of motorcycle crashes.

The MCCS data were collected from three primary sources: police crash reports (PCRs), medical records/autopsy reports, and interviews of crash-involved motorcycle riders (cases) and control motorcycle riders (similarly at-risk non-crash-involved riders). For the crash-involved motorcyclists (cases), crash investigators responded to the crash scenes, documented the evidence, and gathered data from PCRs and interviews with available crash-involved individuals. Interviewees who consented were given voluntary breath tests to determine BAC. For injured parties, blood alcohol information was obtained from medical reports or PCRs when possible. In cases in which injured individuals were not interviewed at the scene, follow-up interviews were conducted later. Medical records were accessed to obtain detailed information about injuries, and patient release forms were executed to secure hospital records and autopsy reports, where applicable. The crash-scene data, crash-vehicle information, and injury data were compiled and recorded

Table 1. Sources of key variables.

Ser.	Variable	Sources*	
		Crash–Involved Motorcycle Rider	Control Motorcycle Rider
1.	Motorcycle riding experience (years)	PCRs, Interview with rider; Motorcycle rider form (variable number 54)†	Interview at the crash scene; Control motorcycle rider form (variable 32)
2.	Rider age (years)	PCRs, Interview with rider; Motorcycle rider form (variable number 89)	Interview at the crash scene; Control motorcycle rider form (variable 72)
3.	Blood alcohol concentration (BAC)	PCRs, Medical records, BAC tests (variable number 104)	Interview at the crash scene; Voluntary breath test during interview; Control motorcycle rider form (variable 87)
4.	Years of training	PCRs, Interview with rider; Motorcycle rider form (variable number 52)	Interview at the crash scene; Control motorcycle rider form (variable 38)
5.	Race of rider	PCRs, Interview with rider; Motorcycle rider form (variable number 96)	Interview at the crash scene; Control motorcycle rider form (variable 79)

*Motorcycle Crash Causation Study: Final Report (J. Nazemetz et al., 2019a); Motorcycle Crash Causation Study: Volume 1—Data Collection and Variable Naming (J. W. Nazemetz et al., 2019b).

†Police crash reports (PCRs) are official documents that record the details of a traffic crash, including information about the involved vehicles, individuals, and contributing factors, typically compiled by responding law enforcement officers at the crash scene.

following detailed guidelines (J. Nazemetz et al., 2019a). For the control motorcyclists, data were collected through voluntary traffic stops or recruitment near the crash sites and matched for time, location, and similar conditions. Control riders were interviewed to gather information about demographics, riding experience, and trip details, and breath tests for BAC were conducted with consent. The vehicle information for control riders was inspected and documented in the same manner as for the crash-involved riders (J. Nazemetz et al., 2019a). Table 1 lists each variable used in this study, along with the corresponding sources (Motorcycle Rider Form and Control Motorcycle Rider Form) from which the data were collected. The table also specifies the variable numbers as they appear in the respective forms. For further details regarding data, refer to Wali et al. (2018).

While the MCCS provides a rich and detailed data set, certain key variables contain missing data. Specifically, rider experience data were missing in 15.62% of cases, and 0.57% of cases lacked rider age data. To address this issue, the median values for the missing variables were imputed based on the non-missing values within specific age groups. Riders were divided into the following age groups: 15–25 years, 26–35 years, 36–45 years, 46–55 years, 56–65 years, 66–75 years, and older than 75 years. The median value for each variable within each of these groups was calculated and then used to replace the missing data, ensuring a more accurate imputation aligned with the age-based characteristics of the riders.

2.2. Conditional logistic regression: Case-control framework

To account for the matched case-control structure of data, conditional logistic regression has been widely used (Cheng et al., 2022; Rothman et al., 2017; Wali et al., 2018; Yoo, 2020). Note that conditional logistic regression accounts for the dependence among the elements of a triplet (one case and two controls) that arises due to matching cases and controls by a set of matching variables. Traditional unconditional logistic regression cannot account for this dependence structure in a case-control design (Wali et al., 2018). The general equation for the conditional logit model is as follows (Boakye et al., 2018; Tay, 2016; Wali et al., 2018):

$$Y_i^* = \beta X_i + \mu_i \tag{1}$$

where Y_i^* indicates the latent unobserved crash propensity (risk) of any rider i, β indicates the vector of parameters to be estimated for a set of explanatory variables (X_i), and μ_i indicates random disturbance. Note that the latent unobserved crash propensity (Y_i^*) can be related to the observed crash propensity (Y_i) (Boakye et al., 2018; Tay, 2016; Wali et al., 2018):

$$Y_i = \begin{cases} 1 \ \ if \ \ Y_i^* > 0 \\ 0 \ \ otherwise \end{cases} \tag{2}$$

Here, $Y_i = 1$ indicates a case (a rider involved in a motorcycle crash), whereas $Y_i = 0$ indicates the control observation (a non-crash-involved rider). The following equations can be used to determine the likelihood of rider i getting involved in a crash (Wali et al., 2018):

$$\begin{aligned} P_i &= prob[\beta X_i + \mu_i > 0] \\ P_i &= prob[\mu_i > (\beta X_i)] \\ P_i &= 1 - F(-\beta X_i) \end{aligned} \tag{3}$$

Note that F indicates the cumulative density function. The coefficients obtained from the logit models provide useful information about the direction of the association with the response variable; however, this does not facilitate interpretation. The odds ratio enables easier interpretation, as provided below:

$$Odds \ \ Ratio = \frac{\left(\frac{p(Y=1|X+1)}{p(Y=0|X+1)}\right)}{\left(\frac{p(Y=1|X)}{p(Y=0|X)}\right)} \tag{4}$$

An odds ratio greater than 1 indicates that the chances of $Y = 1$ (rider involved in a crash) increase with an increase in X (explanatory variable), and vice versa. The percent change in the odds of a response outcome with a unit change in an explanatory variable can be determined as:

$$\% \ Change \ \ in \ \ Odds(Crash \ \ Risk) = 100(Odds \ \ Ratio - 1) \tag{5}$$

While the odds ratios provide direct and meaningful insights, predictive margins can be computed to examine the predicted probabilities of the response outcome at any specific value or over a range of values of the specific explanatory variable. All analysis was performed in the latest version of statistical software Stata v18.

3. Results

3.1. Descriptive statistics

The mean experience level of riders in the control group is 20.52 years, which is significantly higher than the 13.04 years in the case group (Table 2). The mean age of riders in the crash and control groups is 36.55 and 45.10 years, respectively, suggesting that younger riders are more likely to be in the case group (Table 2). For more details about the distribution of riders (both case and control) based on riding experience and age, refer to Figure 2 and Figure 3, respectively.

Notably, the proportion of older and experienced riders is higher in the control group (riders not involved in a crash) (Figures 2 and 3). Statistics also reveal that 40% of the riders in the control group had a negative BAC,

Table 2. Descriptive statistics of key variables.

	Crash-Involved Riders ($N = 350$)			Non-Crash-Involved Riders ($N = 700$)			Independent Group t-test
Variables	Mean (μ_1)	S.D.	Min/Max	Mean (μ_2)	S.D.	Min/Max	(H_a: $\mu_{2\text{-}}\ \mu_1 > 0$)
Motorcycle riding experience (years)	13.039	14.155	0/47	20.516	17.048	0/69	Pass
Rider age (years)	36.546	14.260	16/73	45.066	14.558	17/84	Pass
Negative blood alcohol concentration (BAC)* (1 if yes, 0 otherwise)	0.165	0.372	0/1	0.398	0.489	0/1	Pass
Years of Training							
Training in 2001–2010*	0.091	0.289	0/1	0.290	0.454	0/1	Pass
Training in 2011–2015*	0.069	0.253	0/1	0.196	0.397	0/1	Pass

*Indicates binary variables for which their "mean" values, if multiplied by 100%, will show the corresponding percentages. Where N indicates sample size; μ_1 and μ_2 indicate the mean of crash and control group, respectively; S.D. indicates the standard deviation, H_o indicates null hypothesis ($\mu_2 - \mu_1 = 0$), and H_a indicates alternative hypothesis ($\mu_2\ \mu_1 > 0$). Note that "Pass" means that H_a can be accepted at 95% confidence instead of H_0, and vice versa.

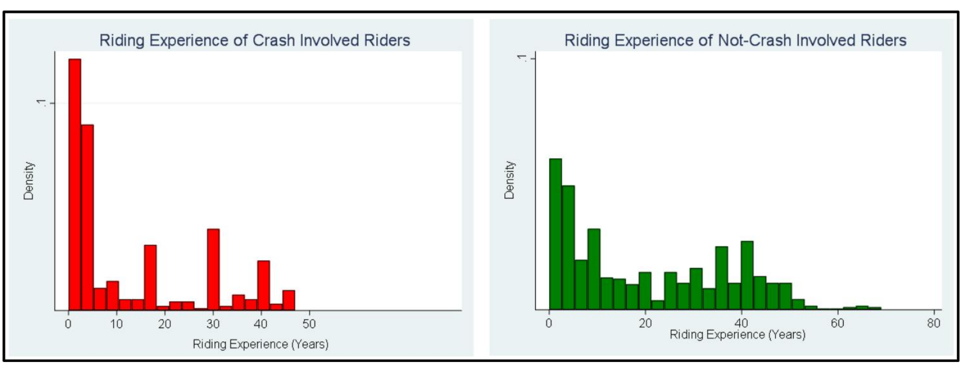

Figure 2. Distribution of riders based on riding experience (years).

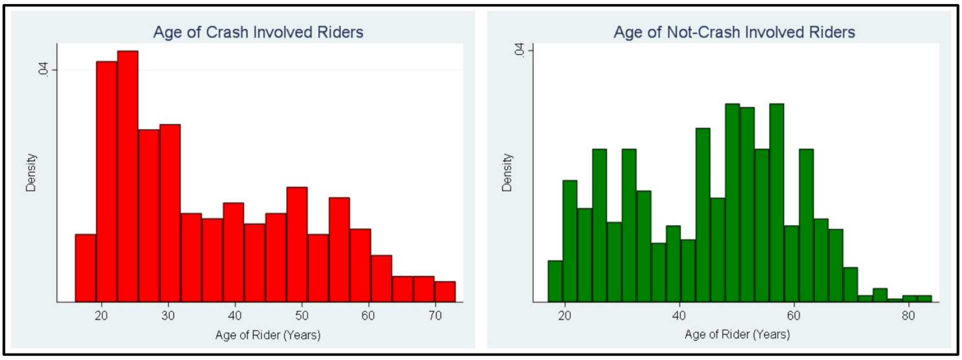

Figure 3. Distribution of riders based on rider age (years).

Table 3. Correlation matrix of the crash and key explanatory variables.

	Crash	Rider Age (Years)	Motorcycle Riding Experience (Years)
Crash	1.000	−0.268*	−0.214*
Rider age (years)	−0.268*	1.000	0.787*
Motorcycle riding experience (years)	−0.214*	0.787*	1.000

* Indicates that the correlation between corresponding variables was significant at a 95% confidence level.

which is significantly higher than the 16.5% in the case group (Table 2). The means of all the variables (except the indicator for Hispanic, African American, and others/not reported riders) were statistically significantly different between the case and control groups (Table 2). All 350 crashes included in the MCCS data set were injury crashes, with less than 0.5% being fatal. No property damage only (PDO) cases were recorded in the data set, primarily because motorcycle crashes typically result in some type of injury, ranging from minor to fatal, due to the inherent vulnerability of motorcyclists (Farid & Ksaibati, 2021; Turner et al., 2013). The absence of PDO cases may also be attributable to the underreporting of noninjury incidents to the police—the primary source of crash data.

3.2. Correlational analysis

Based on the Pearson correlation, rider age and experience have statistically significant correlations with motorcycle crashes (Table 3). Only rider age and riding experience showed a positive significant correlation at a 95% confidence level. All the included variables' variance inflation factors (VIFs) were checked after fitting the final model. The VIF for all other variables was less than 3, which indicates no collinearity issues among the three key explanatory variables included in the model (Table 3). Note that a VIF lower than 10 is acceptable and lower than 5 is good (Jing et al., 2023; Kim, 2019; Shrestha, 2020; Sun et al., 2024).

3.3. Modeling results

To gain deeper insights, conditional logit analysis was conducted while accounting for the case-control setup. The models are systematically derived while considering statistical significance, specification parsimony, and theoretical justification. Based on the results, the key correlates of motorcycle crash propensity include rider age, rider experience, participation in motorcycle training programs, and BAC, as shown in Table 4. The final model specification applies a 95% confidence level criterion to retain variables. Polynomial terms are added to the conditional logit link function to capture the potential nonlinearities associated with rider age. It should be noted that polynomial terms up to the fifth order were considered for the rider age variable, with the second-order polynomial providing the best-fit results. The results of the linear-in-parameters logit model (Model 1) and the nonlinear logit model (Model 2), which includes the square term for rider age, are presented in Table 4.

Table 4 illustrates that motorcycle riding experience is negatively correlated with crash risk in both models, with Model 1 showing a coefficient of −0.0215 (odds ratio 0.9787, t-statistic −2.25), indicating a 2.13% reduction in crash odds per additional year of experience. In Model 2, the coefficient of −0.0256 (odds ratio 0.9747, t-statistic −2.66) suggests a 2.53% reduction in crash risk with each additional year of riding experience. Rider age similarly shows a negative relationship with crash risk. In Model 1, the coefficient of −0.0369 (odds ratio 0.9637, t-statistic −3.60) indicates a 3.63% reduction in crash risk per year of age. In Model 2, the coefficient of −0.1703 (odds ratio 0.8434, t-statistic −4.39) indicates a 15.66% reduction in crash risk with each additional year of age. However, in Model 2, a nonlinear term (square of rider age) is also included, as discussed in Section 4. Motorcycle riders with a negative BAC have a significantly lower crash risk, with Model 1 showing a 74.92% reduction (coefficient −1.3829, odds ratio 0.2508, t-statistic −6.29) and Model 2 showing a 75.41% reduction (coefficient −1.4028, odds ratio 0.2459, t-statistic −6.32). Additionally, motorcycle training significantly reduces crash risk, with riders trained between 2001 and 2010 showing an 84.03% reduction in Model 1 (coefficient −1.8346, odds ratio 0.1597, t-statistic −7.40) and an 85.46% reduction in Model 2 (coefficient −1.9282, t-statistic −7.56). Riders trained between 2011 and 2015 exhibit an even greater reduction in crash risk, with Model 1 showing an 87.79% reduction (coefficient −2.1031, odds ratio 0.1221,

Table 4. Estimation results of conditional logit model.

Variables	Model 1 – Linear Model				Model 2 – Nonlinear Model			
	Coef.	Odds Ratio	t-stat*	% Change in Odds	Coef.	Odds Ratios	t-stat*	% Change in Odds
Motorcycle riding experience (years)	−0.0215	0.9787	−2.25	−2.13	−0.0256	0.9747	−2.66	−2.53
Rider age (years)	−0.0369	0.9637	−3.60	−3.63	−0.1703	0.8434	−4.29	−15.66
Squared term for rider age (rider age x rider age)	–	–	–	–	0.0016	1.0016	3.54	–
Negative blood alcohol concentration (BAC) (1/0)	−1.3829	0.2508	−6.29	−74.92	−1.4028	0.2459	−6.32	−75.41
Years of Training (base = no training or training received before 2001)								
Training in 2001–2010	−1.8346	0.1597	−7.40	−84.03	−1.9282	0.1454	−7.56	−85.46
Training in 2011–2015	−2.1031	0.1221	−7.22	−87.79	−2.3137	0.0989	−7.54	−90.11
Model Summary								
Number of observations	1,050				1,050			
Number of triplets	350				350			
Degrees of freedom	9				10			
Log-likelihood at convergence (model)	−249.9714				−243.8161			
AIC	509.9428				499.6321			
BIC	534.7255				529.3714			

Likelihood ratio test:

$\textit{Likelihood Ratio } (\chi 2) = -2x\ \left[\ln\ (\textit{likelihood of linear model}) - \sum \ln\ (\textit{likelihod of non}-\textit{linear model})\right]$

$\textit{Likelihood Ratio } (\chi 2) = -2x\ [-249.9714 - (-243.8161] = -2x[-6.1553]$

$\textit{Likelihood Ratio } (\chi 2) = 12.31 > 3.841$; *Reject Null hypothesis at 95% Confidence level*

*t-stats are calculated at a 95% confidence level.

t-statistic −7.22) and Model 2 showing a 90.11% reduction (coefficient −2.3137, t-statistic −7.54).

The model summary shows that both models have the same number of observations (1,050) and triplets (350). However, the degrees of freedom differ due to the inclusion of a nonlinear term (the squared term for rider age) in Model 2. The Akaike information criterion (AIC) and Bayesian information criterion (BIC) values for Model 2 (the nonlinear model) are 499.6321 and 529.3714, respectively, which are lower than those for Model 1 (the linear model), with AIC and BIC values of 509.9428 and 534.7255, respectively. These lower AIC and BIC values indicate that Model 2 provides a better fit to the data compared to Model 1. Moreover, the likelihood ratio test compared the linear model (Model 1) with the nonlinear model (Model 2). The test results yield a chi-square (χ^2) statistic of 12.31, with one degree of freedom and a p-value of 0.0005, which exceeds the critical value of 3.841 at the 95% confidence level (Table 4). This leads to the rejection of the null hypothesis, confirming that the nonlinear model (Model 2) provides a significantly better fit for predicting the outcomes compared to the linear model (Model 1) ($p < 0.05$). It should be noted that a model based on fine-grained age categorizations was also developed, but it did not show any significant improvement over Model 2 in terms of AIC and BIC (results not shown).

4. Discussion

The conditional logit models provide valuable insights into motorcycle crash risk, highlighting the significant roles of rider age, experience, formal training, and sobriety, as shown in Table 4. The results and findings discussed in this section refer to the best-fit nonlinear model (Model 2).

The study's findings indicate that younger and less experienced riders are at a significantly higher risk of crashes and injury, with the crash risk diminishing as age and experience increase. Notably, the analysis reveals a significant negative association between rider age and crash risk, where the inclusion of a squared term for rider age effectively captures the nonlinear relationship, highlighting that both younger and older riders face heightened crash risk compared to middle-aged riders. The study reveals that, with a unit increase in the rider's age in years, the odds of involvement in a crash are reduced by 15.66%. This finding suggests a relatively higher crash risk for younger riders, which is intuitive and can be attributed to their potentially risky behavior. Similar findings are suggested by previous studies (Cooper, 1990; Lin et al., 2003; Mullin et al., 2000; Wali et al., 2018). However, the odds ratio alone does not fully capture the nonlinear relationship between rider age and crash risk, which follows an S-shaped

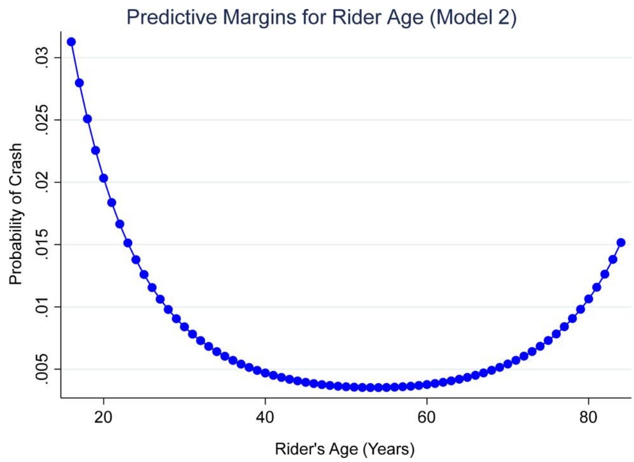

Figure 4. Predicted crash probabilities versus rider age (best-fit nonlinear Model 2).

curve fitted by the conditional logit model. The association between rider age and crash risk varies across different age ranges, and Figure 4 helps visualize the predicted probabilities of crashes at different ages (while holding other exploratory variables at their mean values) based on Model 2 (which is linear in parameters but nonlinear in variables). The predictive margins plot of Model 2, incorporating polynomial terms for rider age, illustrates this nonlinear effect, showing how the risk changes across the age spectrum. The relationship between rider age and crash risk follows a U-shaped pattern, providing valuable insights. Riders younger than 40 and older than 60 have a higher probability of crashes compared to those between 40 and 60 years old. Younger riders, as shown on the left side of the plot, exhibit a relatively higher crash risk than older riders, illustrated on the right side. Although both younger and older riders face an elevated risk of crashes, the risk is notably higher for younger riders. The statistically significant quadratic term for rider age in Model 2 underscores that failing to account for this nonlinearity could lead to underestimation of the effect size and obscure important patterns embedded in the data.

The study also reveals that inexperienced motorcycle riders face a higher risk of being involved in crashes, but the odds of a crash decrease by 2.53% with each additional year of riding experience. This finding is expected, as experienced riders are likely to respond more skillfully, thereby being better equipped to avoid dangerous situations than their less experienced counterparts. Similar findings have been reported in previous studies (Cooper, 1990; Das et al., 2022; Lin et al., 2003; Mullin et al., 2000; Stanojević et al., 2020; Wali et al., 2018). Another key finding of the study is that riders who recently received formal motorcycle training have a significantly lower risk of being involved in a crash compared to those who either never received formal motorcycle training or were trained before 2001. The results show that the odds of a rider being involved in a crash decrease by 85.46% and 90.11% for those who received formal motorcycle training during 2001–2010 and 2011–2015, respectively, compared to those who had no training or were trained before 2001. This underscores the crucial role of motorcycle training in reducing crash risk. This finding is intuitive, as participation in formal training programs increases motorcycle riders' safety awareness and riding skills. Additionally, motorcycle training programs have improved in recent years due to national and statewide efforts to enhance motorcycle safety (NHTSA, 2013; Wali et al., 2018). The findings highlight the significant role of alcohol impairment, showing that the odds of a crash are reduced by 75.41% if the rider has a negative BAC. This indicates that alcohol-impaired or drunk riding greatly increases the likelihood of crashes. This finding is intuitive and consistent with previous studies (Creaser et al., 2007; Høye, 2020; Islam, 2024; Kitali et al., 2022; Pasnin & Gjerde, 2021; Wu et al., 2018).

5. Limitations

This study utilizes comprehensive and meticulously collected data from the MCCS, which includes detailed information on rider-related factors, roadway environments, and motorcycle-related factors. Both the motorcycle crashes (referred to as "cases" in this study) and the controls were carefully matched and collected through extensive interviews, ensuring that the characteristics of the controls closely mirrored those of the crash-involved riders. While the MCCS data provide valuable insights, it is important to note some limitations. The MCCS data were collected in Orange County, California, a region with unique sociodemographic and riding behaviors. As such, the results of this study may not be fully generalizable to other regions of California or to the broader US. Another limitation of the MCCS data set is the potential underinclusion of crashes involving minor injuries or single-vehicle motorcycle crashes, which are less likely to be reported. Although this may introduce some bias, our analysis focuses on crashes collectively; thus, the conclusions drawn remain robust within the context of the available data. Additionally, some data on important factors, such as rider age and experience, were missing, for which a median imputation technique was applied to estimate the missing values based on age group classifications (discussed in Section 2). While this method preserved the integrity of the data set, it carries the potential for bias, as it assumes that the missing values align with the central tendency of the group. Consequently, the findings of this study should be interpreted with caution, as slight biases may affect the estimated associations between these variables and crash risk. Therefore, future studies should aim to collect complete data on all critical variables to provide more accurate and reliable insights into the factors contributing to motorcycle crashes.

6. Conclusions

This study investigates the critical factors contributing to motorcycle crash risk, focusing on younger and inexperienced riders. By analyzing participation in formal motorcycle training programs and the influence of alcohol use, the study provides essential insights into how these elements affect a rider's likelihood of being involved in a crash. Utilizing data from the MCCS and applying a conditional logit model, this research accounts for the matched case-control data structure and successfully captures the nonlinearity in the association between rider age and crash risk.

The findings indicate that younger riders are at a significantly higher risk of crashes, and this risk decreases as age increases. Specifically, each additional year of age is associated with a 15.66% reduction in the odds of a crash. However, the relationship between age and crash risk exhibits nonlinearity. A U-shaped pattern is observed, showing that both younger and older riders have an elevated crash risk compared to riders aged 40 to 60 years, with younger riders facing an even greater risk than their older counterparts. Furthermore, riders with more experience demonstrate a reduced risk of crashes, with each additional year of experience linked to a 2.53% decrease in crash odds. Recent participation in formal motorcycle training programs is also associated with a lower likelihood of crashes. Specifically, riders who completed formal training during the periods 2001–2010 and 2011–2015 show a reduced risk compared to those who either had no training or were trained before 2001. Additionally, the analysis of alcohol impairment revealed that impaired or drunk riding significantly elevates the risk of crashes. Specifically, riders with a negative BAC had a 75.41% lower likelihood of being involved in a crash, underscoring the critical role of alcohol impairment in crash risk.

From a practical standpoint, greater emphasis is needed on the role of rider age and experience in licensing regulations, particularly for younger riders (<40 years), inexperienced riders, and older riders (60+ years). Implementing targeted training programs can enhance riders' skills and improve their safety awareness. Additionally, awareness campaigns focusing on alcohol use and risky riding behaviors—especially among younger riders—could be effective in reducing motorcycle crashes. Future research could explore the relationships between rider age, experience, speed, and injury severity in crashes to provide further insights into motorcycle safety. Additionally, future studies could explore the interactions between rider age and crash risk based on BAC, as well as the potential link between race and BAC, to deepen the understanding of how these factors contribute to crashes. Exploring these indirect factors could offer valuable insights into motorcycle crash prevention strategies. Furthermore, investigating the potential of automated features (rider assistance systems) to help younger (<40 years), older (>60 years), and inexperienced riders avoid crashes or reduce their likelihood could lead to valuable advances in motorcycle safety.

Authors contributions

The authors confirm their contributions to the paper as follows: *Study Conception and Design*: Muhammad Adeel, Numan Ahmad, Behram Wali, Asad J. Khattak; *Data Collection*: Muhammad Adeel, Numan Ahmad; *Analysis and Interpretation of Results:* Muhammad Adeel, Numan Ahmad, Behram Wali; *Draft Manuscript Preparation:* Muhammad Adeel, Numan Ahmad, Behram Wali, Asad J. Khattak. All authors reviewed the results and approved the final version of the manuscript.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This study was funded by the USDOT-funded Southeastern Transportation Center and the USDOT through the Collaborative Sciences Center for Road Safety (CSCRS), a consortium led by the University of North Carolina at Chapel Hill in partnership with the University of Tennessee–Knoxville. The title of the research project (R-20) is "Investigating the Vulnerability of Motorcyclists to Crashes and Injury." The Federal Highway Administration (FHWA) provided the data for this study. During the preparation of this work, the authors used ChatGPT in a few instances to improve its grammar, writing, and readability. However, all authors approved the final version of the manuscript and take full responsibility for its content.

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