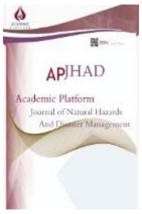

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Investigating Motorcycle Accidents in the Presence of Carriageway Hazards

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Abstract

The notable flexibility and relatively lower purchase and operational expenses of motorcycles, particularly when compared to automobiles, contribute significantly to their shares in traffic. However, the capacity to attain high speeds in the absence of a protective vehicle body raises safety concerns, necessitating an examination of the factors influencing motorcycle accidents. Understanding these factors is crucial for implementing precautions to mitigate the severity and frequency of accidents. In this study, we utilized log-linear analysis to explore the relationships among carriageway hazards, weather and lighting conditions, seeking to understand their influence on the number of motorcycle accidents. The analysis is based on a dataset encompassing motorcycle accidents in Great Britain over the past five years. The study found that motorcycle accidents are more likely during daytime and fine weather conditions when a carriageway hazard is present, especially with objects on the road. The conclusion underscores the importance of clean and divided roads, monitoring parked vehicles, and adopting technology for hazard notification.

Keywords: Carriageway hazards, Motorcycle accidents, Accident analysis, Log-linear analysis.

1. Introduction

Integration of technologies such as electric batteries, GPS tracking, extended range, and improved comfort significantly enhances the capabilities and features of motorcycles. The high maneuverability of motorcycles in traffic serves as an added incentive for individuals, especially post-Covid-19, seeking personal transportation options, leading them to choose motorcycles. These advantages, combined with the affordability of taxes, purchase, and operating costs compared to other motor vehicles, continue to contribute to the growing popularity of motorcycles in road traffic. Acknowledging the potential correlation between the increased presence of motorcycles and a rise in motorcycle accidents underscores the evident need for comprehensive studies on crash causality and prevention. A thorough examination of the literature reveals numerous studies dedicated to gaining insights into the dynamics of motorcycle accidents [1-10]. In a study conducted in the United States, researchers explored the determinants of motorcycle accident severity through the application of the multinomial logit model. The investigation incorporated environmental factors, road conditions, vehicle characteristics, and driver attributes, examining their correlation with five distinct levels of accident severity: property damage only, potential injury, significant injury, disabling injury, and fatality [1].

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Another study in Singapore employed an ordered probit model to analyze factors impacting both injury severity and damage severity in motorcycle accidents. Results indicated that higher engine capacity, collisions with objects, and involvement of pedestrians were associated with more severe accidents [2]. Another accident analysis study conducted for Calgary revealed a correlation between motorcycle accident severities and factors such as road type, speed, and alcohol use [3]. Utilizing a latent class approach with data collected in Iowa, another study established a significant relationship between accident severity and variables including fixed objects, road type, helmet usage, age, and alcohol or drug involvement [4].

In an extensive examination of motorcycle accidents on Thailand's arterial roads from 2011 to 2017, this study employed ordered logistic regression and multiple correspondence analysis to identify factors impacting accident severity. The research found that age, road lanes and the use of helmets significantly influenced the severity of motorcycle accidents [5].

In a systematic review on exclusive motorcycle lanes (EMCL), the study addresses the high incidence of motorcycle accidents in developing countries, particularly in Asia, and explores the effectiveness of segregating motorcycles from the main traffic stream. The review covers various aspects, including geometric design elements of EMCL, motorcyclist's flow characteristics on EMCL, and traffic control measures for EMCL. Despite the successful implementation of EMCL in some Asian countries, the study emphasizes the lack of standard design guidelines and the need for specific geometric standards tailored to motorcycle characteristics. The review concludes that EMCLs are an effective engineering approach to reducing motorcycle accidents and suggests key findings to enhance the effectiveness of EMCLs. It also identifies research gaps and suggests future directions, emphasizing the need for comprehensive guidelines considering the unique characteristics of motorcycles [6].

The study in Thailand aimed to identify factors contributing to motorcycle accidents and fatalities, particularly focusing on rider-at-fault accidents. Decision trees were employed to analyze data from highways (HW) and rural roadways (RR), separating accidents based on speed limit adherence. The research covered 115,154 motorcycle accidents from 2015 to 2020. Key findings highlighted that, regardless of responsible driving, nighttime RR accidents with no lighting resulted in high fatalities. The decision tree emphasized male riders and speeding as primary contributors to fatalities on both HWs and RRs. Recommendations included increasing the age limit for motorcycle licenses, enforcing existing rules, improving road lighting, and addressing speeding concerns. Speed restrictions and anti-intoxication campaigns were proposed for effective accident prevention [7].

Focusing on motorcycle accidents in Portugal, the 2023 study by Santos et. al. harnessed various machine learning models, including decision trees, ordered logistic regression, random forest, gradient boosting, extreme gradient boosting, k-nearest neighbors, and support vector machine, to predict accident severity outcomes. Addressing class imbalance through under-sampling in a comprehensive 10-year dataset, the research highlighted the noteworthy performance of random forest and logistic regression models, especially when developed with a balanced dataset. The study expressed influential risk factors contributing to increased injury severity, such as alcohol consumption, road conditions, road type, motorcycle age, rider's gender, and accident timing. Emphasizing the significance of RF models, particularly when considering a balanced dataset, the findings provide valuable insights into predicting motorcycle accident severity [8].

A recent study highlights that motorcycle accidents contribute to 34% of road traffic fatalities in Southeast Asia, particularly impacting Malaysia. Despite this, motorcycles remain the dominant mode of transport in the region. The study explores factors like motorcycle safety technology, law enforcement, car safety technologies, education, and infrastructure to address the issue. By incorporating the perspectives of Malaysian drivers, the study, which employs the analytical hierarchy process, reveals that motorcyclists prioritize safety technology, while drivers focus on car safety technologies [9].

In this study, we employed log-linear analysis to investigate the factors impacting motorcycle accident occurrences, focusing specifically on carriageway hazards, weather and lighting conditions. The number of accidents were examined based on the optimal model outcome, and interpretations were made regarding the relationships between categorical variables.

2. Method

The fundamental step in statistical data analysis is the judicious selection of analysis methods tailored to variable structures. Contingency tables serve as a prevalent tool for representing categorical data originating from qualitative variables, with two-way tables standing out as the most basic form. While these tables assess analyses against a single hypothesis, more complex contingency tables that involve three or more variables are often employed for data representation. Hypotheses pertaining to mutual independence, conditional independence, and partial independence of variables are subject to examination in contingency table analyses [11, 12]. As the number of variables increases, the conventional contingency table analysis focusing on the relationship between two categorical variables becomes insufficient. Consequently, log-linear modeling of hypothesis tests for interactions among categorical variables assumes a pivotal role in multivariate analysis techniques [13]. The log-linear analysis draws parallels with variance analysis involving factor-dependent variables exhibiting a continuous distribution. It plays a crucial role not only in discerning the optimal model but also in conducting significance tests for the model [14]. This study endeavors to investigate the optimal model. The log-linear model articulates the logarithm of the counts of each cell in the contingency table as a linear combination of all conceivable interactions among the available variables [15-17].

Given the aforementioned considerations, log-linear analysis was employed in this paper to identify the optimal model and assess the significance of variables affecting the number of motorcycle accidents. This statistical method is utilized to explore relationships among more than two categorical variables. The log-linear model expresses the logarithm of the counts of each cell in the probability table as a linear combination of all conceivable interactions between the variables [13-21]. A standard log-linear model can be represented as in Eq. 1.

$$\ln\left(F_{ijk}\right) = \mu + \lambda_i^X + \lambda_j^Y + \lambda_k^Z + \lambda_{ij}^{XY} + \lambda_{ik}^{XZ} + \lambda_{jk}^{YZ} + \lambda_{ijk}^{XYZ} \quad (1)$$

where;
F_{ijk} is the expected counts with respect to the related cell,
X, *Y*, and *Z* are the variables,
i, *j*, and *k* are the number of categories of the related variables,
λ is the relative weight of each variable,
μ constant term.

3. Data Collection and Model Construction

In the analysis, we assessed 1697 motorcycle accident data in England from 2018 to 2022. Out of 538,461 accidents recorded in the past 5 years, 82,227 (15.27%) involved at least one motorcycle [22]. The dataset used in this analysis specifically comprises motorcycle accidents related to carriageway hazards, weather and lighting conditions, excluding self-reported records and NA data. When filtering transportation types, motorcycles of all engine volumes were included. Table 1 shows the crosstab for the dataset, encompassing variables such as carriageway hazard, weather and lighting conditions.

Table 1. The crosstab for the dataset

Weather condition	Lighting condition	Carriageway hazard					*Grand total*
		Animal on road	Object on road	Pedestrian on road	Previous accident	Vehicle or load on road	
Fine	Darkness (Lights lit)	1.24%	7.42%	1.83%	1.18%	2.06%	*13.73%*
	Darkness (No lights)	4.01%	2.89%	0.18%	0.59%	0.24%	*7.90%*
	Daylight	9.37%	34.83%	5.89%	3.42%	7.60%	*61.11%*
Raining	Darkness (Lights lit)	0.00%	3.54%	0.77%	0.18%	0.71%	*5.19%*
	Darkness (No lights)	1.00%	1.65%	0.00%	0.29%	0.12%	*3.06%*
	Daylight	0.29%	5.60%	1.06%	0.77%	1.30%	*9.02%*
Grand total		*15.91%*	*55.92%*	*9.72%*	*6.42%*	*12.02%*	*100.00%*

In the dataset, carriageway hazards include animal, object, pedestrian, previous accident, and vehicle or load on the road. Weather conditions are categorized as fine and raining, while lighting conditions include lights lit in the darkness, no lights in the darkness, and the daylight.

Upon analyzing the existing data, it becomes evident that the majority of motorcycle accidents take place during daylight, in fine weather, and when encountering an object on the road. It is worth noting that the term object encompasses substances like oil, mud, or any solid items on the road, highlighting the significance of road surface cleanliness and the impact of uncertain objects in motorcycle accidents.

We examined Cramer's V values to assess the relationship between categorical variables. Cramer's V, a measure of association between two nominal variables, produces a value between 0 and +1, derived from Pearson's chi-squared statistic. The calculated Cramer's V values are presented in Table 2. Values above 0.4 are generally indicative of a strong association. Therefore, it can be inferred that there is no significant multicollinearity among the variables [23-25].

Table 2. Cramer's V values between variables

	Carriageway hazard	Weather condition	Lighting condition
Carriageway hazard	1.0000		
Weather condition	0.1058	1.0000	
Lighting condition	0.2213	0.1787	1.0000

We assessed three distinct models outlined in Eq. 2-4 to identify the optimal model. After examining the loglikelihood, residual deviation, Akaike information criterion (AIC), mean square error (MSE), root mean square error (RMSE), and mean absolute deviation (MAD) values for each model, our analysis revealed that Model 3 (Eq. 4), incorporating all bilateral interactions, emerged as the most accurate model (Table 3). The models excluded triple interactions to prevent overfitting. Please note that all analyses were conducted based on the number of accidents for each case but were converted to percentages in crosstabs to enhance visualization.

$$\text{Model 1: } \ln(F) = C + CH + WC + LC \tag{2}$$

$$\text{Model 2: } \ln(F) = C + CH + WC + LC + CH * WC + CH * LC \tag{3}$$

$$\text{Model 3: } \ln(F) = C + CH + WC + CH * WC + CH * LC + WC * LC \tag{4}$$

where;
F is the counts of related row,
C is notation for constant term,
CH is notation for Carriageway Hazard,
WC is notation for Weather Condition,
LC is notation for Lighting Condition.

Table 3. Performance indicators of the models

	Model 1	Model 2	Model 3
Loglikelihood	-194.48	-109.45	-78.36
Residual deviance	247.90 (df=22)	77.85 (df=10)	15.66 (df=8)
AIC	404.96	258.90	200.72
MSE	295.55	160.21	7.56
RMSE	17.19	12.66	2.75
MAD	11.96	7.85	2.21

4. Results

The parameter estimation results of the selected model, including standard errors and significance levels of the coefficients are shown in Table 4. As can be seen from table, relationships between the number of accident and carriageway hazard, weather and lighting conditions are evident. Carriageway hazard, weather and lighting condition were included as the three main components, while carriageway hazard-weather condition, carriageway hazard-lighting condition, and weather condition-lighting condition were incorporated as two-way components in the model. To assess the significance of these relationships, please refer to the confidence intervals for the estimated parameters in the table. With the exception of one parameter (Carriageway hazard: Previous accident), all parameters were found to be significant within at least a 90% confidence interval.

Table 4. Parameter estimations of the selected model

	Estimation	Std. error	z-value	p-value	*	Odds ratio
Constant	**2.939**	**0.220**	**13.364**	**<0.0001**	*a*	**18.90**
Carriageway Hazard						
Object on road	**1.944**	**0.233**	**8.329**	**<0.0001**	*a*	**6.99**
Pedestrian on road	**0.502**	**0.273**	**1.836**	**0.0663**	*b*	**1.65**
Previous accident	-0.116	0.310	-0.374	0.7087		0.89
Vehicle or load on road	**0.585**	**0.269**	**2.175**	**0.0296**	*a*	**1.80**
Weather Condition						
Raining	**-2.199**	**0.275**	**-7.988**	**<0.0001**	*a*	**0.11**
Lighting Condition						
Darkness (No lights)	**1.341**	**0.245**	**5.465**	**<0.0001**	*a*	**3.82**
Daylight	**2.116**	**0.233**	**9.098**	**<0.0001**	*a*	**8.30**
Carriageway Hazard*Weather Condition						
Object on road*Raining	**1.303**	**0.255**	**5.102**	**<0.0001**	*a*	**3.68**
Pedestrian on road*Raining	**1.306**	**0.321**	**4.065**	**<0.0001**	*a*	**3.69**
Previous accident*Raining	**1.195**	**0.343**	**3.481**	**0.0005**	*a*	**3.30**
Vehicle or load on road*Raining	**1.244**	**0.310**	**4.013**	**<0.0001**	*a*	**3.47**
Carriageway Hazard*Lighting Condition						
Object on road*Darkness (No lights)	**-2.381**	**0.285**	**-8.366**	**<0.0001**	*a*	**0.09**
Pedestrian on road*Darkness (No lights)	**-4.185**	**0.648**	**-6.462**	**<0.0001**	*a*	**0.02**
Previous accident*Darkness (No lights)	**-1.915**	**0.415**	**-4.61**	**<0.0001**	*a*	**0.15**
Vehicle or load on road*Darkness (No lights)	**-3.551**	**0.501**	**-7.092**	**<0.0001**	*a*	**0.03**
Object on road*Daylight	**-0.624**	**0.248**	**-2.517**	**0.0118**	*a*	**0.54**
Pedestrian on road*Daylight	**-0.942**	**0.294**	**-3.203**	**0.0014**	*a*	**0.39**
Previous accident*Daylight	**-0.817**	**0.336**	**-2.431**	**0.0151**	*a*	**0.44**
Vehicle on road*Daylight	**-0.771**	**0.288**	**-2.675**	**0.0075**	*a*	**0.46**
Weather Condition*Lighting Condition						
Raining*Darkness (No lights)	**0.463**	**0.225**	**2.061**	**0.0393**	*a*	**1.59**
Raining*Daylight	**-0.886**	**0.153**	**-5.778**	**<0.0001**	*a*	**0.41**

[*] Level of significance; [a] 95% confidence interval. [b] 90% confidence interval.

Null deviance: 3166.21 on 29 degrees of freedom

A summary interpreting the contribution of each variable and interaction in the model to the likelihood of a motorcycle crash is presented below. The odds ratios, calculated as the probability of occurrence divided by the probability of non-occurrence, help in quantifying the magnitude and direction of these relationships. All comparisons and interpretations were conducted with all other variables held constant and compared to the respective reference terms.

Carriageway Hazard Terms:

- **Animal on road:** This term is considered as the reference for this category.
- **Object on road:** The odds ratio of 6.99 suggests that the odds of accidents are approximately 7 times higher when there is an object on the road.
- **Pedestrian on road:** Odds ratio indicates 1.65 times higher odds of accidents when there is a pedestrian on the road.
- **Previous accident:** While this term is not statistically significant, the negative coefficient implies a decrease in the log-odds. The odds ratio of 0.89 suggests a slight reduction, approximately 11%, in the odds of accidents when there is a previous accident.
- **Vehicle on road:** The presence of a vehicle on the road is associated with an odds ratio of 1.80, indicating an 80% higher likelihood of accidents.

Weather Condition Terms:

- **Fine:** This term is considered as the reference for this category.
- **Raining:** The occurrence of rain leads to a low odds ratio of 0.11. This implies that the odds of accidents are significantly lower, by approximately 89%, during rainy conditions.

Lighting Condition Terms:

- **Darkness (Lights lit):** This term is considered as the reference for this category.
- **Darkness (No lights):** Darkness with no lights results in an odds ratio of 3.82 indicating that the odds of accidents are about 3.82 times higher in dark conditions with no lights.
- **Daylight:** Daylight significantly leads to a high odds ratio of 8.3. This suggests that the odds of accidents are 8.3 times higher during daylight.

Interaction Terms:

- **Object on road * Raining:** When there is an object on the road and it's raining, the odds of accidents increase by 3.68 times compared to the baseline.
- **Pedestrian on road * Raining:** Similar to the above, the odds increase by 3.69 times during rainy conditions and the existence of pedestrian on road.
- **Previous accident * Raining:** Rainy conditions increase the odds of accidents for those with a previous accident by about 3.30 times.
- **Vehicle on road * Raining:** When a vehicle is on the road and it's raining, the odds increase by approximately 3.47 times.
- **Object on road * Darkness:** In darkness with no lights, the odds decrease significantly to about 0.09 times.
- **Pedestrian on road * Darkness:** Darkness with no lights drastically reduces the odds to about 0.02 times, when there is a pedestrian on road.
- **Previous accident * Darkness:** Darkness with no lights reduces the odds for those with a previous accident to about 0.15 times.
- **Vehicle on road * Darkness:** Darkness with no lights significantly reduces the odds to about 0.03 times, when there is a vehicle on the road.
- **Object on road * Daylight:** When there is an object on the road in the daylight, the odds decrease to about 0.54 times.
- **Pedestrian on road * Daylight:** When there is a pedestrian on the road, daylight further reduces the odds to about 0.39 times.
- **Previous accident * Daylight:** When there is a previous accident on the road in the daylight, the odds decrease for those with a previous accident to about 0.44 times.
- **Vehicle on road * Daylight:** Daylight also reduces the odds to about 0.46 times, when

there is a vehicle on the road.

- **Raining * Darkness (No lights):** Raining in darkness slightly increases the odds to about 1.59 times.
- **Raining * Daylight**: Raining in daylight significantly reduces the odds to about 0.41 times.

Table 5 presents the distribution of the number of accidents based on model estimation and estimation errors for each cell. The data reveals that motorcycle accidents occur most frequently when there is an object on the road in fine weather and daylight conditions.

Table 5. The distribution of the number of accidents according to model estimation

Weather condition	Lighting condition	Carriageway hazard					*Grand total*
		Animal on road	Object on road	Pedestrian on road	Previous accident	Vehicle or load on road	
Fine	Darkness (Lights lit)	1.11% *(-0.13)**	7.78% *(+0.36)**	1.84% *(+0.01)**	0.99% *(-0.19)**	2.00% *(-0.06)**	*13.73%*
	Darkness (No lights)	4.26% *(+0.25)**	2.75% *(-0.14)**	0.11% *(-0.07)**	0.56% *(-0.03)**	0.22% *(-0.02)**	*7.90%*
	Daylight	9.24% *(-0.13)**	34.60% *(-0.23)**	5.95% *(+0.06)**	3.63% *(+0.21)**	7.68% *(+0.08)**	*61.11%*
Raining	Darkness (Lights lit)	0.12% *(+0.12)**	3.18% *(-0.36)**	0.75% *(-0.02)**	0.36% *(+0.18)**	0.77% *(+0.06)**	*5.19%*
	Darkness (No lights)	0.75% *(-0.25)**	1.78% *(+0.13)**	0.07% *(+0.07)**	0.33% *(+0.04)**	0.13% *(+0.01)**	*3.06%*
	Daylight	0.42% *(+0.13)**	5.82% *(+0.22)**	1.00% *(-0.06)**	0.55% *(-0.22)**	1.22% *(-0.08)**	*9.02%*
Grand total		*15.91%*	*55.92%*	*9.72%*	*6.42%*	*12.02%*	*100.00%*

* *Estimation errors*

Among the factors influencing motorcycle accidents, the presence of objects on the road stands out as particularly impactful. The likelihood of an accident surges to 6.99 times higher when an object is on the road, underscoring the critical need for thorough road clearance and the prompt removal of potential obstacles.

Examining daylight conditions reveals that the probability of an accident is 8.30 times higher during the day than in the dark when lights are on. This inclination could be attributed to the general preference of motorcycle drivers for daytime travel. Consequently, relying solely on the examination of daylight conditions may prove insufficient. It might be more judicious to explore the conditions of illumination or lack thereof in darkness relative to each other, or consider interaction terms. Accordingly, the probability of an accident increases to around 3.82 times higher in dark conditions without lights.

Unexpectedly, rainy weather emerges as a mitigating factor, significantly reducing the chance of accidents by approximately 89% compared to fine weather conditions. This reduction can be rationalized by the fact that, similar to daytime situations, motorcyclists tend to reduce their travels in rainy weather and exhibit heightened caution.

When examining interaction terms, specifically those involving rain and the presence of objects on the road, the probability of an accident increases by 3.68 times. These findings emphasize the importance of addressing specific risk factors and implementing targeted measures to enhance road safety. A dedicated emphasis on road cleanliness, visibility conditions, and a thorough understanding of the intricate interplay of multiple factors is crucial.

4. Conclusion

In this study, the impact of carriageway hazards, weather and lighting conditions on the number of motorcycle accidents were examined through log-linear analysis. The results of the model estimation revealed significant relationships between categorical variables and the occurrence of motorcycle accidents.

Examining the model estimation, in the presence of a carriageway hazard, motorcycle accidents are more likely to occur during the daytime and in fine weather conditions when there is an object on the road. The elevated likelihood of accidents in fine weather conditions can be attributed to a variety of factors, including an increased frequency of motorcycle trips and heightened vigilance among riders compared to periods of adverse weather. This heightened probability may arise from a surge in overall motorcycle activity during fine weather, where the greater presence of riders on the road contributes to an escalated risk of accidents.

However, when considering the prevalence of accidents involving objects on the road, which encompasses solid objects, oil, and mud, the significance of road surface cleanliness emerges as a crucial factor in motorcycle accidents.

Other frequent accidents are associated with the presence of animals and vehicles or loads on the road during daylight hours. The increased accident rate during daylight can be attributed to riders' preference for daytime travel. However, if an animal suddenly enters the road, riders may not react quickly enough to avoid a crash. Similarly, when there is a vehicle or load on the road, riders may struggle to determine whether the oncoming vehicle is moving normally or stopping.

In light of these results, even without visibility issues, the presence of a carriageway hazard on the road increases the likelihood of accidents. Particularly when confronted with an object on the road or the sudden appearance of an animal, it may be inevitable for a motorist to instinctively cross into the opposite lane, experience skidding due to the rapid maneuver, roll over by aggregates that have accumulated on the shoulder while trying to escape, or collide with another vehicle. Therefore, it is crucial to maintain a clean and divided road, as well as monitor improperly parked or stopped vehicles or loads. These findings underscore the importance of implementing sustainable measures. This could involve promptly notifying traffic officers and local officials about road hazards using artificial intelligence and image processing systems integrated with surveillance cameras.

For further studies, exploring the factors influencing both the frequency and severity of motorcycle accidents could involve developing accident causality models. These models could incorporate a more extensive set of independent variables, utilizing a disaggregated dataset. To address challenges arising from a substantial number of variables and potential imbalances in the dependent variable categories, advanced models can be designed. Employing sophisticated data manipulation and variable selection techniques, along with diverse classification models, could enhance the depth and accuracy of the analysis.

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Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author Contribution

Kadir Berkhan AKALIN contributed to the design, implementation, analysis of the results and writing the manuscript. The author did not receive any external support.

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