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Investigation of the Effect of Vehicle Color on Safety

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Abstract

The question of how vehicle color may contribute to motor vehicle crashes has weighed on the minds of consumers, safety advocates, and insurance companies for many years. This study uses a stratified induced exposure design where data are placed into two groups. The first group called the color prone crash group comprises the types of crashes where vehicle color visibility may have contributed in causing the crash such as when a vehicle is struck while in transport in multiple vehicle collisions. The second group is called an induced exposure crash group, which generally comprises crashes for which vehicle visibility was not likely a contributing factor in causing the crash, such as when a single vehicle crashes or when a vehicle strikes a parked vehicle or other fixed/stationery objects or simply overturns. Both the negative binomial (NB) and Poisson distributions were used to fit generalized linear models to the data. Model goodness-of-fit tests were utilized to check which model fits better to the data. Model goodness-of-fit tests indicate that the NB model reflected a better fit to the data due to over-dispersion. Results from the NB model confirm that statistically, besides random variations, no vehicle color was found to be safer or riskier than white, the vehicle color used as a baseline color.

Keywords – Vehicle color, traffic, safety, induced exposure, visibility

1. Introduction

To most people color plays an important part when it comes to purchasing a vehicle, clothing or other items, but too often the color is chosen only because of desire—they do not normally consider it as a factor of safety. There is an existing evidence that relates color to conspicuity. It may be a common sense issue that the choice of the right color may make a difference between a vehicle being visible and being involved in a motor vehicle crash.

For decades, a number of risk factors pertaining to highway safety have been identified such as driving under the influence of alcohol or drugs, speeding, inclement weather conditions, lack of road lighting, sharp curves, etc. However, one aspect not been widely studied but has caused some speculations is whether a vehicle's color may affect its conspicuity and hence contribute in the occurrences of traffic crashes.

Over the years, the concern of many vehicle buyers and insurance companies has been a fear of the possible contribution of the vehicle color to the risk of being involved in a crash [1]. One of the most frequent questions to the AAA Foundation for Traffic Safety staff from customers is what vehicle color is the safest and whether the insurance premiums depend on it [1]. This paper focuses on investigating whether there is a relationship between vehicle color and the risk of being involved in a traffic crash. It attempts to answer the question – based on the color, are some vehicles safer than other vehicles? Which is the safest color? With this challenge in mind we designed this study to provide results that may help identify vehicle color(s) that offer the best vehicle conspicuity and consequently to provide sufficient scientific evidence to assist consumers in selecting an appropriate vehicle color that may enhance their safety while on the road.

Psychological studies have proven that color has an effect on behavior, and although they have not explicitly examined the impact of color on crash risk, however, they attest that some colors are more conspicuous than other colors. Generally, studies have determined the most visible colors under different lighting conditions but very few studies have attempted to determine the relationship between vehicle color (conspicuity) and vehicle crash risk [2]. The perception of color differs among individuals and varies with time as new scientific evidences replace previous concepts. For example, the color red has conventionally been associated with passion, warmth, comfort and security, and it has traditionally been used for fire trucks and other emergency vehicles but now, due to safety concerns regarding visibility, lime-yellow color is being embraced [3, 4]. In addition, psychologists suggest that color influences an individual's behavior and the objects conspicuity. They believe that colors may impair visual perception with ensuing errors that may be heightened by color blindness [2]. Even though studies that attempted to establish the relationship between the crash risk and vehicle color are still few, however, their findings do not agree and some of the methodologies used have been questionable [5].

Davison's [6] study attempted to link vision performance of Great Britain's drivers and their crash risks. Davison recommends that since older drivers are associated with a declined vision and color perception, they should be subjected to a screening. A study by Owens [7] used fatal accident reporting system (FARS) database from 1980 to 1990 and found that most fatal crashes involving pedestrians and bicyclists were most likely to be due to reduced visibility as they occurred early in the morning and late evening. Vorko-Jorvic et al. [8] studied risk factors in urban traffic crashes and determined that the risk of fatal crashes was most significant during the period from midnight to early morning when visibility was reduced. Their results were in agreement with the findings of Owens [7]. Nevertheless, all these studies did not explore further to determine if reduced visibility would increase involvement of certain vehicle colors in traffic crashes due to conspicuity problems.

Nathan [9] was among the first researchers to attempt to establish whether some vehicles are safer than other vehicles based on their color due to their conspicuity. In his study, he observed that the color of a vehicle might have an effect pertaining to visibility problems for rear-end type of crashes. He argues that color affects the perceived proximity of an approaching vehicle. He asserts that distant blue and yellow colored objects seem closer while gray colored objects appear to be farther than their actual locations and therefore the safest color would be the one that is highly visible under different lighting, weather, and perceptual conditions. He thus concludes that pink colored cars are the safest vehicles while black colored cars are not safe.

Solomon and King [4] conducted a study to explore if there is a relationship between the color of the fire truck and crash risk in the city of Dallas, Texas. During that time, the city of Dallas fire department used two different color combinations for their fire trucks. The color combinations they used to paint their trucks are red/white and lime-yellow/white. In that study, they used a Bayes conditional probability design with a dataset of 20 traffic crashes. They controlled confounding factors such as weather-conditions, driver training, law enforcement conditions, etc., by using data from the same fire department with vehicles of both color groups serving the same area. They conclude that a combination of lime-yellow/white significantly lower the probability of visibility-related crashes than a combination of red/white when used on fire trucks.

Lardelli-Claret et al. [10] conducted a study in Spain that provided more elaborate findings on a vehicle color and a crash risk. Their research considered a number of variables, including driver, vehicle, and environmental factors. They developed a paired case-control study design by using the Spanish traffic crash database where they identified a driver responsible for each crash. The crash-causing drivers formed the control group and the non-violating drivers formed the case group. Then, they used the conditional logistic regression model to analyze the crash data and their conclusion was that light colored vehicles such as white and yellow had a lower likelihood of being passively involved in a collision than other vehicles, which are dark, colored.

A study by Furness et al. [11] in Auckland, New Zealand examined the effect of vehicle color on the risk of a serious crash by using a case-control study design almost similar to that of Lardelli-Claret et al. [10]. The case group comprised of vehicle drivers who were victims of crashes (non-violators) where one or more occupants of the vehicle was seriously injured or killed. The control group comprised of randomly chosen vehicle drivers at random times. Their research employed multivariate analysis adjusted for several confounding factors such as gender of the driver, age, ethnicity, education level, alcohol use, vehicle age, vehicle speed, seat belt use, etc. They found that silver colored vehicles were the safest while brown, black, and green colored vehicles had significantly higher likelihood of being involved in serious crashes. In addition, yellow, grey, red, and blue colored vehicles exhibited a non-significant risk of being involved in a serious crash.

A study by Newstead and D'Elia [5] conducted in Australia determined a statistically significant relationship between vehicle color and the risk of a collision. They used a more sound statistical method in order to reduce the weaknesses of previous studies. Their study utilized the induced exposure study design by categorizing the types of crashes that are possibly influenced by the vehicle color and those that are not likely to be influenced by it. They developed a log-linear Poisson regression model to analyze the crash data. They set white as a baseline vehicle color. They found that generally colors with lower visibility indices such as black, blue, grey, green, red and silver colored vehicles have a significantly higher crash risk than white. However, no specific vehicle color was found to be significantly safer than white.

Owusu-Ansah [12] conducted a research to investigate the relationship between the vehicle color and the risk of crashes. He utilized the induced exposure procedure similar to that used by Newstead and D'Elia [5] but Owusu-Ansah [12] used both Poisson and negative binomial (NB) models to fit the data while Newstead and D'Elia [5] used the Poisson model only. Owusu-Ansah [12] used crash data from the state of Nevada for the period of 2003-2008. His study found that the NB model fitted better the data than the Poisson model due to overdispersion in the data and the major conclusion from the NB model was that no vehicle color was determined to be statistically safer or riskier than white, the vehicle color that was used as a baseline color. However, interestingly, the wrong Poisson model (i.e., did not fit the Nevada crash data well), concluded that some colors were statistically different than white.

There are different scientific arguments from the chromatic field about the perception of color; the reasoning behind the relationship between vehicle crashes and the color of the vehicle is motivated by the concept of color. As Shin and Lee [3] explain, the refraction index of color and the converging function of our eyes make the locality of an object look differently according to its color. This concept is known as chromatic aberration in chromatics. Based on the concept of receding and advancing color, Shin and Lee [3] argue that indeed vehicle color and crashes are related. They assert that vehicles with advancing colors (i.e., colors with high brightness and high Chroma) are less prone to collisions since they appear to be closer than their actual locations while vehicles with receding colors (i.e., colors with low brightness and low Chroma) are prone to crashes since they appear to be farther than they really are. The colors arranged in descending order (beginning with the most receding color) that were considered by Shin and Lee [3] are blue, green, white, red, black, silver, brown (chestnut) and yellow (gold).

Based on the foregoing discussion, it is worth noting that although several researchers have attempted to uncover the mystery between vehicle color and crash risk, but some of their findings are contradicting to each other. For example, Newstead and D'Elia [5] observed that silver colored vehicles are not safe, but Furness et al. [11] found silver vehicles to be safer than vehicles with other colors. As if that is not enough, Lardelli-Claret et al. [10] found white and yellow colored vehicles to be the safest while Owusu-Ansah [12] notes that no vehicle color is safer than other colors in terms of crash-causing risk.

2. Methodology

2.1 Data

The state of Ohio started to include records of vehicle color in their traffic crash database in 2011. The traffic crash data for the current study were obtained from the Ohio Department of Public Safety (ODPS). This study utilized the state of Ohio's crash data from 2011 to 2015. Table 1 summarizes variables of interest to the current study.

All single-vehicle crashes were retained and for multi-vehicle crashes, only those crashes whose occurrence may have been due to conspicuity were retained. For multi-vehicle crashes, vehicles that meet this criteria were identified by using the variable ACTION in the crash data; vehicles of our interest were those that were recorded as struck or both striking and struck. It is noteworthy to mention that in multivehicle crashes, collisions involving vehicles crossing median or centerline were removed alongside vehicles reported as striking other vehicles. In essence, conspicuity does not seem to play part when a vehicle crosses a median or centerline and collides with vehicles traveling in opposite direction. In other words, the subject vehicle runs off-the-road and its uncontrolled trajectory leads it into the path of the opposite lane vehicle and visibility is not likely to be a contributing factor. Additionally, all cases with missing or incomplete records for variables of interest (Table 1) were also removed from the dataset. As a result, the final dataset consisted of 948,121 cases, which is a sufficient sample size to be able to draw reliable statistical conclusions.

Tab. 1 - Variables and Codes Used for Attributes of Interest

Variable	Code	Description of Codes Used
Crash group	p	1 = Induced exposure group; 2 = Color prone group.
Age of the driver	a	1== ≤ 25; 2= 26-64; 3= ≥ 65 years old
Gender of driver	g	1= Male; 2 = Female
Vehicle color	c	1 = Azure; 2 = Beige, 3 = Black, 4 = Blue, …, etc.
Weather condition	w	1 = Clear; 2 = Cloudy; 3 = Severe weather
Light condition	l	1= Daylight; 2= Dark lighted; 3= Dark unlighted.

Table 2 summarizes the characteristics of the final crash dataset used in this study. Data in Table 2 reveal that 78.1% of the crashes formed the color prone group while 21.9% of the crashes were in the induced exposure group. This implies that almost three-quarters of the crashes belonged in the color prone group. Male and younger drivers were involved in more crashes as compared to their counterparts.

Tab. 2 - Characteristics of 2011-2015 Ohio Crash Data

Variable	Parameter	Number	Percent
Crash Group	Induced exposure	207,873	21.9
	Color Prone	740,248	78.1
	Total	948,121	100
Gender of Driver	Male	536,332	56.6
	Female	411,789	43.4
	Total	948,121	100
Age of Driver	≤25	256,718	27.1
	26 - 64	601,854	63.5
	65+	89,549	9.4
	Total	948,121	100
Weather Condition	Clear	505,595	53.3
	Cloudy	266,704	28.1
	Severe	175,822	18.5
	Total	948,121	100
Light Condition	Daylight	714,336	75.3
	Dark Lighted	108,925	11.5
	Dark Unlighted	124,860	13.2
	Total	948,121	100

Table 3 shows the distribution of vehicle color in the Ohio crash data 2011-2015. Accounting for 15.9% of all vehicle crashes by color, white vehicles were the most prevalent in the crash database. The second most prevalent vehicle color in the database was black consisting of 15.5% of the total crashes. The third most prevalent color was red, accounting for 14.9% of all crashes. Silver, blue, and gray colored vehicles round up the top seven with proportions of 13.7%, 11.2%, and 9.3%, respectively. These colors naturally are the most popular among vehicles on the road [13]. According to DuPont Automotive Color Popularity Report for North America [13], the top five most bought vehicle colors in North America are white (23%), black (18%, silver (16%), gray (13.0%), and red (10%). Although the relative vehicle color distribution may differ from state to state or region to region, but we do not expect dramatic differences from the general trend. Thus, it is not surprising to see that the most popular vehicle colors (expected to make up most of the vehicles running on various highways and streets) to also be the majority of vehicles involved in Ohio traffic crashes.

2.2 Conception of crash groups: induced exposure method

The induced exposure method uses a feature not influenced by a study focus to induce a baseline measure and to control other confounding factors affecting the study parameter. In order to implement the induced exposure method, it was necessary to classify data into two groups. The first group is the color-prone group and the second group is the induced exposure group. The color prone crash group consists of types of crashes where the visibility of the vehicle in terms of color may have contributed to the occurrence of a crash. That is, these are multivehicle crashes but only vehicles in this group are those that were struck, and hence visibility or conspicuity issues may have contributed. Induced exposure group constitutes vehicle crashes that may have occurred for other reasons other than vehicle visibility, that is, single vehicle crashes such as vehicles hitting a tree, overturning, etc.

Tab. 3 - Proportion of Vehicle Color in Ohio Crash Data (2011 - 2015)

Color	Color Code	Frequency	Percent
Azure	AZR	16,238	1.7
Beige	BGE	10,466	1.1
Black	BLK	147,272	15.5
Blue	BLU	106,616	11.2
Brown	BRN	9,451	1.0
Gray	GRY	88,207	9.3
Green	GRN	56,856	6.0
Multicolored	MCL	2,241	0.2
Orange	ONG	6,533	0.7
Purple	PRP	5,343	0.6
Red	RED	140,869	14.9
Silver	SLV	130,364	13.7
Tan	TAN	40,225	4.2
White	WHI	150,477	15.9
Yellow	YLW	36,963	3.9
Total		948,121	100

2.3 Statistical modeling

The Poisson and the NB Regression models are well known statistical methods for fitting count data and model goodness-of-fit tests are available that can be used to check if the model used accurately fits the data. In such situation, a Generalized Linear Model (GLM) is usually used to account for factors that may affect the crash frequency. The GLM is similar to regular linear models that fit a normal distribution to error terms, but can be used when the response variable does not have a normal distribution. Maximum likelihood methods are used to estimate parameters and the model is formulated so that some function, called the link function, of the mean is a linear function of the predictor variables. It also provides a framework for using discrete variables as response variables and incorporating the interacting parameters. In the current study, the SAS software was used to fit the models.

Some previous studies utilized the Poisson regression model, e.g., [5], but the deductions from these models have not been satisfactory. This is due to the much known fact that crash frequencies are usually over-dispersed. As a result, a more accurate model, the NB regression model, which accounts for overdispersion, has been preferred [12], and found to have a better fit than the Poisson regression distribution model. The NB distribution is achieved from applying the binomial theorem with a negative exponent. This model is also known as the Poisson-Gamma model and it can be derived as a mixture of Poisson distributions when the mean is not identical for all entities being modeled and that the Poisson means follow a gamma distribution [2].

Poisson regression is a form of a random linear model where the response variable is assumed to have a Poisson distribution. The probability of any count y can be described by Equation (1):

$$P(Y = y) = \frac{e^{-\mu}u^{y}}{y!} \tag{1}$$

Where:
μ = the mean number of occurrences within a given time interval

Since the mean is equal to the variance, a parameter that affects the mean will affect the variance [15]. It is desirable to use the Poisson regression if the response variable is a small integer. In this model, the explanatory variables define the mean of the response variable and since the mean must be positive but the linear combination can take any value, when modelling an outcome Y using a number of independent variables, $X_1, \ldots, X_n$, the a multivariate log-linear function is usually used as shown in Equation (2) and the link function is the logarithm of the mean.:

$$\log(\mu) = \log(T) + \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n \tag{2}$$

Where:
β_0 = regression constant (model intercept)
$\beta_1 \ldots \beta_n$ = model regression coefficients
T = offset

The offset variable log(T) is used to account for possible different observation periods (T_i) for different subjects [16], for example, different traffic crashes at a certain location for different years. If over-dispersion is present in the data, the negative binomial (NB) regression is used instead of Poisson distribution. In Poisson, the mean is equal to the variance while NB allows the variance to be different from the mean; thus NB is normally used where the variance is larger than the mean and hence the term over-dispersion. The NB model (Poisson-Gamma model) is very similar to the Poisson model, in which the dependent variable k is modelled as a mixture of Poisson variables with a mean assumed to follow a Gamma distribution. It is important to note that the Poisson distribution assumes homogeneity in the data while NB distribution assumes heterogeneity. The link function for negative binomial regression is also the logarithmic function.

2.3.1. Model selection criteria

The goodness of fit between the observed data and the estimated values from a NB distribution or a Poisson distribution is usually determined using the log-likelihood ratio G^2 statistic (also called the deviance) and the Pearson Chi-Square (χ^2) statistics as shown in Equations (3) and (4), respectively:

$$D = G^2 = 2\sum f_o \, log\left(\frac{f_o}{f_e}\right) \tag{3}$$

$$\chi^2 = \sum \frac{(f_e - f_o)^2}{f_e} \tag{4}$$

Where:
f_o = observed frequency in a cell
f_e = expected frequency in a cell

The larger deviance value indicates that the model does not fit the data well. If the model fits the data, both the deviance and the Pearson chi-square statistic divided by the degrees of freedom (DF) should be approximately equal to one [17]. If D/DF and χ^2/DF are greater than one, this indicates that the data is over-dispersed which means that the variance is greater than the mean. Similarly, if D/DF and χ^2/DF are less than one, this means under-dispersion is in the data. If the data is over-dispersed or under-dispersed, it is not right to fit the data in the Poisson model. In the case of over-dispersed data, the NB model is a better model and for under-dispersed data, generalized Poisson or Hurdle models are used.

2.3.2 Model formulation

A crash effect attributable to vehicle color is reflected in an interactive effect on cell counts between the variables of interest. The log-linear model is shown in Equation (5) for either a Poisson or NB distribution. The model used in this paper is based on the procedure developed by Newstead and D'Elia [5] and extended by Owusu-Ansah [12]. The white color is set as a baseline color, i.e., all other colors are compared statistically against the white color in terms of crash risk. The hypothesis test was set as follow:

- Null Hypothesis: H_0 = There is no difference in the risk of crash involvement attributable to vehicle color.
- Alternative Hypothesis: H_1 = There is difference in the risk of crash involvement attributable to vehicle color.

The log linear model following a Poisson or NB distribution is expressed as shown in Equation (5):

$$ln(\mu_{acglpw}) = \alpha + \beta_{aglpw} + \gamma_{acglw} + \delta_{acglpw} \tag{5}$$

Where:
μ = expected crash count for either a Poisson or a NB distribution;
a = driver age group index;
c = index for vehicle color;
g = the gender of the driver index;
l = light condition index;
p = index for vehicle crash group;
w = weather condition index;
α, β, ɣ, and δ are the parameters of the model
.

This model formulation isolates the impact of color from other factors that impact crashes, such as driver and environmental factors. If certain colors are more hazardous than others, the impact would show up as the interaction between color and crash group, which is the δ term in Equation (5). The relative risk of color c relative to white is then given by Equation (6):

$$\rho_i = exp\left(\delta_{acgl1w}\right) \tag{6}$$

It follows that, the 95% confidence intervals for the interaction parameter were calculated for each color using the confidence interval estimator as shown in Equation (7) [14]:

$$ln(\rho_i) \pm Z_{\propto/2}(SE) \tag{7}$$

Where:
i = color code (1=azure, 2 = Beige, 3 = Black, 4 = Blue, …, etc.
$Z_{\alpha/2}$ = value of the standard normal distribution with (1-α) confidence level
SE = estimated standard error

Equation (7) is applied on the assumption that the distribution of the interaction parameters is normally distributed, with mean = 0 and variance = 1. The natural logarithm was taken to achieve normality [14]. The decision criteria would be, if a color with a crash risk ratio less than one is exhibiting a lower crash risk than white color, and a color with a crash risk ratio larger than one is expected to have a higher crash risk than white color.

3. Analysis of results

3.1. Model goodness-of-fit test results

Table 4 summarizes the results of model goodness-of-fit for both Poisson and NB models. The values of deviance and chi-squared divided by the degree of freedom are both much larger than one for the Poisson model which indicates over-dispersion in the data, the situation that Poisson model does not handle well. However, for the NB model, the deviance and chi-squared divided by the degree of freedom are both closer to one. This indicates that the NB model fits our crash data better than the Poisson model. Since the NB regression model fits better for the Ohio crash data used in this paper, only the NB model results are presented here in testing the model hypothesis introduced above in the methodology section.

Tab. 4 - Results of Model Selection Criteria for Poisson and Negative Binomial Models.

Assessment parameter	Poisson Model	Negative Binomial Model
Deviance (D)	8666	1563
Pearson Chi-Square (χ2)	8970	1597
Degree of Freedom (DF)	1332	1332
D/DF	6.5061	1.1742
χ^2/DF	6.7347	1.0215
Log Likelihood	987532	5474110

3.2 Estimated crash risks

Table 5 presents the results of the NB model vehicle color overall estimated relative crash risks for each color compared to white. The relative crash risk of a specific vehicle color shows how risky the color is when compared to white colored vehicles, and the confidence interval shows the probability of the relative risk that lies within it. Lastly, the p-value provides a basis for not rejecting or rejecting the null hypothesis. In this case, the p-value shows whether there is a relationship between the color of the vehicles and crash risk [5]. Table 5 shows that none of the crash risks for each vehicle color are statistically significant. As a result, the null hypothesis is accepted, i.e., there is no difference in the risk of crash involvement attributable to vehicle color.

Tab. 5 - Relative Risk Ratio Estimates for the Negative Binomial Model

Color	Relative Risk	Confidence Level		p Value
		Lower	Upper	
Azure	0.78	0.5692	1.0738	0.1285
Beige	1.13	0.7982	1.5968	0.4928
Black	1.21	0.9433	1.5641	0.1318
Blue	1.01	0.7833	1.2998	0.9446
Brown	0.96	0.6624	1.3887	0.8251
Gray	1.01	0.7789	1.2989	0.9647
Green	1.13	0.8642	1.4869	0.3648
Multicolored	1.42	0.6713	2.9861	0.3609
Orange	1.07	0.6845	1.6847	0.7563
Purple	1.11	0.6718	1.828	0.6876
Red	1.11	0.8657	1.4147	0.4185
Silver	1.02	0.8011	1.3077	0.8524
Yellow	1.13	0.8483	1.4936	0.4123
Tan	0.84	0.641	1.1051	0.2148

The results from the current study agree in all aspects with the previous study by Owusu-Ansah [12], which utilized crash data from the state of Nevada for years 2003-2008. Owusu-Ansah [12] reports that the NB regression model outperformed the Poisson regression model due to the Nevada data being over-dispersed. Equally important, in his study, all of the p-values were larger similar to the current study, and hence none of the vehicle colors are statistically safer or riskier than the vehicle color white.

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4. Discussion

As discussed in the introduction, results from previous studies of the relationship between vehicle color and crash risk presented contradicting results. The main reason may be based on the methodologies utilized in analyzing the crash data. The current study followed footsteps of Owusu-Ansah's study [12] of first seeking to determine the appropriate model between the mostly used Poisson and the negative binomial models for crash data analysis. Standard model selection criteria were used to determine which model fits the Ohio crash data used in the current study better before performing the model estimates. Thus, the negative binomial model was selected to perform the relative risk ratios. Although both studies used the induced exposure study design, Newstead and D'Elia [5], unlike the study by Owusu-Ansah [12], they used the Poisson regression model and they did not mention if they checked their model results for overdispersion. In other words, they did not explicitly show that they tested to check if their model represented the structure or patterns in their data. Without performing such important model goodness-of-fit tests, the conclusions drawn can be questionable due to inability to assess the model as revealed by Owusu-Ansah's study where the Poisson model erroneously showed that orange, purple, black, red, silver, blue, and gray colors were relatively safer than white. Thus, it was a wrong model for their data; therefore it over-stated the significance of the hypothesis testing [12, 16]. Although Newstead and D'Elia [5] overcame the weaknesses of the case-control methods as previously used by Lardelli-Claret et al. [10] and Furness et al. [11] studies by employing the more accepted induced-exposure study design, their results are still doubtful primarily due to their inability to defend whether their model statistically fit the data being modeled. Potentially flawed methodologies used in most of the previous studies that studied the relationship between vehicle color and crash risks are major reasons behind clearly contradictory results and conclusions.

The current study used a similar model design and methodology to that used by Owusu-Ansah [12] with a major exception that the current study utilized crash data from the state of Ohio while the Owusu-Ansah study used crash data from the state of Nevada. It is noteworthy to mention here that there was also another difference between the two studies in the treatment of crash prone group. While a study by Owusu-Ansah used all multi-vehicle crashes in that group, the current study did not include the striking vehicles in multi-vehicle crashes and also multivehicle crashes involving a vehicle crossing the median or centreline were not included.

5. Conclusions

The current study utilized a stratified induced exposure study design in which case vehicles recorded as struck or both striking and struck in multiple vehicle crashes made a crash prone group and vehicles involved in single vehicle crashes were used in the induced exposure group. Initially both Poisson and negative binomial regression models were tested to determine which model fitted better the crash data by using standard statistical goodness of fit model assessment tests. Based on these results, the negative binomial regression model was chosen over the Poisson regression model. The negative binomial model results were then used to compute the relative risk ratios of vehicle colors. The negative binomial regression model results showed that there was no statistically significant relationship between the vehicle color and crash risk, i.e., the model revealed that there was no evidence to say that there is a color that is safer or riskier than the baseline color, white, in terms of crash risk. This paper contributes to the body of literature on vehicle color and crash risk. Specifically, we believe we used a better and more advanced statistical method compared to all used in previous similar studies and thus our results and conclusions are more defensible than the results from previous studies reviewed in this paper.

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