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Research article

Injury-severity analysis of crashes involving defective vehicles and accounting for the underlying socioeconomic mediators

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ABSTRACT

Crashes occur from a combination of factors related to the driver, roadway, and vehicle factors. The impact of vehicles on road crashes is a critical consideration within road safety analysis, even though not much studies have been conducted in this area. This study assessed how various vehicle and other crash factors are significantly associated with crash outcomes. To do this, historical vehicle defect-related crashes were obtained for the state of Alabama from 2016 to 2020. After data cleaning, a crash injury severity model was developed using the random parameters multinomial logit with heterogeneity in means approach to account for possible unobserved heterogeneity in the data. A spatial analysis was further conducted to better understand vehicle defect crashes as a broader societal issue and potentially explore their connection with the socio-demographic characteristics of the drivers of these vehicles. The preliminary data analysis showed that brake and tire defects accounted for about 65% of the vehicle defects associated with the crashes. The model estimation results revealed that improper tread depth and headlight defects were associated with major injury outcomes, while brake defects were more associated with minor injuries. Also, crashes associated with speeding, drunk driving, failure to use seatbelts, and those that occurred on curved roads left with downgrades were likely to result in major injuries. Findings from the spatial analysis showed that postal codes with higher median incomes are more likely to record lower vehicle defect-related crashes, unlike those that have higher proportions of females and African Americans. The study's findings provide data-driven evidence for sustained safety campaigns, workshops, and training on basic vehicle maintenance practices in the low-income communities in the state.

1. Introduction

Every year, thousands of people lose their lives and countless others are injured in road crashes across the globe. While human error is often cited as the primary cause of these crashes, vehicle defects have also been identified as a significant contributor [1]. Even with advanced safety technologies and strict regulations, defects in vehicles can still result in severe crashes, causing injuries, fatalities, and extensive property damage. In the United States, vehicle defect-related crashes have been a persistent safety concern for decades, with design flaws, manufacturing errors, and lack of maintenance leading to numerous incidents [2]. These defects can range from minor

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issues, such as worn-out tires and brakes, to major structural problems [3]. Carfax [2] estimates that greater than one out of every five US vehicles that are on the road have outstanding recalls, meaning that they have a known defective part or design. According to the National Motor Vehicle Crash Causation Survey (NMVCCS) conducted from 2005 to 2007, vehicle defects were found to be 2% of the last failure in the causal chain of events leading to crash out of 5470 crashes that were surveyed. Out of the 2% of crashes associated with vehicle defects, tire problems constituted about 35%, brakes form 22% and other parts constituted the remaining 43% [3]. As the number of older vehicles continues to increase and a high number of defective vehicles continue to be driven on US roads, it is crucial to understand the impact of vehicle defects on road safety and to identify strategies to mitigate the risk of these incidents. This is particularly important in light of efforts towards the development of autonomous vehicles where road safety concerns may shift from the driver to vehicle-related factors and general system failures.

Previous research has largely attributed vehicle crashes to human errors [4–7]. In the seminal study on the Tri-level causes of traffic crashes [1], human factors were cited as probable causes in 92.6% of crashes investigated and environmental factors were cited as the probable cause in 33.8%, while vehicular factors were identified as probably causes in 12.6% of the crashes. The major vehicular causes identified in the study were brake failure, inadequate tread depth, side-to-side brake imbalance, under-inflation, and vehicle-related vision obstructions. In another study, vehicle defects were one of the 15 safety problems identified by the National Highway Traffic Safety Administration during vehicle inspection [8]. Unlike human errors, vehicle defects are more technical in nature and can be addressed through direct solutions [9]. While vehicle defects are typically repairable, the capacity of drivers or vehicle owners to address these issues is influenced by various factors, including financial limitations. For example [10], identified a significant association between the ownership of defective vehicles and the socioeconomic status of drivers. This underscores the importance of adopting a human-centered approach in addressing road safety concerns related to vehicle defects. Implementing suitable countermeasures targeted at drivers and vehicle owners with defective vehicles is crucial. The effectiveness of these measures, such as education and awareness campaign, relies on the accurate identification of the geographic distribution of these drivers. For instance, Carfax [2] suggested that drivers in the southern parts of the US are most likely to have cars with open recalls. Their research found that southern states like Alabama have the highest open recall percentage. As such, efforts to address the issue of defective vehicles and road safety can appropriately be targeted to residents in these states.

In contrast to crash studies that primarily focus on human factors, there has been a limited number of studies conducted to explore the contribution of vehicle defects to crash occurrence and outcomes. One such earlier study conducted an "on-the-spot" investigation of 502 crashes involving commercial vehicles and buses in South Africa [11]. The results from this study revealed that vehicle defects contributed to 9% of the crashes. Another study investigated the contribution of mechanical failures to motor vehicle crashes in the Pretoria region of South Africa [12]. The study data from the crash response unit (ARU) revealed that tires and brakes were the major contributors to mechanical failures resulting in crashes. Further analysis using roadside survey (potential mechanical defect tests) indicated that 40% of the vehicles surveyed on the suburban road and 29% of the vehicles surveyed on the highway had mechanical defects that may contribute to crash occurrence as a result of a mechanical failure. Tire inflation pressure were identified as a cause of concern in minibus surveys. Most recent studies also indicated that mechanical failures are the most common vehicle defects responsible for crashes [13,14].

Regarding vehicle components that are mostly involved in vehicle defect-related crashes, a study identified that brake system defects, running gear defects and tire defects were the key factors that contribute to road crashes [15]. The study also revealed that older vehicles were more prone to crashes due to inadequate service and maintenance, which is consistent with the findings of other research efforts [16–19]. Another study investigated the common vehicle defects that contribute to road crashes using data gleaned from inspecting private passenger vehicles and found that worn out tires and structural integrity were the two most common vehicle defects associated with private passenger vehicles [9]. The study also found that vehicles sent for voluntary inspections have a higher probability of failure as compared to vehicles sent for routine inspections. Using 7 years crash data (2010–2016) from Louisiana [19], also identified worn-out tires and defective brakes as being overrepresented in vehicle defect associated crashes.

Aside from identifying vehicle components that are more likely to fail, some researchers also investigated the factors contributing to those failures. For instance Ref. [20], investigated factors affecting tire failures using ten years (2007–2016) of historical crash data along I-80 in Wyoming. Results from the study revealed that vehicle speeds greater than 75 mph, commercial motor vehicles, summer season, daytime, the presence of rough surface, downgrades, and concrete pavement are all related to higher tire failure occurrences. In addition, tire failure in combination with fire or explosion, rollover, guardrail hits, ran-off road, angle, rear-end, clear weather, speeding, downgrades, and curved segments were found to be associated with severe injuries. In another study, factors affecting brake failure and their corresponding injury were investigated using crash data from Wyoming [21]. It was found that people in older vehicles (>15 years), trucks, and downhill grade segments were more likely to experience brake failures. Brake failure related crashes involving vehicle age greater than 15 years, truck and SUV/Pick up, female driver and airbag deployment results in a more severe injury.

To be able to prioritize the implementation of vehicle defect-related crash countermeasures, there is the need to identify and quantify the extent of contribution of various defects to crashes and crash outcomes. Typically, this process involves the use of some statistical or mathematical analytic tool. Previous studies have used several methods in analyzing factors associated with vehicle defects. Some of the methods used include logistic regression [9], Bayesian data mining [19], Bayesian binary logit [20,21] and Chi-square analysis [21]. However, there are not many studies that explored and quantified the effect of vehicle defects on crash severity, using an advanced statistical/econometric modeling method that can account for unobserved heterogeneity in the crash data [22].

While previous studies have been successful in identifying factors that are associated with various vehicle defects, failing to account for unobserved heterogeneity in crash data during injury-severity analysis can lead to biased parameter estimates and potentially

Table 1
Descriptive statistics of variables associated with vehicle defect crashes.

Variable		Frequency	Percentage
Crash Severity	Major Injury	681	4.52
	Minor Injury	2962	19.68
	No Injury	11411	75.8
Primary Contributing Factors	Defective equipment	7611	50.56
	Driving too fast for condition	1051	6.98
	Misjudging stopping distance	973	6.46
	Followed too close	901	5.99
	Ran off road	417	2.77
	Other -No improper driving	328	2.18
	Ran traffic signal	248	1.65
	Driving under influence (DUI)	129	0.86
	Other	3396	22.56
Gender	Male	9899	65.76
	Female	5155	34.24
Driver Age	15–19	2225	14.78
	20–39	7873	52.3
	40–59	3627	24.09
	more than 60	1329	8.83
Manner of Crash	Single vehicle crash	6282	41.73
	Rear end	4048	26.89
	Side impact (90°)	693	4.6
	Side impact (angled)	632	4.2
	Head on	283	1.88
	Other	3116	20.7
First harmful event	Collision with Vehicle in Traffic	6092	40.47
	Vehicle Defect/Component Failure	1746	11.6
	Collision with Ditch	731	4.86
	Collision with Tree	474	3.15
	Overturn/Rollover	385	2.56
	Collision with Concrete Barrier	349	2.32
	Ran Off Road Right	898	5.97
	Ran Off Road Straight	101	0.67
	Ran Off Road Left	498	3.31
	Other	3780	25.11
Safety Equipment	Shoulder and Lap Belt Used	13296	88.32
	No safety equipment used	630	4.18
	Unknown	1128	7.49
Airbag status	Airbag deployed	2754	18.29
	Airbag not deployed	10496	69.72
	Airbag not installed	1437	9.55
	Others	367	2.44
Vehicle Age	0–5 years	2319	15.4
	6–10 years	2640	17.54
	more than 10 years	10095	67.06
Vehicle Type	Passenger Car	6790	45.1
	Pick-Up (Four-Tire Light Truck)	3154	20.95
	Sport Utility Vehicle (SUV)	2770	18.4
	Tractor/Semi-trailer	872	5.79
	E Single-Unit Truck (2-Axle/6-Tire)	262	1.74
	Others	1206	8.01
Contributing vehicle defect	Brakes	6326	42.02
	Tire Blowout/Separation	3374	22.41
	Improper Tread Depth	1628	10.81
	Headlights	109	0.72
	Wheels	849	5.64
	Taillights	110	0.73
	Others	2658	17.66
Driver Employment Status	Employed	8566	56.9
	Unemployed	2491	16.55
	Self-employed	875	5.81
	Retired	553	3.67
	Others	2569	17.07
Roadway curvature and Grade	Straight and Level	9225	61.28
	Straight with Down Grade	1963	13.04
	Straight with Up Grade	1149	7.63
	E Curve Left and Down Grade	445	2.96
	Others	2272	15.09
Weather	Clear	9296	61.75

(*continued on next page*)

Table 1 (*continued*)

Variable		Frequency	Percentage
	Cloudy	2735	18.17
	Rain	2462	16.35
	Others	561	3.73

erroneous decisions and countermeasures [22]. The dearth of literature in this area limits an understanding of how vehicle defects and other related factors like open recalls are statistically associated with crash occurrence and different crash severities. This research seeks to fill the gap and add more information to the already existing literature in vehicle defect-related crashes. In doing so, the study used crash data from Alabama and adopted the random parameters multinomial logit modeling technique to explore relationships between vehicle defects and other crash factors and crash severity, while accounting for unobserved heterogeneity associated with the crash data. The random parameter multinomial logit approach was adopted because it is a leading heterogeneity modeling method that has extensively been used in several crash studies [23–27] to establish how a set of crash contributing factors are associated with crash severity. By adopting this analytical method, the model estimation results are expected to be more accurate and reliable for decision making. Also, spatial analysis was conducted to examine the correlation between the vehicle defect crashes and the socio-demographic factors of drivers' residential zip code across the study areas. The findings of this study will be useful to guide in the design, development, and roll out of vehicles equipped with more advance technologies and durable features that are not prone to unexpected defects. It will also inform the prioritization of safety measures in areas more prone to vehicle defect crashes.

2. Data description

The Alabama crash data used for this study was obtained from the Critical Analysis Reporting Environment (CARE) software system developed by the University of Alabama Center for Advanced Public Safety (CAPS) for the period covering 2016 to 2020. This database contains all crashes that occur in the state and includes information related to the roadway, crash characteristics, driver attributes, temporal charactistics, vehicle characteristics, crash contributing circumstances, casualty information, etc. This is the primary source of crash data for academic research and policy decisions in the state. To obtain the necessary data for this study, the CARE system was queried to filter only crashes in which the reporting officer reports vehicle defect as a contributing circumstance of the crash. After cleaning the data, 15,054 crashes were available for analysis. Originally, the severity of the crashes was reported using the KABCO scale where K is a fatal crash, A is a suspected serious injury, B is suspected minor injury, C is possible injury, and O is property damage only. However, in this study, three crash severity categories were considered as major injury outcome (defined as crashes in K and A), minor injury outcome (defined as B and C), and no injury (defined as O). Based on this classification, 4.52% of the crashes were major injury, 19.68% were minor injury and the remaining 75.8% resulted in no injury.

Preliminary data analysis revealed that defective equipment was the primary contributing factor in 50.56% of the crashes, indicating that in a little over half of the total crash observations, some form of vehicle defect is deemed to be responsible for the crash. In the remaining 49.44% of the crashes, other factors were the primary contributing factor to the crash, but the vehicle defect played a secondary role. For instance, driving too fast (6.98%), misjudging stopping distance (6.46%) and followed too close (5.99%) were some of the other major primary contributing circumstances associated crashes in which the vehicle had some defect which also contribute either to the crash occurrence or the crash outcome. Considering driver demographics, male drivers (65.76%) were overrepresented in vehicle defect related crashes as compared to females (34.24%). In addition, drivers between 20 and 39 years (52.3%) formed majority of the age group represented in vehicle defect related crashes as compared to drivers between 15 and 19 years (14.78%), 40–59 years (24.09%) and drivers older than 60 years (8.83%).

Regarding the vehicle characteristics, passenger cars (45.1%), SUV (18.4%) and pick up (20.95%) were the major vehicle types associated with this type of crash. Vehicles older than 10 years also formed 67.06% of the total vehicles involved in the crash. A relatively smaller proportion of vehicles were between 0 and 5 years (15.4%) and 6–10 years (17.54%). This revealed that as vehicles age, they may develop some defects which will increase their likelihood of getting into a crash. For the specific vehicle defects, brake

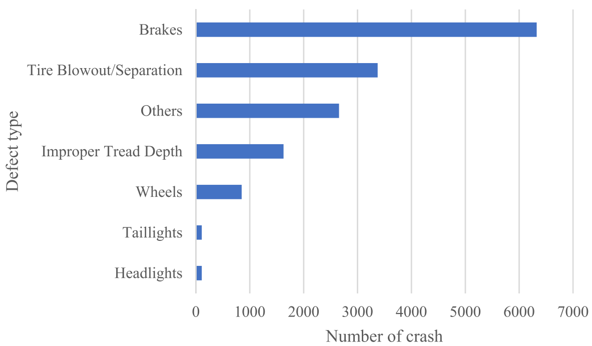


Fig. 1. Distribution of number of crashes by contributing vehicle defects.

failure accounted for 42.02% of the compared to 22.41% for tire blow out, 10.81% for improper thread depth and 5.64% for defective wheels. The descriptive statistics of other variables associated with the vehicle defect crashes are summarized in the Table 1 below and Figs. 1–3 present the distribution of some key crash variables.

The socioeconomic data from about 559 zip codes in Alabama was extracted from the United States Census Bureau (https://data.census.gov/all?q=zip+code&g=040XX00US01$8600000_860XX00US30165). Regarding the number of crashes per zip code, crash frequency ranged from 1 to 215. The average median household income was $52,081, with certain households within a zip code earning as low as $5761 and as high as $138,438. Regarding gender, the average number of females in the zip codes under study was 4,553, and people with only high school diplomas ranged from 0 to 9062. The number of Blacks/African Americans also varied from 0 to 35,694 across zip codes. Table 2 presents the descriptive statistics of the socioeconomic data.

3. Methodology

3.1. Injury severity analysis

Over the years, safety researchers have adopted different modeling techniques to uncover the relationship between crash severity outcomes and their contributing factors to facilitate the proposition of more effective countermeasures. While all modeling techniques have inherent limitations, some are seemingly more robust and can account for unobserved heterogeneity usually associated with crash data [28]. Accounting for unobserved heterogeneity in crash severity studies is essential in improving statistical model inference and has become an acceptable standard in this area of research [22]. Heterogeneity models enable analysts to develop better model estimates by accounting for observation-specific variations in the effects of explanatory variables [22,29,30]. Some of the commonly used heterogeneity models include random parameter ordered probability models [31], random parameter multinomial logit models [30,32,33], random parameter models with heterogeneity in means and variances [34,35], latent class model [36], and latent class logit and mixed logit models [37,38]. This study utilizes a random parameters (mixed) logit model with heterogeneity in means to accommodate potential variations in the observations.

To start with, a severity function S_{kn} that determines the probability that crash severity level k will result in crash n was defined as [39],

$$S_{kn} = \beta_k X_{kn} + \varepsilon_{kn} \tag{1}$$

where X_{kn} is a vector of explanatory variable that affect severity level k (major injury, minor injury, no injury) in crash n, and ε_{in} is the disturbance (error) term [39] assumed to follow an independent and identically extreme value of Type-1 distribution [40] Also, in Eq. (1), β_k represents a vector of estimable parameters that varies across crash observations to account for unobserved heterogeneity [22]. This is expressed mathematically in Eq. (2) as:

$$\beta_n = b + \Theta Z_n + \varphi_n \tag{2}$$

where b is the mean parameter estimate across all crash observations, Z_n is a vector of explanatory variables from crash n that influence the mean of β_n, Θ is a vector of estimable parameters, and φ_n is a stochastic term that captures unobserved heterogeneity across crashes.

By allowing crash-specific unobserved heterogeneity, β_n vector is made to have a continuous density function $P(\beta_n = \beta) = f(\beta|\varphi)$, where φ is a vector of parameters characterizing this function. Thus, the resulting random parameters multinomial logit crash severity probabilities are:

$$P_n(i) = \int \frac{exp\ (\beta_k X_{kn})}{\Sigma\ exp(\beta_k X_{kn})} f(\beta|\varphi) d\beta \tag{3}$$

where $P_n(i)$ is the probability of crash severity k in crash n conditioned on $f(\beta|\varphi)$. This model is estimated by simulated maximum likelihood estimation where the logit probabilities shown in Eq. (3) are approximated by drawing values of β from $f(\beta|\varphi)$ for given

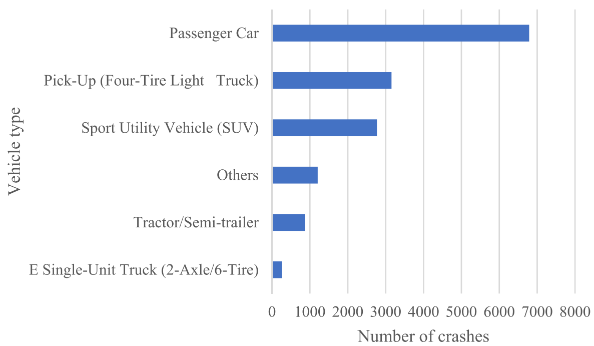


Fig. 2. Distribution of number of crashes by vehicle type.

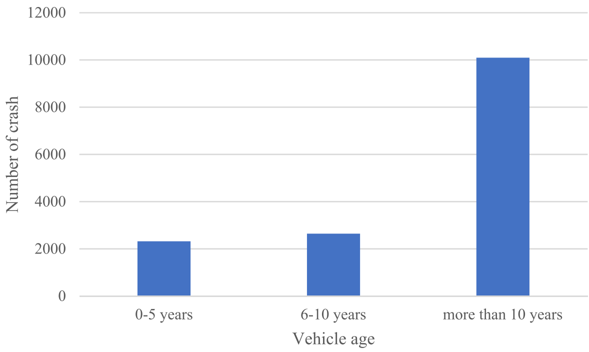


Fig. 3. Distribution of number of crashes by vehicle age.

Table 2
Descriptive statistics of socio-economic variables associated with zip codes in Alabama.

Variable	Mean	Standard Deviation	Min	Max
Number of crashes per zip code	23.7	25.78	1	215
Median household income	52081.37	18559.96	5761	138438
Female	4553.14	5016.94	18	29737
High school diploma	1533.78	1464.43	0	9062
Black alone	2344.41	4132.20	0	35694
Population	8862.13	9617.57	108	57077

values of φ. According to Ref. [41], Halton sequence approach [42] is an efficient method of drawing values to compute the logit probabilities. For this study, 1500 Halton draws was used to estimate possible mixing distributions and the normal probability density function was considered most appropriate for the random parameters among other statistical distributions like uniform, lognormal, Weibull, and triangular distributions. This distribution has also been used in several other safety-related studies [43,44].

Additionally, the marginal effects were computed to investigate the effect of explanatory variables on the crash severity outcome probabilities [39]. By coding all the explanatory variables as indicator variables, the marginal effects are calculated using Eq. (4).

$$ME_{X_{ijk}}^{P_{ij}} = P_{ij}\left(X_{ijk} = 1\right) - P_{ij}\left(X_{ijk} = 0\right) \tag{4}$$

The marginal effects indicate the effect of the explanatory variable increasing from a value of 0 (i.e., no effect) to 1 on the crash severity outcomes [39,45,46]. Therefore, in Eq. (4), the marginal effect of k^{th} indicator variable, X_{ijk} is the probability difference when X_{ijk} changes from 0 to 1 while other variables are constant. The marginal effects for variables with random parameter were computed as the mean of the marginal effects across all crash observations.

3.2. Spatial analysis

Spatial analysis of the crashes was further conducted to understand the correlation between vehicle defect crashes and the underlying socio-demographic factors of the regions (specifically zip codes) where the drivers live. A Multiscale Geographically Weighted Regression (MGWR) model was developed, and the results were compared to those obtained from an Ordinary Least Square (OLS) model to see which of the two models provides a better fit and understanding of the data. OLS as one of the mostly used linear regression for spatial analysis can model the relationship between the response variable and a set of explanatory variables. Given a set of n explanatory variables, the OLS model can be expressed as shown in Eq. (5) [47,48].

$$y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \varepsilon \tag{5}$$

where y is the response variable, x_i is the i-th explanatory variable in the model, β_0 represents the model intercept, β_i is the vector of estimated global coefficient for x_i and ε is the estimated random error.

The MGWR is an improved version of the geographically weighted model (GWR) capable of accommodating the nonstationary relationships between the response variable and the predictors at different spatial scales. Unlike the traditional linear regression that is build on the assumption that the same stimulus triggers the same response across space, the GWR account for the nonstationary behavior of some spatial data, meaning that the relationship between the response variable and the predictors may vary spatially. The GWR accommodate this potential variation by modifying the coefficients of different locations [49]. The GWR model formulation can be represented as follows in Eq. (6).

$$y_i = \sum_{j=0}^{m} \beta_j(u_i, v_i)x_{ij} + \varepsilon_i \tag{6}$$

where y_i is the response variable x_{ij} is the j th predictor variable, $\beta_j(u_i, v_i)$ is the j th coefficient, and ε_i is the error term.

While the GWR can capture the nonstationary spatial relationships, it ignores the influence of scale – a fundamental geographic concept. It assumes that relationship between the response variable and the predictors vary at the same spatial scale. The MGWR relaxes this assumption by allowing the relationship between the response variable and the predictors to vary at different spatial scales [50]. This relationship is expressed as shown in Eq. (7) [48,49].

$$y_i = \sum_{j=0}^{m} \beta_{bwj}(u_i, v_i)x_{ij} + \varepsilon_i \tag{7}$$

where *bwj* in β_{bwj} represents the bandwidth used for calibrating the *j*-th conditional relationship.

Table 3
Model results including the marginal effects.

Variables	In Injury severity of:	Parameter estimates:	t-statistics	Marginal Effects		
				Major Injury	Minor Injury	No Injury
Constant		1.47	17.91			
Random Parameter						
Shoulder and Lap Belt Used	Major Injury	−3.01	−3.75	−0.0066	0.0009	0.0057
Standard deviation “Shoulder and Lap Belt Used” (Normally distributed)		1.94	3.24			
Male driver	Minor Injury	−1.13	−5.29	−0.0006	0.011	−0.0104
Standard deviation “Male” (Normally distributed)		1.99	6.83			
Overturn/Rollover	Minor Injury	0.69	2.19	−0.0014	0.012	−0.0106
Standard deviation “Overturn/Rollover” (Normally distributed)		2.66	2.9			
Heterogeneity in means						
Shoulder and Lap Belt Used: Tire blowout or separation		0.56	3.57			
Male driver: Tire blowout or separation		−0.34	−2.81			
Overturn/Rollover: Tire blowout or separation		0.54	1.84			
Crash characteristics						
DUI	Major Injury	0.61	2.46	0.0008	−0.0001	−0.0006
Head on crash	Major Injury	0.79	3.21	0.001	−0.0002	−0.0008
No shoulder and lap belt used	Major Injury	0.78	6.22	0.0056	−0.0011	−0.0045
Airbag deployed	Minor Injury	1.27	14.22	−0.0011	0.0177	−0.0166
Collision with a ditch (First harmful event)	No Injury	−0.38	−3.38	0.0007	0.0021	−0.0029
Driving too Fast for Conditions	No Injury	−0.35	−3.73	0.001	0.003	−0.0039
Rear end collision	No Injury	0.36	5.61	−0.0039	−0.0108	0.0127
Driver Characteristics						
Teenage driver (13–19 years)	Minor Injury	0.48	4.86	−0.0004	0.0086	−0.0081
Driver Age (20–39 years)	Minor Injury	0.45	5.74	−0.0015	0.0275	−0.026
Employed	No Injury	0.39	7.86	−0.006	−0.0219	0.0279
Driver age (40–59 years)	No Injury	−0.25	−3.17	0.0021	0.0058	−0.0079
Road and Environmental Characteristics						
Curve Left and Down Grade	Major Injury	0.70	3.32	0.0014	−0.0003	−0.0011
Rain	Major Injury	−0.60	−3.94	−0.003	0.0006	0.0025
Vehicle Characteristics						
Improper Tread Depth (Vehicle defect)	Major Injury	1.12	7.65	0.0079	−0.0015	−0.0064
Pick up	Major Injury	−0.48	−3.82	−0.0032	0.0005	0.0027
Brake (Vehicle defect)	Minor Injury	0.43	6.79	−0.0009	0.0229	−0.022
Component failure (first harmful event)	Minor Injury	−0.46	−4.18	0.0002	−0.0041	0.0039
Passenger car	No Injury	0.21	4.09	−0.0027	−0.0109	0.0136
Wheels (Vehicle defect)	No Injury	0.33	2.66	−0.0004	−0.0016	0.002
Headlight (vehicle defect)	No Injury	−1.12	−4.59	0.0005	0.0011	−0.0015
Vehicle age (less than 6 years)	No Injury	0.39	5.26	−0.0015	−0.0057	0.0072
Vehicle age (6–10 years)	No Injury	0.26	3.99	−0.0012	−0.0049	0.0061
Model Statistics						
Number of Observations	15054					
Log-likelihood at constants	−16538.51					
Log-likelihood at convergence	−9396.51					
McFadden Pseudo r squared	0.43					

4. Results

4.1. Injury severity model results

The estimated results for the vehicle defect related crash severity are summarized in Table 3. Variables were entered into the model if they were found to be significant at 0.05 significance level. The McFadden Pseudo ρ^2 for the estimated model was 0.43. In all, 25 variables were found to be significant, indicating their significant associations with crash severity. The indicator variables for "Shoulder and Lap belt Used", "Male driver", and "Overturn/Rollover" were found to be random parameters. The model was estimated using Nlogit version 6.

Regarding the random parameters, the indicator variable "Shoulder and Lap belt used" defined for the major injury function had a mean of −3.01 and a standard deviation of 1.94. From the normal distribution curve these numbers indicate that for 6.04% of crashes where the seat and lap belts were used, the probability of major injury was high but for the remaining 93.96% of crashes where shoulder and lap belts were used, the probability of major injury was low. The indicator variable for "Male driver" (defined for the minor injury function) had a mean of −1.13 and a standard deviation of 1.99. On the normal distribution curve, these numbers indicate that for 28.51% of crashes involving male drivers, there was a higher probability of minor injury. For the remaining 71.49%, the probability of minor injury was low. Furthermore, the indicator variable "Overturn/Rollover" defined for the minor injury had a mean of 0.69 and standard deviation of 2.67, revealing that for 60.20% of crashes where the vehicle overturned or rolled over, the probability of minor injury was high. For the rest of the 39.80% of crashes where the vehicle overturned or rolled over, the probability of minor injury was low. Concerning the heterogeneity in means of the random variables, the indicator variable for "tire blowout/ separation" increased the mean of the "shoulder and lap belt use" and "overturn/rollover" random parameter variables and decreased the mean of the male driver random parameter variable. This reveals that tire blowouts or separation crashes involving drivers using shoulder and lap belts were more likely to result in major injury. Also, tire blow out or separation crashes where vehicles rolled over or overturned were more likely to result in minor injuries. However, tire blowouts/separation crashes involving male drivers were less likely to result in minor injuries.

The marginal effects result showed that crashes, where shoulder and lap belt were used, were less likely to result in major injury while the likelihood of minor and no injury was high. For crashes involving male drivers, the probability of major and no injury was low while the likelihood of minor injury is high. Lastly, the indicator variable, "Overturn/Rollover" increased the probability of minor injury by 1.2% and decreased the likelihood of major and no injury by 0.14% and 1.06% respectively. The marginal effects of the non-random variables were summarized below.

4.2. Crash characteristics

Several variables related to the crash characteristics were found to significantly influence the injury severity of the crashes. The marginal effects of head-on crashes, drivers charged with drinking under the influence, and drivers not using lap and shoulder belts increased the probability of major injury by 0.001, 0.0008, and 0.0056 respectively while the probability of minor and no injury is low. In addition, crashes involving collision with a ditch and driving too fast for the condition were more likely to result in major and minor injuries while the probability of no injury was low. In crashes where an airbag was deployed, the probability of major and no injury was low while the probability of minor injury was high. Similarly, the "rear end collision" indicator variable reduced the probability of major and minor injury by 0.0039 and 0.108 respectively and increased the of no injury by 0.0127.

4.3. Driver characteristics

Regarding the demographics associated with the at-fault driver, the indicator variable for "Teenage driver (15–19)" and "Driver aged (20–39)" increased the probability of minor injury by 0.0086 and 0.0275 respectively while the probability of major and no injury was low. However, crashes involving drivers between 40 and 59 years were more likely to result in major and minor injury while the probability of no injury was low. In addition, the marginal effects showed that crashes involving employed drivers reduced the likelihood of major and minor injury by 0.006 and 0.0219 respectively while the probability of no injury increased by 0.0279.

4.4. Road and environmental characteristics

The nature of the roadway plays an important role in the occurrence of crashes. Crashes that occurred on roads that are curved left with downgrades were likely to result in major injuries while the probability of minor and no injury is low. Also, the indicator variable for rain reduced the probability of major injury by 0.003 while the probability of minor and no injury was high.

4.5. Vehicle characteristics

Some of the vehicle defect variables are discussed in this section. For instance, the indicator variable for improper tread depth increased the likelihood of major injury by 0.0079 while the probability of minor and no injury was low. It was further found that crashes involving defective brakes were less likely to result in major and no injury while the probability of minor injury was high. In addition, crashes involving wheel defect were less likely to result in major and minor injuries while the probability of no injury was high. Furthermore, indicator variable for headlight defect increased the probability of major and minor injury by 0.005 and 0.0011 respectively while the probability of no injury was low.

Regarding vehicle type, crashes involving pick up trucks with a defective component were less likely result to in major injury while the probability of minor and no injury is low. Conversely, the marginal effect of the passenger car indicator variable reduced the probability of major and minor injuries by 0.0027 and 0.0109 while the probability of no injury was low. Also, crashes involving vehicles aged less than 6 years and vehicles aged between 6 and 10 were both less likely to result in major and minor injury while the probability of no injury was high.

4.6. Spatial analysis results

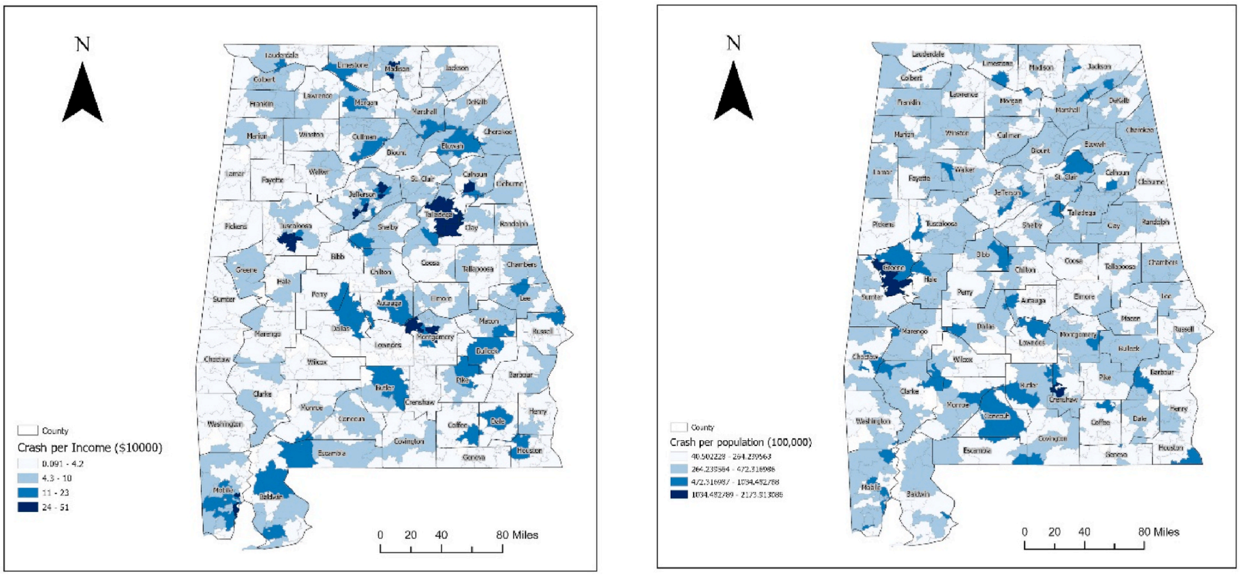
The number of crashes was aggregated by postal code of the at-fault driver's residence (this information was obtained by the reporting officer from the license of the driver). Fig. 4 (a and b) presents the distribution of vehicle defect-related crashes based on the average income and population of the residential code of the driver. The maps were generated using ArcGIS Pro. The number of crashes was normalized using the population and median household income for the residential postal code of the at-fault driver. From the choropleth map, postal codes in counties like Mobile, Baldwin, Greene, Talladega, Jefferson, and Montgomery recorded a significantly high number of vehicle defect crashes based on median household income. Regarding the population, postal code areas in counties like Greene, Conecuh, Mobile, St. Clair and Shelby recorded high number of crashes per 100,000 population.

Considering how crash numbers were distributed based on social and economic variables like population and median household income, a thorough spatial analysis was conducted using other variables like postal code race and educational background information to investigate how these factors affect vehicle defect related crashes using Ordinary Least Square (OLS) and Multiscale Geographically Weighted Regression (MGWR) models. Prior to developing the model, a Variance Inflation Factor (VIF) test was conducted to select variables that will improve regression results and reduce multicollinearity among predictors. A VIF of 5 was selected as a threshold. Median household income has a VIF score of 1.416543, female population had a score of 3.621027, High school diploma holder population had a score of 4.423583, and Black/African American population had a score of 2.460583.

4.7. Spatial regression results

The study used the MGWR and OLS to explore the spatial relationship between the frequency of crashes in different postal codes and various social/economic variables. The two models were also compared based on the goodness of fit. Using the R-squared and the corrected Akaike information criterion (AICc), the MGWR was observed to outperform the OLS (see Table 5). The Variance Inflation Factor (VIF) was also used in selecting the independent variables to avoid multicollinearity. This was done to avoid using independent variables that are highly correlated with each other. A VIF threshold of 5 was chosen in selecting variables based on previous research by Ref. [51]. Variables like Median household income, number of people with high school diploma, number of black/African American in the postal code area, and the number of females were selected for the model (See Table 4). The model was estimated using ArcGIS pro.

The result of the OLS shows that the number of females have a positive correlation with the number of vehicle defect related



(a) (b)

Fig. 4. Distribution of the number of crashes per (a) Income and (b) Population.

Table 4
VIF scores for selected variables.

	Median household income	Female pop	High school diploma pop	Black/African American alone pop
VIF scores	1.42	3.62	4.42	2.46

Table 5
OLS and MGWR estimation results for exploring the relationship between number of crashes and selected social/economic variables.

Variables	OLS	t-statistics	MGWR			
	Coefficient		Coefficient			Optimal Number of Neighbors
			Mean	Max	Std Dev	
Intercept	1.85	1.40	0.0083	0.3428	0.1533	41
Median Household Income	−0.000022	−0.88	−0.041	0.1386	0.0701	55
Female pop	0.000767	3.93	0.2068	0.6336	0.2159	55
Only high school Diploma pop	0.01	16.13	0.5095	0.8655	0.1501	35
Black/African American pop	0.002	13.41	0.3052	0.5355	0.1599	55
R squared	0.8797		0.9554			
AICc	4047.0898		124.4677			

crashes. The variables “Black/African American” and “Only high school diploma” also have strong positive correlation with the number of crashes involving drivers in the postal codes. However, the variable “Median Household Income” has a negative correlation with the frequency of crashes. This trend is similar in the MGWR model. In comparing both models, the MGWR fits better with a higher R-squared value (0.96) as compared to OLS (0.88). The MGWR also has significantly lower AICc scores than OLS.

5. Discussion

Road crashes are often influenced by vehicle defects, which encompass faults or malfunctions in mechanical or electrical components that can compromise the vehicle’s safety, reliability, and performance. Some common vehicle defects, identified from historical crash data, include braking system failure, tire blowouts, and improper tire thread depth. When these defects coexist with other crash-contributing factors, they can lead to more severe crash outcomes. For example, if a vehicle experience braking system failure while speeding, the likelihood of a severe crash increases significantly. To investigate the impact of various crash factors on the severity of vehicle defect-related crashes, this study utilized an advanced econometric modeling technique that considers unobserved heterogeneity across crash observations. This research is particularly crucial given the ongoing development of autonomous vehicles. As the world moves towards a future with self-driving cars, safety concerns may shift from human error to vehicle-related factors and general system failures. Therefore, understanding the contribution of vehicle defects to crash severity becomes increasingly important to ensure the safety and reliability of autonomous vehicle technology.

In order to gain deeper insights into the impact of vehicle defects on crash occurrences and injury severity, this research used historical crash data from Alabama. The initial analysis revealed that brake defects accounted for a significant proportion, representing 42% of all the defects that were deemed to be associated with the crashes, followed by tire blowouts which made up 22.4%. A related study also highlighted the prevalence of worn tires and defective brakes in vehicle defect-related crashes, indicating that these issues were overrepresented [3]. Additionally, it was observed that airbags were not deployed in around 70% of the crashes, and approximately 67% of the defective vehicles were more than a decade old. These findings provide valuable information about the key factors contributing to crashes and injury severity related to vehicle defects in the state of Alabama. A study by DEKRA Automobil GmbH [15] found that older vehicles are more prone to crashes because of poor maintenance. These findings underscore the safety concerns related to aging vehicles and insufficient or improper vehicle maintenance. As a result, it becomes crucial to prioritize regular maintenance and timely repairs to identify and rectify any potential defects that could lead to serious crashes. By taking proactive measures, such as regular inspections and addressing issues promptly, we can significantly reduce the risk of road crashes caused by vehicle defects and ensure safer road conditions for everyone. As common in most road traffic crash studies [52–54], factors such as driving too fast for condition, DUI, road curvature, and non-compliance with the use of lap and shoulder belts increased the probability of major injury outcomes. However, vehicle defects can play a significant role in the final crash outcomes. An earlier study noted that vehicle defects were among the last in the chain of events leading to final crash outcome [3]. Most vehicle defects like brake failure can limit the ability of the driver to bring the vehicle to a stop during a crash event.

Approximately 42% of the crashes in this study were linked to brake defects, and these defects were found to be more associated with minor injuries. It is possible that some drivers, aware of their braking system issues, choose to drive with a sense of caution, possibly avoiding situations that require sudden or hard braking. Such drivers could be considered risk-takers. The results also showed that improper tread depth or worn-out tires are associated with major injury crashes. These vehicle defects are more likely to result in tire blowouts. At higher speeds, tire blowouts could lead to severe injury outcomes. Implementing measures to encourage drivers to prioritize regular vehicle maintenance can help to minimize the risk of crashes. Such measures can include installing in-vehicle safety features that alert the driver to check the tire road worthiness after a set threshold. By addressing and eliminating vehicle defects from the chain of events leading to the final crash outcomes, we could potentially limit the severity of crash outcomes.

The random parameters account for the potential variations of the effects of the random variables across the crash observations due to unobserved factors contributing to the crash outcomes. For instance, the results showed that the probability of major injury crashes is high for only 6.04% of the crashes when shoulder and lap belt is used. It implies that seatbelt use reduces the possibility of severe outcomes for 93.96% of vehicle defect-related crashes. While seatbelt is associated with severe injury outcomes for a small proportion of the observations, tire blowout during a crash increases the likelihood of severe injury outcomes.

Generally, vehicle defect-related crashes can be attributed to the neglect of basic vehicle maintenance, which may be due to ignorance or financial constraints faced by some vehicle owners. To understand these crashes as a broader societal issue and potentially explore their connection with socio-demographic characteristics, a spatial analysis was undertaken. This study delved into the social, economic, and educational backgrounds of drivers based on their residential zip codes. Previous studies (e.g., Adanu et al. [55]) have observed that drivers that share a common regional socioeconomic context are more likely to experience similar road safety problems. The ability to identify clusters of drivers with common road safety problems presents an opportunity for a targeted implementation of countermeasures. To explore the complex interplay of these factors and to identify potential clusters of drivers who were involved in vehicle defect-related crashes a Mixed Geographically Weighted Regression model was employed within ArcGIS 3.0. This innovative method allowed coefficients of explanatory variables to vary across different spatial locations. Unlike the traditional Geographically Weighted Regression (GWR), this approach considered the distinct characteristics of various neighborhoods for each explanatory variable, offering a more nuanced and detailed analysis of the relationship between socio-demographic factors and vehicle defect-related crashes. The results of this analysis validated findings in previous studies regarding the driver population that is most likely to be involved in vehicle defect-related crashes. It was found that there is a negative correlation between median household income and the frequency of vehicle defect crashes, indicating that drivers from lower-income zip codes are more prone to such incidents. While a previous study by Ref. [10] demonstrated that drivers from low-income areas have lower overall crash rates, they also found that crashes specifically related to vehicle defects are more prevalent in lower-income areas. The study posited that their observation may be attributed to the financial burden associated with vehicle maintenance, repairs, and acquiring newer vehicle models. Interestingly, our study found that zip codes with a higher number of female residents were associated with a higher frequency of vehicle defect-related crashes. Although female drivers are often perceived as more cautious, previous research from PEMCO Insurance [56] indicated that female drivers are less likely to engage in self-maintenance of their vehicles compared to men. This may perhaps be due to a lower knowledge of the mechanical design and operation of vehicles among female drivers. Also, while women are more inclined to rely on repair shops, they may also face higher price quotes compared to men [57]. These factors, among others, contribute to a lower likelihood of female drivers to maintain their vehicles properly and therefore exposing them to vehicle defect-related crashes.

Regarding racial and educational attainment distributions, zip codes with a higher population of African Americans and those that had a higher number of individuals with only a high school diploma exhibited a positive correlation with vehicle defect-related crashes. Interestingly, these zip codes are also associated with higher levels of poverty in the state. Indeed, data on poverty rates among different racial groups in Alabama, as reported by Alabama Possible, a statewide nonprofit organization in 2017 indicated that 31.2% of African Americans and 16.54% of individuals with only a high school diploma in Alabama were living in poverty [58]. These regions are therefore good candidates for the implementation of countermeasures related to education and awareness creation, and policies for subsidies on basic vehicle maintenance. Incentive schemes may also be developed to encourage vehicle owners in the poorer regions of the state to undertake regular vehicle checks.

6. Conclusions

Vehicle defects have the potential to influence the severity of crashes. This study focused on investigating the factors associated with vehicle defect-related crash injury severity. A random parameter multinomial logit model with heterogeneity in mean was developed to uncover the relationship between the response variable (crash severity levels) and the explanatory factors while accounting for the existence of unobserved heterogeneity within the crash observations. The crash data used for this study was obtained from the Critical Analysis Reporting Environment (CARE) software system developed by the University of Alabama Center for Advanced Public Safety (CAPS) for the period covering 2016 to 2020. Preliminary data analysis revealed that defective equipment was the primary contributing factor in 50.56% of the crashes, indicating that in a little over half of the total crash observations, some form of vehicle defect is deemed to be responsible for the crash. With regard to the specific defects, it was observed that brake defects accounted for a significant proportion, representing 42% of all vehicle defects associated with the crashes, followed by tire blowouts at 22.4%. The model estimation results revealed some interesting findings. For instance, it was found that crashes that occurred on roads that are curved left with downgrades were likely to result in major injuries. Also, it was revealed that crashes involving drivers between 40 and 59 years were more likely to result in major and minor injury while younger drivers had lower probability of sustaining major injuries.

To better understand vehicle defect crashes as a broader societal issue and potentially explore their connection with socio-demographic characteristics, a spatial analysis was undertaken using a Mixed Geographically Weighted Regression model that delved into the social, economic, and educational backgrounds of drivers based on their residential zip codes. It was found that there is a negative correlation between median household income and the frequency of vehicle defect crashes, indicating that drivers from lower-income zip codes are more prone to such incidents. It was further observed that zip codes with a higher population of Black Americans and individuals with only a high school diploma exhibited a positive correlation with a higher frequency of vehicle defect-related crashes.

While the study presents intriguing findings, it is essential to acknowledge that the crash data relies on police-reported incidents, and the accuracy of the collected data cannot be independently verified by the authors. This becomes particularly crucial as reporting officers had to assess the contributing role of vehicle defects in the crash, a determination often subject to the subjective judgment of the reporting officer in low injury severity incidents. This introduces a potential bias in the study's data, although it is worth noting that this challenge is not exclusive to the database used. Nevertheless, the study's findings offer valuable and data-driven insights, emphasizing the need for ongoing safety campaigns, workshops, and training initiatives focused on basic vehicle maintenance practices in low-income communities within the state. Subsequent research endeavors could extend the scope of this study by incorporating multiple states to examine whether the prevalence of vehicle defect-related crashes is influenced by mandatory policies on annual vehicle inspections in some states.

Data availability statement

The data used for this study will be made available upon reasonable request.

CRediT authorship contribution statement

Emmanuel Kofi Adanu: Writing – review & editing, Writing – original draft, Methodology, Data curation, Conceptualization. **Richard Dzinyela:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation. **Sunday Okafor:** Writing – review & editing, Writing – original draft, Data curation. **Steven Jones:** Writing – review & editing, Writing – original draft.

Declaration of competing 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.

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