Original Research Article

A MANOVA & ANOVA Based Investigation of Vehicle Class Differences in Occupant Injury Metrics

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ABSTRACT

This study investigates the influence of vehicle type on crash-test injury outcomes by analyzing multiple biomechanical metrics, including head injury criteria (HIC), chest deflection, femur loads, neck injury measures, rib deflection, abdominal force, and pelvic force, for both drivers and passengers. A multivariate analysis of variance (MANOVA) followed by ANOVA tests examined that vehicle type has a statistically significant effect across basically all the injury merits (Wilks' $\Lambda = 0.21$, $F(57,13683) = 48.72$, $p < 0.001$). The strongest differences were observed in side-impact head injury (HIC36), abdominal force, and rib deflection. Passenger cars exhibited higher torso-related injury measures, vans showed elevated neck injury risks, and trucks demonstrated comparatively lower torso injuries but increased femur forces. These findings indicate that no single vehicle category provides uniform protection from all body regions. The study recommends that consumer safety regulators consider differentiated crash standards by vehicle type and that consumer safety ratings explicitly communicate the injury trade-offs that exist across different vehicle classes.

Keywords: crash-test injuries; injury biomechanics; MANOVA; vehicle safety standard; consumer safety ratings

INTRODUCTION

Motor vehicles are integral to modern transportation, yet crashes remain a leading cause of injury and death. According to recent data, more than 40,000 people died in motor vehicle crashes in 2023, with an estimated annual economic cost exceeding $340 billion (1). These statistics highlight the need for continued research into how vehicle design and classification affect occupant protection.

Understanding how injury outcomes vary across vehicle classes is crucial for improving crash safety standards. Vehicle geometry, mass distribution, and restraint systems all contribute to how energy is transferred to occupants during collisions (2). However, few studies have systematically examined how injustice metrics differ across major vehicle categories — Passenger Cars (PCs), Multiple-purpose vehicles (MPVs), trucks, and vans — using a multivariate statistical approach (3).

To address this complexity, the present study applies a Multivariate Analysis of Variance (MANOVA) and Analysis of Variance (ANOVA) to investigate crash-test data obtained from the National Highway Traffic Administration (NHTSA) (4, 5). By examining 19 biomechanical injury metrics for drivers and passengers.

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These dependent variables include key indicators such as head injury (HIC), chest deflection, femur loads, and neck tension forces, among others. The findings aim to provide insights into how the terrain and driver interactions influence injury risk profiles, ultimately informing vehicle design improvements regarding safety standards.

METHODOLOGY AND MATERIALS

Data Description

The comprehensive dataset used in this study contains crash-test results obtained from the National Highway Traffic Safety Administration, which evaluate vehicle safety performance across multiple injury categories. Each row represents the measurements recorded from controlled crash tests, including frontal and side impacts for both driver and passenger positions. In total, the dataset includes 21 variables representing biomechanical injury metrics and vehicle classification. Vehicle categories include passenger cars (PCs, n = 1,733), multi-purpose vehicles (MPV, n = 2,218), trucks (n = 618), and vans (n = 10). The small sample size for vans is acknowledged as a limitation that may affect statistical power and the homogeneity assumptions of MANOVA and reduce statistical reliability (6).

Analysis of variance (ANOVA) is a statistical test for detecting differences in group means when there is one parametric dependent variable and one or more independent variables (7). The method divides the total variation in the dependent variable into components attributable to systematic group differences and random errors. Mathematically for a one-way ANOVA with k groups and n total observations, the total sum of squares is decomposed as

$$SS_T = SS_B + SS_i \tag{1}$$

Where SS_T is the total sum of squares, SS_B is the between-groups sum of squares, and SS_i is the within-group (error) sum of squares. The test statistic is

$$F = MS_B / MS_i = \{SS_B / (k - 1)\} / SS_i / (n - k)\} \tag{2}$$

where MS_B and MS_i are the mean squares between and in the groups.

ANOVA relies on the assumptions: first, observations are independent; second, the dependent variable is normally distributed within groups; third the variances of the groups are homogeneous. When these conditions are practically met, the F-distribution provides an unbiased basis for hypothesis testing.

The advantage of ANOVA lies in its ability to control the Type I error (the null hypothesis is true, but we incorrectly reject it) rate when comparing multiple means simultaneously, avoiding the inflation that occurs in repeated pairwise t-tests. It's analytically straightforward and interpretable. However, ANOVA is limited in that it only assesses differences in a single dependent variable at a time and is sensitive to violations of homogeneity and normality.

Comparatively, MANOVA is an expanded form of ANOVA. Both tests use means from groups of scores in a dataset and the spread (or variance) among those scores to see whether the differences in mean group scores are statistically meaningful. The key difference in going from the ANOVA to the MANOVA is that in the ANOVA test there is only one dependent variable (the measure that an experimenter is assessing to see if it is different when other variables change), and the MANOVA has two or more dependent measures rolled into the same statistical test." Formally, let $\mathcal{Y}$ be an n × p matrix of responses (p dependent variables, n observations) and X the design matrix encoding group membership. The multivariate linear model is

$$\mathcal{Y} = X\mathbf{B} + \mathbf{E} \tag{3}$$

Where **B** is the matrix of regression coefficients and E the residual matrix. The hypothesis test compares two sums of squares and cross-products (SSCP) matrices:

$$T = H + \mathbf{E} \tag{4}$$

Where H is the hypothesis (between-groups) SSCP matrix and **E** is the error (within-groups) SSCP matrix. Multivariate test statistics include Wilks' Lambda, Piullai's Trace, Hotelling-Lawley Trace, and Roy's Largest Root. For example, Wilks' Lambda is

$$\Lambda = | \mathbf{E} | / | H + \mathbf{E} | \tag{5}$$

Where | . | denotes determinant. Smaller values of Λ indicate greater groups differences.

MANOVA shares ANOVA's assumptions of independence, multivariate normality of the dependent variable within groups, and equality of covariance matrices across groups (homogeneity of covariance). When these are satisfied, MANOVA provides greater statistical power than separate univariate tests by incorporating correlation among outcomes and controlling the overall Type I error rate.

The advantage of MANOVA is its ability to detect multivariate patterns of group differences that might be missed in univariate analyses. It is particularly useful when dependent variables are conceptually or empirically related. However, MANOVA can be sensitive to violations of covariance homogeneity and is less interpretable when the number of dependent variables is large relative to sample size. Additionally, significant MANOVA results often require follow-up univariate ANOVAs and discriminant analyses to identify the specific variables driving group differences (Table 1).

Table 1. The List of Variables and The Associated Definition and Descriptive Statistics

Variables	Type	Definition	Descriptive Statistics	
Vehicle-type	Categorical	It's the type of vehicle, including MPV, PC, truck, van.	MPV: 2218; PC: 1733;	Truck: 618; Van: 10
HIC15_DRIV	Numerical	Frontal impact driver HIC15 (head injury criterion in 15 milliseconds)	Mean: 213.988 SD: 86.552	Min: 67.312 Max: 821.865
CHEST_DEFL_DRIV	Numerical	Frontal impact diver chest deceleration	Mean: 23.476 SD: 4.798	Min: 9.493 Max: 46.786
LEFT_FEMUR_DRIV	Numerical	Frontal Impact Driver Left Femur Load	Mean: 1535.020 SD: 1041.695	Min: 48.207 Max: 5927.830
RIGHT_FEMUR_DRIV	Numerical	Frontal Impact Driver Right Femur Load	Mean: 1807.817 SD: 991.629	Min: 56.017 Max: 6801.413
NIJ_DRIV	Numerical	Frontal Impact Driver NIJ	Mean: 0.295 SD: 0.072	Min: 0.16 Max: 0.61
NECK_TENS_DRIV	Numerical	Frontal Impact Driver Neck Tension	Mean: 1284.386 SD: 403.7	Min: 488.055 Max: 2593.037
NET_COMP_DRIV	Numerical	Frontal Impact Driver Neck Compression	Mean: 238.991 SD: 201.66	Min: 7.858 Max: 1323.928
HIC15_PASS	Numerical	Frontal Impact Passenger HIC15	Mean: 273.549 SD: 85.937	Min: 96.481 Max: 822.84
CHEST_DEFL_PASS	Numerical	Frontal Impact Passenger Chest Deceleration	Mean: 14.531 SD: 4.169	Min: 6.729 Max: 39.275
LEFT_FEMUR_PASS	Numerical	Frontal Impact Passenger Left Femur Load	Mean: 1473.885 SD: 790.804	Min: 11.247 Max: 5293.405
RIGHT_FEMUR_PASS	Numerical	Frontal Impact Passenger Right Femur Load	Mean: 1363.922 SD: 808.192	Min: 9.222 Max: 4218.653
NIJ_PASS	Numerical	Frontal Impact Passenger NIJ	Mean: 0.399 SD: 0.109	Min: 0.18 Max: 0.99
NECK_TENS_PASS	Numerical	Frontal Impact Passenger Neck Tension	Mean: 822.560 SD: 231.317	Min: 227.056 Max:2031.697
NET_COMP_PASS	Numerical	Frontal Impact Passenger Neck Compression	Mean: 345.976 SD: 173.096	Min: 15.102 Max: 1221.61
SIDE_HIC_36_DRIV	Numerical	Side Impact Driver HIC36	Mean: 99.304 SD: 63.801	Min: 0 Max: 387.926
RIB_DEFLECTION_DRIV	Numerical	Side Impact Driver Max Thorax Rib Deflection	Mean: 21.670 SD: 7.073	Min: 0 Max: 52.008

Continued Table 1. The List of Variables and The Associated Definition and Descriptive Statistics

Variables	Type	Definition	Descriptive Statistics	
ABDOMEN_FORCE_DRIV	Numerical	Side Impact Driver Total Abdomen Force	Mean: 727.013 SD: 281.285	Min: 0 Max: 2234.137
SYMPHYSIS_FORCE_DRIV	Numerical	Side Impact Driver Public Symphysis Force	Mean: 1410.084 SD: 516.656	Min: 0 Max: 3969.616
SIDE_HIC_36_PASS	Numerical	Side Impact Passenger HIC36	Mean: 192.207 SD: 132.381	Min: 0 Max: 819.636
PELVIC_FORCE_PASS	Numerical	Side Impact Passenger Total Pelvic Force	Mean: 2551.289 SD: 1051.09	Min: 0 Max: 6357.052

RESULTS

The details of results, including both ANOVA tests and MANOVA test and their associated practical indications, are shown below. As summarized in Table 2, the one-way ANOVA results reveal statistically significant differences across multiple injury metrics among the four vehicle classes. MANOVA revealed significant main effects of vehicle type on injury metrics (Wilks' $\Lambda = 0.21$, $F(57,13683) = 48.72$, $p < 0.001$) (Figure 1).

The ANOVA test results indicate that vehicle type has a statistically significant effect on nearly all injury metrics measured in the crash-test dataset. For each outcome, the F-value was highly significant which is the p-value is less than 0.001 in most cases which stands for the average injury levels differ across vehicle categories. The largest effect sizes were observed for side-impact head injury criteria (SIDE_HIC_36 for both driver and passenger) and abdominal force (ABDOMEN_FORCE_DRIV). This means that a substantial proportion of the variation in these injury

Table 2. ANOVA results for vehicle-class differences in occupant injury metrics (F-values, p-values, and effect sizes) (5)

Metric	n_total	F_value	p_value	eta_squared
SIDE_HIC_36_DRIV	4579.0	4951.535744	0.000000e+00	0.384220
ABDOMEN_FORCE_DRIV	4579.0	4790.786506	0.000000e+00	0.341476
SIDE_HIC_36_PASS	4579.0	4957.475237	0.000000e+00	0.385694
RIB_DEFLECTION_DRIV	4579.0	4374.730285	1.264871e-217	0.197254
PELVIC_FORCE_PASS	4579.0	4294.173348	1.273096e-174	0.161707
SYMPHYSIS_FORCE_DRIV	4579.0	4185.636821	1.355193e-113	0.108519
NECK_TENS_PASS	4579.0	4119.804619	1.078591e-74	0.072838
HIC15_DRIV	4579.0	491.066870	3.078181e-57	0.056351
NECK_TENS_DRIV	4579.0	488.380242	1.364999e-55	0.054780
HIC15_PASS	4579.0	466.889145	2.513413e-42	0.042019
NIJ_PASS	4579.0	451.117220	1.724016e-32	0.032432
NET_COMP_PASS	4579.0	446.386892	1.593918e-29	0.029520
CHEST_DEFL_DRIV	4579.0	442.065053	8.283626e-27	0.026843
LEFT_FEMUR_DRIV	4579.0	436.412320	3.007781e-23	0.023320
NIJ_DRIV	4579.0	433.052110	3.965702e-21	0.021214
NET_COMP_DRIV	4579.0	425.674972	1.822722e-16	0.016557

Continued Table 2. ANOVA results for vehicle-class differences in occupant injury metrics (F-values, p-values, and effect sizes) (5)

Metric	n_total	F_value	p_value	eta_squared
LEFT_FEMUR_PASS	4579.0	417.891075	1.531352e-11	0.011596
CHEST_DEFL_PASS	4579.0	411.562743	1.508116e-07	0.007525
RIGHT_FEMUR_PASS	4579.0	45.556664	8.374298e-04	0.003630
RIGHT_FEMUR_DRIV	4579.0	42.798323	3.863459e-02	0.001832

Notes: n_total: the total number of observations or total sample size across all groups in a study; F_value the ratio of systematic variance (differences between group means) to unsystematic variance (random variation within groups). It measures how much the group means differ relative to the variability inside each group; P_value: the probability of obtaining an F_value as large as the one observed if the null hypothesis were true; eta_sauared: it measures the proportion of total variance in the dependent variable that is explained by the independent variable. It's an effect size measure.

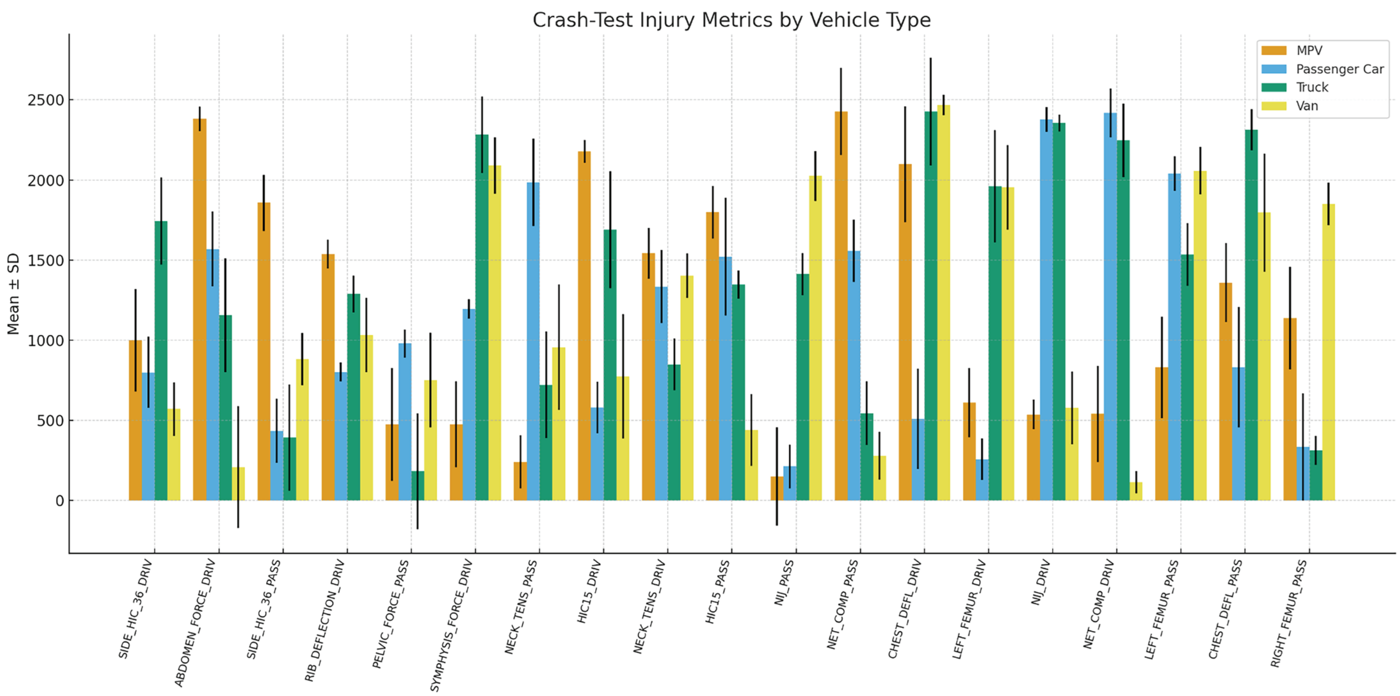

Figure 1. Conceptual framework illustrating the relationship between vehicle class, crash dynamics, and occupant injury metrics.

outcomes is explained by vehicle type. In practical terms, vehicle design differences between Passenger Car (PC), Multi-Purpose Vehicles (MPV), Trucks, and Vans strongly influence how much force the head and abdomen experience during side impact. Injury variables such as rib deflection, pelvic force and symphysis forces have smaller effect sizes. These outcomes are still significantly affected by vehicle type, but the variation explained is less dramatic than for head and abdomen measures. Metrics like neck tension, HIC15 (frontal head injury), and femur forces have smaller effect sizes. While vehicle type does influence these outcomes, other factors like crash speeds, restraint system, occupant posture likely explain most of the variation. For right femur force (diver and passenger), the F-value were either marginally significant or only weakly associated with vehicle type. This suggests femur loads are relatively consistent across vehicle categories. The coefficient table for SIDE_HIC_36 (driver) illustrates how specific vehicle types compare against the baseline category likely MPV or whichever is first in your dataset). For instance: Passenger Cars (PC) show significantly higher SIDE_HIC_36 scores than the baseline, indicating greater head injury risk in side impact; Trucks and Vans, by contrast, show negative coefficient, suggesting lower SIDE_HIC_36 scores compared to the baseline (Table 3).

The results of the multivariate analysis of variance indicate that injury outcomes vary significantly across vehicle types. The Tukey's Honestly Significant Difference (HSD) post-hoc test was conducted to identify specific group differences. Comparisons with $P < 0.05$ were considered statistically significant, indicating that the mean injury metric values between those vehicle types differed beyond random variation which concludes passenger cars consistently showed higher injury values in several key regions, including chest deflection, rib deflection, abdomen force, and pelvic forces, suggesting greater loading on the torso and lower body during crash events. (5) By contrast, vans demonstrated significantly higher neck-related measures, such as neck tension and the NIJ index, highlighting a greater vulnerability of van occupants to neck injury. Trucks generally exhibited lower torso-

Table 3. MANOVA Test Results

Injury Metric	Significant Comparisons (Tukey HSD, P<0.05)	General Trend/Interpretation
SIDE_HIC_36_DRIV	MPV — PC, MPV — Truck, PC — Van	PCs higher; Trucks lower; Van mixed
ABDOMEN_FORCE_DRIV	almost all pairs significant (expect none)	PCs >> others; Trucks lower
SIDE_HIC_36_PASS	MPV — PC, MPV — Truck, MPV — Van, PC — Truck, PC — Van	PCs higher; Trucks lower
RIB_DEFLECTION_DRIV	All pairs significant	PCs > others; Vans lowest
PELVIC_FORCE_PASS	MPV — PC, MPV — Truck, PC — Van	PCs higher; Vans lower
SYMPHYSIS_FORCE_DRIV	Most paris significant (except Truck — Van)	PCs higher; Trucks lower
NECK_TENS_PASS	All pairs significant	Vans and Trucks much higher; MPVs lower
HIC15_DRIV	MPV — PV, MPV — Truck, PC — Truck	mixed, mostly PCs higher
NECK_TENS_DRIV	Most pairs significant (except Truck — Van)	Vans highest; MPVs lowest
HIC15_PASS	MPV — Truck, MPV — Van, PC — Truck, PC — Van, Truck — Van	Vans & Trucks higher than PCs & MPVs
NIJ_PASS	PC — Truck, MPV — Truck	Trucks > PCs & MPVs
NET_COMP_PASS	MPV — PC, MPV — Truck	PCs lower; mixed with Vans
CHEST_DEFL_DRIV	MPV — PC, MPV — Truck, MPV — Van, PC — Truck, PC — Van	PCs > others; Trucks > Vans
LEFT_FEMUR_DRIV	MPV — Truck, PC — Trucks	Trucks higher; other comparisons NS
NIJ_DRIV	Almost all pairs significant	Vans highest; PCs lowest
NET_COMP_DRIV	MPV — PC, MPV — Truck, MPV — Van, PC — Truck, Truck — Van	PCs lowest; Vans lowest
LEFT_FEMUR_PASS	MPV — PC, MPV — Truck, PC — Truck	PCs lower; Truck higher; Vans mixed
CHEST_DEFL_PASS	MPV — PC, MPV — Truck	PC slightly higher; most NS
RIGHT_FEMUR_PASS	Only MPV — PC significant	PCs lower; other NS
RIGHT_FEMUR_DRIV	No significant differences	Femur loads not vehicle-type dependent

Notes: Injury metric: to estimate the severity or likelihood of injury to a human body region during a crash test; HSD is to identify specific group differences.

related injury loads compared to passenger cars, though they occasionally displayed elevated femur loads. Multi-purpose vehicles tended to fall between passenger cars and vans, sharing some risk patterns with both.

Overall, these findings suggest that while passenger cars may pose risks for torso injuries, vans present increased risks of neck-related injuries, and trucks offer some protective benefits in certain regions while showing trade-offs in leg injury metrics. This underscores the importance of tailoring safety designs to the unique crash dynamics of each vehicle type.

CONCLUSION

This study shows that vehicle type significantly influences crash-related injury outcomes, with passenger cars producing higher torso-related injury measures, vans showing elevated neck injury risks, and trucks demonstrating somewhat lower torso injuries but higher femur forces. These findings suggest that no vehicle class provides uniform protection across all body regions, highlighting the need for targeted design improvements. Passenger cars should enhance torso protection, vans should improve neck restraint systems, and trucks should address leg injury risks. Regulators could consider class-specific safety requirements, while consumers would benefit from clearer, region-specific safety ratings. Future research should further explore how road and terrain conditions interact with vehicle type to influence injury patterns.

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CONFLICT OF INTERESTS

The author declares no conflicts of interest related to this work.

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