Identification and Characterization of Pedal Misapplication Crashes
Using National and State Databases

Colin P. Smith, Rini Sherony, and Hampton C. Gabler

Abstract Pedal Misapplication (PM) is a driver error in which a driver presses one pedal when intending to press another. The purpose of this research is to identify PM crashes and analyze their characteristics. As PM is typically not coded, data sources that contain descriptive crash narratives: the National Motor Vehicle Crash Causation Survey (NMVCCS) database and the North Carolina (NC) state crash database, were selected. Using a keyword search algorithm, 33 PM crashes were identified in NMVCCS, representing 1,944 annual crashes in the US or 0.22% of the sample. From the NC state crash database, 3,274 PM crashes were identified, representing 0.18% of all police-reported NC crashes. These cases represent scenarios where the narrative indicated PM, which is a subset of all PM crashes.

These PM crashes were typically rear-end or road departure crashes in moderate- to low-speed commercial/residential areas. Within the sample, female drivers and elderly drivers were more often involved in a PM crash, which generally featured slightly lower injury severities and often involved inattention or fatigue. Anecdotally, PM crash narratives contained repeated evidence of unexpected events, driver inexperience, distraction, shoe-malfunction, extreme stress, and medical conditions/emergencies. These patterns are critical for understanding PM crashes, which are challenging to identify.

Keywords Crash epidemiology, Parsed crash narrative, Pedal misapplication, Crash characterization.

I. INTRODUCTION

Pedal misapplication (PM) is a driver error in which a driver presses one pedal when intending to press another. According to crash data, PMs most often manifest as accelerator-for-brake PMs, i.e. the driver presses the accelerator when intending to press the brake [1]. This type of PM results in a sudden inadvertent acceleration, as opposed to the intended controlled deceleration, and poses crash risk. One example of PM is a 2003 incident investigated by the National Transportation Safety Board (NTSB) in Santa Monica, California. An 86-year-old driver repeatedly and mistakenly pressed the accelerator, thinking it was the brake, while veering uncontrollably into a farmers' market, killing 10 pedestrians and injuring 63 others [2].

Sudden inadvertent accelerations have been reported for decades, and the primary cause of inadvertent accelerations is PM. The National Highway Traffic Safety Administration's (NHTSA) Office of Defects Investigation (ODI) denied a defect petition of over 200 complaints regarding inadvertent acceleration in January 2021, stating that "In every instance in which event data was available for review by ODI, the evidence shows that [these] crashes in the complaints cited by the petitioner have been caused by pedal misapplication" [3]. PMs are challenging to identify in crash data because they are not coded directly into databases. Because of this, relatively few studies have ventured to identify PM crashes among crash data. These studies have utilized data from the 1990s and 2000s to propose a PM frequency of less than 1% of all crashes and to propose that both younger and elderly drivers, as well as women, are more likely to commit a PM that results in a crash. Specifically, Lococo *et al.* investigated PM crashes by analyzing the National Motor Vehicle Crash Causation Survey (NMVCCS) database and the North Carolina (NC) state crash database (2004-2008), as well as media reports of PM [1]. Padmanaban *et al.* analyzed a larger set of NC data (1994-2009) using slightly different methods and arrived at similar conclusions [4]. Additional research regarding PM characteristics includes an investigation into the role of pedal design, in which Collins *et al.* found an increased correlation between pedal design variables and PM rate when taken in conjunction with PM driver characteristics [5], and a driving simulator experiment that concluded there was a possible role of executive dysfunction among older drivers in pedal error and no significant relationship between gender and pedal error [6]. This paper aims to shed light on this obscured crash mechanism by identifying PM crashes among the most recent crash data from the 2010s and 2020s, as well as exploring a wider variety of factors hypothesized to be associated with PM and comparing

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them to those of all crashes.

II. METHODS

Data Sources

PMs are not directly coded into any national or state databases, so an indirect way of identifying PM is required to analyze these crashes. By selecting data sources that include a text narrative of each crash, a search could be performed on these narratives to identify crashes that may have resulted from a PM. The NMVCCS database and the NC state crash database both contain detailed crash narratives based on physical evidence at the scene as well as interviews with drivers and/or witnesses.

1) The National Motor Vehicle Crash Causation Survey (NMVCCS) Dataset

The NMVCCS is a nationally representative sample of serious crashes collected by NHTSA. The NMVCCS database includes 6,949 total crashes that occurred from 1 January 2005 to 31 December 2007 [7]. Crashes collected within the first six months of data collection, i.e. the "phase-in period", and crashes that did not satisfy the selection criteria were given case weights of zero. The remaining 5,470 crashes represent 2,188,970 crashes. Over 600 variables relating to the crash, vehicles, persons, roadway and environment were collected. The NMVCCS crash narratives are typically on the order of a few paragraphs and are written by trained crash investigators, with a focus on the factors related to pre-crash events.

When analyzing these two databases, it is important to recognize that they neither represent all crashes nor identical populations of crashes. The population of crashes which these datasets represent are determined by the case inclusion criteria. For NMVCCS, the sample includes crashes on a public trafficway involving a passenger vehicle that was towed due to damage and that required Emergency Medical Services (EMS) to be dispatched to the scene. Police and at least one of the first crash-involved vehicles must have been present at the scene when the NMVCCS investigator arrived, and a completed Police Accident Report (PAR) must have been made available.

2) North Carolina (NC) Dataset

The NC state crash database is a comprehensive collection of all police-reported crashes in NC. In this study, crashes from 1 January 2014 to 31 May 2020 were analyzed. This dataset included 1,869,886 crash narratives, 1,678,318 of which included over 160 variables of associated crash data involving 3,030,754 vehicles and 4,171,533 persons.

The narratives in the NC state crash database are typically on the order of a few sentences and are written by the responding law-enforcement officer as a part of the PAR. The NC state crash database has more broad crash inclusion criteria than NMVCCS. Simply, the crash must have occurred on public property and resulted in an injury, a fatality, or at least $1,000 worth of property damage. However, these criteria are not as strictly followed as those of NMVCCS – for example, some agencies choose to report crashes that occurred on private property [4].

Searching for Pedal Misapplication Cases

A custom keyword search algorithm was developed, based on established methods, to parse through each crash narrative and determine whether it included words commonly used in the description of a PM, as determined by Lococo *et al*. [1]. Two keyword searches were performed. The first keyword search looked for words that may be indicative of a mistake: "instead", "mistak", and "inadvert". The second keyword search looked for words that may be indicative of a pedal-related event: "pedal", "peddle", "brak", "gas", "accel", and "slip". Partial words and common misspellings were used to allow for flexibility in identifying various forms of a word. For example, the keyword "brak" identifies both "The driver meant to hit the brake" and "The driver thought they were braking". The results of these two searches were merged so that only those narratives with at least one keyword from each set were included. These cases were considered potential PMs.

Each potential PM was reviewed manually by a researcher to determine whether a PM had in fact occurred. Only cases where the driver intended to press one pedal and instead pressed another were included. The researcher also identified the vehicle in which the PM occurred, and which pedals were confused.

Pedal Misapplication Analysis

The analysis compared the set of confirmed PM crashes to the entire set of crashes included in the respective database. The all-crash datasets included data on all vehicles, whereas the PM datasets only included data associated with the vehicle in which the PM occurred. Unfortunately, the two databases, NMVCCS and NC, did not include identical factors. Factors hypothesized to be associated with PM were selected from each database for analysis. These selected factors are shown in Table I. Cases that contained unknown values for particular factors were excluded from the analysis of those factors under the assumption that the distribution of the unknown data was the same as the distribution of the known data. For significance testing, a chi square goodness of fit test with α=0.05 was performed for select factors to examine whether the distribution of PM crashes was represented by the distribution of all crashes.

TABLE I

FACTORS SELECTED FOR ANALYSIS FROM EACH DATABASE

	NMVCCS	**NC**
Alcohol and Drugs	BAC Test Result	Alcohol Involvement
	Time of Crash	-
Date and Time	-	Crash Date
	Crash Weekday	Crash Weekday
Vehicle Speed	Police Reported Travel Speed	Estimated Speed at Impact
Crash Type	First Harmful Event Crash Type	First Harmful Event at Crash Level
Weather	Weather Factors	Weather Conditions
	Driver Age	Driver Age
	Driver Sex	Driver Gender
Driver	Driver Height	-
	Driver Fatigue	-
	Driver Inattention	-
	Driver License Status	-
Crash Severity	Maximum Injury Severity	Maximum Injury Severity
Monetary Damage	-	Damage Amount
Environment	Posted Speed Limit	Authorized Speed Limit
	-	Predominant Development Type
Vehicle	Body Type	Vehicle Type

III. RESULTS

The keyword search returned 110 potential PMs from NMVCCS, 33 of which were confirmed to be PMs. These cases represent 0.47% of all NMVCCS cases and 0.22% of all NMVCCS weighted cases. Therefore, the estimated prevalence of PM among NMVCCS-qualified crashes is at least 0.22%. Of these 33 PMs, 26 had non-zero case weights and are represented in the following factor analysis. These 26 weighted cases represent 4,859 total crashes and 1,944 crashes per year.

The keyword search returned 9,521 potential PMs from the NC state dataset, 3,274 of which were confirmed to be PMs. These cases represent 0.18% of all crashes included in the dataset and 504 crashes per year. Therefore, the estimated prevalence of PM among all NC state crash database-qualified crashes is at least 0.18%.

The characteristics of these crashes are organized into four categories: driver, crash, environment, and crash causation factors. These categories attempt to acknowledge the fundamental questions surrounding PM, such as who commits PMs that result in crashes? What type of crashes do PMs result in? Where and when do these crashes happen? And, lastly, why do they happen?

Driver Factors

Figure 1 and Fig. 2 display the distributions of driver age among all crashes and PM crashes in NMVCCS and NC,

respectively. There was a substantial increase in the proportion of older drivers in PM crashes for both datasets. Notably, drivers over the age of 74 years constituted only 3.7% of all crashes in NMVCCS and 7.0% in NC, yet 22.0% and 18.2% of PM crashes in those datasets. Younger drivers, on the other hand, accounted for a substantially larger proportion of PM crashes than of all crashes in NMVCCS only, where drivers under the age of 25 made up 27.4% of all crashes and 34.5% of PM crashes. In NC, the difference in PM among younger drivers was small. For both databases, p-values were calculated (p<0.01 for both cases). Since the p-values were smaller than the alpha level of 0.05, the null hypothesis was rejected with significant evidence to suggest that the PM crash distributions of age were not represented by their associated all-crash distributions.
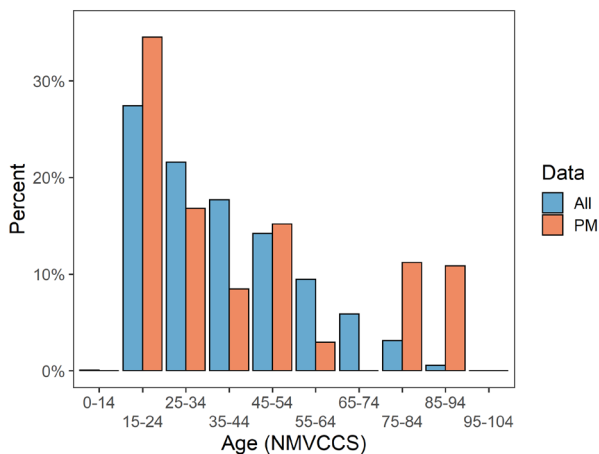
Fig. 1. Distribution of driver age among drivers in all crashes and PM drivers in NMVCCS.
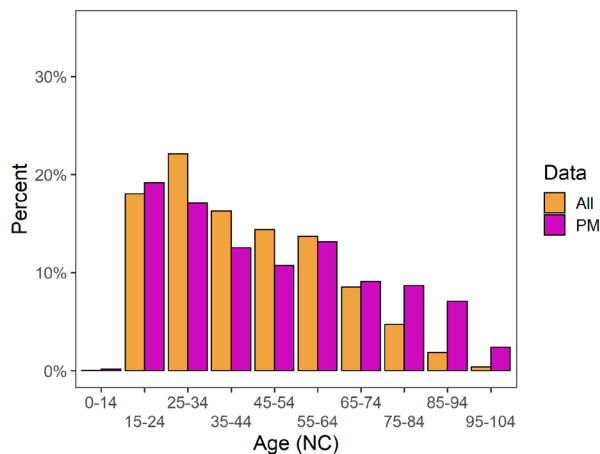
Fig. 2. Distribution of driver age among drivers in all crashes and PM drivers in NC.

As illustrated in Fig. 3 and Fig. 4, the sex (NMVCCS) or gender (NC) of drivers who commit a PM that resulted in a crash in both datasets was, to varying degrees, majority female, while the majority of drivers involved in all crashes among both datasets were male. PM drivers were 63.8% female in NMVCCS and 52.9% female in NC. In the chi-squared tests for both cases, the null hypothesis was rejected with significant evidence to suggest that the PM crash distributions of sex or gender were not represented by their associated all-crash distributions (p<0.01 for both cases).
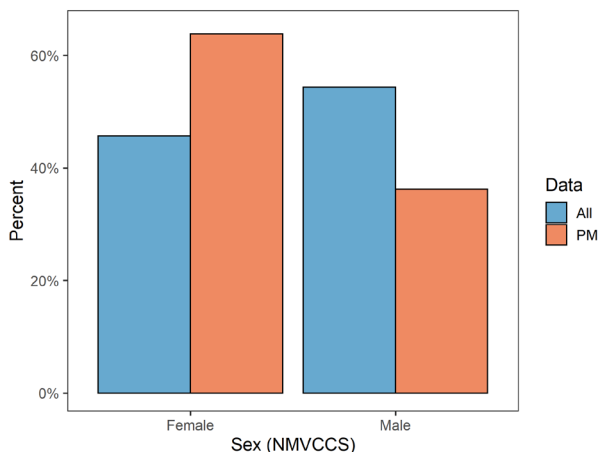

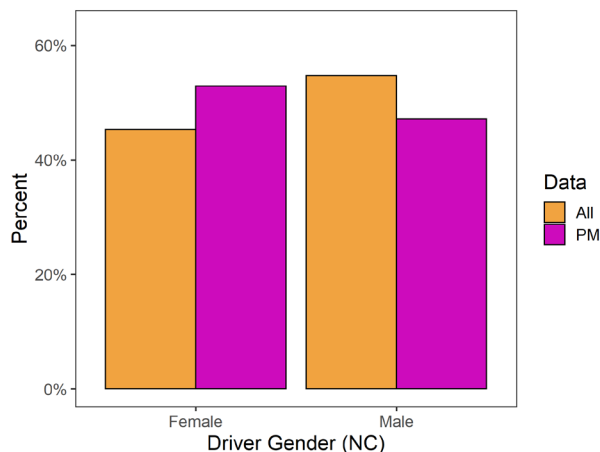Fig. 3. Distribution of driver sex among drivers in all crashes and PM drivers in NMVCCS.

Fig. 4. Distribution of driver gender among drivers in all crashes and PM drivers in NC.

Additionally, a shift towards drivers of shorter stature was observed among PM crashes in NMVCCS (Fig. 5). The median driver height shifted from 170 cm to 179 cm for all crashes to 160 cm to 169 cm for PM crashes. This factor was not available in the NC dataset.

In terms of driver license status in NMVCCS, Fig. 6 shows a large increase in the number of drivers with only a permit (0.3% of all crashes, 5.2% of PM crashes) and a decrease in the number of drivers who were not licensed, had a suspended, revoked or invalid license, or other. There were zero cases of the latter in the NMVCCS PM crash dataset. This factor was also not available in the NC dataset.
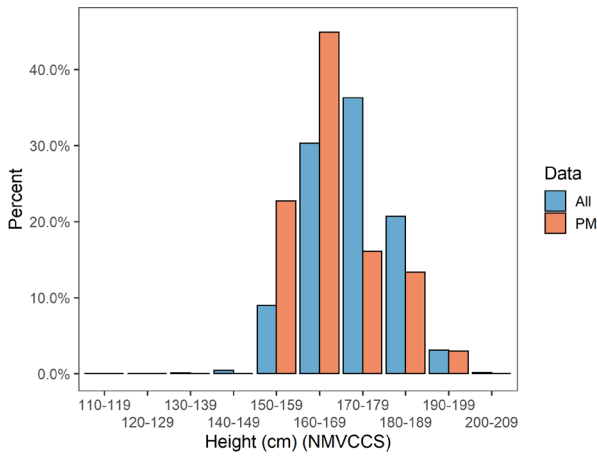
Fig. 5. Distribution of driver height among drivers in all crashes and PM drivers in NMVCCS.
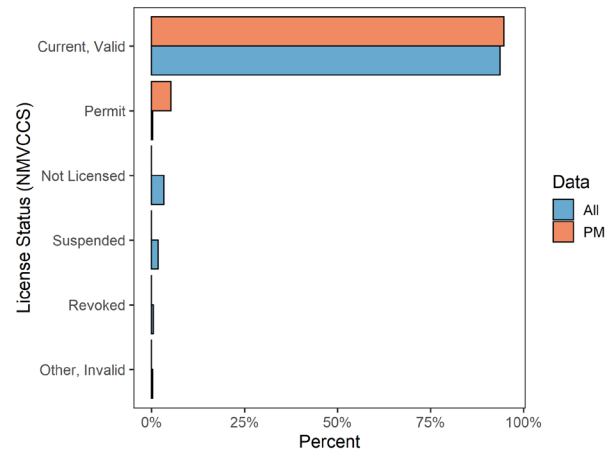

Fig. 6. Distribution of driver license status among drivers in all crashes and PM drivers in NMVCCS.

Fatigue and inattention were also investigated as two potential factors as they correlate to PM crashes. Figure 7 and Fig. 8 illustrate similar trends, where both fatigue and inattention were present in approximately one in ten drivers for the all-crash dataset and in nearly one in four PM drivers.
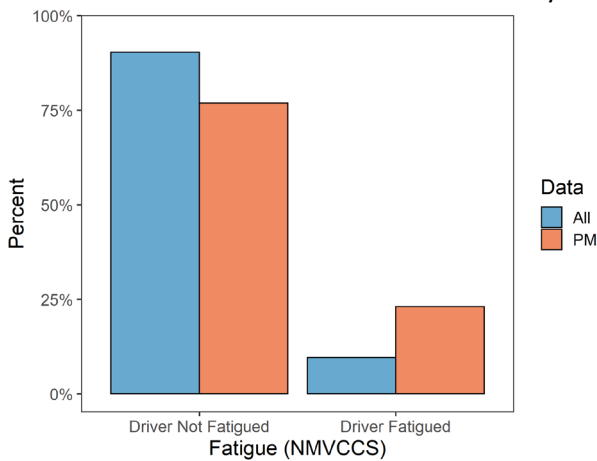

Fig. 7. Distribution of driver fatigue among drivers in all crashes and PM drivers in NMVCCS.
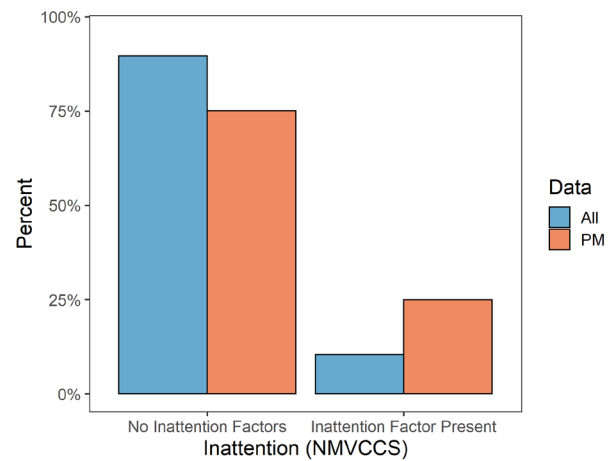
Fig. 8. Distribution of driver inattention among drivers in all crashes and PM drivers in NMVCCS.

Figure 9 and Fig. 10 illustrate the vehicle type involved in a crash. Similar to all crashes, PMs that resulted in crashes were almost all committed by drivers of passenger vehicles (i.e. passenger cars, utility vehicles, light trucks, and light vans). The increased variability observed in the NMVCCS data can be explained in part by the significantly smaller sample size.
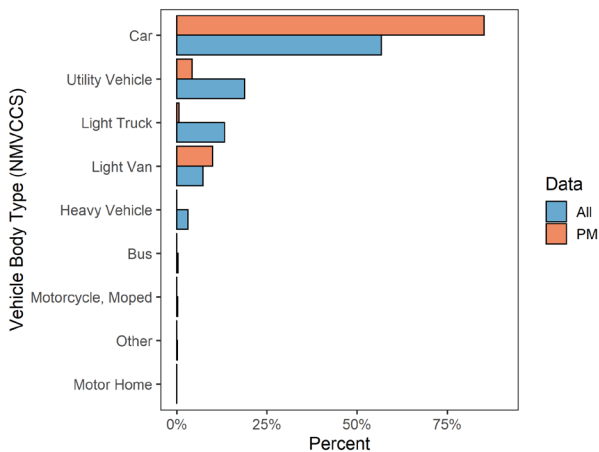

Fig. 9. Distribution of vehicle type among vehicles in all crashes and PM crashes in NMVCCS.
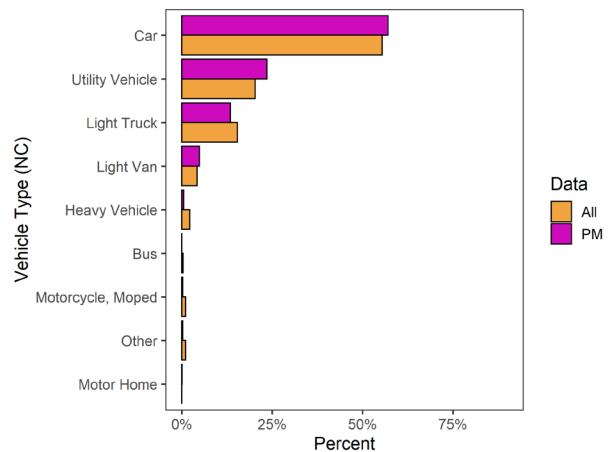

Fig. 10. Distribution of vehicle type among vehicles in all crashes and PM crashes in NC.

Lastly, the role of alcohol was analyzed. The results showed a decrease in the role of alcohol among PM

crashes as compared to all crashes in NMVCCS and NC. Figure 11 records the BAC test result factor for each driver from NMVCCS, while Fig. 12 records the alcohol involvement factor for each crash in NC as determined by the responding law enforcement officer's judgement. This may underscore the true prevalence of alcohol involvement.
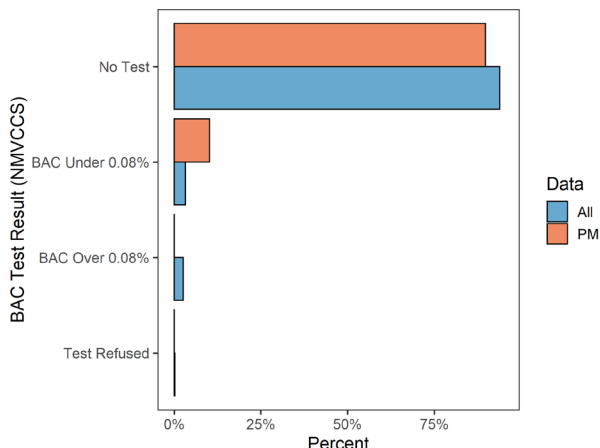

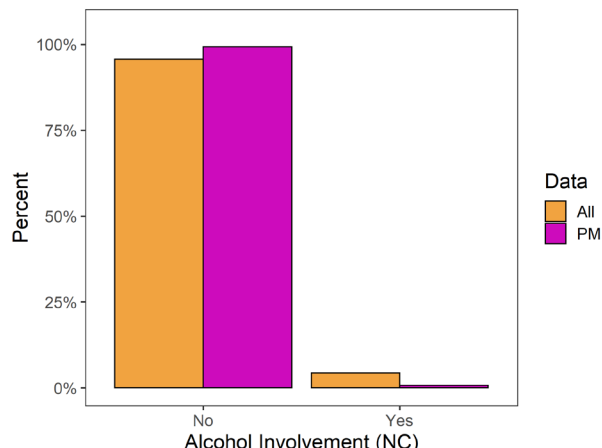Fig. 11. Distribution of BAC test result among drivers in all crashes and PM drivers in NMVCCS.

Fig. 12. Distribution of alcohol involvement among all crashes and PM crashes in NC.

Crash Factors

In both datasets, PM crashes resulted in rear-end or roadside departure crashes more often than they did not (Fig. 13 and Fig. 14), although the relative proportions of these crash types are not similar in either dataset. In NMVCCS, almost half of all PM crashes were roadside departure crashes, and a smaller proportion of PM crashes were rear-end crashes than of all crashes. In NC, almost half of PM crashes were rear-end crashes, nearly double the proportion of rear-ends among all crashes. Roadside departure crashes made up the second largest proportion of PM crash types and was also larger than that of all crashes.
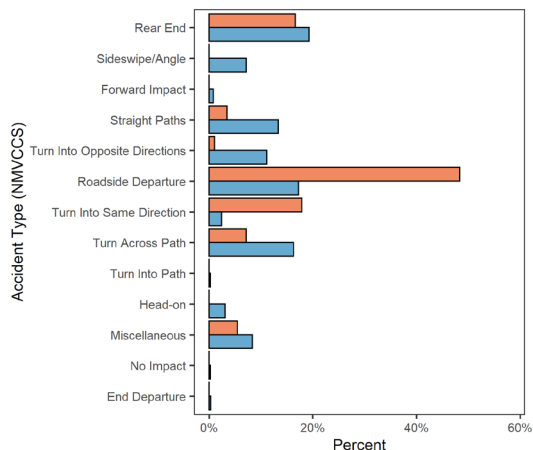

Fig. 13. Distribution of first harmful event crash type among all crashes and PM crashes in NMVCCS.
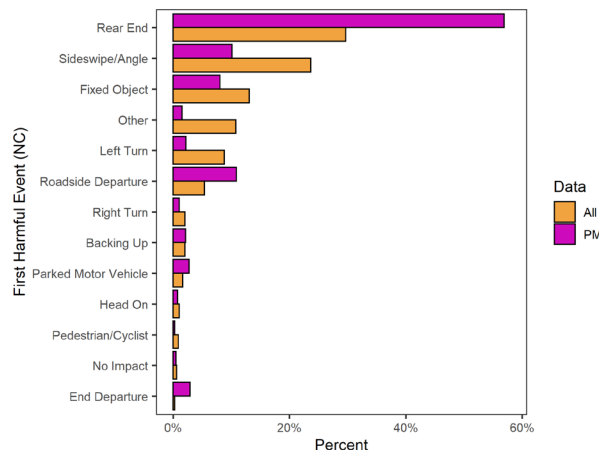
Fig. 14. Distribution of first harmful event at crash level among all crashes and PM crashes in NC.

Figure 15 illustrates that vehicles in PM crashes in NC were typically at lower speeds than those in all crashes. NMVCCS contains a similar factor, however more than half of PM vehicle speeds and over 40% of all vehicle speeds were not reported.

The amount of damage caused by these crashes is displayed in Fig. 16. The damage amount distributions were comparable between PM and all crashes. Since crashes were only included in the NC state crash database if they resulted in an injury, a fatality or damage over $1,000, damage from $0 to $1,000 was underrepresented for both PM and all crashes.
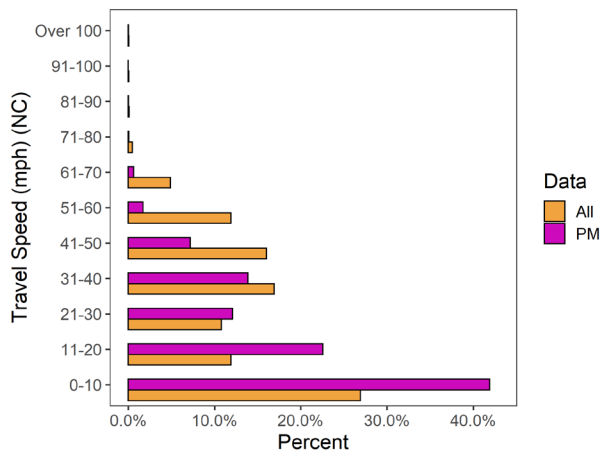
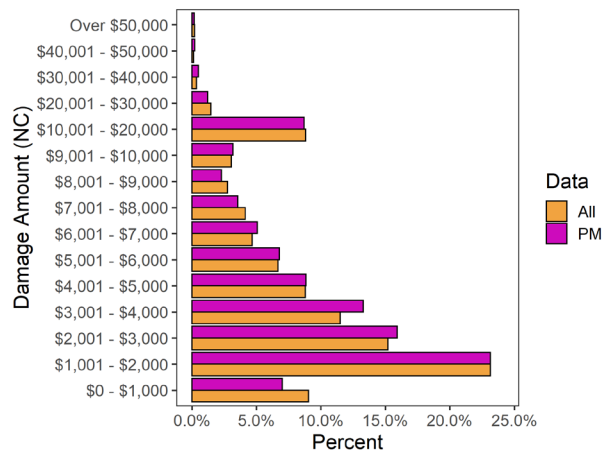Fig. 15. Distribution of estimated speed (mph) at impact among vehicles in all crashes and PM vehicles in NC.

Fig. 16. Distribution of damage amount among all crashes and PM crashes in NC. Note that the damage amount axis interval increases to $10,000 at $10,001–$20,000.

PM crashes in these datasets were also characterized by fewer fatalities. Figure 17 and Fig. 18 display the maximum injury severities for PM and all crashes for NMVCCS and NC, respectively. As mentioned before, the NC state crash database includes crashes that involve property damage only if it amounts to more than $1,000. Thus, the increased proportion of crashes that have no injuries as compared to NMVCCS is, in part, a result of the crash inclusion criteria. In both datasets, higher proportions of possible injuries and lower proportions of fatalities, incapacitating injuries, and non-capacitating injuries were observed.
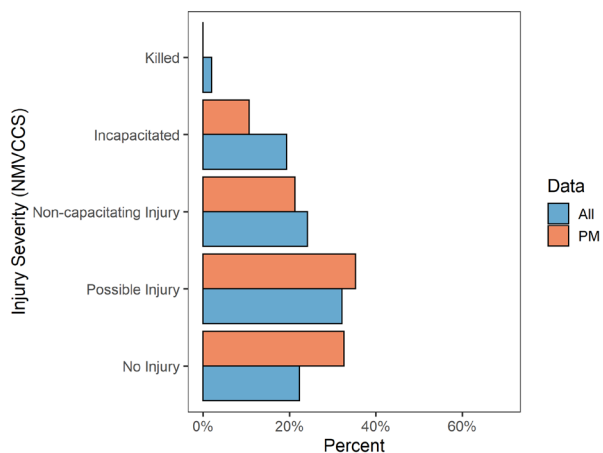

Fig. 17. Distribution of maximum injury severity among all crashes and PM crashes in NMVCCS.

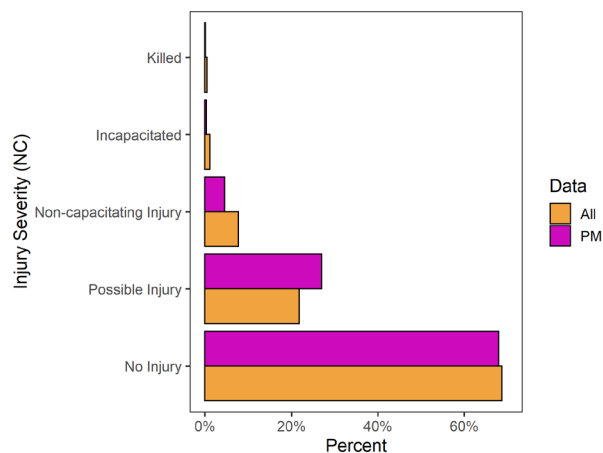Fig. 18. Distribution of maximum injury severity among all crashes and PM crashes in NC.

Environment Factors

PM crashes in NC have higher proportions of commercial and residential crash settings (over 90% combined) compared to all crashes. Figure 19 illustrates that rural settings (i.e. Farms, Woods, Pastures), which constituted approximately one-quarter of all crashes, made up less than 5% of PM crashes.
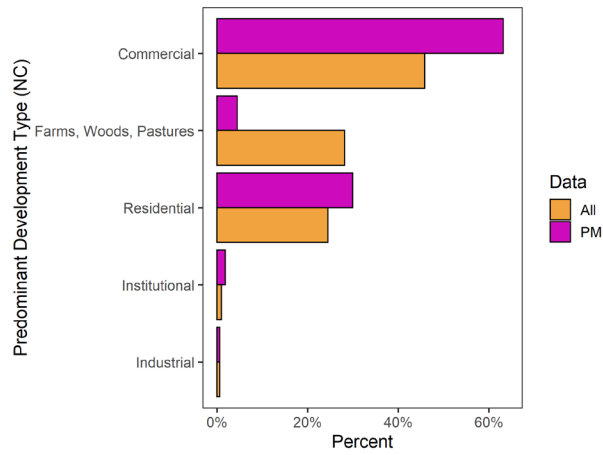
Fig. 19. Distribution of predominant development type among all crashes and PM crashes in NC.

When analyzing these settings for their speed limits, it is observed that PM crash settings had higher proportions of lower speed limits compared to the settings of all crashes. The NMVCCS posted speed limit factor reports speed limit per vehicle (Fig. 20), while the NC authorized speed limit factor reports speed limit per crash (Fig. 21).
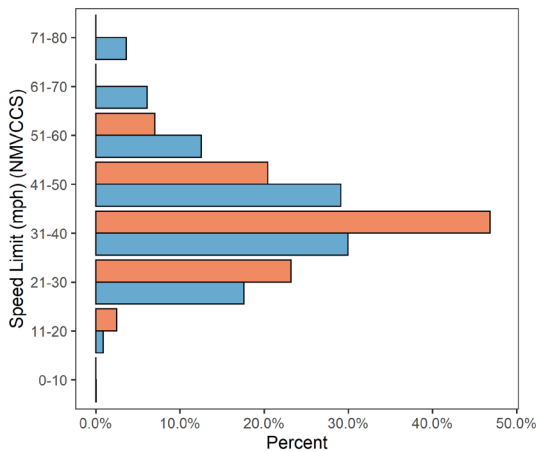

Fig. 20. Distribution of posted speed limit (mph) among vehicles in all crashes and PM vehicles in NMVCCS.
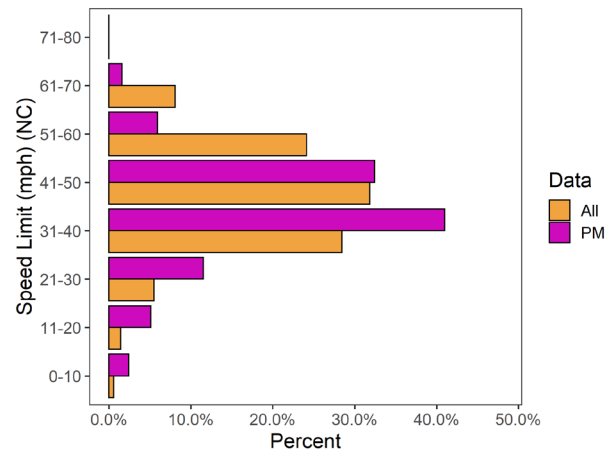
Fig. 21. Distribution of authorized speed limit (mph) among all crashes and PM crashes in NC.

The proportions of these crash settings that had adverse weather conditions present at the time of crash were investigated. Figure 22 shows that weather was slightly less frequently a factor in PM crashes than in all crashes. Similar results were observed in NC (Fig. 23), with a lower proportion of adverse conditions (all factor levels except clear and cloudy) among PM crashes.

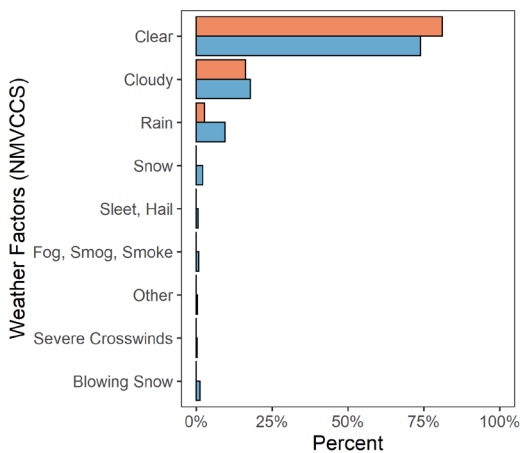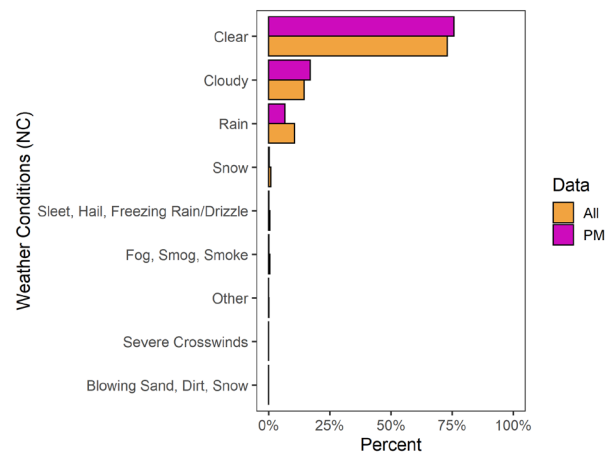Fig. 22. Distribution of weather factors among all crashes and PM crashes in NMVCCS.

Fig. 23. Distribution of weather conditions among all crashes and PM crashes in NC.

The largest proportions of PM crashes in NMVCCS occurred during the hours of 14:00, 07:00, and 18:00 (Fig. 24). The largest increases in proportion compared to all crashes were during the hours of 14:00, 07:00, and 23:00.
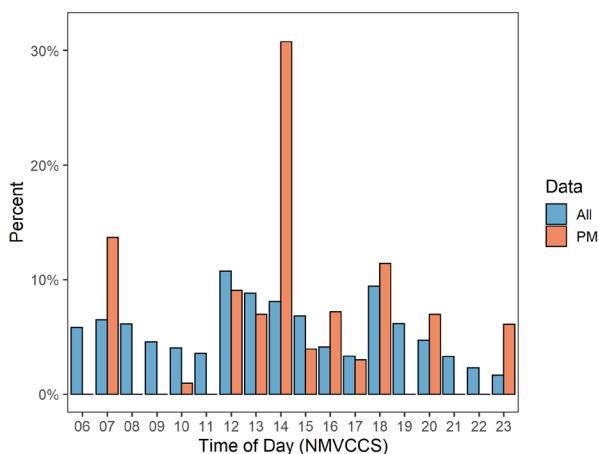

Fig. 24. Distribution of crash time (hour) among all crashes and PM crashes in NMVCCS.

In the NC data, crash date was examined (Fig. 25) and, from crash date, crash weekday was derived (Fig. 26). To better visualize the distribution of crash date, a 28-day rolling average was calculated and superimposed onto the chart. The decrease in crash rate from March 2020 to the end of the data range is likely due to reduced travel induced by COVID-19 quarantines. The distribution of crash weekday illustrates that there is no substantial difference between the proportion of all crashes and PM crashes on any given day of the week.
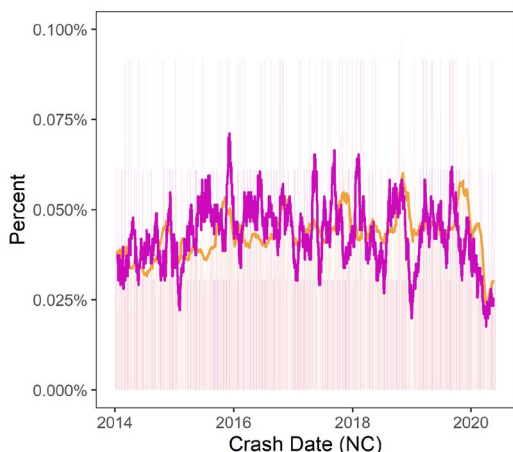

Fig. 25. Distribution of crash date among all crashes and PM crashes in NC with a superimposed 28-day rolling average.
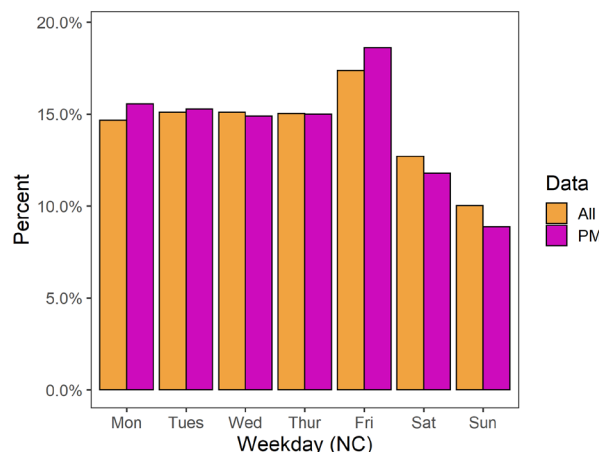
Fig. 26. Distribution of crash weekday among all crashes and PM crashes in NC.

Crash Causation Factors

The overarching objective of characterizing PM crashes is to determine the reason behind the error so that potential countermeasures can be developed. While there is not yet a comprehensive understanding as to all of the reasons why drivers press the wrong pedal, some anecdotal factors and explanations associated with PM as described in the crash narratives during the manual inspection of potential PMs were observed (e.g. "the driver claimed that they pressed the accelerator instead of the brake because …"). Repeated factors and explanations associated with PM crash narratives are as follows:

- unexpected events, e.g. car pulling out in front, leading car braking suddenly, animal in the road;
- distraction, e.g. spilling coffee, trying to tie a shoe, looking at cell phone, sneezing, stop-and-go traffic, looking back at occupants;
- shoe malfunction, e.g. flip-flop falling off, difficulty distinguishing pedals with large boots, objects caught under feet, shoes getting caught, shoe slipping off one pedal and onto another;
- inexperience or unfamiliarity, e.g. inexperienced drivers of all ages, drivers who are unfamiliar with a

vehicle that they do not drive regularly;
- extreme stress or recent trauma, e.g. car radio stolen from the parking lot of the funeral home in which they were planning the funeral of their late mother, upcoming retirement, the well-being of a sick friend, an incomplete recovery from a recent heart surgery, a relative who almost drowned in a recent kayaking accident;
- medical conditions or emergencies, e.g. leg spasming or cramping, choking, vomiting, anxiety attack, feeling sick or dizzy.

IV. Discussion

The prevalence of PM crashes nationally was estimated to be at least 0.22% of all NMVCCS-qualifying crashes. The prevalence of PM crashes in NC from 1 January 2014 to 31 May 2020 was estimated to be at least 0.18% of all police-reported crashes.

Drivers involved in PM crashes were characterized as more likely to be older than 74 years old and female than their all-crash counterparts. Evidence suggested younger drivers may also have an increased PM crash rate in NMVCCS, although these results were not corroborated by the NC analysis. Therefore, this analysis partially supports the results presented in the literature [1][4]. It is possible that the lower proportion of PM crashes among young drivers observed in NC is a result of the state's adoption of a graduated licensing system, which has been shown to reduce young teen crash rates [8]. PM drivers are also more likely to be of shorter stature, fatigued, or inattentive, carry a permit instead of a license, and driving passenger vehicles. Sex and age likely confound with height in NMVCCS, as females and younger people have a lower height on average. It is possible that these populations experience higher rates of PM crashes because of a poor fit within their vehicle resulting in an imperfect access to the pedals. Age and license status in NMVCCS may also be confounded, as younger drivers are more likely to only have a permit.

PM crashes were characterized as majority rear-end and roadside departure crashes, although the relative proportions of either are not clear. The disparity in the proportions of rear-end and roadside departure crashes between the two datasets is possibly explained by the crash-inclusion criteria of the NMVCCS (must have occurred on a public trafficway, one passenger vehicle must have been towed due to damage, etc.). It is likely that many PM rear-ends did not meet these qualifications and were not represented. PM crashes have also been characterized by similar damage amounts, and slightly lower crash severities. The maximum injury severity in the crashes is less likely to be a fatality, incapacitating injury or non-capacitating injury, yet more likely to be a possible injury. This result may not be entirely representative of PM crashes, though. Fatally injured or incapacitated drivers are less likely to be able to self-report their PM to the investigator, so it would be less likely to be written in the narrative, identified as a PM, and included in this analysis. Vehicles involved in PM crashes occurred at lower speeds than those in all crashes.

The locations of these crashes were characterized as overwhelmingly commercial and residential, often having slightly lower speed limits and better weather than that of all crashes. Lower travel speeds follow from lower speed limits and relate to the business areas and neighbourhoods where these crashes tend to occur.

Almost a third of these crashes in NMVCCS occur between the hours of 14:00 and 15:00. The next two most frequent times of these crashes, early in the morning and early in the evening, match the patterns of the typical work-day commute. The hours with the greatest increase in proportion of PM crashes as compared to all crashes are early morning and late at night, suggesting a possible relationship with fatigue. As for crash date, the 28-day rolling average of PM crash proportion is similar to that of all crashes. PM crashes appear to be as indiscriminate towards day of the week as all crashes.

Anecdotally, it was noted that some PM crashes occur as a result of unexpected events, driver distraction, shoe malfunction, driver inexperience or unfamiliarity with the vehicle, extreme stress or recent trauma, and medical conditions. While weather was not observed to be particularly characteristic of PM crashes in general, many narratives indicated that a foot slipped from a pedal and onto another because the sole of the shoe was wet. Weather, and rain in particular, may show a stronger effect in the subset of pedal slips.

As a whole, a likely confounding variable is traffic. Not only is a misapplication of the accelerator more likely to result in a crash when there are more vehicles around, but a driver is also more likely to be stressed, distracted and fatigued, particularly during a rush hour before or after a long working day. Additionally, there is more traffic in commercial and residential areas as compared to rural areas, and higher traffic often reduces

travel speed.

Limitations

The analysis is limited by the inclusion criteria of the respective databases. For example, a crash which occurred on private property or one which resulted in no injuries or fatalities and damage of less than $1,000 may not have been included in the NC state dataset. Likewise, a crash which occurred in a parking lot or did not require an EMS to be dispatched or a passenger vehicle to be towed would not have been included in the NMVCCS dataset.

The narratives were written by crash investigators or law-enforcement officers using available evidence, such as driver and witness testimony. Therefore, the identification of PM from the narrative is limited by the reliability of that testimony and the inclusion of those details in the narrative by the author. If the driver did not realize or admit to the PM, it would not have been captured. If the author of the narrative did not decide to include those details in the narrative, it would not have been captured. Also, since PMs are self-reported, the probability of identification in crashes in which the driver is fatally injured or incapacitated is reduced.

The keyword searches identified every case that matched the chosen keywords as written. It is possible that cases which described a PM with uncommon language, abbreviations, or egregious misspellings were not captured by the search. Each of the above limitations had the potential to cause the observed prevalence of PM crashes in each dataset to underestimate the true PM crash frequency of each population.

The primary limitation of the NMVCCS analysis is that it contained only a small sample size of PM crashes (n=33). After eliminating cases with case weights of zero, the sample size became n=26. Sample size was further reduced per factor by eliminating unknown factor levels under the assumption that the distribution of the factor among the unknown crashes was equal to that of the known crashes, with a minimum sample size of n=20 for driver fatigue. Further details regarding sample size per factor can be found in Table A1 (NMVCCS) and Table A2 (NC), included in the appendix.

The conclusions drawn from the NMVCCS data and the comparisons made between the two datasets are limited due to the age of the NMVVCS data. The NMVCCS was conducted from 2005 to 2007 while the NC data was observed between 2014 and 2020. This study assumed that PM crash frequency and characteristics have not changed dramatically over time.

V. Conclusions

The keyword search parsed through millions of crash records from the NMVCCS and NC datasets, and nearly 10,000 crashes were manually inspected to confirm over 3,000 PM crashes. These crashes were analyzed for 26 factors hypothesized to correlate with PM and were compared to the set of all crashes from their respective datasets. This analysis substantiates some of the findings of previous research and introduces many new factors never previously analyzed with respect to this unique crash mechanism.

VI. Acknowledgements

VII. References

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VIII. APPENDIX

TABLE A1

NUMBER OF OBSERVATIONS ANALYZED FOR EACH FACTOR ANALYZED IN NMVCCS

Table	Variable	Description	All	PM
CRASH	TIME	Time of Day	5,470	26
CRASH	INJSEVA	Max. Injury Severity	5,279	26
CRASH	DAYWEEK	Weekday	5,470	26
CV	BACTEST	BAC Test Result	9,841	25
CV	DLSTATUS	Driver's License Status	9,605	25
CV	TRSPEED	Travel Speed	9,449	24
ENV	SPLIMIT	Speed Limit	10,033	26
OCC	AGEYEAR	Age	10,035	26
OCC	HEIGHT	Height	7,894	22
OCC	SEX	Sex	10,127	26
PCA	ACCTYPE	Accident Type	10,080	26
PCA	FATIGUE	Fatigue	7,692	20
PCA	INATTEN	Inattention	7,971	22
PCA	WEATHER	Weather	5,466	26
GV	BODYTYPE	Vehicle Body Type	10,494	26

TABLE A2

NUMBER OF OBSERVATIONS ANALYZED FOR EACH FACTOR IN NC

Table	Variable	Description	All	PM
Accident	ALC_INVLV	Alcohol Involved	1,678,318	3,088
Accident	CRASH_DATE	Crash Calendar Date	1,647,859	3,088
Accident	CRASH_DATE	Crash Weekday	1,678,318	3,088
Accident	SEVERITY	Injury Severity	1,628,539	3,060
Accident	FRST_HMFL_TXT	First Harmful Event at Crash Level	1,676,499	3,088
Accident	WTHR_TXT	Weather Condition	1,678,318	3,088
Accident	DEV_TXT	Predominant Development Type	1,678,318	3,088
Accident	SPDLMT	Authorized Speed Limit	1,644,628	2,966
Accident	DMG_AMT	Damage Amount	1,669,247	3,077
Vehicle	VEHTYPE_TXT	Vehicle Type	2,972,452	3,016
Vehicle	DRIVER_AGE	Age of Driver	2,829,464	3,008
Vehicle	EST_SPEED	Estimated Speed Prior to Impact	2,835,163	2,885
Person	GENDER	Gender	2,824,673	3,016