

Evaluating the Accuracy and Reliability of Police-Reported Crash Data: A Comparative Analysis of Crash Reports and Visual Evidence from Crash Videos

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Abstract

Police-reported crash data are essential for transportation safety analysis, but their utility is often hampered by issues including underreporting and inconsistencies. Comparing crash videos with police reports provides a valuable method for identifying these discrepancies and improving data accuracy. This study identifies discrepancies in police reports by comparing them to crash videos. Iowa crash reports were compared to videos from the Iowa Advanced Traffic Management System (ATMS) for 2022. A spatiotemporal matching approach was used. Key crash elements were manually reduced from corresponding videos and compared to those from the corresponding crash reports. The accuracy of each element, along with its 95% confidence interval, was computed. Crash elements observable on-site, such as environmental conditions, light conditions, and vehicle damage, demonstrated high accuracy levels. Elements requiring inference and reliance on witness accounts, such as the manner of crash or collision, the first harmful event, and the sequence of events during the incident, showed lower accuracy and greater variability. The results highlight inconsistencies in derived elements, particularly the major cause of the crash, which relies on the accuracy of the elements it is derived from. These findings underscore the benefit of incorporating video data into crash data workflows to enhance reporting accuracy and reliability. Policymakers and safety professionals can use the insights on these inconsistencies to improve traffic safety measures and make informed decisions. Additionally, outcomes can be used to help train officers in coding crash reports. This study highlights the importance of developing systematic methods to integrate multiple data sources for improved traffic safety analytics.

Keywords

Crash Reporting, Crash Data Accuracy, Video Analytics, Reporting Bias

1. Introduction

Police-reported crash data are essential for improving transportation safety through engineering, planning, policy development, informing education and outreach, and research. These activities rely on complete, accurate, and reliable crash data to provide essential information. The integrity of these data significantly influences the ability to diagnose safety issues, formulate policies, and implement interventions to reduce road traffic crashes and fatalities. However, due to inherent limitations in data collection processes, the accuracy of crash data, particularly police-reported crash data, is often questioned.

Determining what constitutes a reportable crash varies significantly across states (and even within agencies), adding a layer of complexity to the reporting process. For instance, in accordance with Iowa laws (IA Code Section 321.266) [1], a reportable crash is defined as one in which all damages, including both vehicle and property, are estimated to be \$1,500 or more. Additionally, the presence of an injury or fatality triggers the reporting requirement.

Since police officers arrive at the crash scene after an incident has occurred, they rely heavily on witness statements and their observations to complete crash reports. This data collection method introduces several challenges, including potential inaccuracies and inconsistencies, due to the limited time, resources, and reliance on subjective accounts from those involved in the crash and other witnesses. These challenges underscore the importance of analyzing the accuracy of police-reported crash data and understanding its limitations.

The importance of accurate and reliable crash data cannot be understated, as it is essential for effective safety analysis and decision making [2]. Underreporting patterns vary by region [3], while reporting biases significantly affect data-driven conclusions [4]. Previous research has highlighted several issues with the accuracy of data, such as underreporting and other discrepancies in the recorded data [2]–[8]. The impact of human factors such as police officer judgment and human recall bias on data accuracy affects the quality of police crash reports [7] [9]–[14].

Numerous studies have investigated the potential of using video data in enhancing the collection of crash data. Visual records of traffic incidents are provided by videos from traffic cameras, windshield-mounted cameras, and other sources, offering additional information that can be used to verify and supplement police reports. Studies by Dopfer and Wang [15], Van der Horst [16], and Goodall and Lee [17] have demonstrated the potential of using video data to analyze traffic scenarios and safety issues, and verify crowd-sourced reports, thereby improving the accuracy and reliability of traffic monitoring and management.

Despite these advancements, there is still much to explore about the integration

of video data with police-reported crash data. The potential discrepancies between crash reports and visual evidence from videos need thorough investigation to identify and understand the consistencies and inconsistencies in the data.

The objective of this study was to identify and document the consistencies and inconsistencies present in police-reported crash data by exploring the potential discrepancies between crash reports and the visual evidence presented in crash videos. By doing this, the study aims to equip professionals who use this crash data, for example, experts in safety diagnostics, safety management personnel, and researchers, with a deeper understanding of the limitations and reliability of this data. With this information, these professionals will be better equipped to make informed decisions and exercise caution when utilizing crash data for their work, ultimately contributing to more accurate analyses and effective safety measures.

2. Literature Review

2.1. Crash Reporting

Crash data is pivotal for developing effective road safety strategies and in safety research. One critical factor that leads to bias in crash reports is underreporting. Underreporting has been evaluated using sources such as hospital records [4] [18], the General Estimates System (GES) data from the National Highway Traffic Safety Administration (NHTSA) [11], and incident reports (which are sometimes used when a crash is not considered reportable) [5]. The research has consistently found that crashes with higher injury levels and fatalities are more likely to be reported (and more accurately) than lower-severity and property damage only crashes [5] [6] [19]–[23]. Underreporting creates biases in crash estimates and skews model results. To address this issue, multiple studies have proposed advanced statistical models to estimate true crash frequencies, correct for reporting biases, and improve the reliability of crash severity predictions.

Other studies have delved into human factors contributing to bias in crash data. The reliability of police reports is scrutinized by Farmer [9]. He compared the police reports to more precise measures like delta-V (crash severity) and Abbreviated Injury Scale (AIS) from the National Automotive Sampling System (NASS). The results reveal significant discrepancies, with police reports often overstating injury severity, leading to potentially misleading conclusions in safety research. Regev [12] investigated the underreporting of driver distraction as a cause of crashes by comparing police officers' assessments in hypothetical crash scenarios to real-world crash reports. The study revealed that officers more accurately reported in-vehicle distractions, especially mobile phone use, in hypothetical scenarios than in actual crash reports. This showed a significant underreporting of driver distraction in police reported crashes.

Milne [10] delved into the precision of witness statements within the criminal justice system. The study identified common errors such as omissions, distortions, and the introduction of new information when officers transform accounts from verbal interviews to written forms. This research highlights the cognitive chal-

allenges officers face in accurately transcribing verbal accounts into written statements and the consequent impact on legal proceedings. Likewise, the findings of this study can be directly related to the field of police-reported crashes. In road traffic crash scenarios, witness statements play a crucial role in determining the sequence of events and assigning liability. The process of converting these verbal accounts into written reports by law enforcement carries similar risks of inaccuracies. Misinterpretations or alterations in these statements can lead to incorrect conclusions about the causes and responsibility for traffic incidents.

Previous studies highlight the significance of high-quality crash data to enhance road safety measures and policies [2] [3] [7]. The studies also shed light on the challenges in data collection, which lead to issues such as under-reporting and inconsistencies. Imprialou and Quddus [2] emphasized the need for accurate, complete, and reliable data for effective traffic safety analysis. Janstrup *et al.* [7] focused on under-reporting, particularly due to police distrust, and highlighted the importance of human factors in reporting through a survey. Ahmed *et al.* [3] provided a comprehensive review of types of data errors across 46 countries, categorizing them as reporting or recording errors. They found that higher-income countries typically have fewer errors and identified policing systems as the primary source of error.

2.2. Utility of Videos

Multiple studies have investigated the application of video data to promote road safety. These studies demonstrate video data's value in enhancing our understanding of events that occur on the roadway [15]-[17]. Dopfer and Wang [15] analyzed windshield-mounted camera footage of traffic crashes to investigate the potential of these videos in understanding crashes. They discussed using computer vision techniques to analyze a variety of traffic scenarios and assessed the ability of these methods to reconstruct accidents, while identifying the limitations of this technology for fully capturing crash dynamics. Goodall and Lee [17] used traffic camera videos to verify Waze user reports of crashes and disabled vehicles. The videos were established as a reliable "ground truth" against which the accuracy of the reports could be measured. This study demonstrated the potential for integrating video with crowd-sourced data for improved traffic monitoring. Van der Horst [16] employed long-term video observations at urban intersections to analyze traffic safety issues such as crashes, conflicts, and road user behaviors at these intersections. The video data provided a direct observational approach, contributing valuable data for road safety research. Video data, whether from windshield cameras or fixed traffic cameras, has emerged as a reliable source for reconstructing crashes, validating incident reports, and analyzing road user behavior, making it an increasingly powerful tool for road safety research.

3. Data

This study uses two primary data sources: Advanced Traffic Management System (ATMS) crash videos and Police crash reports.

3.1. Advanced Traffic Management System (ATMS) Crash Videos

The Iowa Department of Transportation (DOT) has installed over 500 traffic cameras along selected routes, primarily focusing on interstate roads, particularly at interchanges, although some routes outside this category are also covered. These cameras are managed by the Advanced Traffic Management System (ATMS) of Iowa. However, the videos recorded by these cameras are only accessible for a limited period of seven days. To overcome this limitation, the Institute for Transportation (InTrans) has developed software that automates downloads by using user-emulating software, creating a Crash Video Database. The primary objective of this automated system is to have records of incidents on video, aiding in the identification of potential causes and targeted interventions, particularly in work zones. The video downloading process commenced in August 2021.

The ATMS crash videos present certain limitations that must be acknowledged. Notably, there are instances where the entirety of a crash event may not be captured by the cameras. To effectively utilize these videos for our project, it is important that both the initial and final events of the crash are visible. Additionally, it's important to recognize that certain crucial details, such as driver distractions or impairment due to drugs or alcohol, may not be discernible through video footage alone.

3.2. Police Crash Reports

The Iowa Crash Reporting Guide serves as a reference for law enforcement in completing crash reports. Adhering to the guidelines outlined in the Reporting Guide streamlines the process, ensuring that reports are completed thoroughly, accurately, and consistently. This approach aims to maximize the potential benefits for crash investigation and prevention efforts. Most crashes in Iowa are reported electronically through Traffic and Criminal Software (TraCS). In 2022, over 95% of reportable crashes were collected via TraCS [24]. These reports are submitted to the Iowa DOT and integrated into a centralized database. Database extracts are created for public access, such as through the Iowa Crash Analysis Tool (ICAT). Crash data utilized for comparison were extracted from this database.

Given that law enforcement officers are not present at the time of the crash, it's important to acknowledge that reliance on witness statements becomes necessary for certain parts of the report, despite the guidelines provided by the crash reporting guide. Moreover, the reporting guide underscores the importance of officers exercising their judgment and drawing upon their experience when completing the report. Also, since not all crashes are reported, ATMS videos contain some crashes that may not be in the crash reporting database.

4. Methodology

4.1. Data Preparation

The InTrans team began downloading and coding the ATMS video download in August 2021. Coding involves reviewing the downloaded video and entering key

information into a spreadsheet, such as whether the video captures a crash, and providing a brief description if so. Since the cameras sometimes pan to locate potential crashes, they may miss a crash or fail to capture it in full, depending on the camera's positioning at the time. As a result of this, details on whether the crash is visible or if the video only shows the aftermath are also recorded. At the time this analysis was conducted, video data had been coded from August 2021 to May 2023.

Since the commencement of ATMS video downloads, the year 2022 represents the only complete year that video data were manually reviewed and coded. During this period, a total of 697 videos were documented as containing visible crashes, spanning January to December 2022. For this study, these videos were rewatched to assess whether the videos captured the full crash. Of the 697 videos reviewed, only 153 provided a comprehensive picture of the entire crash sequence, including both the initial and final events.

As ATMS videos may capture crashes that were not formally reported, and as a result, do not have a corresponding police crash report. To address this discrepancy, we developed a dashboard using Shiny in R, using a spatiotemporal logic to identify which ATMS videos align with crashes documented in the crash report database. To be considered a match, a video-detected crash was required to occur within 0.5 miles of the camera location on the same route and within a plus or minus 30-minute window of the time recorded in the crash report. It was found that out of the 153 ATMS crash videos analyzed, only 83 of them had corresponding records within the crash database.

To provide context for the 83 matched crashes, their characteristics were compared to all crashes recorded on primary and state highways corresponding to ATMS camera locations in Iowa ($n = 19,421$). **Table 1** presents distributions by crash severity and manner of collision for both groups.

The matched sample had a lower proportion of property damage only (PDO) crashes (57.8%) than the broader population (75.0%), with injury crashes correspondingly overrepresented across all severity levels. With respect to the manner of collision, rear-end crashes accounted for a larger share of the matched sample (44.6%) than the population (24.2%). Non-collision/single vehicle crashes appear at similar proportions in both groups (31.3% vs. 31.8%).

Table 1. Comparison of matched crashes and broader crash population.

Element	Matched Crashes ($n = 83$)		Broader Crash Population ($n = 19,421$)	
Category	n	%	n	%
CRASH SEVERITY				
PDO	48	57.8	14,558	75.0
Possible/Unknown Injury	18	21.7	2,574	13.3
Suspected Minor Injury	12	14.5	1,752	9

Continued

Suspected Serious Injury	4	4.8	413	2.1
Fatal	1	1.2	126	0.6
MANNER OF COLLISION				
Rear-End	37	44.6	4,705	24.2
Non-Collision/Single Vehicle	26	31.3	6,171	31.8
Sideswipe Same Direction	11	13.3	2,391	12.3
Broadside	1	1.2	1,823	9.4
Angle	2	2.4	489	2.5
Head-On	1	1.2	263	1.4
Other/Not Reported/Unknown	5	6.0	3,579	18.4

Note: Broader population excludes 671 records with missing values (3.3% of total). Percentages may not sum to 100 due to rounding.

4.2. Data Analysis

For every crash recorded on video that also had a corresponding crash report, a detailed comparison was conducted between the events captured in the footage and the coded elements derived from the corresponding crash report. The crash videos were manually reviewed and coded for the comparisons. To ensure consistency in how video-coded elements were interpreted, coding was guided by the Iowa Investigating Officer's Crash Reporting Guide, which is the same reference used by the officers who completed the crash reports. A single reviewer conducted all video coding, and while formal inter-rater reliability could not be established, the use of a shared coding reference helped minimize subjective interpretation across variables.

The 83 videos correspond to a total of 83 crashes, involving a collective count of 155 vehicles. To organize the crash records efficiently, the elements from the crash records, relevant to the project, were categorized into crash-level and vehicle-level elements. Crash level encompasses elements that pertain to the crash as a whole, with consistent coding across all vehicles involved in a given crash. **Table 2** shows crash level elements and their descriptions, including if the data element is directly coded by the responding officer or if it is derived from the coded data.

Table 2. Crash level elements.

Element	Description	Type
FIRSTHARM	First Harmful Event	Coded
CRCOMANNER	Manner of Crash/Collision	Coded
MAJORCAUSE	Major Cause of Crash/Collision	Derived
ECONTCIRC	Contributing Circumstances—Environment	Coded
WEATHER1	Weather Conditions 1	Coded
LIGHT	Light Conditions	Coded

Continued

CSURFCOND	Surface Conditions	Coded
LIGHTING	Lighting Conditions	Coded
LOCFSTHARM	Location of First Harmful Event	Coded
RAMP	Mainline or Ramp	Derived
RCONTCIRC	Contributing Circumstances—Roadway	Coded
ROADTYPE	Type of Roadway Junction/Feature	Coded
FIXOBJSTR	Fixed Object Struck (by Vehicle)	Derived
TRAFCONT	Traffic Controls	Coded
HORIZONTALIGN	Horizontal Alignment (Curve)	Coded
VERTALIGN	Vertical Alignment (Grade)	Coded

In contrast, the vehicle level comprised elements relating to the individual drivers or vehicles involved in the crash. For the vehicle level, it is expected that each vehicle involved in a particular crash will have distinct values for these elements. **Table 3** shows vehicle-level elements and their descriptions. This categorization facilitates a structured analysis of the crash data, allowing for a comprehensive examination of both the general characteristics of the crashes and the specific details pertaining to each vehicle involved. **Table 3** presents coded elements along with their descriptions that are not visually discernible in the crash videos. These elements are important for crash data analysis.

Most of these elements have designated fields in crash reports and are entered directly into the crash report database as recorded by the police officer. Other elements, known as derived elements, lack specific fields in the report and are not coded directly.

Table 3. Vehicle-level elements.

Element	Description	Type
SEQEVENTS 1	Sequence of Events 1st Event	Coded
SEQEVENTS 2	Sequence of Events 2nd Event	Coded
SEQEVENTS 3	Sequence of Events 3rd Event	Coded
SEQEVENTS 4	Sequence of Events 4th Event	Coded
VISIONOBS	Vision Obscurement	Coded
DCONTCIRC1	Contributing Circumstances 1—Driver	Coded
VCONFIG	Vehicle Configuration	Coded
DEFECT	Vehicle Defect	Coded
VACTION	Vehicle Action	Coded
INITIMPACT	Point of Initial Impact	Coded
MOSTDAMAGE	Most Damaged Area	Coded

Instead, they are derived from the values of other elements. Examples of derived elements include the primary cause of the crash (MAJORCAUSE), whether the crash involved drugs or alcohol (DRUGALCREL), if the crash occurred on a ramp (RAMP), the class of road where the crash took place (ROADCLASS), if a fixed object was struck during the incident (FIXOBJSTR), and similar factors. These derived elements are assigned values based on a logical process that cycles through various other elements. This project focused more on MAJORCAUSE, which is derived through a sequential logic process that cycles through up to 72 conditions across five field groups: collision with fixed object (FIRSTHARM, SEQUEVENTS), driver contributing circumstances (DCONTCIRC), driver distraction (DRIVERDIST), sequence of events (SEQUEVENTS, CARGOBODY, TRAFCONT, VACCATION), and remaining coded conditions, including a default value assigned when all contributing fields are recorded as unknown. The process assigns the value corresponding to the first condition met. **Figure 1** illustrates this process. The complete derivation logic is provided in the supplementary document.

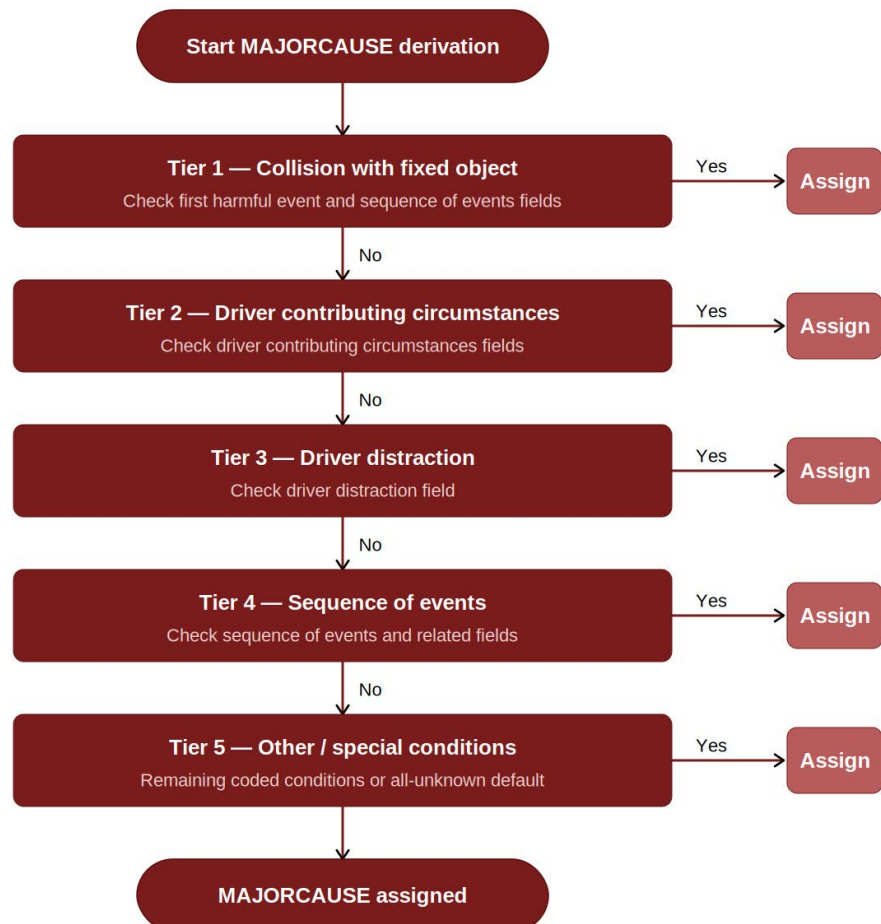


Figure 1. MAJORCAUSE derivation process.

After comparing the crash videos with the coded elements in both groups, the number of observations that were coded differently for each element was tallied

to ascertain the overall accuracy of the element. Subsequently, the accuracy of each element, along with its 95% confidence interval, was computed. The normal approximation which is used when the sample size is large and the binomial distribution is close to the normal shape, was not used. Rather, the exact Clopper-Pearson method was used. This method is particularly suitable for smaller sample sizes, as it avoids the normal approximation used in standard confidence interval computations and instead uses the Binomial distribution. By using the Binomial distribution, the Clopper-Pearson method calculates the exact lower and upper bounds for the confidence interval. This ensures that even with small sample sizes or rare events, the resulting confidence interval provides an accurate reflection of the potential variability in the data.

Table 4. Elements not discernible in crash videos.

Element	Description	Type
ALCRESULT	Alcohol Test Results	Coded
ALCTEST	Alcohol Test Given?	Coded
AIRBAGDEP	Airbag Deployment	Coded
CHARGED	Driver Charged?	Coded
CSEVERITY	Crash Severity	Coded
DAGEBIN1	Driver Age Bin	Coded
DEATHLCTN	Died at Scene/En Route	Coded
DRIVERAGE	Driver Age	Coded
DRIVERCOND	Driver Condition	Coded
DRIVERDIST	Driver Distraction	Coded
DRIVERGEN	Driver Gender	Coded
DRUGALCREL	Drug or Alcohol Related	Derived
DRUGRESULT	Drug Test Results	Coded
DRUGTEST	Drug Test Given?	Coded
EJECTION	Ejection	Coded
EJECTPATH	Ejection Path	Coded
MAKE	Vehicle Make	Coded
MODEL	Vehicle Model	Coded
OCCPROTECT	Occupant Protection	Coded
OCCUPANTS	Vehicle Occupants	Coded
REPAIRCOST	Cost of Repair	Coded
SEATING	Seating Position	Coded
TRAPPED	Occupant Trapped?	Coded
TRNSPRTSRC	Source of Transport	Coded
VYEAR	Vehicle Year	Coded
DRIVERDIST	Driver Distraction	Coded
DRIVERGEN	Driver Gender	Coded

The Clopper-Pearson method uses the relationship between the Binomial distribution and the Beta distribution to form the confidence interval. The formula is shown in Equation (1) [25]:

$$\left[B(\alpha/2; X, n - X + 1), B(1 - \alpha/2; X + 1, n - X) \right] \quad (1)$$

where:

$B(\cdot; \alpha, \beta)$ is the quantile function for the beta distribution with shape parameters α and β .

Given an observation X , the computation of the lower limit p_L and the upper limit p_U are given by Equation (2) and Equation (3), respectively [26]:

$$\sum_{k=X}^n \binom{n}{k} p_L^k (1 - p_L)^{n-k} = \alpha/2 \quad (2)$$

$$\sum_{k=0}^X \binom{n}{k} p_U^k (1 - p_U)^{n-k} = \alpha/2 \quad (3)$$

where:

k : number of successes in the binomial distribution, where k ranges from X to n .

n : total number of trials.

X : number of observed successes.

$\alpha/2$: significance level for the lower tail of the distribution.

The Clopper-Pearson confidence interval is implemented in most statistical software packages, and R was used in this case.

Additionally, for selected categorical elements, such as crash severity, the accuracy or consistency of coded elements was evaluated for each category. For instance, the accuracy of the coded elements when the crash is fatal was calculated, along with its corresponding confidence interval. This was to provide a further understanding of the accuracy levels across different categories within the dataset, enhancing the reliability and depth of the analysis.

5. Results

5.1. Consistency by Element Group

The values for each element were compared to the same event from the crash video using data dictionaries provided by the Iowa DOT for consistency. Accuracy, defined here as the percent agreement between the police reported values and the corresponding video-coded values, was estimated for each element along with 95% confidence intervals using the exact or Clopper-Pearson method in R.

Crash Level Elements:

Figure 2 shows a dot plot with 95% confidence intervals representing the accuracy of crash level elements when compared with video data. Each dot represents the accuracy for each element, and the horizontal lines represent the 95% confidence intervals for these estimates.

Most elements, including weather conditions (WEATHER1), light conditions

(LIGHT), surface conditions (CSURFCOND), lighting conditions (LIGHTING), location of first harmful event (LOCFSTHARM), traffic controls (TRAFCONT), and vertical alignment (VERTALIGN), had high accuracies close to 100% with tight confidence intervals indicating precise estimates of the accuracy. Other elements, such as the first harmful event (FIRSTHARM), manner of crash or collision (CRCOMANNER), environmental contributing circumstances (ECONTCIRC), roadway contributing circumstances (RCONTCIR), type of roadway junction or feature (ROADTYPE), and horizontal alignment (HORIZALIGN), showed accuracy levels close to 90% with tight confidence intervals as well.

This indicates that law enforcement personnel are performing commendably in accurately coding these elements. This effectiveness is not unexpected, as these elements are comparatively easier to code correctly. The investigating officers can directly observe most of these factors themselves, eliminating the over-reliance on witness statements.

Derived Elements—elements that are obtained from values of other elements:

Whether the crash occurred on a mainline or a ramp (RAMP) is derived from the route identification (RouteID) number of the roadway on which the crash occurred. This value is derived based on whether the RouteID is eleven or fifteen characters long. If the RouteID is fifteen characters long, then the last four characters identify which ramp the crash is located on. Also, whether a fixed object along the roadway was struck during the event of the crash (FIXOBJSTR) is also a derived element. The fixed object struck element uses various harmful event fields to identify the fixed object struck. The derivation of this field uses a hierarchy of first checking MOSTHARM, which is then followed in order by SEEVENTS1, SEEVENTS2, SEEVENTS3, and SEEVENTS4. The results of the accuracy of these elements in crash reports (93% for RAMPS and 92% for FIXOBJSTR) leave some room for improvement. The derivation process may need to be updated to account for the errors.

The major cause of the crash or collision (MAJORCAUSE) recorded the lowest accuracy (65%) and the widest confidence interval, ranging from 57% to 72% for crash level elements. This element attempts to identify the primary cause of the crash. This element is not a coded field from the investigating officer's report; rather, it is derived from various other coded elements that contributed to the crash. Specifically, it includes the first harmful event (FIRSTHARM), the sequence of event (SEEVENTS1, SEEVENTS2, SEEVENTS3, SEEVENTS4), driver contributing circumstances (DCONTCIRC1, DCONTCIRC2), vehicle action before crash (VACTION), driver distraction (DRIVERDIST), the vehicle cargo type (CARGOBODY), and the traffic control devices present (TRAFCONT). The lower accuracy range of MAJORCAUSE is expected, considering its reliance on the precision of these associated elements. It is important to acknowledge that all elements contributing to MAJORCAUSE can be identified in the crash video, with the exception of driver distraction (DRIVERDIST). Refer to **Table 4**.

Determining the primary cause of the crash is very important as this helps in

safety analytics and is essential in developing targeted interventions to prevent similar incidents in the future. These interventions include improvements in road and vehicle designs to improve safety. The accuracy of the major cause of the crash or collision is essential for law and policymakers to develop and implement effective traffic laws and regulations.

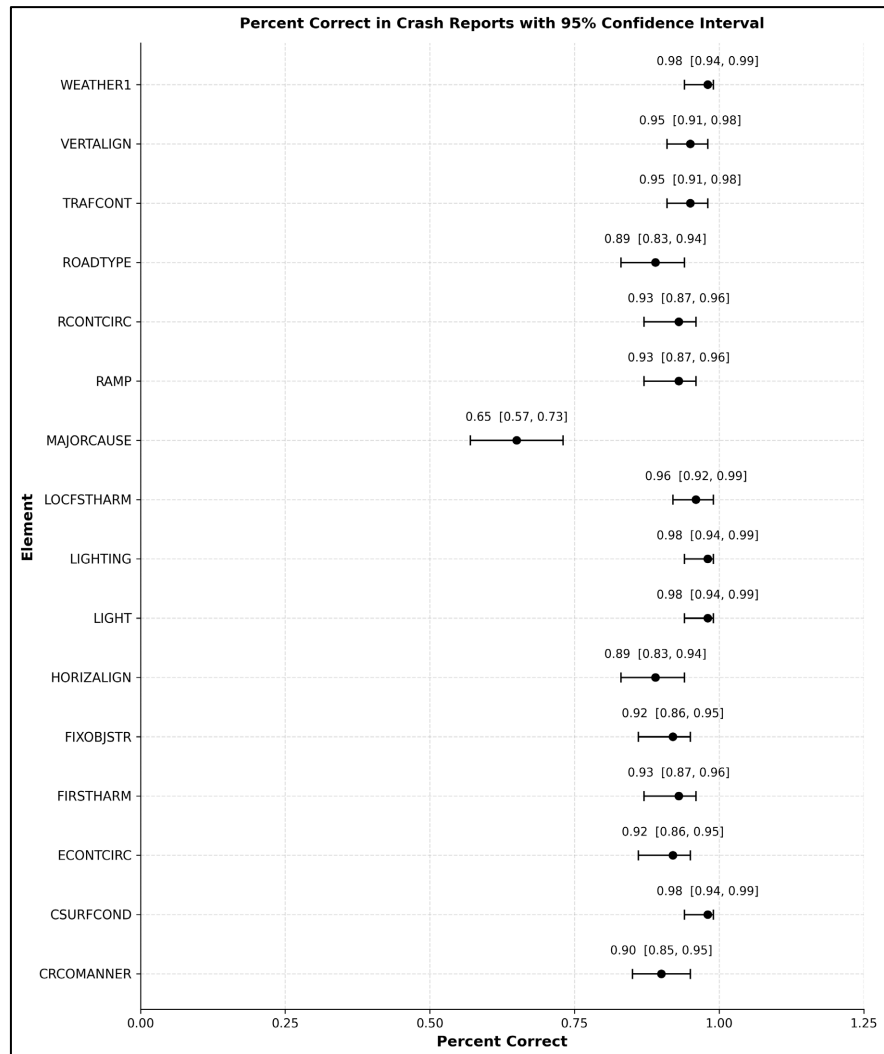


Figure 2. Percent correct in crash reports with 95% confidence intervals for crash level elements.

Vehicle Level Elements:

Figure 3 shows a dot plot with 95% confidence intervals representing the accuracy in terms of percent correct in crash reports for vehicle-level elements when compared with video data. Each dot represents the accuracy for each element, and the horizontal lines represent the 95% confidence intervals for these estimates.

The sequence of events 1 and 2 elements (SEQEVENTS1 and SEQEVENTS2) exhibited the lowest accuracy of about 80%, with relatively wider 95% confidence intervals, indicating a lower accuracy and a fairly higher uncertainty. This lower

accuracy may reflect the complexity of the crash or inconsistent witness testimonies, as omissions and distortions are introduced when converting verbal accounts into written reports [10] [12], though this hypothesis was not directly tested in the current study. On the other hand, sequence of events 3 and 4 elements (SEQEVENTS3 and SEQEVENTS4) showed higher accuracies of above 90%. It is hypothesized that concluding crash events may be more physically evident and therefore easier to code accurately, though this was not directly tested. The confidence intervals for these are narrower, indicating less uncertainty in the accuracy. The driver contributing circumstances 1 element (DCONTCIRC1) has an accuracy of 85% and a relatively wider confidence interval, indicating a potential avenue for improvement.

The most damaged area of the vehicle element (MOSTDAMAGE) and the vehicle configuration element (VCONFIG) had accuracies close to 100% with tight confidence intervals. This is not surprising as these elements are observable post-crash, with the officer likely on the scene. Vehicle defect (DEFECT) and vision obscuration (VISIONOBS), being more challenging to discern in videos, unsurprisingly, showed accuracy ranges near 100% with tight confidence intervals.

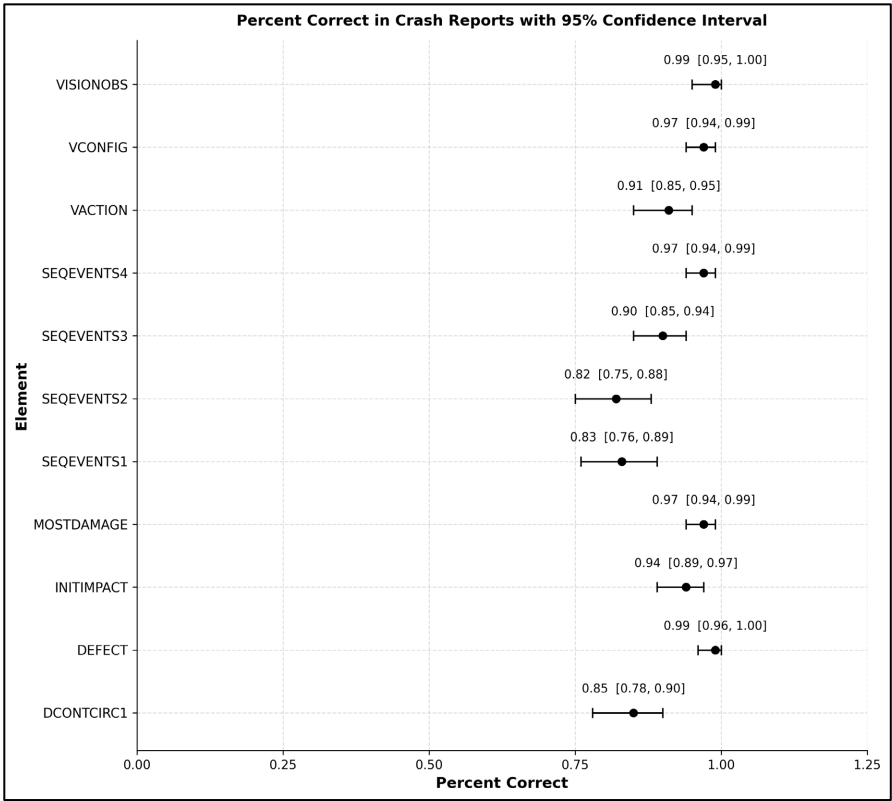


Figure 3. Percent correct in crash reports with 95% confidence intervals for vehicle-level elements.

5.2. Consistency by Category

For selected categorical elements, the value recorded by the investigating officer

is taken as a reference point. This approach differs from the previous analysis, where video evidence serves as the ground truth. Here, the police report category is held fixed, and the accuracy of associated report elements is assessed within each category. The remaining report details are compared against the corresponding video evidence to determine if they match. The proportion of matching records is reported with a 95% confidence interval. For instance, when a crash is classified as fatal in the police report, the accuracy of every accompanying detail is calculated and reported with its corresponding confidence limits.

Manner of Crash or Collision:

Out of the 83 crashes analyzed, 36 were rear-end collisions, 28 were single-vehicle incidents (non-collisions), and only 12 were sideswipe-same direction crashes. **Figure 4** shows the consistency between crash reports and video data, presenting accuracies within a 95% confidence interval for various crash types. Only three crash types were considered since the others had fewer than 2 occurrences in the dataset.

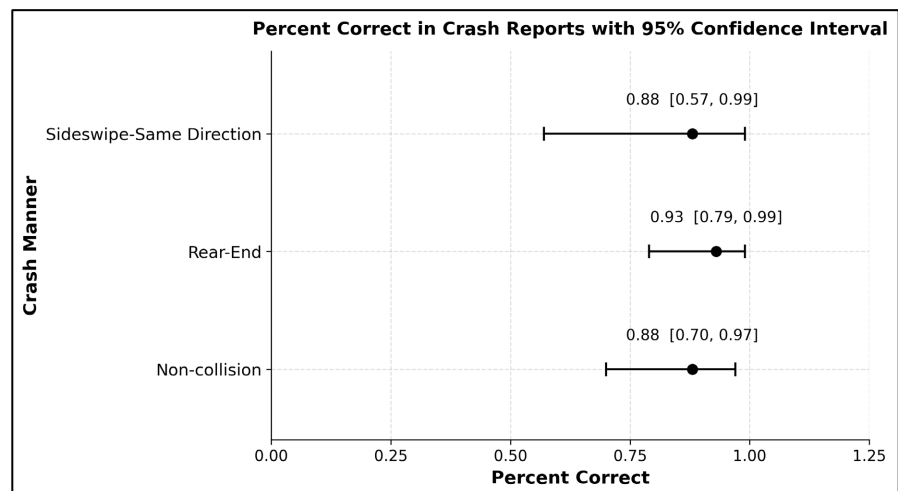


Figure 4. Percent correct in crash reports with 95% confidence intervals for manner of crash or collision.

Sideswipe-same direction crashes had an accuracy of 88% with a wide 95% confidence interval of 57% to 99%, suggesting considerable uncertainty in this estimate. Single-vehicle (non-collision) crashes also had an accuracy of 88% but a 95% confidence interval range of 70% to 97%. This also indicates some uncertainty, but not as much as Sideswipe-same direction. Rear-end collisions had the highest accuracy in this category, with 93% and a narrower confidence interval ranging from 79% to 99%. The fact that all point estimates were close to or above 88% suggests a generally high percent correct in police reports for these factors, given the data and sample size available. However, the Rear-End category appears to have the most precise estimate, indicating a higher accuracy in crashes involving rear-end collisions.

Weather Conditions:

Out of the 83 crashes studied, 55 occurred under clear weather, 13 during cloudy conditions, 4 in rain, and 6 in snow. **Figure 5** presents the accuracy of crash reports when compared to crash videos, within a 95% confidence interval for the various weather conditions. Only four weather conditions were considered since the others had no occurrences in the dataset.

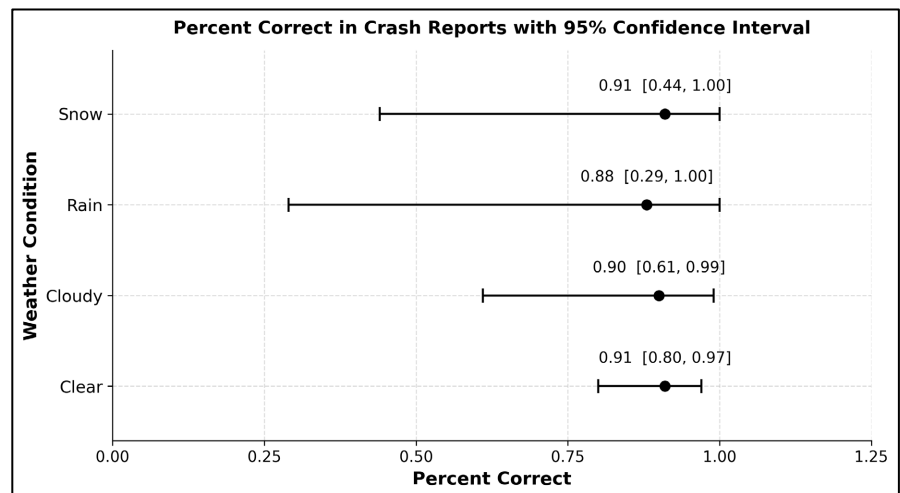


Figure 5. Percent correct in crash reports with 95% confidence intervals for weather conditions.

Crashes in Snow ($n = 6$) and Rain ($n = 4$) conditions had high point estimates, but the very wide confidence intervals reflect the small sample sizes and should be interpreted with caution. The narrower interval for Cloudy conditions, as compared to Snow and Rain, shows a bit more certainty in the estimate of consistency. Clear conditions had the highest accuracy at 91% and the narrowest 95% confidence interval. This narrow interval suggests the accuracy of crashes or collisions occurring in clear weather conditions in police reports is likely to be at least 80% and as high as 97%. Therefore, given the data and sample size available, there is generally a higher accuracy in crash data for crashes occurring in Clear conditions compared to the others.

Crash Severity:

Out of the 83 crashes analyzed, 45 were classified as PDO crashes. There were 19 possible injury crashes, 11 minor injury crashes, 4 major injury crashes, and 1 fatal crash. **Figure 6** shows the accuracy between crash reports and video data, within a 95% confidence interval for each crash severity category. No confidence interval is shown for fatal crashes because the dataset contained only one fatal crash.

For all severity levels, the point estimates of accuracy were 89% or above. However, the confidence intervals for major injury ($n = 4$) and fatal incidents ($n = 1$) were very wide. These categories are too small for reliable inferential conclusions. The narrower confidence intervals for Possible Injury and PDO (property damage only) incidents suggest more reliable estimates for these categories. However, the

apparent trend of higher accuracy with increasing severity should be interpreted cautiously, given the uncertainty in the more severe categories, though it is consistent with findings in the literature [4] [18] [22] [23].

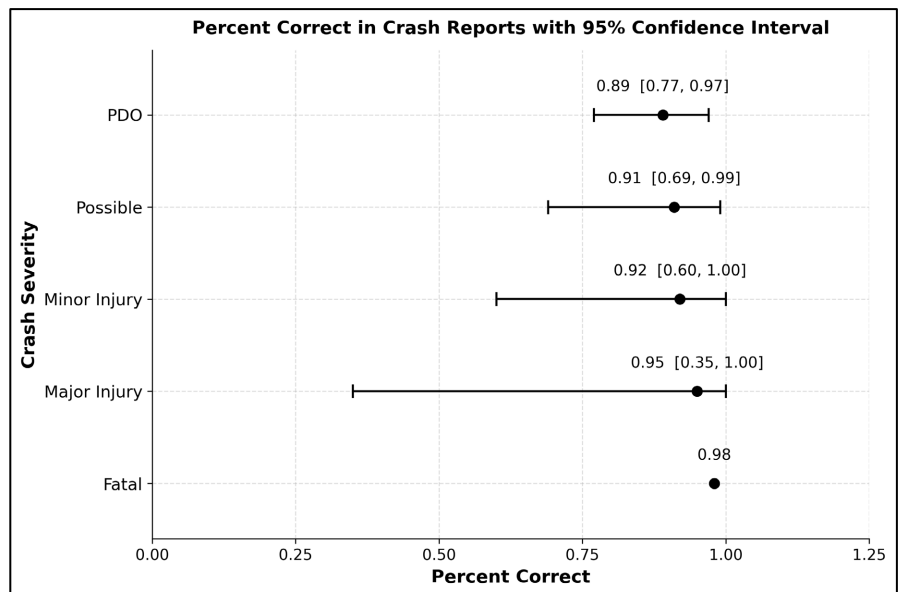


Figure 6. Percent correct in crash reports with 95% confidence intervals for crash severity.

Vehicle Configuration:

Among the 83 crashes analyzed, 61 involved passenger cars, 24 involved four-tire trucks, 41 involved SUVs, and 18 involved larger trucks. **Figure 7** shows the accuracy between crash reports and video data, presenting accuracy within a 95% confidence interval for various vehicle configurations.

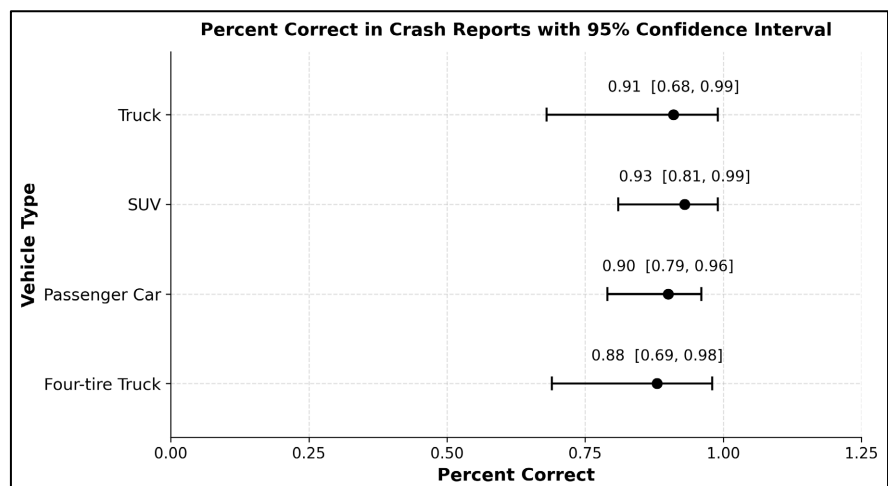


Figure 7. Percent correct in crash reports with 95% confidence intervals for vehicle configuration.

Police reports generally had accuracy values ranging from 88% to 93% for ele-

ments when crashes involve these vehicle types. The confidence interval for incidents involving trucks is wider, indicating some uncertainty in the estimate. However, the SUV category stands out with the highest estimate and a relatively narrow confidence interval, suggesting that police reports are particularly more accurate for incidents involving SUVs.

Number of Vehicles in Crash:

Among the crashes analyzed, 27 involved a single vehicle, 45 involved two vehicles, 6 involved three vehicles, and 5 involved four vehicles. **Figure 8** shows the accuracy between crash reports and video data, presenting accuracy within a 95% confidence interval for incidents involving a varying number of vehicles.

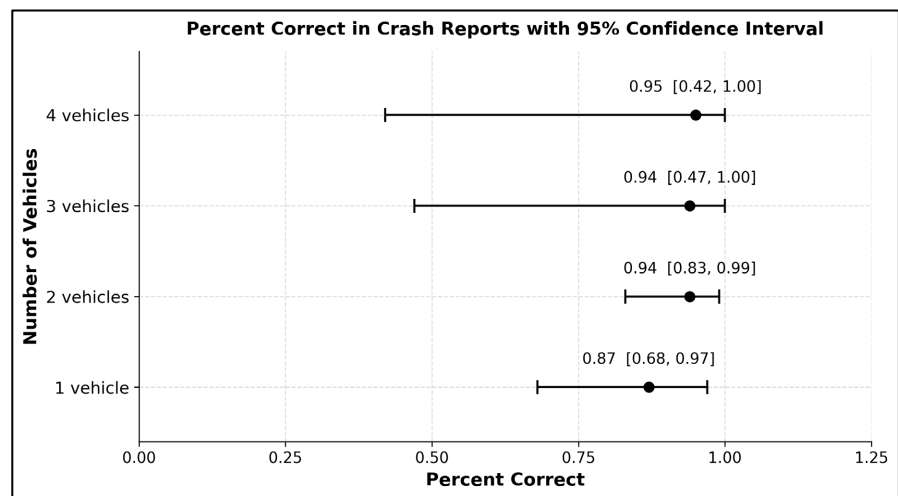


Figure 8. Percent correct in crash reports with 95% confidence intervals for the number of vehicles in the crash.

Police reports are generally more accurate with regard to incidents involving multiple vehicles, with accuracy apparently increasing with the number of vehicles involved. However, the wide confidence intervals for incidents with three ($n = 6$) or four ($n = 5$) vehicles indicate substantial uncertainty, and these estimates should be treated as descriptive summaries only. The much narrower confidence interval for two-vehicle incidents suggests more confidence in the accuracy of reports for those crashes. The apparent trend of increasing accuracy with vehicle count should be interpreted with caution, given the small samples in the higher-vehicle categories. One possible explanation for the lower accuracy in single-vehicle crashes is that drivers may be more likely to provide inaccurate accounts, whether due to memory impairment or motivations to avoid blame [11] [13]. This hypothesis was not tested in the current study and warrants further investigation.

On average, crash reports are fairly accurate across various factors such as vehicle type, weather conditions, crash types, and the number of vehicles involved. The width of the confidence intervals varies significantly, with wider confidence intervals showing the presence of uncertainty in the estimate. Conversely, other factors, such as when SUVs are involved or incidents during clear weather condi-

tions, show narrower confidence intervals, indicating more precise estimates of accuracy. The very wide confidence intervals in some categories, particularly for severe incidents and less common conditions, are attributable to small sample sizes, and the corresponding estimates should be interpreted accordingly.

6. Conclusions

The study sought to evaluate the consistencies and inconsistencies in police reported crash data by comparing crash reports to the visual evidence presented in crash videos. The results indicate that elements observable after the crash, such as environmental and weather conditions, road surface conditions, vehicle configuration, and extent of damage, generally have higher accuracy levels due to the investigating officer's presence on-site after the crash. However, elements related to the crash location, such as road type, location of crash, horizontal alignment, and objects struck, could be improved as they are readily identifiable; minor discrepancies in their accuracy might stem from reporting errors.

Elements that necessitate reliance on witness accounts, such as the manner of crash or collision, the first harmful event, and the sequence of events during the incident, exhibit relatively lower accuracies. Lower accuracy ranges are estimated for the primary cause of the crash, reflecting its dependency on the accuracy of the elements it is derived from.

Among the factors analyzed, there is no clear evidence indicating that any single factor significantly enhances the accuracy of crash reports over others. Instead, the accuracy appears to be relatively consistent across different factors, although the precision of these estimates varies due to wide confidence intervals witnessed in some cases. These wide confidence intervals introduce uncertainties and may stem from inadequate representation of certain factors in the analyzed sample.

It's crucial for professionals who use this crash data, such as experts in safety diagnostics, safety management personnel, and researchers, to be aware and mindful of these inconsistencies. The levels of inaccuracies in the data should be considered whenever using it for analysis or decision-making. Additionally, the insights from this study can be used to inform officer training programs, improve crash reporting guidelines, and support efforts to integrate video data into crash data workflows to enhance reporting accuracy.

7. Limitations

This study identified some limitations related to the utilization of crash videos sourced from traffic cameras for evaluating police-reported crash data. One limitation concerns coverage. Since not all locations are equipped with traffic cameras, not all crashes are documented and accessible for analysis. Additionally, these cameras may not capture every detail leading up to a crash. While the overall sample size utilized was sufficient to identify inconsistencies in crash data, the unavailability of a more representative sample for certain categories, such as only one fatal crash being included in the sample, affects the reliability of confidence inter-

val estimates for those categories.

A related limitation concerns selection bias. Of the 697 videos documented as containing visible crashes in 2022, only 153 captured the full crash sequence, and only 83 of those had corresponding police crash reports. As shown in **Table 1**, the matched sample differs from the broader crash population on ATMS-monitored routes in notable ways. Injury crashes are overrepresented in the matched sample relative to the broader population, and rear-end collisions account for a disproportionately large share of matched crashes compared to the broader population. As a result, the accuracy estimates reported here may not reflect the full range of crash types and conditions present in the broader population, and caution is warranted when generalizing these findings.

There is also a geographic generalizability limitation. The ATMS camera network is installed primarily along primary and state highways in Iowa, which means the analyzed crashes are not representative of crashes occurring on urban arterials or intersections. Crash dynamics, reporting complexity, and officer judgment demands may differ substantially across these road types. As a result, the accuracy estimates reported here may not generalize beyond the specific network studied, and future research should examine police-reported crash data quality across a broader range of road types and settings.

Another limitation pertains to the constraints of the crash videos themselves. The study did not address critical factors like distracted driving or impairment due to alcohol or drugs. While the crash videos may capture the crash events comprehensively, certain factors remain less discernible in the footage. This limitation hinders the ability to comprehensively analyze these important aspects of crash incidents.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Supplementary Document

This document contains more information about the MAJORCAUSE-derived elements used in this project.

Majorcause

1) Corresponding APS Field: No direct fields used. Fields from the various Z-tables in the crash database are used, including FIRSTHARM, SEQUEVENTS1, SEQUEVENTS2, SEQUEVENTS3, SEQUEVENTS4, DCONTCIRC1, DCONTCIRC2, TRAFCONT, DRIVERDIST, CARGOBODY, and VACTION.

2) Data Inputs: Derived based on fields in the crash database.

3) Data Processing Description: The major cause field is derived based on various attributes within the crash data. The following summarizes the conditions for deriving the major cause. The process will cycle through the conditions below in the given sequence until a condition is met and the corresponding value returned as the major cause.

FIRSTHARM = 31 or SEQUEVENTS1 = 31 or SEQUEVENTS2 = 31 or SEQUEVENTS3 = 31 or SEQUEVENTS4 = 31:

Return value of 1

DCONTCIRC1 = 1 or DCONTCIRC2 = 1

Return value of 2

DCONTCIRC1 = 2 or DCONTCIRC2 = 2

Return value of 3

DCONTCIRC1 = 12 or DCONTCIRC2 = 12

Return value of 4

DCONTCIRC1 = 47 or DCONTCIRC2 = 47

Return value of 5

DCONTCIRC1 = 43 or DCONTCIRC2 = 43

Return value of 6

DCONTCIRC1 = 40 or DCONTCIRC2 = 40

Return value of 7

DCONTCIRC1 = 41 or DCONTCIRC2 = 41

Return value of 8

DCONTCIRC1 = 42 or DCONTCIRC2 = 42

Return value of 9

DCONTCIRC1 = 44 or DCONTCIRC2 = 44

Return value of 10

DCONTCIRC1 = 45 or DCONTCIRC2 = 45

Return value of 11

DCONTCIRC1 = 46 or DCONTCIRC2 = 46

Return value of 12

DCONTCIRC1 = 97 or DCONTCIRC2 = 97

Return value of 13

DCONTCIRC1 = 22 or DCONTCIRC2 = 22

Return value of 14

TRAFCONT = 9 and (DCONTCIRC1 = 98 or DCONTCIRC2 = 98)

Return value of 15

(DCONTCIRC1 = 13 or DCONTCIRC2 = 13) and (SEQEVENTS1 = 4 or SEQEVENTS2 = 4 or SEQEVENTS3 = 4 or SEQEVENTS4 = 4)

Return value of 16

(DCONTCIRC1 = 13 or DCONTCIRC2 = 13) and (SEQEVENTS1 = 5 or SEQEVENTS2 = 5 or SEQEVENTS3 = 5 or SEQEVENTS4 = 5)

Return value of 17

DCONTCIRC1 = 13 or DCONTCIRC2 = 13

Return value of 18

DCONTCIRC1 = 10 or DCONTCIRC2 = 10

Return value of 19

DCONTCIRC1 = 5 or DCONTCIRC2 = 5

Return value of 20

DCONTCIRC1 = 3 or DCONTCIRC2 = 3

Return value of 21

VACTION = 6 and (DCONTCIRC1 = 9 or DCONTCIRC2 = 9)

Return value of 22

DCONTCIRC1 = 8 or DCONTCIRC2 = 8

Return value of 23

DCONTCIRC1 = 7 or DCONTCIRC2 = 7

Return value of 24

DCONTCIRC1 = 30 or DCONTCIRC2 = 30

Return value of 25

DCONTCIRC1 = 31 or DCONTCIRC2 = 31

Return value of 26

DCONTCIRC1 = 32 or DCONTCIRC2 = 32

Return value of 27

DCONTCIRC1 = 33 or DCONTCIRC2 = 33

Return value of 28

DCONTCIRC1 = 96 or DCONTCIRC2 = 96

Return value of 29

DCONTCIRC1 = 11 or DCONTCIRC2 = 11

Return value of 30

DRIVERDIST = 3

Return value of 31

DRIVERDIST = 4

Return value of 32

DRIVERDIST = 5

Return value of 33

DRIVERDIST = 6

Return value of 34

DRIVERDIST = 96
 Return value of 35
 DRIVERDIST = 10
 Return value of 36
 DRIVERDIST = 11
 Return value of 37
 DRIVERDIST = 14
 Return value of 38
 DRIVERDIST = 15
 Return value of 39
 DRIVERDIST' in (12, 13, 16, 97)
 Return value of 40
 DRIVERDIST = 98
 Return value of 41
 SEEVENTS1 = 1 or SEEVENTS2 = 1 or SEEVENTS3 = 1 or SEEVENTS4
 = 1
 Return value of 42
 SEEVENTS1 = 2 or SEEVENTS2 = 2 or SEEVENTS3 = 2 or SEEVENTS4
 = 2
 Return value of 43
 SEEVENTS1 = 3 or SEEVENTS2 = 3 or SEEVENTS3 = 3 or SEEVENTS4
 = 3
 Return value of 44
 DCONTCIRC1 = 6 or DCONTCIRC2 = 6
 Return value of 45
 (DCONTCIRC1 = 18 or DCONTCIRC2 = 18) or (SEEVENTS1 = 6 or SE-
 QEVENTS2 = 6 or SEEVENTS3 = 6 or SEEVENTS4 = 6)
 Return value of 46
 DCONTCIRC1 = 15 or DCONTCIRC2 = 15
 Return value of 47
 DCONTCIRC1 = 16 or DCONTCIRC2 = 16
 Return value of 48
 DCONTCIRC1 = 17 or DCONTCIRC2 = 17
 Return value of 49
 DCONTCIRC1 = 14 or DCONTCIRC2 = 14
 Return value of 50
 DCONTCIRC1 = 21 or DCONTCIRC2 = 21
 Return value of 51
 DCONTCIRC1 = 50 or DCONTCIRC2 = 50
 Return value of 52
 DCONTCIRC1 = 51 or DCONTCIRC2 = 52 or DCONTCIRC1 = 52 or
 DCONTCIRC2 = 51
 Return value of 53

TRAFCONT = 7 and (DCONTCIRC1 = 53 or DCONTCIRC2 = 53)
Return value of 54
DCONTCIRC1 = 53 or DCONTCIRC2 = 53
Return value of 55
DCONTCIRC1 = 54 or DCONTCIRC2 = 54
Return value of 56
SEQEVENTS1 = 7 or SEQEVENTS2 = 7 or SEQEVENTS3 = 7 or SEQEVENTS4 = 7
Return value of 57
SEQEVENTS1 = 10 or SEQEVENTS2 = 10 or SEQEVENTS3 = 10 or SEQEVENTS4 = 10
Return value of 58
DCONTCIRC1 = 55 or DCONTCIRC2 = 55
Return value of 59
SEQEVENTS1 = 8 or SEQEVENTS2 = 8 or SEQEVENTS3 = 8 or SEQEVENTS4 = 8
Return value of 60
SEQEVENTS1 = 9 or SEQEVENTS2 = 9 or SEQEVENTS3 = 9 or SEQEVENTS4 = 9
Return value of 61
CARGOBODY = 18
Return value of 62
DCONTCIRC1 = 56 or DCONTCIRC2 = 56
Return value of 63
DCONTCIRC1 = 20 or DCONTCIRC2 = 20
Return value of 64
VACTION = 9 and (DCONTCIRC1 = 19 or DCONTCIRC2 = 19)
Return value of 65
VACTION = 15 and (DCONTCIRC1 = 19 or DCONTCIRC2 = 19)
Return value of 66
VACTION = 13
Return value of 67
DCONTCIRC1 = 4 or DCONTCIRC2 = 4
Return value of 68
DCONTCIRC1 = 58 or DCONTCIRC2 = 58
Return value of 69
DCONTCIRC1 = 98 or DCONTCIRC2 = 98
Return value of 70
DCONTCIRC1 = 99 or DCONTCIRC2 = 99
Return value of 71
(DCONTCIRC1 = 77 or DCONTCIRC2 = 77) and VACTION = 77 and TRAFCONT = 77 and CARGOBODY = 77 and DRIVERDIST = 77 and (SEQEVENTS1 = 77 or SEQEVENTS2 = 77 or SEQEVENTS3 = 77 or SEQEVENTS4 = 77)

QEVENTS4 = 77)

Return value of 72

DCONTCIRC1 = 88 or DCONTCIRC2 = 88

Return value of 73

If no conditions above are met

Return value of 99