Supplementary Information for: Customizing Large Language Models for Reliable and Interpretable Traffic Crash Prediction and Safety Interventions

Yang Zhao[1, 2+], Pu Wang[1, 2+], Yibo Zhao[1, 2], Hongru Du[1, 2], and Hao (Frank) Yang[1, 2*]

[1]Center for Systems Science and Engineering, Johns Hopkins University, Baltimore, MD, USA.
[2]Department of Civil and Systems Engineering, Johns Hopkins University, Baltimore, MD, USA.
[+]The authors contributed equally.
[*]The corresponding authors information:haofrankyang@jhu.edu

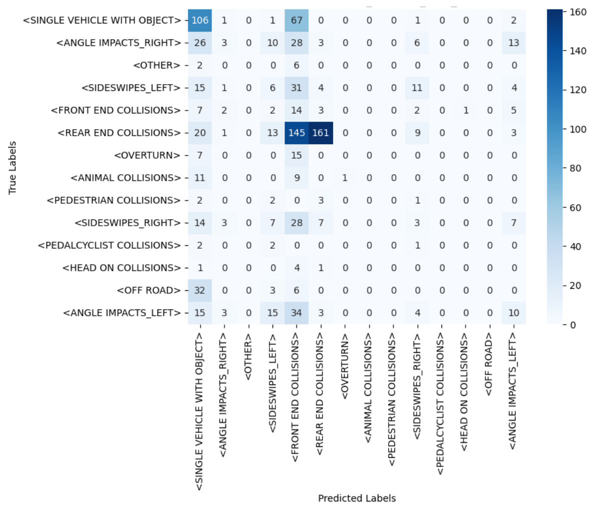
1 Zero-shot and Few-shots Results with Vanilla Large Language Models

Vanilla pretrained large language models (LLMs), such as Llama 3.1, demonstrate powerful zero-shot and few-shot capabilities, allowing them to perform various tasks without requiring a fine-tuning process[1]. However, for crash prediction tasks, due to the limited domain-specific data available in pre-training, these models may struggle to capture the nuanced patterns and factors unique to crash data. Fine-tuning on crash-related datasets is therefore essential to enhance model accuracy and relevance in predicting traffic crash outcomes.

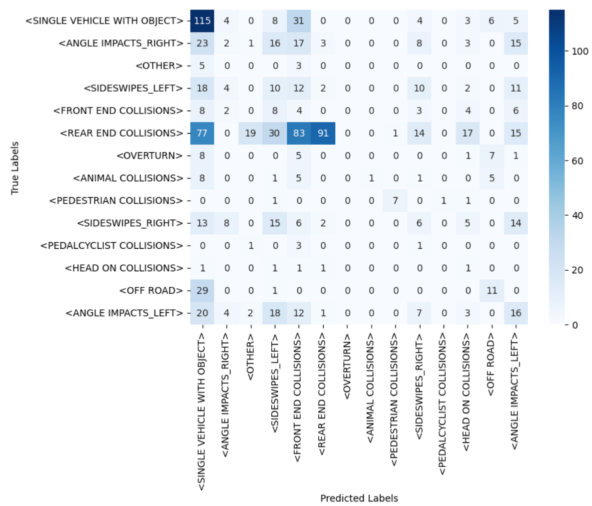
To evaluate the vanilla LLMs' capabilities in zero-shot and few-shot predictions for crash prediction tasks, we conducted a series of experiments comparing their performance with and without fine-tuning. We used Llama 3.1 8B as the base for the experiment, and predicted crash types on 1,000 randomly selected samples from the validation splits of the Washington and Illinois datasets, respectively. The results of the zero-shot and few-shots results are shown in Table 1. We can observe that the zero-shot and few-shots results are significantly low, and the fine-tuning process has substantially improved the LLMs' ability in predicting crashes. Figure 1 shows the confusion matrix for the zero-shot and few-shots predictions, where the LLM without fine-tuning only predicts several categories such as *Front End Collision*.

Supplementary Table 1: The Comparison of the Crash *Type* Prediction Results Using Zero-shot, Few-shots, and Fine-tuning Methods.

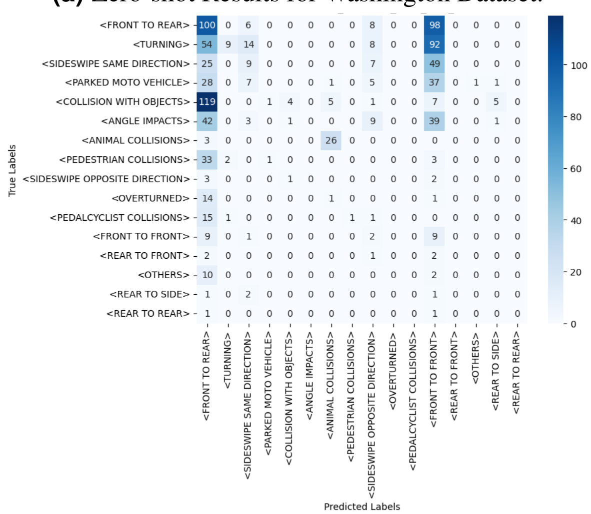
Washington Dataset			
Prediction Method	**Accuracy**	**Precision**	**F1-score**
Zero-shot	0.303	0.432	0.329
Few-shots	0.264	0.468	0.282
Fine-tuning	**0.756**	**0.763**	**0.755**
Illinois Dataset			
Prediction Method	**Accuracy**	**Precision**	**F1-score**
Zero-shot	0.157	0.331	0.125
Few-shots	0.229	0.289	0.172
Fine-tuning	**0.701**	**0.768**	**0.721**



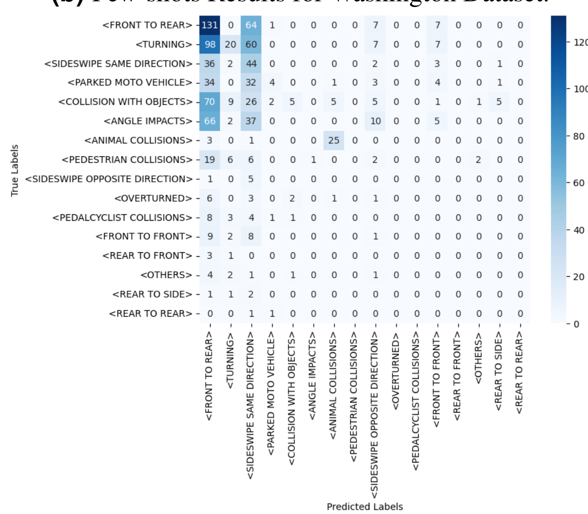
(a) Zero-shot Results for Washington Dataset.



(b) Few-shots Results for Washington Dataset.



(c) Zero-shot Results for Illinois Dataset.



(d) Few-shots Results for Illinois Dataset.

Supplementary Figure 1: Confusion Matrix for Zero-shot and Few-shots Results in Washington and Illinois Datasets. We used Llama-3.1 8B model and use 1,000 samples from validation set for each dataset. Five randomly selected examples were used for each few-shots prediction.

2 Definitions of Prediction Targets

Supplementary Table 2: Crash Prediction Targets Explanation for Washington Dataset. The possible values and their explanations for the prediction targets in the *Severity* and *Type* tasks are presented. **Abbr.** denotes abbreviations.

Task	k	Option	Abbr.	Explanation
Severity (S_k)	1	No Apparent Injury	NI	No visible injuries reported at the scene.
	2	Possible Injury	PI	Any injury reported to the officer or claimed by the individual.
	3	Minor Injury	MI	Any injury other than fatal or disabling at the scene.
	4	Serious Injury	SI	Any injury that prevents an individual from walking, driving, or continuing their normal activities.
	5	Fatal	F	Any injury that directly results in the death of a living person within 30 days of a motor vehicle crash.
Type ($T_k^{\mathscr{W}}$)	1	Single Vehicle With Object	SVO	Collision involving a single vehicle and a stationary object.
	2	Angle Impacts Right	AIR	Vehicles collide at an angle, impacting on the right side.
	3	Sidewipes Left	SL	Vehicles sideswipe each other on the left side.
	4	Front End Collision	FEC	Collisions where the front ends of vehicles impact each other.
	5	Rear End Collision	REC	Collisions where one vehicle impacts the rear of another.
	6	Overturn	OT	Crashes where a vehicle overturns.
	7	Animal Collision	AC	Collisions involving animals.
	8	Pedestrian Collision	PC	crashes where a vehicle collides with a pedestrian.
	9	Sidewipes Right	SR	Vehicles sideswipe each other on the right side.
	10	Pedalcyclist	PCC	Collisions involving cyclists.
	11	Head On Collision	HOC	Head-on collisions between vehicles.
	12	Off Road	OR	Crashes involving vehicles going off the road.
	13	Angle Impact Left	AIL	Vehicles collide at an angle, impacting on the left side.
	14	Other	OTH	Any other types not classified in specific categories.

Supplementary Table 3: Crash Prediction Targets Explanation for Illinois Dataset. The possible values and their explanations for the prediction targets in the *Severity* and *Type* tasks are presented. **Abbr.** denotes abbreviations.

Task	k	Option	Abbr.	Explanation
	1	Pedalcyclist Collisions	PCC	Collision involving a vehicle and a cyclist.
	2	Sideswipe Opposite Direction	SR	Vehicles traveling in opposite directions sideswipe each other.
	3	Pedestrian Collision	PC	Collision involving a vehicle and a pedestrian.
	4	Front To Rear	FR	A rear-end collision where one vehicle impacts the back of another.
	5	Collision With Object	CO	Collision involving a vehicle and a stationary object, such as a pole or tree.
	6	Turning	TU	Collision occurring while one or more vehicles are making a turn.
Type ($T_k^{\mathscr{I}}$)	7	Parked Motor Vehicle	PMV	Collision involving a moving vehicle and a parked vehicle.
	8	Sideswipe Same Direction	SSD	Vehicles traveling in the same direction sideswipe each other.
	9	Animal Collision	AC	Collision involving a vehicle and an animal.
	10	Overturned	OT	A crash where a vehicle overturns, either flipping or rolling over.
	11	Front To Front	FF	Head-on collision where the front ends of two vehicles collide.
	12	Rear To Front	RF	A vehicle impacts another from the rear, pushing it forward.
	13	Rear To Rear	RR	A rare collision where two vehicles impact each other from the rear.
	14	Angle Impact	AI	Vehicles collide at an angle, typically at an intersection.
	15	Rear To Side	RS	A vehicle's rear collides with the side of another vehicle.
	16	Others	OTH	Any other types of collisions not classified into the above categories.

3 Example Prompts

Example Prompt - #EC46221

*You are a helpful assistant designed to predict the **task target** of a traffic crash. You need to make prediction based on the information below:*

General Information

This incident occurred on May 12, 2022, at 6:00 PM, in Bremerton, Kitsap, on the 304 route increasing milepost direction at milepost 2.1. The location is an Urban - Principal Arterial, not at an intersection and not related to a driveway. The roadway is classified as an urban multilane undivided non-freeway.

Infrastructure Information

The level of access control is Non Limited Access Least Restrictive, the speed limit is 25 mph, and the average annual daily traffic is 18,000 vehicles. The road width is 44 feet, and the road surface is made of asphalt. The right and left shoulders width is 0 feet, and the surface type of the left shoulder is unknown. This road is not median-separated and does not have any barrier or width in the median. The data does not specify if the accident occurred in a work zone. The conditions during the time of the accident included daylight and a dry road surface.

Event Information

There were no pedestrians involved, 2 vehicles involved. The accident has no influence of alcohol or drugs. There were no objects involved. Vehicle1 was moving westward, in the direction of decreasing milepost, Vehicle2 was also moving westward, in the same direction of decreasing milepost. Both vehicles were moving straight.

Unit Information

The unit 1, is a non-commercial vehicle. The front airbag was deployed. The vehicle had no defects. The driver was going straight ahead, was not ejected, and was cited for following too closely. Person 1: Motor Vehicle Driver, Female, 36, Lap & Shoulder Used.

The unit 2, is a non-commercial vehicle. The airbag was not deployed. The vehicle had no defects. The driver was slowing, was not ejected, and had no violations or contributing factors. Person 1: Motor Vehicle Driver, Female, 48, Lap & Shoulder Used.

Targets

Please predict the *Injury* number of the crash choosing from the following tokens (4 options available).
Assistant: <ZERO>

Please predict the *Severity* of the crash choosing from the following tokens (5 options available).
Assistant: <NO APPARENT INJURY>

Please predict the crash *Type* of the crash choosing from the following tokens (14 options available).
Assistant: <REAR END COLLISIONS>

Supplementary Figure 2: **One of the Prompt Examples from Washington Dataset (1/4).**

Example Prompt - #EC38982

*You are a helpful assistant designed to predict the **task target** of a traffic crash. You need to make prediction based on the information below:*

General Information

This incident occurred on April 5, 2022, at 5:00 PM, in an unknown city, Pierce county, on the 512 route increasing milepost direction at milepost 11.47. The location is an Urban - Principal Arterial, not at an intersection and not related to a driveway or any other specific location characteristic. The level of access control is Limited Access Fully Controlled, speed limit is 60, average annual daily traffic is 93000.

Infrastructure Information

The road width is 48, the road surface is made of Asphalt, the right and left shoulders width is 10 and 4 respectively, and the surface type of the left shoulder is Asphalt. This road is median-separated, with a cable barrier in the median and the width of the median is 46. It is unknown if the accident occurred in a work zone, the crash happened during daylight and the road surface condition was dry.

Event Information

There were no pedestrians involved, 2 vehicles involved. The accident has no influence of alcohol or drugs. There were no objects involved. Vehicle1 was moving straight, in the direction of decreasing milepost. Vehicle2 was stopped in traffic, legally standing, also in the direction of decreasing milepost. The first vehicle was moving straight when the second vehicle was legally stopped in traffic.

Unit Information

The unit 1 is an unknown commercial vehicle. The airbag was not deployed. The vehicle had no defects. The driver was going straight ahead, was not ejected and followed too closely which is a contributing factor in the accident. Person 1: Motor Vehicle Driver, Male, 39, Lap & Shoulder Used. The unit 2 is a Vanette Under 10,000 lb, non-commercial vehicle. The airbag was not deployed. The vehicle had no defects. The driver was stopped for traffic, was not ejected and had no violations or factors contributing to the accident. Person 2: Motor Vehicle Driver, Male, 29, No Restraints Used.

Targets

Please predict the *Injury* number of the crash choosing from the following tokens (4 options available).
Assistant: <ONE>

Please predict the *Severity* of the crash choosing from the following tokens (5 options available).
Assistant: <NO APPARENT INJURY>

Please predict the crash *Type* of the crash choosing from the following tokens (14 options available).
Assistant: <REAR END COLLISIONS>

Supplementary Figure 3: **One of the Prompt Examples from Washington Dataset (2/4).**

Example Prompt - #72236

*You are a helpful assistant designed to predict the **task target** of a traffic crash. You need to make prediction based on the information below:*

General Information

This crash occurred in St. Clair County on 3/6/2022 at 18:00 hours. The crash happened in the city of Fairview Hts, classified as 10,000 – 25,000 area, on Illinois Route No.159 at milepost 26.28. The roadway is classified as Other Principal Arterial, and the location was identified as an Urban Multilane Undivided Non-Freeway. This crash was related to an intersection.

Infrastructure Information

The road surface was Dry, with Darkness Lighted Road lighting conditions and Clear weather at the time of the crash. The crash occurred on a Divided, no median barrier Two-way with Traffic Signal in place, and it was confirmed that the crash did not occur in a work zone.

Event Information

The crash involved 1 vehicles. The primary driver behavior in the crash was Failing To Yield Right-of-Way, secondary behavior was Vision Obscured (Signs, Tree Limbs, Buildings, Etc.).

Unit Information

Vehicle 0, a 2019 model, was moving Northeast and was traveling straight ahead before the crash. There was also a passenger, a 42-year-old female, seated in the unknown position. The driver was a 46-year-old male with no visible distractions, sitting in the Driver position. The driver's blood alcohol content was was not offered.

Targets

Please predict the *Injury* number of the crash choosing from the following tokens (4 options available).
Assistant: <ONE>

Please predict the *Severity* of the crash choosing from the following tokens (5 options available).
Assistant: <SERIOUS INJURY>

Please predict the crash *Type* of the crash choosing from the following tokens (16 options available).
Assistant: <PEDESTRIAN COLLISIONS>

Supplementary Figure 4: **One of the Prompt Examples from Illinois Dataset (3/4).**

Example Prompt - #76893

*You are a helpful assistant designed to predict the **task target** of a traffic crash. You need to make prediction based on the information below:*

General Information

This crash occurred in Madison County on 7/11/2022 at 1:00 o'clock. The crash happened in the city of Godfrey, classified as 10,000 – 25,000 area, on None at milepost 0.0. The roadway is classified as Unknown, and the location was identified as an Urban Multilane Divided Non-Freeway. This crash was not related to an intersection.

Infrastructure Information

The road surface was Dry with Daylight lighting conditions and Clear weather at the time of the crash. The crash occurred on a Divided - w/median barrier Two-way with Stop Sign in place, and it was confirmed that the crash did not occur in a work zone.

Event Information

The crash involved 2 vehicles. The primary driver behavior in the crash was Failing To Yield Right-of-Way, with secondary driver behavior was (Unable to Determine).

Unit Information

The crash involved 2 vehicles. The primary cause of the crash was Failing To Yield Right-of-Way, with secondary contributing cause (Unable to Determine).Vehicle 0, a 2008 model, was moving West and was traveling straight ahead before the crash. Vehicle 1, a 2006 model, was moving South and was traveling straight ahead before the crash. The driver was an 86-year-old male with no visible distractions, sitting in the Driver. The driver's blood alcohol content was not offered. There was also a passenger, an 84-year-old female, seated in the Passenger. The driver was a 17-year-old male with no visible distractions, sitting in the Driver. The driver's blood alcohol content was not offered.

Targets

Please predict the *Injury* number of the crash choosing from the following tokens (4 options available).
Assistant: <ONE>

Please predict the *Severity* of the crash choosing from the following tokens (5 options available).
Assistant: <POSSIBLE INJURY>

Please predict the crash *Type* of the crash choosing from the following tokens (16 options available).
Assistant: <ANGLE IMPACTS>

Supplementary Figure 5: One of the Prompt Examples from Illinois Dataset(4/4).

4 Experimental Settings

4.1 TrafficSafe LLM Settings

In our experiments, we follow LoRA[2] to fine-tune LLaMA 3.1 models. Specifically, we update only the input and output layers directly, while all remaining layers are frozen and trained through LoRA. We use AdamW[3] as optimizer with a learning rate of 3e-4, and train the models on 8*Nvidia A100 80GB Memory GPU with DeepSeed [1]. We fine-tune the model for 3 epochs and select the best model on the validation dataset by F1-score to test the performance.

4.2 Baseline Models Settings

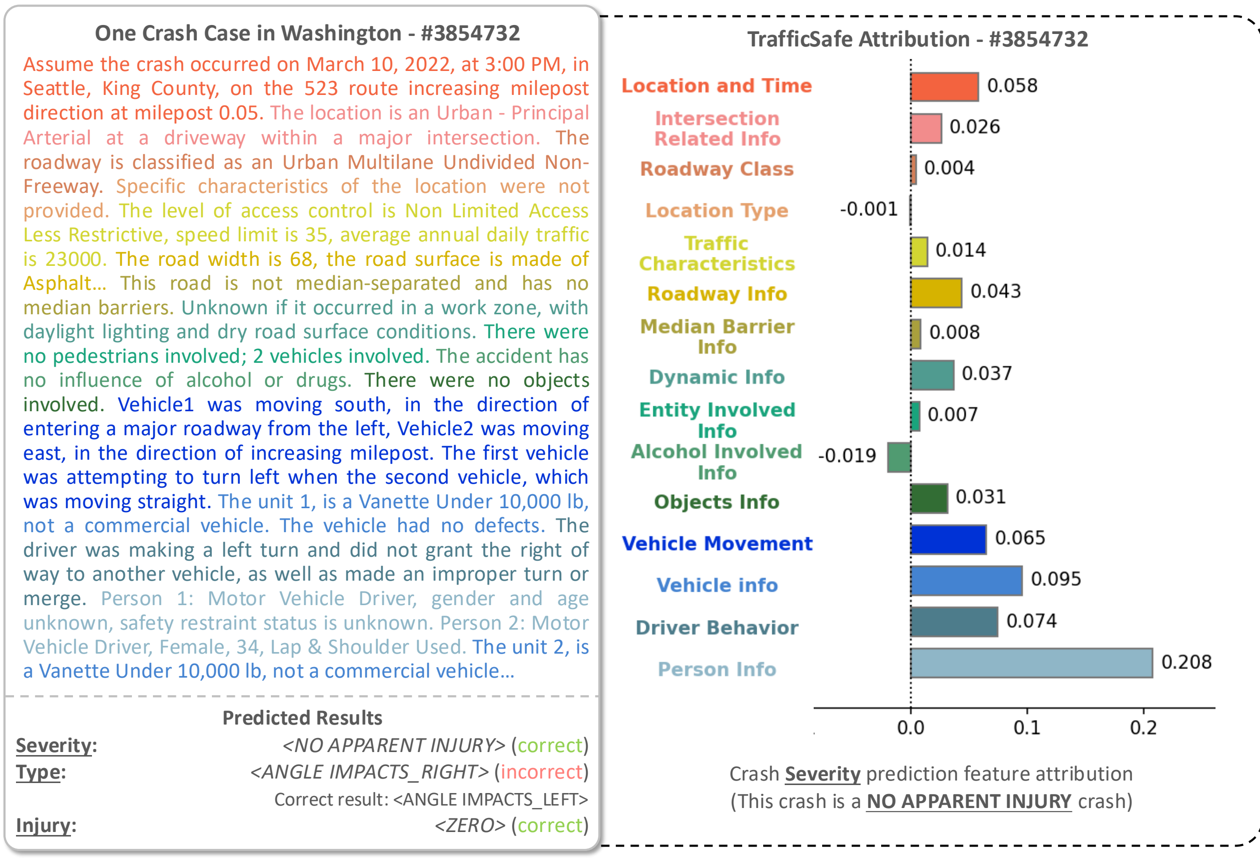
We used grid search method to find the optimal parameters for baseline methods. Table 4 shows the search ranges we used to perform the grid search. The search iteration was set to 40 for all baseline models.

Supplementary Table 4: Hyperparameter Search Ranges for Baseline Methods.

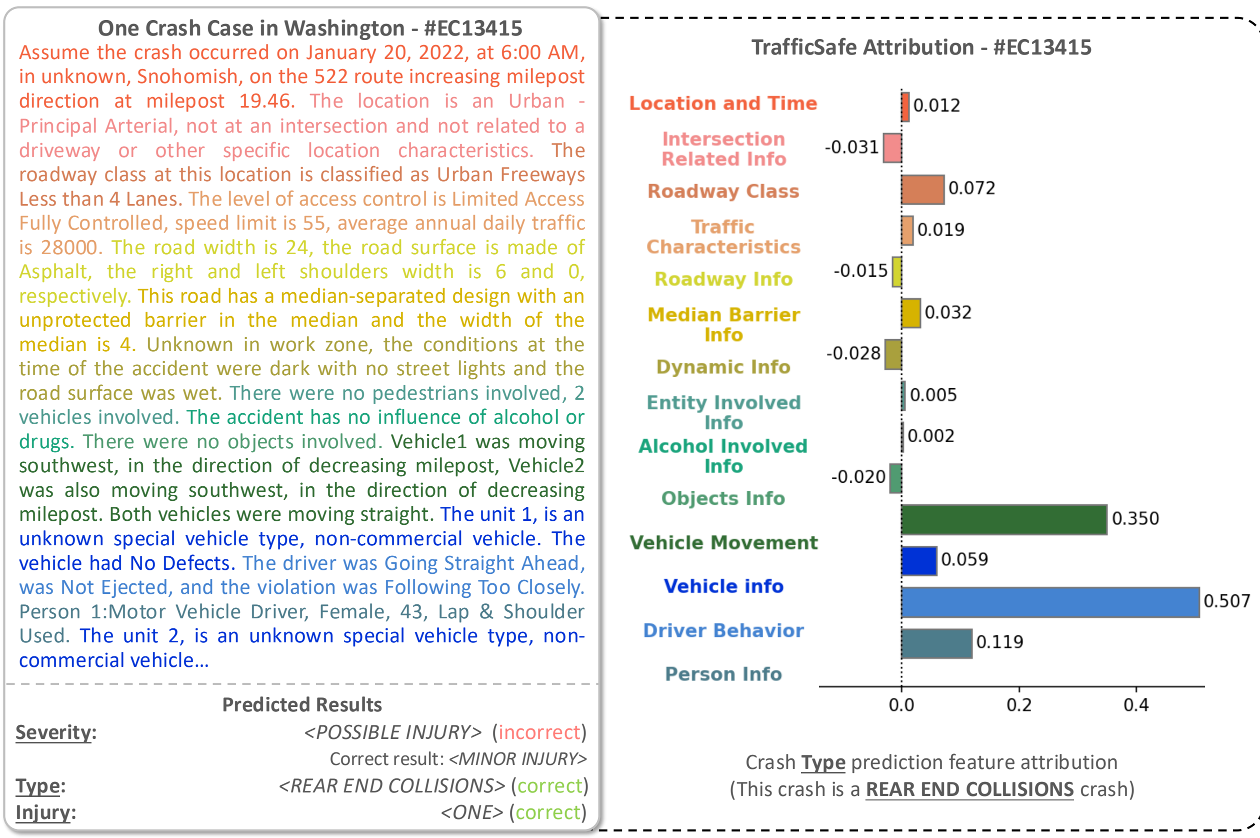
Method	Parameter	Search Range
Adaboost	n_estimators	Integer(40,140)
	learning_rate	Real(1e-4, 1e-3)
	algorithm	Categorical([SAMME, SAMME.R])
Random Forest	n_estimators	Integer(120,240)
	max_features	Categorical([sqrt, log2])
	max_depth	Integer(3,15)
	min_samples_split	Integer(2,10)
	min_samples_leaf	Integer(1,8)
	min_weight_fraction_leaf	Real(0, 0.5)
	max_leaf_nodes	Integer(120,400)
	n_jobs	Integer(1,3)
	class_weight	Categorical([balanced, balanced_subsample])
Decision Tree	max_features	Categorical([sqrt, log2])
	max_depth	Integer(2,15)
	min_samples_split	Integer(2,10)
	min_samples_leaf	Integer(1,8)
	min_weight_fraction_leaf	Real(0, 0.5)
	max_leaf_nodes	Integer(50, 100)
Logistic Regression	tol	Real(0, 1)
	max_iter	Integer(300, 400)
	multi_class	Categorical([auto, ovr, multinomial])
	n_jobs	Integer(1,3)
Catboost	iterations	Integer(120,180)
	learning_rate	Real(1e-4, 1e-3)
	depth	Integer(2,10)
XGBoost	max_depth	Integer(2,15)
	learning_rate	Real(0.0001, 0.001)
	subsample	Real(0.5, 1.0)

[1] https://www.deepspeed.ai/

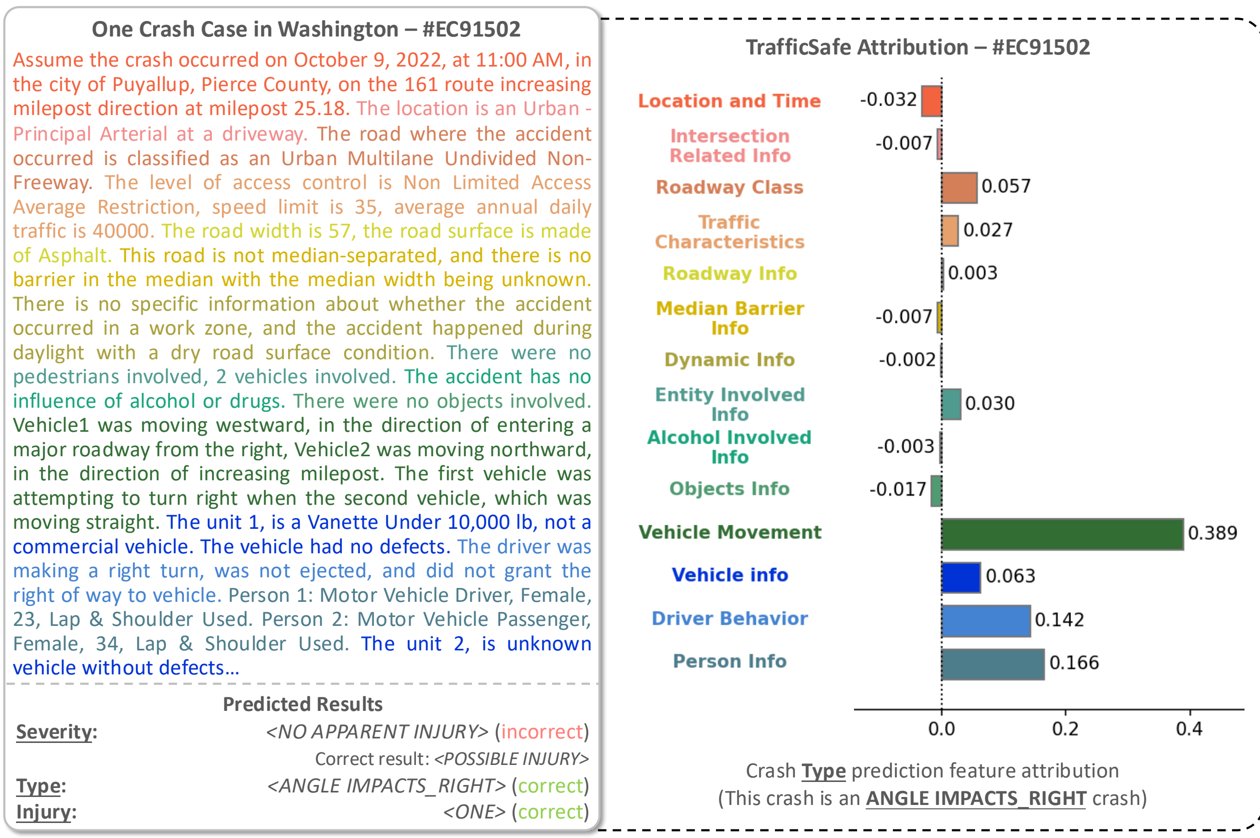
5 Example Event-level Feature Attribution Results



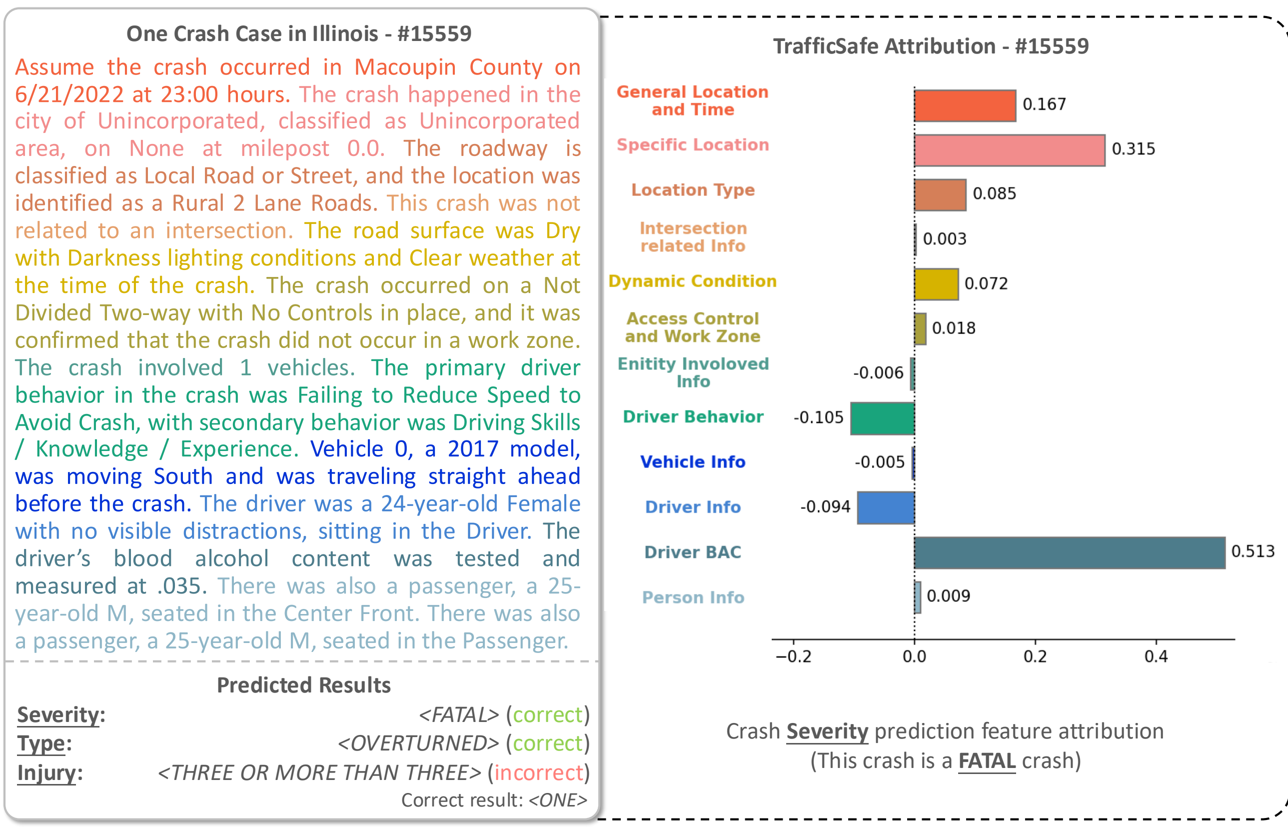
Supplementary Figure 6: One Example of Sentence-based Feature Attribution Results for A Crash Resulting in *No Apparent Injury* in Washington Dataset (1/6).



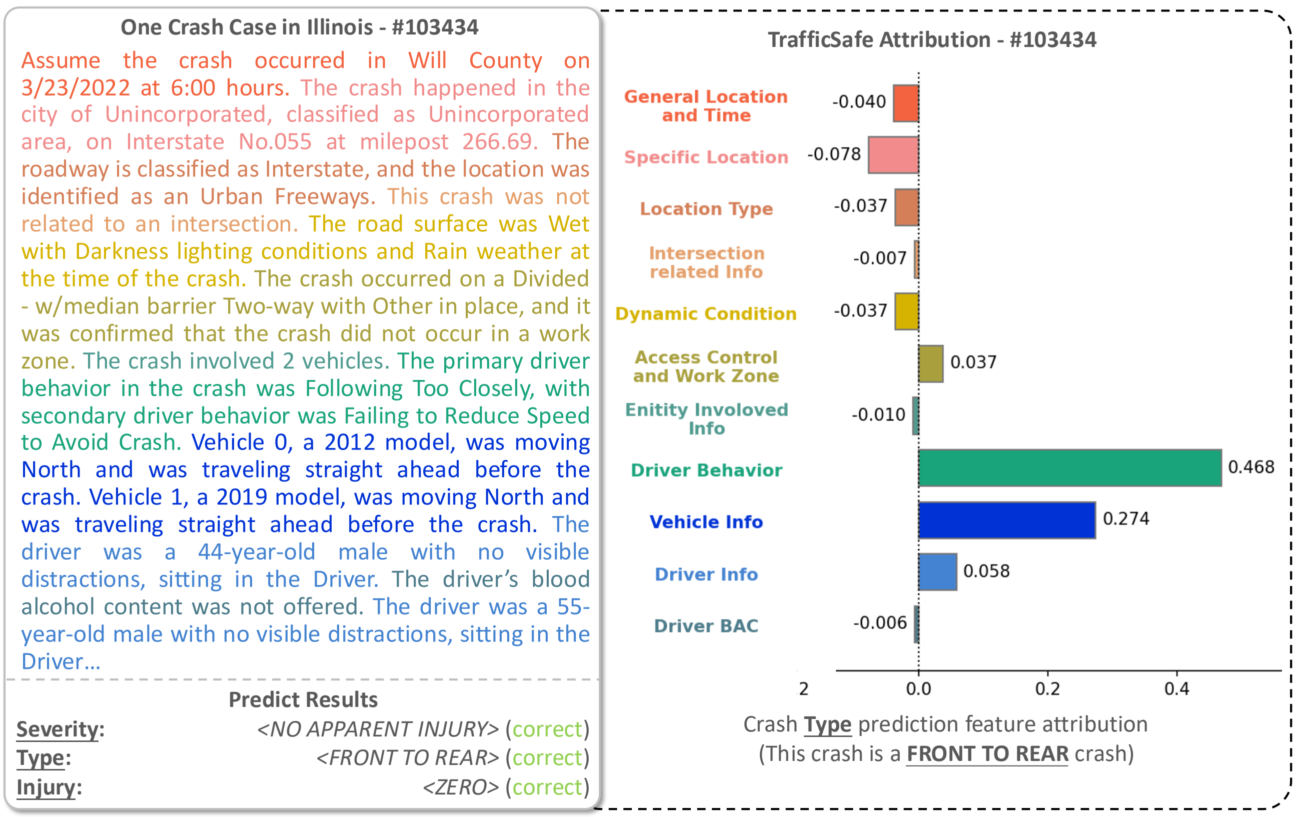
Supplementary Figure 7: One Example of Sentence-based Feature Attribution Results for A Crash Resulting in *Front Rear Collision* in Washington Dataset (2/6).



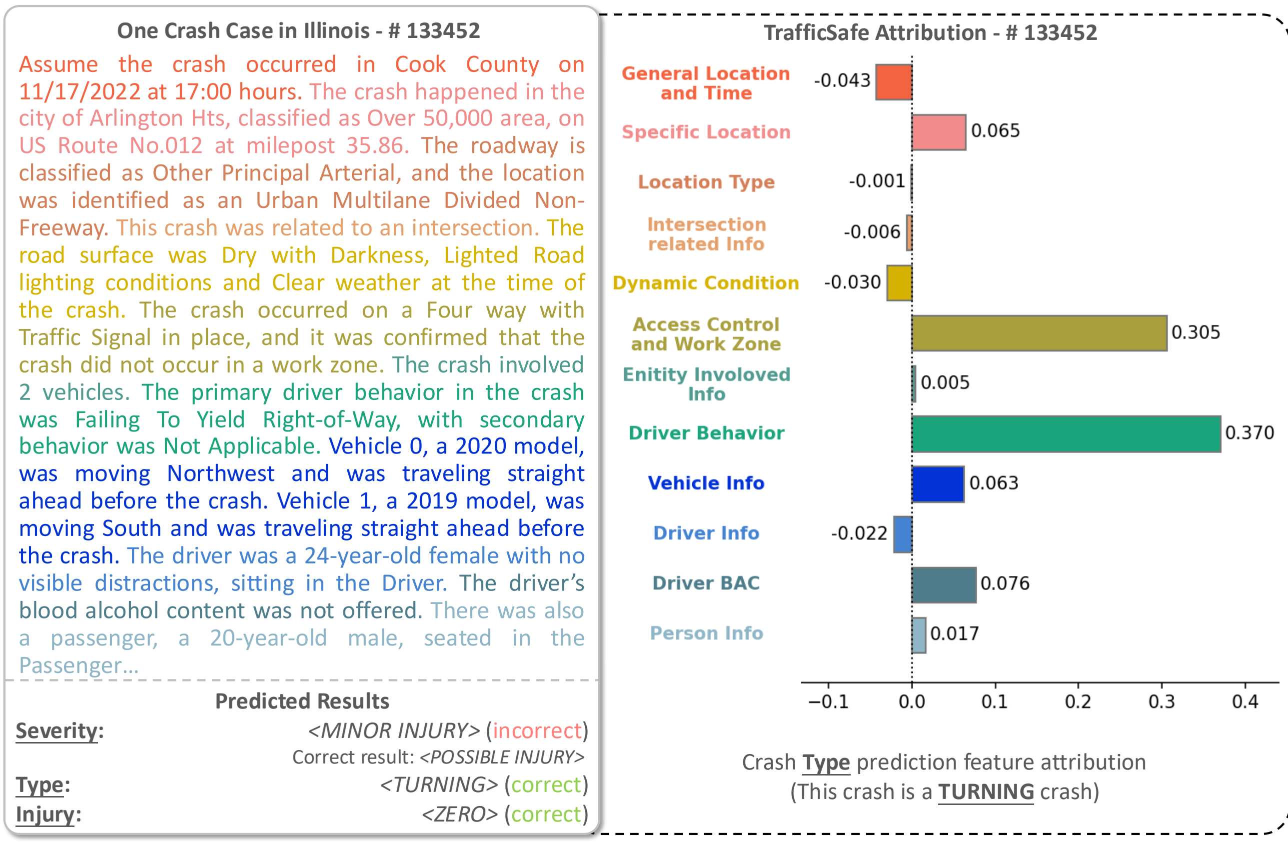
Supplementary Figure 8: One Example of Sentence-based Feature Attribution Results for A Crash Resulting in *Angle Impact Right* in Washington Dataset (3/6).



Supplementary Figure 9: One Example of Sentence-based Feature Attribution Results for A Crash Resulting in *Fatal* in Illinois Dataset (4/6).



Supplementary Figure 10: One Example of Sentence-based Feature Attribution Results for A Crash Resulting in *Rear End Collision* in Illinois Dataset (5/6).



Supplementary Figure 11: One Example of Sentence-based Feature Attribution Results for A Crash Resulting in *Single Vehicle with Object* in Illinois Dataset (6/6).

6 The Summary of the TOP 5 Ratios of Feature Contributions

Supplementary Table 5: Top 5 Ratios for Feature Contributions Across Different Sentence in Washington Dataset. This table summarizes the feature attribution results of various sentences across the entire test set. It shows the probability of different sentences appearing in the top 5 contribution factors, based on their feature contribution on the four most frequent types of crashes and the severity of crash. In the *Type* task, "REC" represents *rear end collisions*, "SVO" represents *single vehicle with object collisions*, "AIR" represents *angle impact on right side collisions*, and "AIL" represents *angle impact on left side*. In the *Severity* task, "NI" represents *no apparent injury*, "PI" represents *possible injury*, "MI" represents *minor injury*, "SI" represents *serious injury*, and "F" represents *fatal crash*. Text Sentences column displays examples of sentences under a specific semantic category, and the curly braces indicate that this part of information is composed of sentences describing the text within them. The feature contribution indicates the potential significance of a sentence on model predictions, encompassing both positive and negative influences. For each result, the number in parentheses indicates its rank within this type of crash.

TOP 5 Ratio / Text Sentences	Feature Contributions for *Type* (Rank)				Feature Contributions for *Severity* (Rank)				
	REC	SVO	AIR	AIL	NI	PI	MI	SI	F
Location and Time: This Crash occurred on {*Month Day, Year, Time*}, {*County Name*}, on the {*Route ID*} route at milepost {*Milepost*}.	0.16 (7)	0.30 (7)	0.06 (14)	0.24 (6)	0.61 (4)	0.59 (4)	0.58 (4)	0.58 (5)	0.58 (5)
Intersection Related Info: The location is an {*Roadway Type*}, {*not at / at*} an intersection and {*is / is not*} related to a driveway.	0.07 (14)	0.31 (6)	0.10 (11)	0.02 (16)	0.08 (11)	0.09 (13)	0.08 (13)	0.08 (13)	0.08 (13)
Location Type: The location is classified as {*Description of Special Location Type*}.	0.03 (16)	0.22 (11)	0.01 (16)	0.05 (14)	0.02 (15)	0.03 (16)	0.03 (16)	0.03 (16)	0.03 (16)
Roadway Class: The roadway classification is {*Description of Number of Lanes, Urban/Rural, and Functional Class*}.	0.06 (15)	0.19 (13)	0.10 (11)	0.03 (15)	0.05 (13)	0.06 (14)	0.07 (14)	0.07 (14)	0.08 (14)
Traffic Characteristics: The level of access control is {*Access Control*}, speed limit is {*Speed Limit*}, average annual daily traffic is {*AADT*}.	0.17 (6)	0.17 (15)	0.04 (15)	0.10 (12)	0.11 (10)	0.15 (9)	0.17 (8)	0.17 (8)	0.17 (8)
Roadway Info: The road is {*description of roadway width, surface type, left and right shoulder's width and surface type*}.	0.13 (11)	0.42 (2)	0.12 (9)	0.19 (7)	0.58 (5)	0.47 (7)	0.44 (7)	0.43 (7)	0.43 (7)
Median Barrier Info: This road {has / has not} a median-separated with a {Type and width} barrier.	0.12 (12)	0.34 (5)	0.16 (8)	0.08 (13)	0.02 (16)	0.14 (10)	0.16 (9)	0.16 (10)	0.16 (10)
Dynamic Info: This crash {was / not} occurred in work zone, the light is {Light Condition} and the road surface is {Road Surface Condition}.	0.15 (9)	0.24 (10)	0.12 (9)	0.13 (10)	0.13 (9)	0.12 (11)	0.13 (11)	0.13 (11)	0.13 (11)
Entity Involoved Info: There were {Num of Pedestrian} pedestrians involved, {Num of Vehicles} vehicles involved.	0.22 (5)	0.21 (12)	0.31 (5)	0.18 (8)	0.03 (14)	0.03 (15)	0.05 (15)	0.05 (15)	0.05 (15)
Alcohol Involved Info: The crash {*has / has not*} be influenced by alcohol or drugs.	0.11 (13)	0.36 (3)	0.18 (7)	0.15 (9)	0.14 (8)	0.15 (9)	0.15 (10)	0.16 (10)	0.17 (9)
Objects Info: There were {*Num of Objects*} objects involved. {*Description of Objects*}.	0.13 (10)	**1.00 (1)**	0.10 (11)	0.13 (10)	0.07 (12)	0.09 (12)	0.12 (12)	0.12 (12)	0.12 (12)
Vehicle Movement: Vehicle{*ID*} was moving {*Moving Direction*}, {*Vehicle Movement*}.	**0.99 (1)**	0.07 (16)	**1.00 (1)**	**0.97 (1)**	0.50 (7)	0.51 (6)	0.48 (6)	0.48 (6)	0.48 (6)
Vehicle Info: The unit 1, is a {*vehicle*} type, the vehicle had {*Defects Description*} defects.	0.78 (4)	0.18 (14)	0.88 (2)	0.86 (3)	0.65 (3)	0.64 (2)	0.63 (2)	0.62 (2)	0.62 (2)
Airbag Status: Vehicle{*ID*} {*has / has not*} airbag, the airbag is {*Description of Airbag*}.	0.15 (8)	0.30 (7)	0.23 (6)	0.26 (5)	0.71 (2)	0.63 (3)	0.62 (3)	0.61 (3)	0.61 (3)
Driver Behavior: The driver was driving {*Description of Driver's Behavior and Status*}.	0.92 (2)	0.36 (3)	0.83 (3)	0.89 (2)	0.52 (6)	0.57 (5)	0.58 (5)	0.59 (4)	0.59 (4)
Person Info: Person 1: Motor Vehicle {*Driver / Passenger*}, {*Gender*}, {*Age*}, {*Safety Restrictions Usage*}.	0.82 (3)	0.27 (9)	0.73 (4)	0.71 (4)	**0.78 (1)**	**0.71 (1)**	**0.70 (1)**	**0.70 (1)**	**0.70 (1)**

Supplementary Table 6: Top 5 Ratios for Feature Contributions Across Different Sentences in Illinois Dataset. This table summarizes the feature attribution results of various sentences across the entire test set. It shows the probability of different sentences appearing in the top 5 contribution factors, based on their feature contribution on the four most frequent types of crashes and the severity of crash. In the *Type* task, "FR" represents *front-to-end collisions*, "TU" represents *turning collisions*, "PMV" represents *parked moto vehicle collisions*, and "CO" represents *collisions with object*. In the *Severity* task, "NI" represents *no apparent injury*, "PI" represents *possible injury*, "MI" represents *minor injury*, "SI" represents *serious injury* and "F" represents *fatal crash*. Text Sentences column displays examples of sentences under a specific semantic category, and the curly braces indicate that this part of information is composed of sentences describing the text within them. The feature contribution indicates the potential significance of a sentence on model predictions, encompassing both positive and negative influences. For each result, the number in parentheses indicates its rank within this type of crash. '/' indicates that these sentences didn't appear as a top 5 feature.

TOP 5 Ratio / Text Sentences	Feature Contributions for *Type* (Rank)				Feature Contributions for *Severity* (Rank)				
	FR	**TU**	**PMV**	**CO**	**NI**	**PI**	**MI**	**SI**	**F**
General Location and Time: This crash occurred in {*County Name*} on {*Day / Month / Year*} at {*Time*} hours.	0.32 (6)	0.17 (9)	0.32 (6)	0.27 (8)	0.14 (11)	0.31 (8)	0.33 (8)	0.44 (5)	0.45 (5)
Specific Location: The crash happened in the {*City Name*}, classified as {*Population Size*} area, on {*RouteID*} at milepost {*Milepsot*}.	0.53 (4)	0.48 (5)	0.72 (4)	0.35 (5)	0.37 (6)	**0.82 (1)**	0.73 (2)	**0.69 (1)**	0.72 (2)
Location Type: The roadway is classified as {*Road Class*}, and the location was identified as {*Location Type*}.	0.27 (8)	0.31 (7)	0.25 (7)	0.08 (11)	0.61 (4)	0.65 (4)	**0.79 (1)**	0.65 (3)	0.66 (4)
Intersection-Related Info: This traffic crash {*was / was not*} related to an intersection.	0.09 (12)	0.09 (11)	0.03 (12)	/ (12)	0.02 (12)	0.03 (12)	0.05 (12)	0.04 (12)	0.05 (12)
Dynamic Condition: The road surface was {*Surface Condition*} with {*Light Condition*} and {*Weather Condition*} at the time.	0.26 (9)	0.12 (10)	0.14 (9)	0.32 (6)	0.36 (7)	0.34 (7)	0.22 (10)	0.24 (11)	0.30 (8)
Access Control and Work Zone: The crash occurred on a {*Access Control description*}, and the crash {*did / did not*} occur in a work zone.	0.61 (3)	0.65 (4)	0.13 (10)	0.31 (7)	0.26 (8)	0.57 (5)	0.40 (6)	0.36 (7)	0.40 (6)
Entity Involoved Info: The crash involved {*Num of Vechiles*} vehicles, {*Num of Pedestrians*} Pedestrians.	0.18 (11)	0.06 (12)	0.16 (8)	0.90 (3)	0.70 (2)	0.08 (11)	0.51 (4)	0.38 (6)	0.07 (11)
Driver Behavior The primary behavior of the driver was {*Driver Behavior 1*}, with secondary behavior is {*Driver Behavior 2*}.	0.92 (2)	**0.94 (1)**	0.32 (6)	0.55 (4)	**0.80 (1)**	0.70 (2)	0.71 (3)	0.69 (2)	0.68 (3)
Vechile Info: Vehicle {*ID*}, {*vechile Type and Production Year*}, was {*Vechile Movement*} before the crash.	**0.98 (1)**	0.73 (3)	0.91 (3)	0.92 (2)	0.69 (3)	0.19 (10)	0.37 (7)	0.33 (9)	0.24 (9)
Driver Info: The driver was a {*Age-year-old Gender*} with {*Driver Distraction and Vision Obstruction Situation*}, sitting in {*Siting Position*}.	0.39 (5)	0.41 (6)	0.97 (2)	0.24 (9)	0.57 (5)	0.66 (3)	0.44 (5)	0.50 (4)	0.36 (7)
Driver BAC: The driver's blood alcohol content was tested and measured at {*Driver's BAC test result*}.	0.28 (7)	0.85 (2)	**1.00 (1)**	**0.99 (1)**	0.25 (9)	0.21 (9)	0.20 (11)	0.31 (10)	**0.85 (1)**
Person Info: There was also a passenger, a {*Age-year-old Gender*}, seated in {*Siting Position*}.	0.18 (11)	0.19 (8)	0.04 (11)	0.08 (11)	0.23 (10)	0.44 (6)	0.25 (9)	0.35 (8)	0.22 (10)

7 Feature Contributions Training Stage

Supplementary Table 7: Feature Contributions for Data Components at Training Stage for the *Severity* and *Type* Tasks in the Washington and Illinois Datasets. Three metrics (accuracy, precision, and F1-score) are used for the calculation.

Dataset	Components	Severity			Type		
		Accuracy	Precision	F1-score	Accuracy	Precision	F1-score
Washington	General	0.014	0.160	0.125	0.072	0.069	0.070
	Infrastructure	0.097	0.069	0.050	0.036	0.064	0.041
	Event	0.110	0.091	0.119	**0.388**	**0.365**	**0.382**
	Unit	**0.314**	**0.316**	**0.340**	0.257	0.270	0.264
Illinois	General	0.071	0.019	0.038	0.093	0.076	0.090
	Infrastructure	0.059	0.015	0.019	0.086	0.102	0.089
	Event	0.158	0.202	0.173	**0.283**	**0.302**	**0.288**
	Unit	**0.234**	**0.305**	**0.287**	0.279	0.279	0.278

Reference

1. Zhao, W. X., Zhou, K., Li, J., Tang, T., Wang, X., Hou, Y., Min, Y., Zhang, B., Zhang, J., Dong, Z., *et al.* A survey of large language models. *arXiv preprint arXiv:2303.18223* (2023).
2. Hu, E. J., Shen, Y., Wallis, P., Allen-Zhu, Z., Li, Y., Wang, S., Wang, L. & Chen, W. Lora: Low-rank adaptation of large language models. *arXiv preprint arXiv:2106.09685* (2021).
3. Loshchilov, I. & Hutter, F. Decoupled weight decay regularization. *arXiv preprint arXiv:1711.05101* (2017).