

Bike and E-bike agents: Large Language Model-Driven E-Bike Accident Analysis and Severity Prediction

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Abstract—E-bikes have rapidly gained popularity as a sustainable form of urban mobility, yet their safety implications remain underexplored. This paper analyzes injury incidents involving e-bikes and traditional bicycles using two sources of data, the CPSRMS (Consumer Product Safety Risk Management System Information Security Review Report) and NEISS (National Electronic Injury Surveillance System) datasets. We propose a standardized classification framework to identify and quantify injury causes and severity. By integrating incident narratives with demographic attributes, we reveal key differences in mechanical failure modes, injury severity patterns, and affected user groups. While both modes share common causes, such as loss of control and pedal malfunctions, e-bikes present distinct risks, including battery-related fires and brake failures. These findings highlight the need for tailored safety interventions and infrastructure design to support the safe integration of micromobility devices into urban transportation networks.

Index Terms—large language models, agentic systems, transportation

I. INTRODUCTION

Electric bicycles (e-bikes) have experienced a sharp rise in popularity, driven by their convenience, cost-effectiveness, and environmental benefits. In the United States, sales surged from fewer than 300,000 in 2019 to over 1.1 million in 2022, a nearly fourfold increase [1]. Interest and usage have grown as well: the share of American bike riders who reported using an e-bike more than doubled, from 7.8% in 2021 to 19.4% in 2023 [2]. However, this growth has been paralleled by a concerning increase in safety-related incidents. The Consumer Product Safety Commission (CPSC) reports that from 2017 to 2021, there were 53 deaths associated with the use of e-bikes [3]. Moreover, e-bike injuries accounted for approximately 15% of all reported micromobility-related injuries during the same period [4]. These trends underscore the urgent need to examine the mechanical, electrical, and human factors contributing to e-bike incidents. A critical component of this effort is investigating strategies to enhance rider safety. For example, the use of protective equipment, particularly helmets, remains a primary safeguard, directly reducing the severity of head injuries. Helmet use has been shown to lower the probability of fatal head injuries on e-bikes by 10%, from 89%

to 79% [5]. Nevertheless, the residual risk remains substantial, highlighting the need for continued improvements. Advances in e-bike technology provide a complementary pathway to address diverse safety challenges. Recently, researchers have developed devices aimed at preventing accidents related to charging. One such innovation is SingMonitor [6], which leverages mobile device microphones to remotely monitor and evaluate the charging health of e-bike batteries.

Although some preventive measures, emerging technologies, and recent policies have been effective in specific contexts for enhancing e-bike safety, they are not easily extendable to a comprehensive, systematic analysis of e-bike accident causes and impacts. This limitation arises from the scarcity of representative data, the diversity of data structures, and the prevalence of text-based incident descriptions, which are difficult for human experts to systematically interpret and analyze. Developing universal frameworks capable of integrating these unstructured accident descriptors, uncovering hidden patterns, and generating actionable safety insights is therefore essential. Recent advances in machine learning and artificial intelligence provide powerful tools to address these challenges. For example, tree-structured machine learning techniques have been successfully applied to analyze risk patterns among e-bike riders in China [7]. Large Language Models (LLMs) are particularly well-suited for handling and analyzing unstructured data; in the domain of autonomous systems, surveys have shown how foundation models are applied in end-to-end tasks such as perception, reasoning, simulation and planning in driving contexts [8] — however, their application in traffic accident analysis remains relatively novel. Agentic systems powered by large language models (LLMs) have revolutionized the mining of unstructured data across diverse fields, demonstrating strong performance in analyzing highly heterogeneous datasets and delivering comprehensive insights that advance specialized scientific domains. This success stems largely from recent technical advancements. One standard approach to adapting large language models to domain-specific data is supervised fine-tuning (SFT). Recent work, however, has shown that SFT does not always degrade general capabilities when properly

tuned (e.g., small learning rates) [9]. Besides, reinforcement learning has enhanced models' reasoning capacity, enabling stronger multistep logical problem-solving, particularly in multi-agent systems [10, 11]. These reasoning capabilities have already shown promise in areas such as biomedicine [12, 13, 14], recommendation systems [15, 16], and fake news detection [17, 18, 19]. Moreover, improvements in algorithms and hardware have significantly increased the efficiency of LLM training and inference [20, 21].

Specifically, this paper investigates the use of emerging LLM-based tools to address the challenges of mining unstructured data in the context of e-bike and bicycle accidents (Figure 1). Our analysis draws on two widely used consumer safety datasets: the CPSRMS (Consumer Product Safety Risk Management System Information Security Review Report) and NEISS (National Electronic Injury Surveillance System). Both provide structured injury records with well-defined product categorizations, alongside narrative incident reports. We examine how LLM-powered agents can transform these narratives into actionable insights by extracting critical safety-related information and converting it into structured formats. This approach enables the identification of key human, environmental, and equipment-related factors that influence both the occurrence and severity of e-bike incidents. More broadly, the study illustrates how AI-driven data processing can advance our understanding of e-bike safety risks, thereby supporting evidence-based policymaking and informing the development of improved design standards.

II. RELATED WORK

This section presents a taxonomy of e-bike safety investigations, categorized by various targeted viewpoints such as aspects related to human behavior, technical limitations of e-bikes themselves, and the surrounding infrastructure. In-depth studies have been conducted to explore the influence of various human factors, such as age, gender, riding habits, and the type of e-bike used, on the incidence of accidents. These investigations underscore the crucial role human factors play in e-bike accidents. For example, a significant proportion of e-bike accidents involve individuals between 40 and 65 years of age, as shown by the study conducted by [22]. With respect to gender, data from a survey involving 685 e-bike users in Denmark reveal that being female is negatively correlated with perceived safety [23]. Furthermore, the use of cell phones while walking or riding significantly increases the risk of road injuries [24]. Another research direction seeks to classify e-bikers into distinct categories to examine their impact on e-bike safety, noting that various groups may demonstrate different behaviors. In particular, people tend to favor the e-bike in rural regions over urban ones [25]. This geographical variation is attributed to disparities in infrastructure, regulatory frameworks, and cultural practices [25, 26]. Therefore, taking into account these regional contexts is vital for a comprehensive understanding of the safety implications at the global level. Research on methods to incentivize e-bike users to improve their safety by modifying their riding behavior is essential. Public awareness campaigns

and bike safety education are key strategies in this regard. A study assessed the effect of a national helmet promotion campaign in China aimed at riders on motorcycles and electric bikes. The results showed a general increase in helmet use [27]; however, correct helmet wear practices decreased. The study recommends revising the campaign to incorporate education along with legislative measures to ensure proper helmet usage. In addition to the influence of human factors, the occurrence of accidents can often be traced back to the technical limitations inherent in e-bikes, rather than their operators. One notable issue is the quality of batteries or chargers, which are often cited as primary causes of incidents such as ignition, explosions, or sparking. These technical failures present significant hazards, including fire, explosion, and burn risks to users [28]. Another critical factor in e-bike accidents is the condition and integrity of the tires. Approximately 200 million tires have been reported to be ineffectively discarded each year due to failures predominantly caused by punctures [29]. Moreover, the braking system is crucial in maintaining the safety of electric bikes, and the braking mechanisms on electric bikes require even more attention than those on traditional bicycles [30]. The impact of infrastructure on safety cannot also be overstated. The dimensions of the paths and lanes are vital infrastructural elements that affect the safety of the e-bike. Research indicates that as the width of the paths increases and the surfaces become smoother and flatter, traffic conflicts, including those involving e-bikes, diminish [31]. Furthermore, comparing the risk profiles of e-bikes with those of other transportation methods offers a valuable context to understand e-bike safety. E-bikes tend to have injury severity profiles that align more closely with those of bicycles, rather than with motorcycles [32, 33]. While these comparative studies offer valuable insights into how e-bike injuries differ from those involving other two-wheelers, they are generally constrained by the use of single-source structured datasets, such as hospital records or national crash reports. These sources often lack rich contextual information—such as detailed incident narratives or environmental factors—that could illuminate underlying risk mechanisms. In addition, inconsistencies in variable definitions, such as how injury severity or incident causes are classified, limit comparability across studies. These challenges highlight the need for more comprehensive and standardized approaches to understanding the differential safety risks associated with e-bikes and traditional bicycles.

III. METHODS

To analyze both the CPSRMS and NEISS datasets, we employ four specialized LLM agents to extract and interpret information (Figure 1). These agents include: a data classifier, an information extractor, an injury cause determiner, and an incident component link detector (Figure 2). The outputs are subsequently visualized and evaluated using econometric and statistical methods, as illustrated in Figure 1.

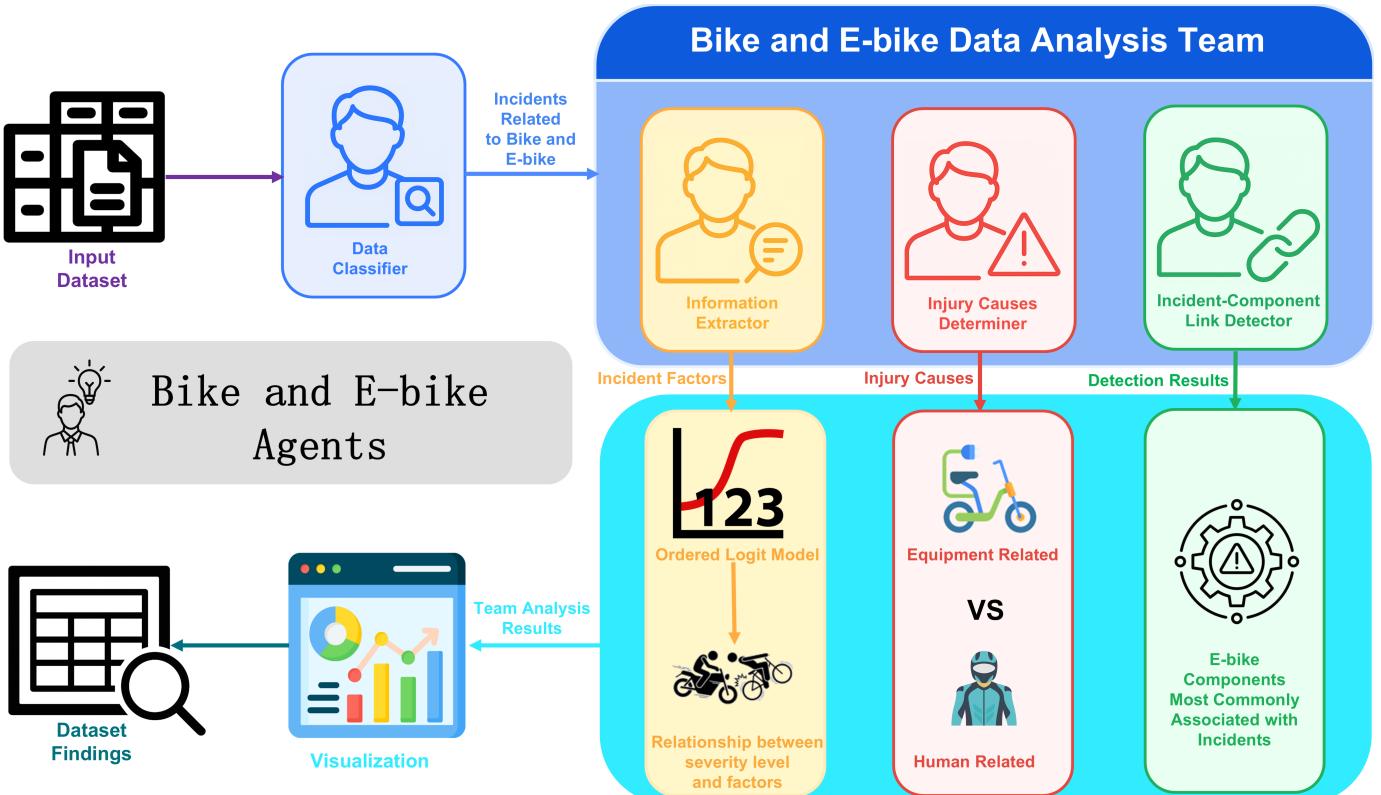


Fig. 1: The overall workflow of Bike and E-bike agents. The dataset classifier agent filters out the accidents related to bikes and e-bikes. Such incidents are then passed to the bike and e-bike data analysis team for further processing, which includes: information extractor, injury causes determiner, and incident-component link detector. The information extractor identifies incident factors, which are then analyzed using an ordered logit model to explore their relationship with injury severity levels. The injury causes determiner identifies the cause of each injury and categorizes them as human-related, equipment-related, or both. The incident-component link detector examines whether each incident is associated with specific e-bike components and identifies the components most frequently linked to incidents. Finally, the analysis results are visualized.

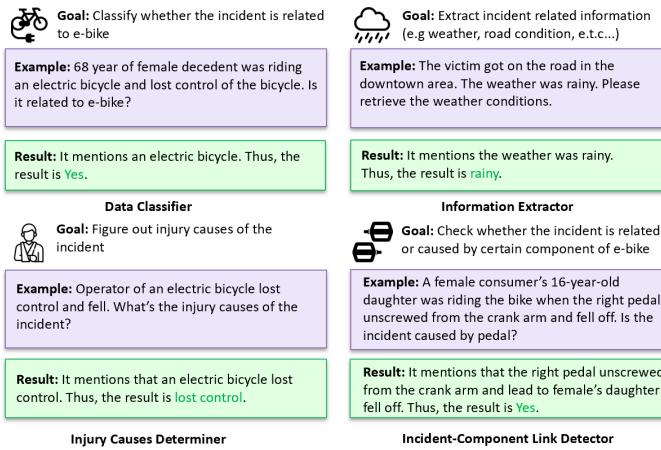


Fig. 2: Example workflow of the four agents to analyze e-bike accidents

A. Analyzing Unstructured Incident Narratives with LLMs

1) Data Classifier: The first agent determines whether an incident involves an e-bike or a traditional bicycle by analyzing the narrative descriptions for relevant keywords. If such a keyword is detected, the incident is labeled as “yes”; otherwise, it is labeled as “no.” This classification then serves as the input for the subsequent three agents.

2) Information Extractor: The second agent extracts key incident details, including the number of transportation modes involved, time of occurrence, weather, and road conditions, which are then used as inputs for an ordered logit model to assess incident severity.

3) Injury Causes Determiner: Based on the extracted incident details, the injury cause determiner identifies the underlying causes of each injury. It classifies incidents as human-related, equipment-related, or a combination of both.

4) Incident-Component Link Detector: Finally, the incident-component link detector assesses whether an incident is associated with specific e-bike (or bile) components, as defined in Table I. This provides insights into the components most frequently linked to incidents.

TABLE II: Predictor Variables: Definitions, Source, and Counts by Dataset

Variable	Definition & Values	Source	Count (CPSRMS Bike / CPSRMS E-Bike / NEISS Bike / NEISS E-Bike)
Age	1: Children (≤ 14)	Already Exist	17 / 6 / 3 / 10
	2: Youth (15–24)	Already Exist	15 / 8 / 1 / 9
	3: Adults (25–64)	Already Exist	97 / 54 / 4 / 44
	4: Seniors (65+)	Already Exist	34 / 16 / 3 / 13
Gender	1: Female	Already Exist	47 / 34 / 3 / 10
	2: Male	Already Exist	116 / 87 / 5 / 40
Incident Cause and Type	1: Human-Related (e.g., collisions, rule breaks)	Extracted	106 / 88 / 4 / 42
	2: Equipment-Related (e.g., battery, brake issues)	Extracted	96 / 100 / 5 / 47
	3: Both	Extracted	9 / 9 / 0 / 7
Weather	1: Favorable (clear, unspecified)	Extracted	161 / 99 / NA / NA
	2: Adverse (rain, snow, fog)	Extracted	2 / 4 / NA / NA
Road Condition	1: Favorable (dry, unspecified)	Extracted	156 / 97 / NA / NA
	2: Adverse (wet, icy, potholes)	Extracted	7 / 6 / NA / NA
Time	1: Favorable (daylight, unspecified)	Extracted	155 / 95 / NA / NA
	2: Adverse (night, midnight)	Extracted	8 / 8 / NA / NA
Number of Transportation Modes	1.0	Extracted	108 / 80 / 71 / 920
	2.0	Extracted	45 / 21 / 34 / 577
	3.0	Extracted	7 / 3 / 9 / 155
	4.0	Extracted	3 / 1 / 4 / 15

TABLE I: Mechanical and visibility components explored and corresponding keywords

Mechanical/Visibility Component	Keyword(s)
Brake System	Brake, Pads, Cable
Steering System	Handlebar, Stem, Cockpit
Pedals	Pedal
Drive System	Drive belt or chain
Wheel/Tire	Wheel or Tire, Spokes
Front Fork	Front Fork
Frame	Bicycle Frame
Saddles/Seats	Saddle or Seat
Visibility	Lamp, Lights, Reflectors

B. Incident Severity Analysis-Ordered Logit Model

We investigate the relationship between severity levels and incident-related factors using an ordered logit model, which is well suited for analyzing ordinal dependent variables. Such variables are ranked but the differences between categories are neither equal nor precisely measurable. In this study, severity level is treated as an ordinal outcome, defined with seven

sequential categories in CPSRMS and four categories in NEISS. For CPSRMS, severity ranges from 1 (Incident, no injury – least severe) to 7 (Death – most severe). The classification is based on CPSRMS report descriptions and internal coding, which differs substantially from the conventional KABCOU scale commonly used in U.S. crash data (typically four or five levels, depending on the state) [34]. For NEISS, severity is derived from the standardized diagnosis variable (diag), which captures treatment outcomes (e.g., treated and released versus hospitalized), and spans from 1 (Mild – least severe) to 4 (Fatal – most severe). Records with undefined severity values (-1) were excluded from both datasets.

For an ordinal outcome variable ordered categories Y and K , the model can be expressed as Equation 1:

$$\log(P(Y \leq j)) = \theta_j - \mathbf{X}\boldsymbol{\beta} \quad (1)$$

- $P(Y \leq j)$ is the cumulative probability that the response is in category j or lower.
- θ_j are the threshold parameters that separate the categories.
- \mathbf{X} is the vector of predictor variables.
- $\boldsymbol{\beta}$ is the vector of coefficients for the predictor variables.

For predictor variables X , we incorporate variables that might impact incident severity, encompassing both those in the dataset and those extracted from the narrative variable via the ChatGPT model. Table II details these predictor variables, indicating their dataset origin or extraction status.

Due to the high proportion (76%) of unspecified race data in the e-bike incident dataset, the race variable was omitted from the analysis as it would likely contribute little variance to the regression model. To better understand the impact of weather, road conditions, and time on severity, these variables were divided into adverse and favorable categories. Weather was labeled as adverse (2) for conditions such as rain, snow, or fog, and favorable (1) otherwise or if unspecified. Road conditions were deemed adverse (2) for wet, icy, or dangerous settings, and favorable (1) for dry or unspecified situations. Similarly, time was considered adverse (2) during evening, night, or midnight, and favorable (1) during day or when unspecified. An ordered logit model was used via the “ologit” command in STATA to evaluate these variables’ effects on severity and their statistical significance.

IV. EXPERIMENTS

The experiments in this section are designed to address the following research questions: (1) What demographic characteristics are associated with bike and e-bike incidents? (2) How are incidents distributed across human-, equipment-, or combined-related causes? (3) What age- and gender-related patterns emerge in common injury causes? (4) What are the most frequent injury causes linked to human, equipment, or combined factors? (5) What severity levels are most prevalent by age and gender? (6) How are severity levels distributed across human-, equipment-, or combined-related incidents? (7) What is the correlation between incident factors for bikes and e-bikes and the resulting severity levels?

A. Experiment Settings

1) Datasets: This study draws on two complementary data sources: the Consumer Product Safety Risk Management System (CPSRMS) and the National Electronic Injury Surveillance System (NEISS). Both are maintained by the U.S. Consumer Product Safety Commission (CPSC) and provide detailed records of consumer product-related injuries, including those involving micromobility devices such as bicycles and e-bikes. The CPSRMS dataset consists of incident reports submitted by consumers, manufacturers, and health professionals between 2017 and 2023. Each record includes structured fields, such as incident year, location, severity, and demographic characteristics (e.g., age and gender), as well as unstructured components, most notably a free-text narrative describing the incident. Because key variables (e.g., weather, road conditions, and contributing causes) are often embedded within these narratives, advanced natural language processing techniques are required for systematic extraction. Using a classification agent to detect e-bike-related keywords, we identified 460 e-bike incidents and 133 traditional bicycle incidents in CPSRMS. The NEISS dataset, by contrast, is a

structured surveillance system that contains standardized fields such as product codes (to classify incident types), diagnosis, injury location, patient demographics, and treatment outcomes. Each record also includes a brief narrative (narr) that provides contextual details and can be leveraged to extract supplementary information (e.g., crash mechanism or helmet use). For this study, we analyzed NEISS records from 2017 to 2023 and identified 1,675 e-bike-related cases and 120 traditional bicycle cases. Compared with traditional transportation safety databases such as FARS (Fatality Analysis Reporting System [35]) or CRSS (Crash Report Sampling System [36]), which rely solely on predefined structured variables, CPSRMS poses greater analytical challenges because of its narrative-rich format. NEISS, by contrast, provides consistent coding of injury characteristics while still offering contextual details through its short narrative field. By integrating these two sources—CPSRMS, which blends structured and narrative data, and NEISS, which is predominantly structured with supplementary narrative—we enable a more robust comparative analysis of injury causes, affected populations, and severity outcomes across e-bike and traditional bicycle incidents¹. This dual-dataset framework offers a more comprehensive perspective on emerging micromobility safety trends.

2) LLM Model details: In this study, we apply the GPT4 [37] model to execute the four agents mentioned in Section 3.1. We use zero-shot prompting and Table III provides detailed examples of the prompts used and the corresponding expected outcomes for each variable we seek to extract.

Should corresponding information be absent, the output will state, "There are no certain information mentioned in the incident." The variables extracted, transportation mode, time, weather, road conditions, and cause of the incident, were selected because they are often cited in literature as crucial factors in accident occurrence and severity [38, 39, 40]. Other variables were omitted either due to inconsistent narrative reporting or minimal relevance to severity modeling.

3) Evaluation metrics: To evaluate the performance of our proposed method, we applied a confusion matrix, as detailed in Table IV. We review every incident description, check whether the detected component was the main cause or not, and check for missing components.

TABLE IV: Confusion Matrix

	Predicted Positive	Predicted Negative
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

Where:

- **TP:** Number of cases correctly predicted to have physical components or visibility issues as the primary cause.
- **FP:** Number of cases incorrectly predicted to have physical components or visibility issues as the primary cause.

¹We compare e-bikes and bicycles because both share road space, yet differ in speed, mechanical complexity, and risk factors. Highlighting these contrasts clarifies which safety issues are unique to e-bikes.

TABLE III: Some Prompt Examples and Expected Outcomes

Variable	Examples of Prompt	Expected Outcomes
Transportation Mode	Please retrieve the transportation modes in the incident: “A 66-year-old male riding an electric bicycle eastbound on a road was seriously injured after colliding with a southbound vehicle at the intersection.”	‘electric bicycle’
Time	Please retrieve the time information in the incident: “73-year-old male died after crashing his electric bicycle. He was riding his bike when he hit a speed bump. He went airborne, then landed and crashed. He was taken to mc where he was pronounced dead later that afternoon.”	‘afternoon’
Weather	Please retrieve the weather information in the incident: “2 people on the bike and truck driver were headed in the same direction on a road when it rained.”	‘rainy’
Incident Causes	Please retrieve the incident cause information in the incident: “A 39-year-old male has died in a bicycle crash. He was riding an electric bike when he lost control and hit a bridge railing.”	‘crash’

- **TN:** Number of cases correctly predicted to *not* have physical components or visibility issues as the primary cause.
- **FN:** Number of cases incorrectly predicted to *not* have physical components or visibility issues as the primary cause.

We evaluated 460 cases of electric bikes in the CPSRMS dataset and 1675 cases in the NEISS dataset. For each case, we assessed nine classes, covering physical components and visibility issues listed in Table V. This resulted in 18 confusion matrices (one per class per dataset).

For each class, we calculated the F1 score, which balances precision and recall.

$$F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (2)$$

Where:

$$\text{Precision} = \frac{TP}{TP + FP} \quad \text{and} \quad \text{Recall} = \frac{TP}{TP + FN} \quad (3)$$

We also calculated the overall weighted F1 score in the $N = 9$ classes as follows:

$$F1_{weighted} = \frac{\sum_{i=1}^N F1_i \times Support_i}{\sum_{i=1}^N Support_i} \quad (4)$$

Where $F1_i$ is the F1 score for class i and $Support_i$ is the number of true instances for class i .

B. Classification Results

The final results of the classification performance are presented in Table V.

TABLE V: Classification Performance Results for the CPSRMS Dataset

Caused By	TP	FP	FN	Precision	Recall	F1 Score
Brake System	23	1	8	0.96	0.74	0.84
Pedal	91	0	23	1.00	0.80	0.89
Wheel/Tire	37	3	3	0.93	0.93	0.93
Seat	1	0	2	1.00	0.33	0.50
Front Fork	11	1	4	0.92	0.73	0.81
Visibility Issues	4	2	0	0.67	1.00	0.80
Drive Belt/Chain	4	1	0	0.80	1.00	0.89
Bicycle Frame	5	0	2	1.00	0.71	0.83
Steering System	6	0	4	1.00	0.60	0.75
Weighted F1 Score					0.87	

TABLE VI: Classification Performance Results for the NEISS Dataset

Caused By	TP	FP	FN	Precision	Recall	F1 Score
Brake System	13	4	4	0.76	0.76	0.76
Pedal	3	0	1	1.00	0.75	0.86
Wheel/Tire	34	4	2	0.89	0.94	0.92
Saddle/Seat	4	1	2	0.80	0.67	0.73
Front Fork	8	0	0	1.00	1.00	1.00
Visibility Issues	3	2	0	0.60	1.00	0.75
Drive Belt/Chain	5	1	0	1.00	0.83	0.91
Bicycle Frame	1	0	1	1.00	0.50	0.67
Steering System	8	8	4	0.50	0.67	0.57
Weighted F1 Score					0.84	

We noticed that the proposed E-bike Agents framework considerably decreases the time and effort needed for initial data structuring, at the same time, achieves an average weighted F1 score of 0.87 and 0.84 for CPSRMS and NEISS dataset respectively across key variables, reflecting high accuracy. Our results shed light on the great potential of using LLMs in critical domains, such as transportation accidents analysis.

C. Visualization

1) *Initial Exploration:* The datasets do not explicitly specify whether injuries are linked to traditional bicycles, e-bikes, or their underlying causes. As described in Section 3.1, incidents were categorized for analysis. From the CPSRMS dataset, we identified 133 bicycle-related and 460 e-bike-related incidents. From the NEISS dataset, we identified 120 bicycle-related and 1,675 e-bike-related incidents. We present visualizations of both datasets to highlight the hidden information prior to applying our methods. In the CPSRMS dataset, most incidents, regardless of whether they involved a bicycle or an e-bike, occurred on streets or highways in urban areas, with the highest

frequency observed in 2022. Adults, seniors, and males were disproportionately affected. The NEISS dataset shows similar patterns: most incidents occurred on streets or highways, with adults and males being most affected. Additionally, the NEISS data indicate that white individuals are disproportionately represented among those injured in bicycle and e-bike incidents. Figures 3 and 4 summarize these findings.

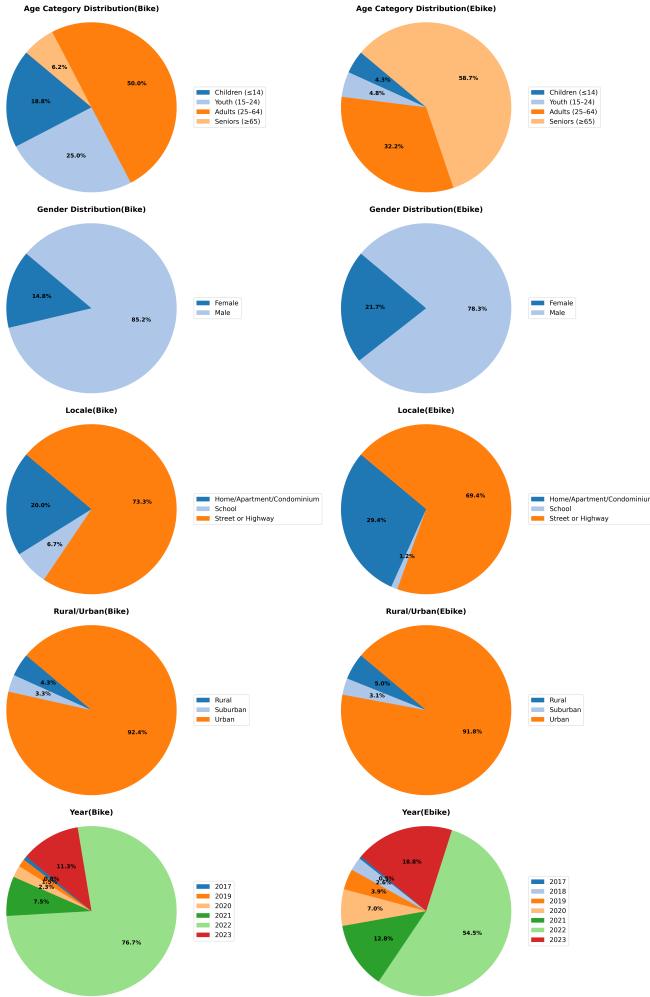


Fig. 3: Distribution of CPSRMS bicycle- and e-bike–related incidents by location, land use, year, gender, and age category.

2) *Causes of bike and ebike accidents:* We determined the leading causes of bike and e-bike injuries categorized by age and gender (Figures 5 6). Collisions and falls consistently appear among the top three causes for all groups, indicating that reasonable infrastructure design and bike and e-bike design enhancements are important to reduce bike and e-bike injuries. Additionally, equipment-related problems, particularly issues with batteries, pedals, and malfunctions, are common causes of injury. These findings can guide bike and bike design enhancements for safer use.

For the CPSRMS dataset, the analysis identified collisions, bike falls, and loss of control as the main human-related causes. Equipment-related problems mainly involve pedals, batteries,

and malfunctions. For NEISS dataset, the incidents are mainly related to human-related incidents, which indicate similar main human-related causes. Figures 7 8 illustrate the leading causes in human, equipment, and combined incidents.

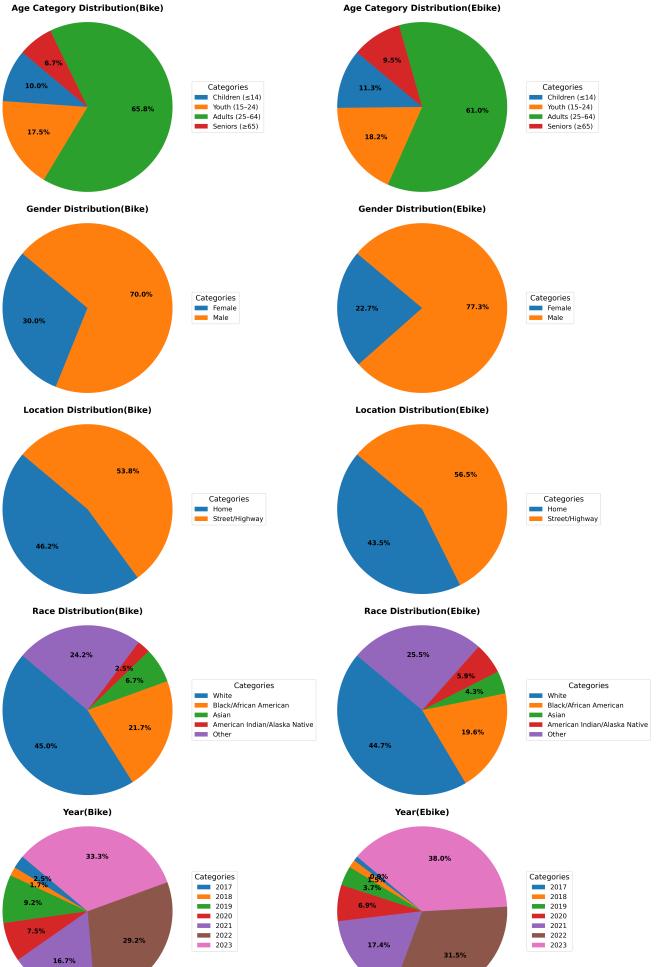


Fig. 4: Distribution of NEISS bicycle- and e-bike–related incidents by location, land use, year, gender, and age category.



Fig. 7: Top three most frequent injury causes of bicycle and e-bike incidents in the CPSRMS dataset, categorized as human-related, equipment-related, or both.

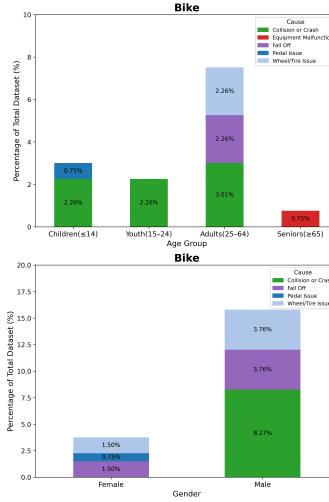
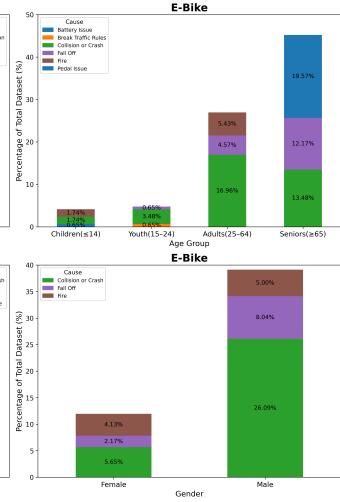
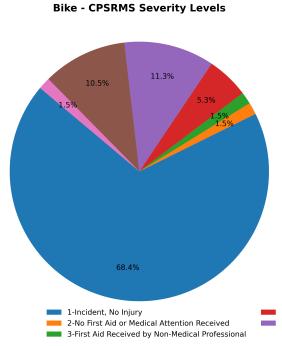


Fig. 5: Top three most frequent injury causes of bicycle and e-bike incidents by age group and gender in the CPSRMS dataset.



Bike - CPSRMS Severity Levels



E-bike - CPSRMS Severity Levels

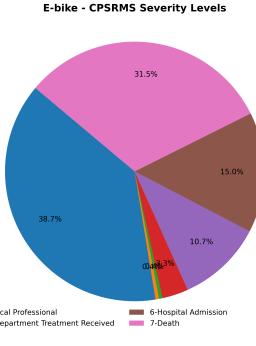


Fig. 9: Severity level distribution in the CPSRMS dataset.

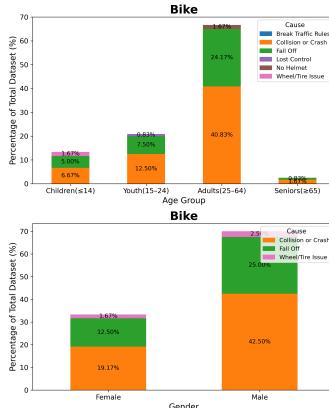
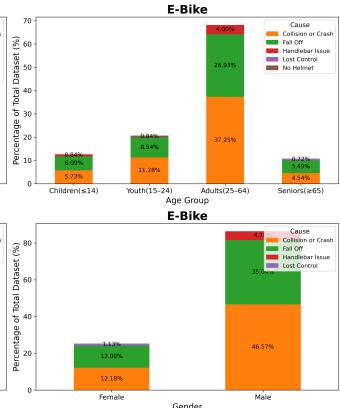
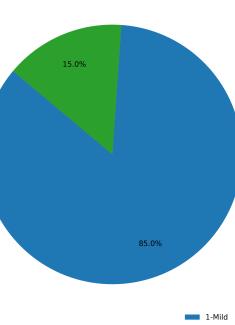


Fig. 6: Top three most frequent injury causes of bicycle and e-bike incidents by age group and gender in the NEISS dataset.



Bike - NEISS Severity Levels



E-bike - NEISS Severity Levels

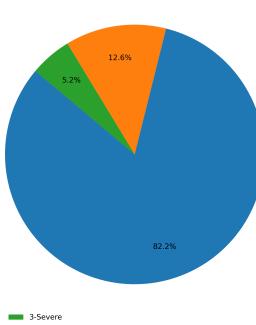


Fig. 10: Severity level distribution in the NEISS dataset.

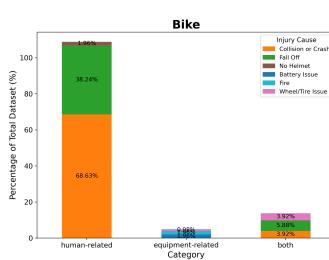
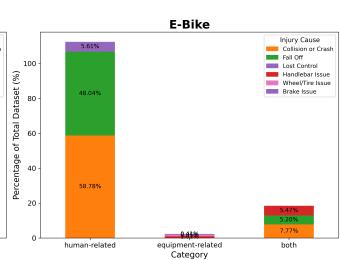


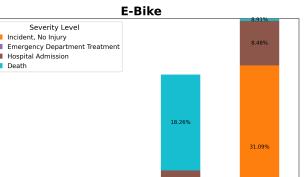
Fig. 8: Top three most frequent injury causes of bicycle and e-bike incidents in the NEISS dataset, categorized as human-related, equipment-related, or both.



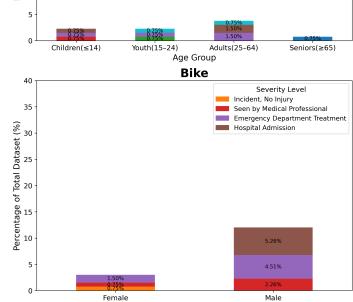
Bike - NEISS Severity Levels



E-Bike - NEISS Severity Levels



Bike - CPSRMS Severity Levels



E-Bike - CPSRMS Severity Levels

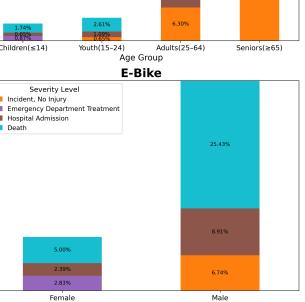


Fig. 11: Injury severity of bicycle and e-bike incidents by age group and gender in the CPSRMS dataset.

3) *Injury severity analysis:* In our study, we examined the injury severity as detailed in the dataset. Figures 9 10 present the incident severity ranked from most to least frequent.

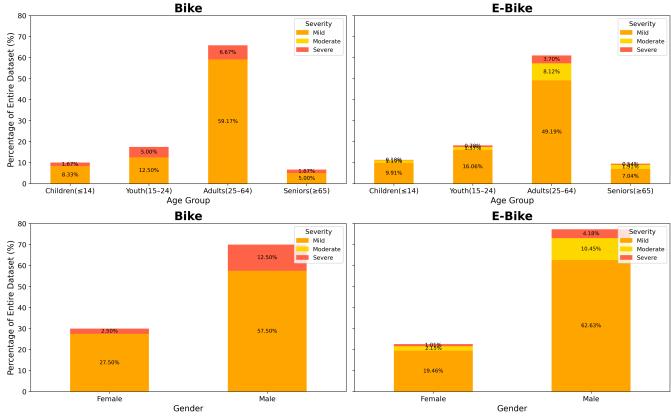


Fig. 12: Injury severity of bicycle and e-bike incidents by age group and gender in the NEISS dataset.

We performed an intersection analysis of incident causes against their severity. Findings show that human-related incidents result in a significantly higher fatality rate. Conversely, equipment failure incidents generally lead to milder outcomes, often reporting no injuries, as shown in Figure 13 14.

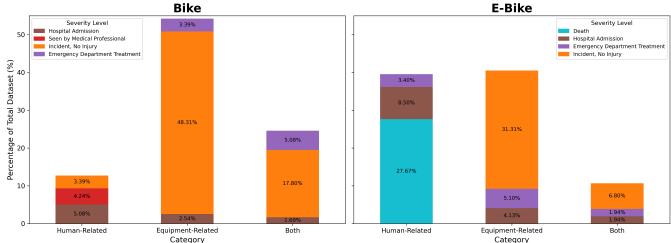


Fig. 13: Most Frequent Injury Severities in Human- and Equipment-Related CPSRMS Incidents

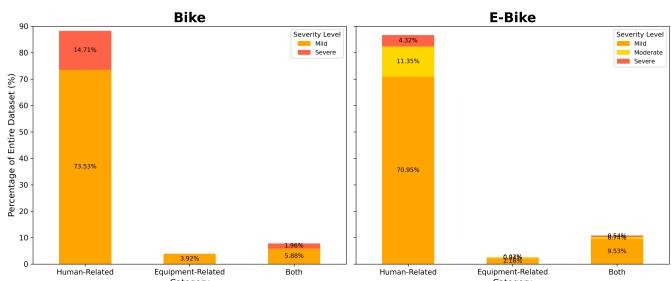


Fig. 14: Most Frequent Injury Severities in Human- and Equipment-Related NEISS Incidents

4) Link between incident and e-bike components: Compared to traditional bicycles, e-bikes represent a relatively new mode of transportation. Given their more complex mechanical and electrical systems, it is important to examine the specific components—particularly mechanical ones—that may contribute to injury risk. Understanding these differences can offer insights into design, maintenance, and safety improvements tailored for e-bikes. We utilized the reported field containing a narrative of the incident to investigate the link between e-bike mechanical components and the incidents. Our goal was

to assess whether each incident was associated with certain e-bike components and if the component directly caused the incident. Figure 15 and 16 present the count of incidents in the CPSRMS and NEISS dataset associated with and caused by these mechanical/visibility components.

The analysis identified that the pedal, wheel/tire, brake systems and steering systems are the most commonly mentioned keywords in e-bike incident reports, as well as the main contributors to these incidents. This indicates that e-bike standards should place greater emphasis on these components. Although less frequently, components like the front fork, bike frame, and seat were also mentioned in reports.

D. Predicting bike and e-bike accident severity

Our goal is to investigate the connection between incident severity and contributing factors. We used an ordered logit model to determine the relationship between severity levels and relevant variables. In Tables VII and VIII, the ordered logit regression results are presented alongside the likelihood ratio statistics, providing insights into how various factors interact with vehicle type (bike vs. e-bike) to influence injury outcomes.

TABLE VII: Ordered Logit Regression Results for CPSRMS Dataset
Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Variable	Coefficient	Std. Error	Significance
human-related × bikedummy	-0.274	(1.224)	
human-related × ebikedummy	4.257	(2.260)	*
equipment-related × bikedummy	-2.084	(0.600)	***
equipment-related × ebikedummy	0.735	(2.235)	
both-related × bikedummy	0.946	(0.827)	
both-related × ebikedummy	1.884	(2.414)	
agecategory × bikedummy	0.494	(0.303)	
agecategory × ebikedummy	-0.677	(0.141)	***
numberofmodes × bikedummy	1.814	(1.075)	*
numberofmodes × ebikedummy	0.130	(0.230)	
ebikedummy			
goodroadcondition × ebikedummy	-0.116	(0.946)	
goodtime × bikedummy	-2.328	(1.332)	*
goodtime × ebikedummy	-0.333	(0.614)	
Initial Log Likelihood		-719.04648	
Final Log Likelihood		-503.86005	
Pseudo R ²		0.2993	
Observations		546	

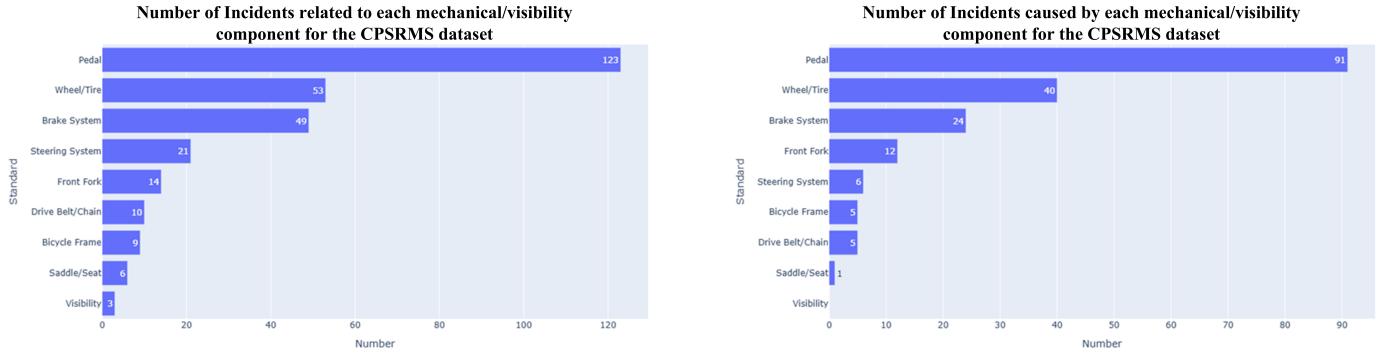


Fig. 15: Number of CPSRMS Incidents by Mechanical and Visibility Component

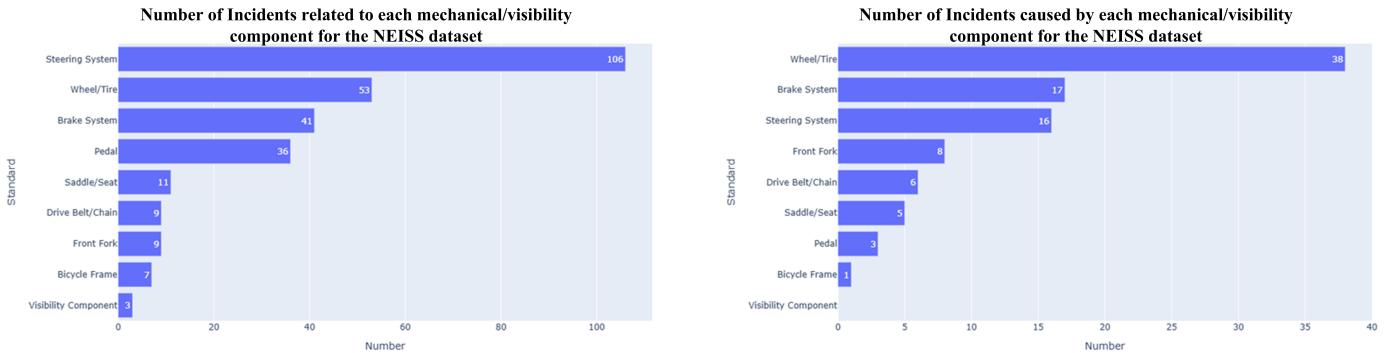


Fig. 16: Number of NEISS Incidents by Mechanical and Visibility Component

TABLE VIII: Ordered Logit Regression Results for NEISS Dataset

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Variable	Coefficient	Std. Error	Significance
human-related × ebikedummy	0.067	(0.422)	
equipment-related × ebikedummy	1.402	(0.822)	*
both-related × ebikedummy	0.254	(0.404)	
sex × ebikedummy	-0.428	(0.167)	**
agecategory × ebikedummy	0.361	(0.088)	***
whitedummy × ebikedummy	0.194	(0.130)	
streethighwaydummy × ebikedummy	-0.420	(0.190)	**
homedummy × ebikedummy	-0.417	(0.198)	**
Initial Log Likelihood	-1036.1962		
Final Log Likelihood	-1018.2025		
Pseudo R ²	0.0174		
Observations	1,795		

For the CPSRMS dataset (Table VII), several interaction terms remain statistically significant after re-estimation. Age plays an important role: *agecategory* × *ebikedummy* is negative and highly significant ($\beta = -0.677$, $p < 0.01$), implying that older individuals in e-bike incidents tend to experience less severe outcomes, possibly due to more cautious behavior. In contrast, the corresponding bicycle interaction is positive but not significant.

Incident type also matters. Equipment-related incidents for bicycles show a strong negative and significant effect (*equipment-related* × *bikedummy*; $\beta = -2.084$, $p < 0.01$), indicating that equipment-related factors are associated with less severe outcomes in traditional bike cases. For e-bikes,

however, equipment-related incidents are positive but not significant, highlighting a mode-specific difference.

Other predictors show mixed results. Human-related factors are only marginally significant for e-bikes ($\beta = 4.257$, $p < 0.1$), while number of modes is positively associated with severity in bicycles ($\beta = 1.814$, $p < 0.1$). Time and road condition interactions generally remain insignificant, although riding in "good time" conditions shows a negative effect for bicycles ($\beta = -2.328$, $p < 0.1$), suggesting fewer severe outcomes.

Turning to the NEISS dataset (Table VIII), the results highlight several consistent patterns. Demographics remain critical: sex is significant and negative (*sex* × *ebikedummy*; $\beta = -0.428$, $p < 0.05$), suggesting that female e-bike riders are less likely to experience severe injuries relative to males. Age is again positive and highly significant ($\beta = 0.361$, $p < 0.01$), underscoring that older e-bike riders tend to face higher injury severity.

Contextual factors are also important. Both street/highway and home locations are significantly negative (*streethighwaydummy* × *ebikedummy*; $\beta = -0.420$, $p < 0.05$; *homedummy* × *ebikedummy*; $\beta = -0.417$, $p < 0.05$), indicating that incidents in these locations are generally less severe compared to other contexts. By contrast, human- and both-related categories show no significant effects in this dataset.

In summary, the CPSRMS results emphasize the importance of incident type and contextual factors for severity, with equipment-related incidents reducing severity for traditional bikes and age reducing severity for e-bikes. In contrast, the NEISS findings point strongly to demographic and location

effects, where sex, age, and specific environments shape injury outcomes. Taken together, these findings highlight the need for targeted safety interventions that differentiate between e-bike and bicycle users, as well as between rider demographics and environmental contexts.

V. CONCLUSION

This study extends existing e-bike safety research by integrating both CPSRMS and NEISS datasets to compare e-bike and traditional bicycle incidents. By combining structured variables with narrative-derived factors, we provide a richer perspective on how demographic, behavioral, and contextual variables shape injury severity.

The regression analysis on CPSRMS highlights several important findings. Male riders consistently face higher risks of severe outcomes in e-bike incidents, while older individuals appear less vulnerable in e-bike crashes, possibly reflecting more cautious riding behaviors, yet show higher severity when riding traditional bicycles. Location also matters: rural and suburban incidents are associated with lower severity compared to urban ones, underscoring the interplay between riding environments and crash outcomes. Moreover, human-related causes demonstrate a tendency to increase severity for e-bikes, while equipment-related causes, though frequently reported, show no consistent statistical effect. Road conditions, when included, did not exhibit a significant influence, suggesting that rider behavior and demographic characteristics remain more predictive of injury outcomes than surface conditions alone. For traditional bicycles, age and location emerge as key determinants of severity. Older riders are more likely to experience severe injuries, which may reflect greater physical vulnerability, while rural and suburban incidents are associated with lower severity than urban ones. These findings suggest that while bicycles and e-bikes share some common risk factors, the mechanisms driving severity differ across the two modes: demographics dominate for bicycles, whereas behavioral and human-related causes are more prominent for e-bikes. A key methodological contribution of this study lies in the use of large language models (LLMs) to process and classify unstructured narratives in CPSRMS and NEISS. Traditional safety datasets, such as FARS or CRSS, contain predefined variables, but CPSRMS primarily consists of text-based reports. By applying LLMs, we were able to systematically extract structured predictors, such as human- vs. equipment-related causes, that could then be incorporated into statistical models. This approach not only expands the analytical utility of narrative-heavy datasets but also demonstrates the potential of LLMs as tools for scalable, reproducible transportation safety research. Beyond e-bikes, the same framework could be extended to other emerging mobility modes or under-researched incident types. Taken together, these results emphasize the multifaceted nature of micromobility risk. For bicycles, injury severity is strongly shaped by rider age and the crash environment, while for e-bikes, human-related causes and gender play a more central role. Equipment-related issues remain important for prevention but do not consistently affect severity once crashes

occur. This distinction suggests that improving rider education and behavior may be more effective for reducing injury severity, while equipment standards and regulation can help reduce incident occurrence in the first place.

From a policy perspective, the findings stress the importance of tailoring interventions to the unique characteristics of e-bike use. Infrastructure planning should account for urban areas where risks of higher-severity injuries are concentrated, while safety campaigns may need to target male and younger riders who are at disproportionate risk. For bicycles, interventions focused on older riders and urban riding contexts may yield the greatest safety benefits. Regulatory oversight of e-bike equipment, particularly batteries and braking systems, remains critical to mitigate ignition, failure, and other hazards that differentiate e-bikes from traditional bicycles. Finally, integrating LLM-powered narrative analysis demonstrates a scalable approach for leveraging unstructured safety data, offering a replicable framework for other emerging modes of micromobility.

In summary, e-bikes share some injury patterns with bicycles but also introduce distinct risks shaped by rider demographics, human-related causes, and the complexity of their components. Addressing these risks requires a dual strategy: behavioral interventions to mitigate human-related causes of severe injuries, and technical standards to reduce the likelihood of equipment-related incidents. For bicycles, attention should focus on protecting older riders and reducing risks in urban environments. Future research should extend this framework to longitudinal data and evaluate the real-world effectiveness of targeted policy measures, thereby supporting the safe integration of e-bikes and bicycles into modern transportation systems.

REFERENCES

- [1] U.S. Department of Energy. Fotw #1321, december 18, 2023: E-bike sales in the united states exceeded one million in 2022, 2023. [Online]. Available: energy.gov/eere/electric-vehicle-program, Accessed: Sep. 23, 2025.
- [2] Physical Activity Council. Annual trend study 2023: Among americans who rode a bicycle at least once, 19.4% reported using an e-bike. <https://www.peopleforbikes.org/news/electric-bicycle-market-insights-2024>, 2023. Accessed: September 23, 2025.
- [3] J. Tark. Micromobility products-related deaths, injuries, and hazard patterns: 2017–2021. Cpsc report, United States Consumer Product Safety Commission, 2022.
- [4] U.S. Consumer Product Safety Commission. Micromobility products-related deaths, injuries, and hazard patterns: 2017–2022. Technical report, U.S. Consumer Product Safety Commission, 2023. [Online]. Available: [cpsc.gov/psm-reports/micromobility-products-related-deaths-injuries-and-hazard-patterns-2017-2022](https://www.cpsc.gov/psm-reports/micromobility-products-related-deaths-injuries-and-hazard-patterns-2017-2022), Accessed: Sep. 23, 2025.
- [5] Wenxin Ma, Zhiyong Liu, and Ruimin Li. Effect of helmet-wearing regulation on electric-bike riders: A case study of two cities in china. *Transportation Safety and Environment*, 6(3), 2023.
- [6] Xiangyong Jian, Lanqing Yang, Yijie Li, Yi-Chao Chen, and Guangtao Xue. Singmonitor: E-bike charging health

- monitoring using sound from power supplies. *Applied Sciences*, 13(5):3087, 2023.
- [7] Chen Wang, Siyuan Kou, and Yanchao Song. Identify risk pattern of e-bike riders in china based on machine learning framework. *Entropy*, 21(11):1084, 2019.
- [8] Haoxiang Gao, Zhongruo Wang, Yaqian Li, Kaiwen Long, Ming Yang, and Yiqing Shen. A survey for foundation models in autonomous driving, 2024.
- [9] Jiacheng Lin, Zhongruo Wang, Kun Qian, Tian Wang, Arvind Srinivasan, Hansi Zeng, Ruochen Jiao, Xie Zhou, Jiri Gesi, Dakuo Wang, Yufan Guo, Kai Zhong, Weiqi Zhang, Sujay Sanghavi, Changyou Chen, Hyokun Yun, and Lihong Li. Sft doesn't always hurt general capabilities: Revisiting domain-specific fine-tuning in llms, 2025.
- [10] Siheng Xiong, Ali Payani, Ramana Kompella, and Faramarz Fekri. Large language models can learn temporal reasoning. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar, editors, *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 10452–10470, Bangkok, Thailand, August 2024. Association for Computational Linguistics.
- [11] Siheng Xiong, Ali Payani, Yuan Yang, and Faramarz Fekri. Deliberate reasoning for llms as structure-aware planning with accurate world model. *arXiv preprint arXiv:2410.03136*, 2024.
- [12] Jiashu He, Mingyu Derek Ma, Jinxuan Fan, Dan Roth, Wei Wang, and Alejandro Ribeiro. Give: Structured reasoning with knowledge graph inspired veracity extrapolation. *International Conference of Machine Learning*, 2025.
- [13] Jiashu He, Jinxuan Fan, Bowen Jiang, Ignacio Houine, Dan Roth, and Alejandro Ribeiro. Self-give: Associative thinking from limited structured knowledge for enhanced large language model reasoning. *arxiv.org/abs/2505.15062*, 2025.
- [14] Chong Wang, Mengyao Li, Junjun He, Zhongruo Wang, Erfan Darzi, Zan Chen, Jin Ye, Tianbin Li, Yanzhou Su, Jing Ke, Kaili Qu, Shuxin Li, Yi Yu, Pietro Liò, Tianyun Wang, Yu Guang Wang, and Yiqing Shen. A survey for large language models in biomedicine, 2024.
- [15] Xiaochuan Xu, Zeqiu Xu, Peiyang Yu, and Jiani Wang. Enhancing user intent for recommendation systems via large language models, 2025.
- [16] Peiyang Yu, Zeqiu Xu, Jiani Wang, and Xiaochuan Xu. The application of large language models in recommendation systems, 2025.
- [17] Xiaochuan Xu, Peiyang Yu, Zeqiu Xu, and Jiani Wang. A hybrid attention framework for fake news detection with large language models, 2025.
- [18] Peiyang Yu, Xiaochuan Xu, and Jiani Wang. Applications of large language models in multimodal learning. 2024.
- [19] Can Jin, Hongwu Peng, Qixin Zhang, Yujin Tang, Dimitris N Metaxas, and Tong Che. Two heads are better than one: Test-time scaling of multi-agent collaborative reasoning. *arXiv preprint arXiv:2504.09772*, 2025.
- [20] Can Jin, Tong Che, Hongwu Peng, Yiyuan Li, Dimitris Metaxas, and Marco Pavone. Learning from teaching regularization: Generalizable correlations should be easy to imitate. *Advances in Neural Information Processing Systems*, 37:966–994, 2024.
- [21] Ze Yang, Yihong Jin, and Xinhe Xu. Hades: Hardware accelerated decoding for efficient speculation in large language models. *arXiv preprint arXiv:2412.19925*, 2024.
- [22] T. Weber, G. Scaramuzza, and K.-U. Schmitt. Evaluation of e-bike accidents in switzerland. *Accident Analysis & Prevention*, 73:47–52, 2014.
- [23] Sonja Haustein and Mette Møller. E-bike safety: Individual-level factors and incident characteristics. *Journal of Transport & Health*, 3(3):386–394, 2016.
- [24] Jun Ren, Yue Chen, Fenfen Li, Cheng Xue, Xiaoya Yin, Juanjuan Peng, Ji Liang, Qiming Feng, and Shumei Wang. Road injuries associated with cellular phone use while walking or riding a bicycle or an electric bicycle: A case-crossover study. *American Journal of Epidemiology*, 190(1):37–43, 2021.
- [25] Yu Hu, Daan Ettema, and Arman Sobhani. To e-bike or not to e-bike? a study of the impact of the built environment on commute mode choice in a small chinese city. *Journal of Transport and Land Use*, 14(1):479–497, 2021.
- [26] Christopher R. Cherry and Elliot Fishman. E-bikes in europe and north america. In Ralph Buehler and John Pucher, editors, *Cycling for Sustainable Cities*, pages 157–172. MIT Press, Cambridge, MA, 2021.
- [27] Peishan Ning, Huiying Zong, Li Li, Peixia Cheng, David C. Schwebel, Yang Yang, Lei Yang, Youyou Wu, Min Zhao, and Guoqing Hu. Effectiveness of a helmet promotion campaign, china. *Bulletin of the World Health Organization*, 100(5):329–336, May 2022.
- [28] Lijuan Lei. Study on the fire risk assessment of the electric bicycle based on the ahp. In *Proceedings of the 2014 7th International Conference on Intelligent Computation Technology and Automation (ICICTA)*, pages 729–732, Shenzhen, China, 2014. IEEE.
- [29] J. M. Jafferson and H. Sharma. Design of 3d printable airless tyres using NTopology. *Materials Today: Proceedings*, 46:1147–1160, 2021.
- [30] Pedro Huertas-Leyva, Matteo Dozza, and Nicola Baldanzini. E-bikers' braking behavior: Results from a naturalistic cycling study. *Traffic Injury Prevention*, 20(sup3):62–67, 2019.
- [31] J. Chen, Z. Xie, and C. Qian. Traffic conflict models on shared-use paths used by pedestrians, cyclists, and electric bicycle riders. In *Proceedings of the 10th International Conference of Chinese Transportation Professionals: Integrated Transportation Systems: Green, Intelligent, Reliable*, pages 1925–1931, Beijing, China, August 2010. American Society of Civil Engineers.
- [32] Elke M. J. Verstappen, Dan Thao Vy, Heinrich M. Janzing, Loes Janssen, Rein Vos, Marieke G. J. Versteegen, and Dennis G. Barten. Bicycle-related injuries in the

- emergency department: a comparison between e-bikes and conventional bicycles: a prospective observational study. *European Journal of Trauma and Emergency Surgery*, 47(6):1853–1860, 2021.
- [33] Qian Qian and Jing Shi. Comparison of injury severity between e-bikes-related and other two-wheelers-related accidents: Based on an accident dataset. *Accident Analysis & Prevention*, 190:107189, 2023.
- [34] Federal Highway Administration. Coding instructions for the model minimum uniform crash criteria (mmucc) 5th edition. Fhwa report, U.S. Department of Transportation, 2020.
- [35] National Highway Traffic Safety Administration. Fatality analysis reporting system (fars) database. Traffic safety dataset, U.S. Department of Transportation, 2023.
- [36] National Highway Traffic Safety Administration. Crash report sampling system (crss). Traffic safety dataset, U.S. Department of Transportation, 2023.
- [37] OpenAI. Gpt-4 technical report, 2024.
- [38] Thomas Weber, Gianluca Scaramuzza, and Klaus-Ulrich Schmitt. Evaluation of e-bike accidents in switzerland. *Accident Analysis & Prevention*, 73:47–52, 2014.
- [39] Guangnan Zhang, Kelvin K.W. Yau, and Xuesong Gong. Risk factors associated with traffic violations and accident severity in china. *Accident Analysis & Prevention*, 42(6):1927–1933, 2010.
- [40] Jianyu Wang, Shuo Ma, Pengpeng Jiao, Lanxin Ji, Xu Sun, and Huapu Lu. Analyzing the risk factors of traffic accident severity using a combination of random forest and association rules. *Applied Sciences*, 13(1):31, 2023.