FINAL PROJECT REPORT

Tesla Autonomous Deaths: Comparative Safety And Root-Cause Analysis

Description

Analyze a dataset of 286 Tesla fatality reports (2013–2023) using EDA, NLP, and statistical testing to compare safety performance between Autopilot/FSD and manual driving, and identify root-cause clusters for targeted product roadmap improvements.

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Executive Summary

This report analyzes 294 fatal Tesla crashes from 2013 to 2023 to compare crash severity and root causes between Autopilot/Full Self-Driving (FSD) and manual driving modes. Statistical tests found no significant difference in fatalities per crash between the two modes; however, natural language processing revealed distinct crash themes: manual driving is more associated with signal misjudgment and detection failures, while Autopilot crashes more often involve excessive speed and loss of control. Recommendations include improving in-cabin monitoring for manual drivers, enhancing Autopilot performance in complex scenarios, and strengthening lane detection systems. The study also calls for greater data transparency from Tesla and the use of exposure-adjusted metrics for accurate risk assessment. Limitations include the absence of non-fatal crash data and exposure measures, as well as rapidly evolving Autopilot features. Despite these, the findings provide valuable insights to support safer autonomous vehicle development, regulatory oversight, and informed consumer understanding.

Introduction

Vehicle automation has advanced significantly in the past decade, offering improvements in road safety, increased convenience for drivers, and a reduction in human error. Over 50 million vehicles are projected to be equipped with Level 2 systems by 2024, which provide features such as lane centering and adaptive cruise control, but require full driver attention under the SAE J3016 classification (Yano Research Institute; Boate). Tesla, with over one million vehicles using Autopilot or Full Self-Driving (FSD), is a leading manufacturer in this transition (Lesjak). However, despite company disclaimers, these types of systems are often misread by customers as fully autonomous, contributing to misuse and heightened safety concerns. (Threewitt).

From 2013 to 2025, more than 500 fatal Tesla crashes have been recorded, with several suspected to involve Autopilot or Full Self-Driving (FSD) mode (Tesla Death; NHTSA). Tesla's driver-assistance capabilities have also come under increasing federal examination in the wake of these accidents. In October 2024, the US Justice Department opened a criminal probe into whether Tesla misled investors and consumers to believe it was safer with Autopilot and FSD, specifically whether its marketing overstated autonomy and downplayed the risk of abuse (Isidore).

This sequence of events and queries has had concrete and measurable effects on Tesla. From a financial perspective, Tesla shares have shown volatility following reports of fatal crashes and regulatory probes. For instance, after the NHTSA launched a probe into Autopilot in August 2021, Tesla's shares fell by 5.03% subsequently (Nasdaq).

From a reputational standpoint, public trust in Tesla's self-driving claims has waned: just 13 percent of U.S. drivers say they would trust riding in a self-driving vehicle, while 60 percent remain afraid to do so. (Moye). Likewise, a March 2023 Forbes poll found only 9 percent of

Americans trust self-driving cars, with 68 percent admitting fear of riding in one (Novak). Furthermore, in 2024, Tesla was forced to recall over 2.4 million vehicles to update its Autopilot software after NHTSA concluded the system could be misused and increase crash risk (Shepardson & Sriram). These developments show how safety issues are not only regulatory concerns but also economic, legal, and brand challenges for Tesla.

Given this context, this project aims to perform a rigorous, data-driven examination of fatal Tesla crashes to determine how Autopilot/FSD compares with manual driving in fatality rates and to uncover the most common contributing factors. To address our research goals, the study will pursue these objectives: statistically compare the severity of fatal crashes between Autopilot/FSD and Manual driving modes. Apply natural language processing (NLP) techniques to analyze the narrative descriptions in the dataset and uncover at least five recurring themes or causes of fatal crashes, such as driver distraction, system misuse, or environmental factors. Explore whether these root-cause themes vary between manual and automated driving contexts, offering insight into mode-specific risk factors.

Tesla is the primary stakeholder in this analysis, using the findings to improve system design and safety notifications to reduce liability. Secondary stakeholders include regulators, who can update driver-assistance rules; consumers, who better understand Autopilot risks; and investors, who can assess reputational and financial impacts. This study turns real-world crash data into actionable insights, supporting informed decisions and responsible innovation in vehicle automation.

The remainder of this paper is organized as follows: Section 2 reviews existing literature on autonomous vehicle safety, ADAS systems, machine learning applications, and crash narrative analysis. Section 3 presents an overview of the automotive industry and emerging trends. Section 4 details the data sources and research methodology used in the study. Section 5 outlines the key findings and analysis for each research objective. Section 6 offers targeted recommendations drawn from the results, followed by the overall conclusion. Section 7 discusses the study's limitations and proposes directions for future research.

Literature Review

Recent research on safety and autonomous driving highlights that trust, perception of risk, and system performance are key to public acceptance as well as crash prevention. Kenesei et al. highlight that perceived ease of use and perceived usefulness are mediated by trust in the intention to accept AVs. Positive perceptions alone are not sufficient; safety and care must also be perceived. Although social influence plays a smaller role, individual perceptions of risk and trust remain decisive. From a safety perspective, Wang et al. illustrate that AV technologies, particularly those that involve direct takeovers (e.g., stability control, emergency braking), can prevent millions of crashes globally. Their effectiveness increases when they are activated close to collision events, suggesting that deployment strategies should consider country-specific crash patterns.

Gulino et al. propose a dual-indicator strategy that incorporates comfort and safety for the assessment of Advanced Driver Assistance Systems (ADAS). They conclude that optimal interventions, whether steering or braking, are context-sensitive, and improving user experience is just as important as promoting safety performance. Wang et al. also note that while AVs reduce human error, most accidents are still caused by errant human drivers, with only 6% of AV-related accidents being the fault of the AVs. Therefore, technology must improve on how it can foresee external risk. Overall, improving safety needs tech, trust, regulation, and simple risk mitigation.

It is improbable that autonomous cars will work well in every driving scenario. The capacity of technology to predict every potential traffic scenario is limited, especially for infrequent occurrences. The non-human agent may be unable to complete every component of the driving duty, requiring shared control over the system (Janssen et al.). Developers anticipate that well-calibrated autonomous driving systems perform better in dynamic driving tasks than human-driven cars, leading to rapid user adjustment. However, drivers may go through an adjustment phase during which they change their behavior to fit the ADS's driving habits (Xu et al.).

A key factor in confidence in automated vehicle capabilities is situational awareness. The ability of the driver to regain situation awareness in time is crucial during a takeover request (Li et al.). Such events may cause the driver's cognitive workload to spike suddenly, and repetitive duties like monitoring the road may cause the driver to become sleepy, both of which could result in hazardous circumstances (Capallera et al.).

Vehicle crash prediction has greatly benefited from modern machine-learning methods. Obasi and Benson demonstrated that Random Forest and Logistic Regression models could achieve up to 87% accuracy in forecasting the severity of traffic accidents using ten years of UK data (2005–2014). Channamallu et al. analyze autonomous-vehicle crash datasets (2014–2024) with algorithms such as decision trees, gradient boosting, bagging, and ensembles; they find that Random Forests offer the best balance between sensitivity and specificity for injury-prediction tasks. Natural language processing (NLP) also finds applications in extracting information from crash narratives. Sharma and Du apply Stanford CoreNLP and GloVe embeddings to classify Level 3 automated-vehicle crash reports, revealing factors such as lighting conditions.

Valcamonico et al. used an intention-to-end NLP + ML pipeline combining Hierarchical Dirichlet Processes topic modeling with Random Forest classification to label NHTSA crash narratives for severity, optimizing the trade-off between accuracy and interpretability.

The type and condition of a road strongly influence crash severity: intersections and driveways tend to yield fewer bodily injuries, while ramps and roundabouts see more. Icy surfaces raise injury risk, yet poor lighting and alcohol or drugs correlate with fewer BI-type crashes, whereas work-zone collisions are more injurious (Lee et al.). Traditional safety studies rely on sparse, unpredictable crash records, making site-specific analysis time and resource-intensive. Feng et al. propose using connected-vehicle hard braking events as a faster, cheaper proxy to flag potential hazards, mapping their relation to crash locations via colocation analysis. In a northern Nevada case study, hard braking clusters closely aligned with crash sites, demonstrating that connected vehicle data can efficiently enhance traffic safety evaluation.

Regulators face difficulties in ensuring safety, legal liability, data privacy, and balancing innovation with general acceptance (Salatiello and Felver 12). Authorities can regulate self-driving cars by instituting ethical standards and adaptable frameworks to manage technological and jurisdictional complexities (Mordue et al. 174). Ethics shape consumers' ethical attitudes, influencing their intentions to adopt AI-powered mobility services (Qian et al. 122). Gaining public trust in self-driving cars requires addressing safety, ethical, and reliability issues through transparency and validation (Kuru 1).

Across studies, three themes emerge: technological performance in crash prevention and prediction, the critical role of human factors such as trust, risk perception, and situational awareness, and the necessity of regulatory and ethical frameworks. Integrating advanced data streams (e.g., ML models, connected vehicle data) with user-centered design and adaptable policy can drive safer, more accepted autonomous driving systems.

Industry Overview

The automotive industry undertakes the designing, development, production, marketing, and sale of motor vehicles. As a cornerstone of economic growth, this industry has employed millions and has been a source of technological innovation worldwide (Sneci). The automotive market in the United States is one of the largest in the world, supporting over 10 million jobs and an approximate wage contribution of nearly $730 billion, generated through operations in assembly, parts production, research and development, design, and testing (Alliance for Automotive Innovation).

In 2023, the global market was valued at roughly $3.6 trillion, while 93.9 million vehicles against production were produced, China coming forward as a leader with 30.16 million, 10.61 million in the U.S., and 8.99 million in Japan (Joshi). Aside from light-vehicle sales of 11.5 million units in the U.S., foreign automakers also make about 4.9 million vehicles locally (SelectUSA). From the above, it is deduced that there are almost 1.47 billion vehicles operating in the whole world, and this only goes to show the scale and magnitude of the industry (KROLL; Joshi).

Electric mobility is the fastest-growing segment of the industry. Almost 14 million new electric vehicles were registered worldwide in 2023, with a 35 percent increase over last year; EVs represent about 18 percent of car sales. By the end of 2024, they are expected to top 17 million units with a share of surely over 20 percent of global new-car registrations (IEA; EVBoosters). In 2023, plug-in electric vehicle sales in the United States surpassed 1.4 million units, accounting for 9.1 percent of the overall new light-duty vehicle sales, thus pushing the total number of vehicles since December 2010 to about 4.7 million (Kane; U.S. Department of Energy).

The automotive industry's rapid transition to electrification is mandated by emissions regulations, including a 90% cut in CO_2 emissions by 2040 in the EU and a rule in the U.S. forcing 60% zeroemission heavy-duty sales by 2032, pushing automobile manufacturers in haste toward the production of electric cars (IEA). The breakthrough in battery technology, causing pack costs to go below USD 100/kWh, had been the threshold of price parity with ICE vehicles, while purchase incentives allowed the registrations of EVs to skyrocket by 35% in 2023 (IEA).

The competitive landscape spans traditional giants and new entrants. Toyota leads in hybrid technology and fuel efficiency, Volkswagen Group (Audi, Porsche, Lamborghini) excels in engineering and brand diversity, General Motors and Ford adapt their portfolios toward electrification and advanced safety, and Chinese automakers such as BYD rapidly expand EV production and global market share (Reynolds; ICCT; Zhu; Le Monde).

The automotive circular-economy market hit $153.6 billion in 2024 (11.5% CAGR ’24–’34), OEMs are using recycled plastics and bio-composites, and plants like Audi’s Brussels facility operate carbon-neutral via on-site solar and biogas (Globe Newswire). Automakers are also investing in battery recycling to reduce raw material demand and lower the environmental impact of EV production (Jiang et al.), which projected that recycling and reuse could cut lithium, cobalt, and nickel demand by up to 93% and lifecycle carbon emissions by roughly 36–38% through 2060 (Guzman).

The 2020–2023 semiconductor shortage significantly disrupted supply chains, leading automakers to cut an estimated 19.6 million vehicles from production and extend chip lead times from roughly 3–4 months to 10–12 months (Caron). Limited public charging stations hinder EV uptake (Innovation News Network), and China’s rare-earth export curbs have disrupted automakers’ supply chains, forcing sourcing overhauls (Waldersee and Steitz). Meanwhile, rising competition from startups and tech firms is pressuring traditional automakers to innovate rapidly on technology, cost, and user experience.

Data Collection & Methodology

The dataset we use in this research comes from the publicly available Kaggle.com repository named "Tesla Autonomous Deaths Data - Updated 2023," itself an update over a compilation provided by TeslaDeaths.com (Kaggle). TeslaDeaths.com compiled crash records from various sources, including National Highway Traffic Safety Administration (NHTSA) reports and numerous news archives, to create a central Excel spreadsheet for accessibility (Tesla Deaths). The version hosted on Kaggle ("Tesla Deaths.xlsx") comprises 294 individual fatal-crash entries spanning the years 2013 through 2023. Each entry is captured across 24 distinct fields, including fully structured columns such as Case Number, Year, Date, Country, State, Vehicle Model, whether Autopilot was claimed or later verified, and numerical counts of injuries & fatalities and several semi-structured text fields, such as narrative excerpts, Source URLs, investigator Notes, and up to four "Deceased" name fields. Because all of these records have already been merged into one cohesive file, no further data integration steps are necessary.

Under the terms of the Creative Commons CC0 waiver, this dataset is released into the public domain: all copyright and related rights have been irrevocably waived. Consequently, any user is free to copy, modify, distribute, or otherwise utilize the data, including for commercial purposes, without seeking permission or attributing the original authorship (Creative Commons). Within our project workflow, both the raw download and our intermediate, cleaned versions of the dataset are securely stored in a private WhatsApp group, accessible only to the project team and our supervising instructor. Although the dataset does include the names of deceased individuals, these details are already part of the public record; to respect privacy, we will omit personal names from any analytical outputs. Because the data consist exclusively of secondary, publicly available information, our research activities do not fall under the purview of Institutional Review Board

(IRB) oversight.

The dataset was provided as a single pre-combined Excel file, requiring structured cleaning and validation. We began by standardizing column names and removing irrelevant fields such as case numbers, autopilot claim flags, source links, and personal identifiers. Missing data was visualized using 'missingno'; key fields were filled with placeholders ('-') and later recorded to 0 where appropriate. All count-based columns such as Deaths, Tesla Driver, Tesla Occupant, Other Vehicle, Cyclists/Peds, and Autopilot Deaths were converted to integers. To ensure consistency, we validated and corrected aggregate columns such as Deaths and TSLA+cycl/peds. The Date column was converted to datetime format (date only), and Year, Month, and Day were extracted for temporal analysis. Records with zero fatalities were removed to focus strictly on fatal incidents. These preprocessing steps ensured a clean, consistent, and analysis-ready dataset that supports our project's statistical, NLP, and visualization objectives.

Our analysis incorporated both statistical and machine learning methods to address the project's three objectives. For Objective 1, we performed an independent two-sample *t*-test to evaluate whether fatality counts significantly differ between Tesla's Autopilot and manual driving modes. For Objective 2, we applied Latent Dirichlet Allocation (LDA), a topic modeling algorithm, on the crash descriptions to uncover five recurring themes that likely represent root causes of fatal crashes (e.g., signal violations, loss of control). To fulfill Objective 3, we cross-analyzed these discovered themes with driving modes to determine which root causes were more commonly associated with Autopilot versus manual driving. Additional exploratory data analysis (EDA), such as temporal trends, severity segmentation, geographical pattern and vehicle model breakdowns, was conducted using visual tools (bar charts, heatmaps, line plots, and pie charts) to support data-driven insights.

Analysis, Findings & Discussion

The project revealed critical insights about the nature, severity, and thematic causes of Tesla-related fatal crashes. Basic EDA showed a clear upward trend in Tesla fatalities post-2018, especially in the United States (257 total deaths), with California leading (89 deaths). Most fatalities occurred in November and December, and on the 7th day of each month. The majority involved single deaths, with Model S and Model 3 showing the highest crash reports. This temporal clustering may reflect seasonal factors like weather or holiday travel. There was also a rise in crashes in the fourth quarter, suggesting cyclical or behavioral contributors. Tesla vehicles with higher market penetration were involved in more fatalities, while multiple-fatality incidents were rare but highlight severe crash types. These patterns align with Lee et al., who found road conditions, time, and location influence crash severity.

Objective 1 focused on statistically comparing crash severity between Autopilot and Manual modes. An independent two-sample t-test found no significant difference in average deaths per crash (Autopilot: 1.13; Manual: 1.20; p-value = 0.398). A Poisson regression model, accounting for year, country, and Tesla model, also showed no significant associations with death counts. These results suggest that, based on reported data, Autopilot is not linked to greater or fewer deaths per crash. Literature from NHTSA and IIHS supports that automation may reduce some human error but raises concerns about overreliance and disengagement. Wang et al. noted AV technologies, especially those activated near collisions can prevent crashes, but effectiveness depends on context. However, Capallera et al. warn that sudden handovers can cognitively overload drivers, potentially offsetting safety benefits. The lack of exposure-adjusted metrics limits confirming AV safety claims.

Objective 2 applied NLP to crash narratives, extracting five root-cause themes via LDA: Signal Misjudgment, Excessive Speed, Detection Failure, Loss of Control, and Lane Departure. These patterns appear across human and automated contexts and align with findings by MIT and RAND. Signal misjudgment often involved ignoring stop signs or lights, while detection failures showed limits in recognizing non-vehicular road users. Sharma and Du’s work supports lighting and visibility issues in AV crashes. NLP clustering uncovered nuanced patterns hidden in raw text, with topic modeling grouping crashes across models and locations, consistent with Valcamonico et al.'s approach.

Objective 3 compared crash themes by driving mode. Manual driving linked more to Signal Misjudgment (23.6%) and Detection Failure (15.2%), while Autopilot crashes featured Excessive Speed (26.1%) and Loss of Control (26.1%). Lane Departure was common in both. These differences reflect distinct risks from human limits or system design. Xu et al. and Janssen et al. suggest automated systems may outperform humans in some cases, but drivers need time to adapt and may struggle to regain situational awareness in mixed-control settings. Overall, findings support improving human support and Autopilot under stress, echoing Gulino et al.'s call for adaptive, comfort- and safety-focused interventions in driver assistance.

Recommendations and Conclusion

To address the findings of this project, several key recommendations are proposed. For Manual Mode, improving in-cabin monitoring systems is essential to detect distraction and misjudgment. For Autopilot, enhancements should focus on better performance in high-speed and complex driving scenarios. Strengthening lane detection and control systems is a critical safety measure applicable to both modes. From a research standpoint, employing exposure-adjusted metrics such as deaths per million miles driven can enable more accurate risk comparisons. Additionally, Tesla should improve transparency by providing clearer public data and specifying system use conditions.

This project achieved all its three objectives to analyze Tesla fatal crash data comprehensively. Based on the analyses, the null hypothesis, where there is no significant statistical difference in crash severity between Autopilot and Manual modes, cannot be rejected. However, topic modeling showed that the types of crashes differ by mode with each presenting an interesting risk pattern. These findings stress the importance of continuing risk mitigation efforts in both human and automated driving systems.

Limitation of the Study

This study has some limitations that should be considered in interpreting the results of the study. First, the dataset used contains data regarding fatal crashes only, and non-fatal incidents were not analyzed; hence, there is a limited scope. Second, the depth of detail in the crash narratives varies and may be inconsistently reported, thus introducing an element of reporting bias. Third, no exposure data exists in terms of distance traveled in miles or time, making it difficult to present some context with respect to crash rates. Fourth, in topic modeling, the interpretation of themes is subject to human judgment to an extent, leaving some room for subjectivity. Fifth, with Autopilot features developing so fast, a set of results can become outdated in relation to the most recent system updates. Sixth and finally, the dataset did not account for external factors such as road conditions, weather, and impairment of the drivers.

Despite these limitations, the study provides actionable insights and presents a robust analytical framework to better understand the rapidly transforming safety terrain of autonomous driving systems.

Next Steps and Future Considerations

Subsequently, we can suggest many research directions to advance the automotive safety and automation field further with the findings and limitations of this study. Some of the variables could act as factors of exposure: miles driven and time spent driving. These are necessary for considering risk more tightly and working toward comparisons between Autopilot and manual driving modes. When additional studies can be expanded to analyze incidents such as non-fatal crashes and near-miss incidents, we would have a fuller approach toward overall vehicle safety beyond fatal results.

In addition, the use of robust real-time telemetry and sensor data from vehicles, as well as driver monitoring systems, would provide more insight into crash causation and driver behavior leading to critical events. Utilizing cutting-edge natural language processing methods including transformer-based approaches, could improve the extraction of subtle and intricate crash factors from narrative reports. Future research should investigate environmental and behavioral factors including weather, road surface state, driver impairment, and other backgrounds to assist in putting crash risk in perspective. Coordinating and sharing data agreements between researchers and manufacturers would enhance the access to a more variety of datasets and allow for independent validation of safety claims.

In addition, studying the cognitive workload and eventual adaptation of drivers during the transition from manual driving to automated driving, is another important area to promote human-machine interfaces and safety interventions. Finally, ongoing monitoring of technological developments and system updates is necessary to capture evolving safety performance and emerging challenges over time. Ultimately addressing these issues will provide a more complete picture of autonomous vehicle safety and support the development of safer, and more trusted automated driving systems.

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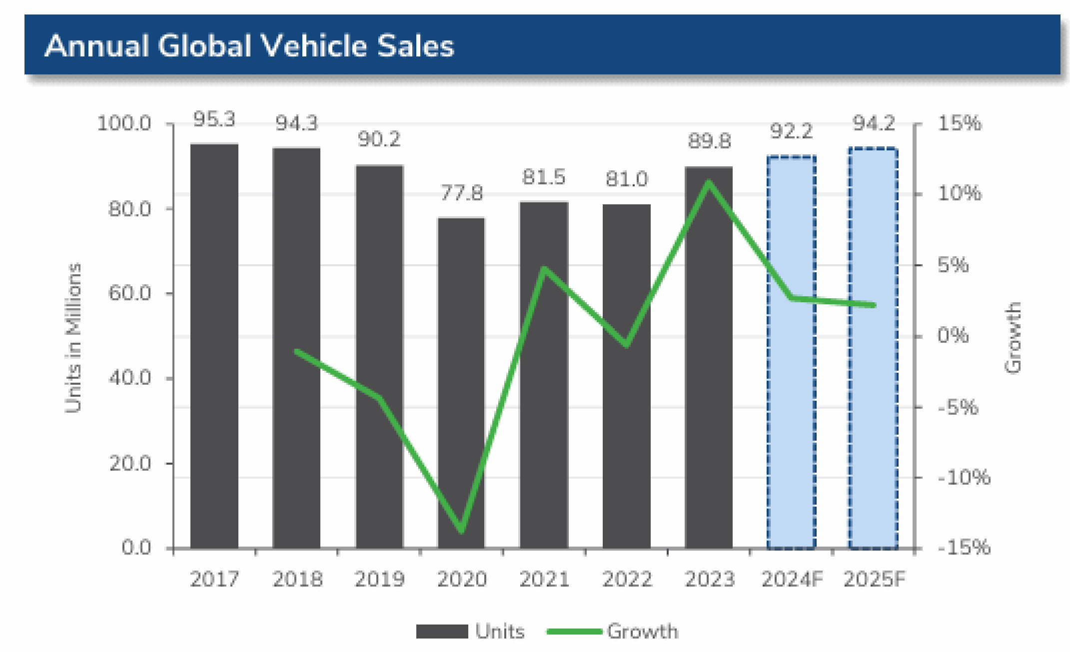
Appendices

Appendix A



Note. From *Automotive Industry Report: Spring 2024,* by KROLL, 2024.

(https://www.kroll.com/-/media/kroll-images/pdfs/executive-summary-automotive-industry-insights-spring-2024.pdf)

Appendix B

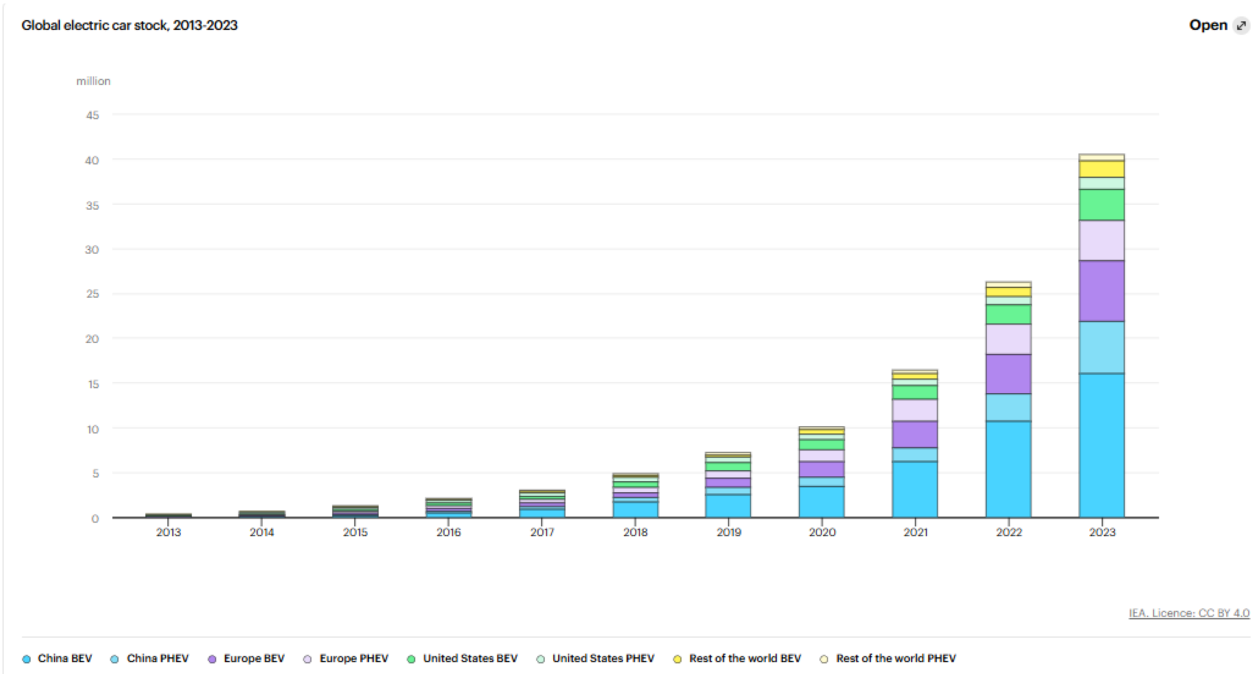
2023 Global Bestselling Brands

	Brand	Bestselling Vehicle	Brand % of 2023 Market Share	2022 Rank
1.	TOYOTA	Toyota Corolla	10.7%	1
2.		Volkswagen Tiguan	6.0%	2
3.	HONDA	Honda CR-V	4.6%	3
4.	HYUNDAI	Hyundai Tucson	4.5%	4
5.	Ford	Ford F-Series	4.4%	10

Note. From *Automotive Industry Report: Spring 2024,* by KROLL, 2024.

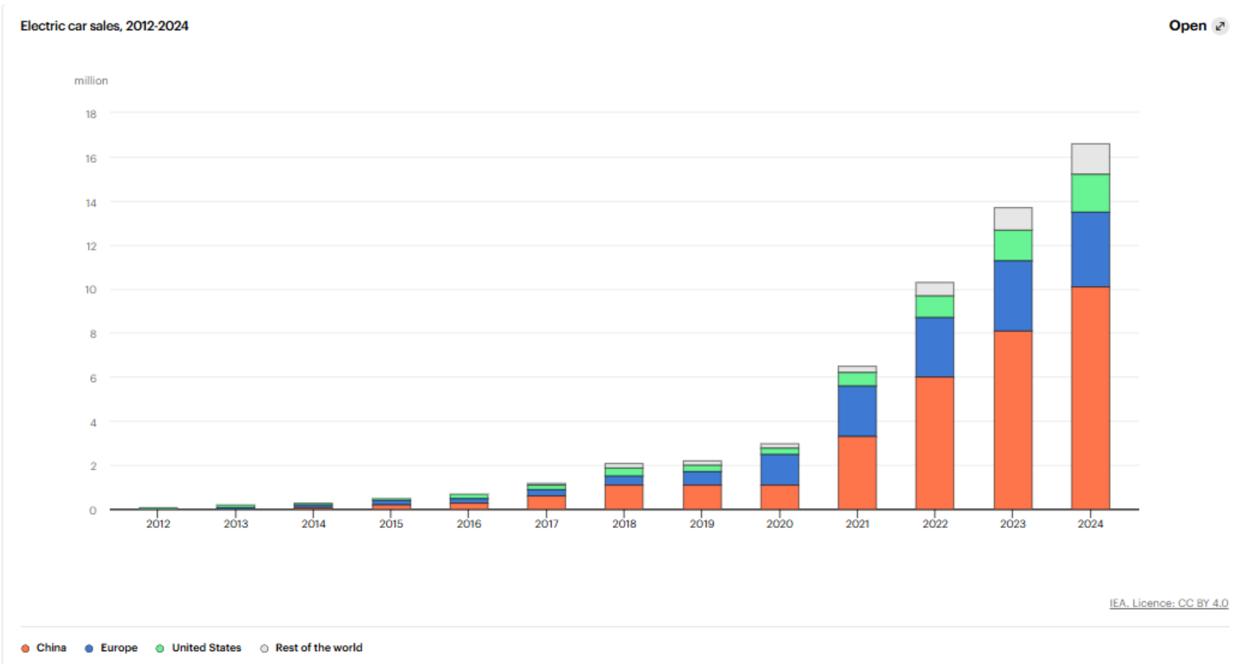
(https://www.kroll.com/-/media/kroll-images/pdfs/executive-summary-automotive-industry-insights-spring-2024.pdf)

Appendix C



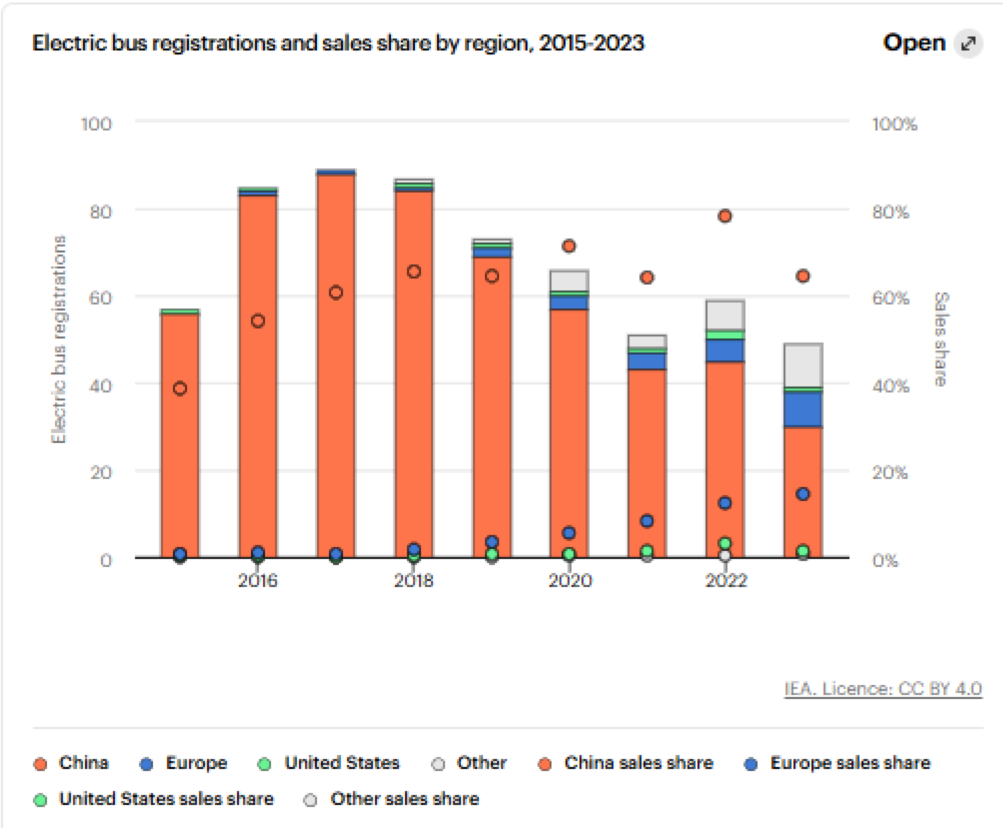
Note. From *Trends in Electric Cars*, by IEA, Accessed 11 June 2025. CC BY 4.0 (https://www.iea.org/reports/global-ev-outlook-2024/trends-in-electric-cars)

Appendix D



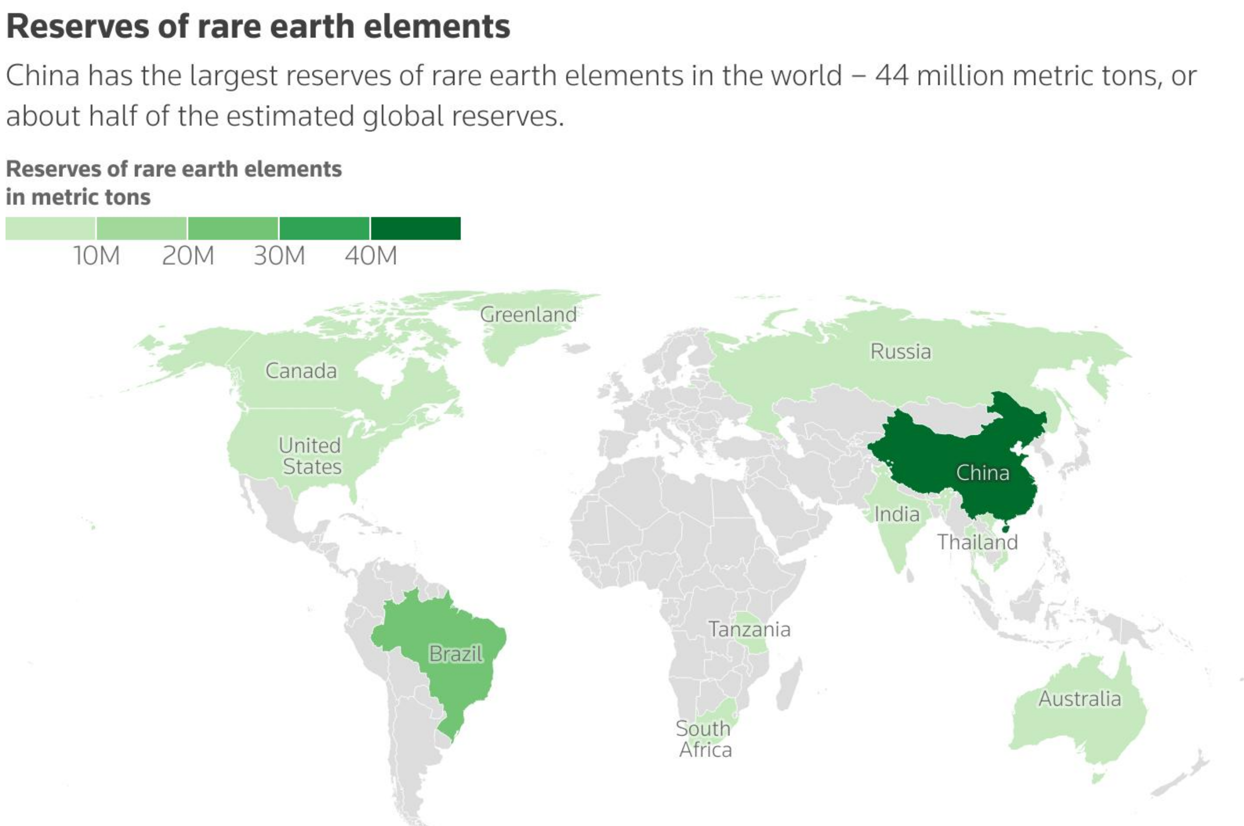
Note. From *Trends in Electric Cars*, by IEA, Accessed 11 June 2025. CC BY 4.0 (https://www.iea.org/reports/global-ev-outlook-2024/trends-in-electric-cars)

Appendix E



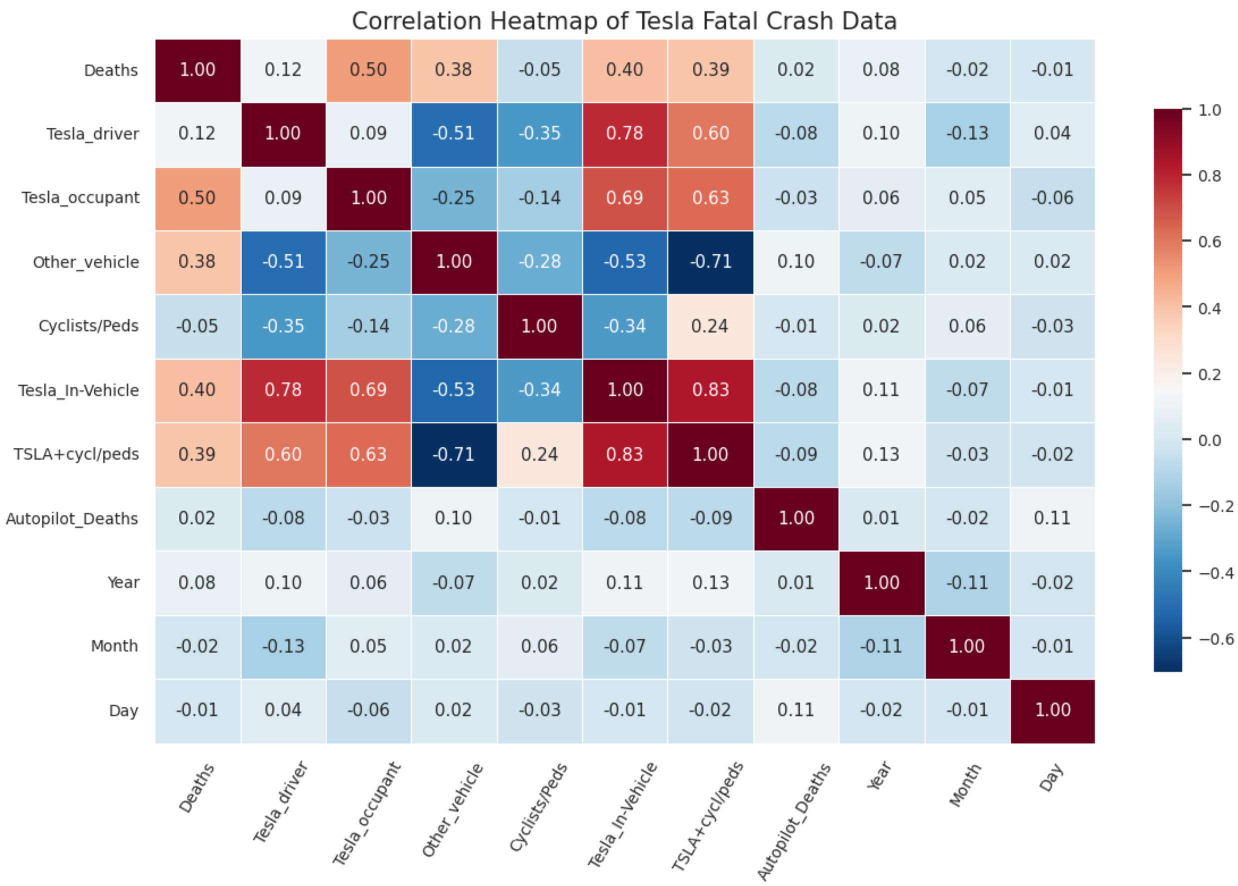
Note. From *Trucks and Buses*, by IEA, Accessed 11 June 2025. CC BY 4.0 (https://www.iea.org/reports/global-ev-outlook-2024/trends-in-electric-cars)

Appendix F

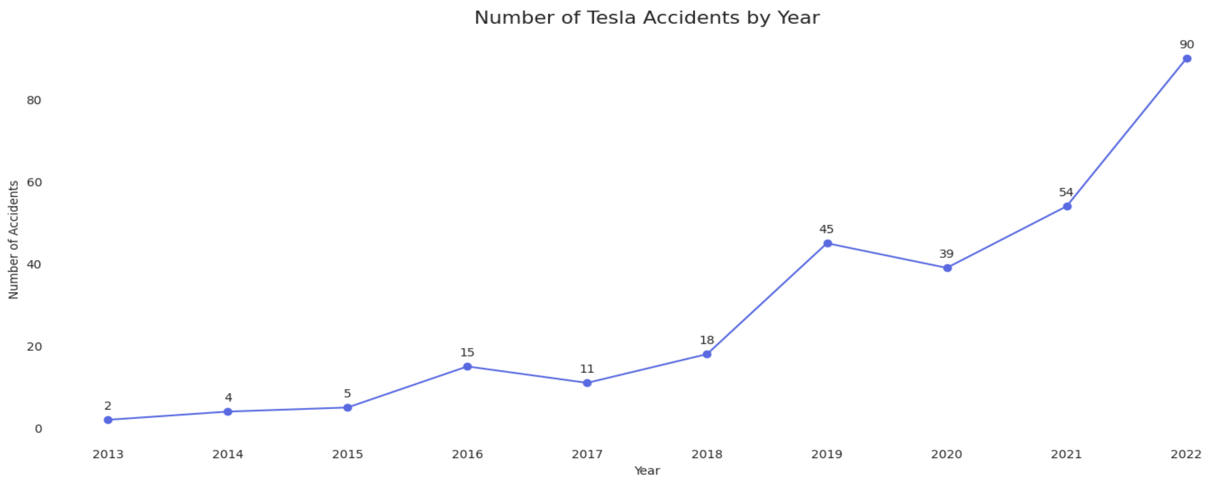


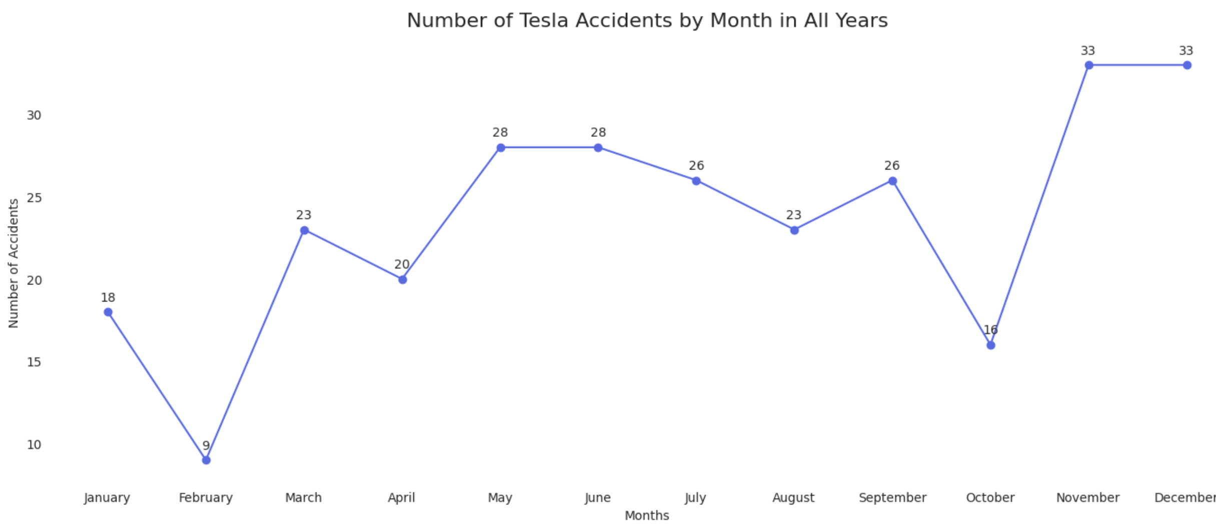
Note. From China's rare earth export curbs hit the auto industry worldwide, by Victoria Waldersee and Christoph Steitz, 2025. (https://www.reuters.com/business/autos-transportation/some-european-auto-supplier-plants-shut-down-after-chinas-rare-earth-curbs-2025-06-04/)

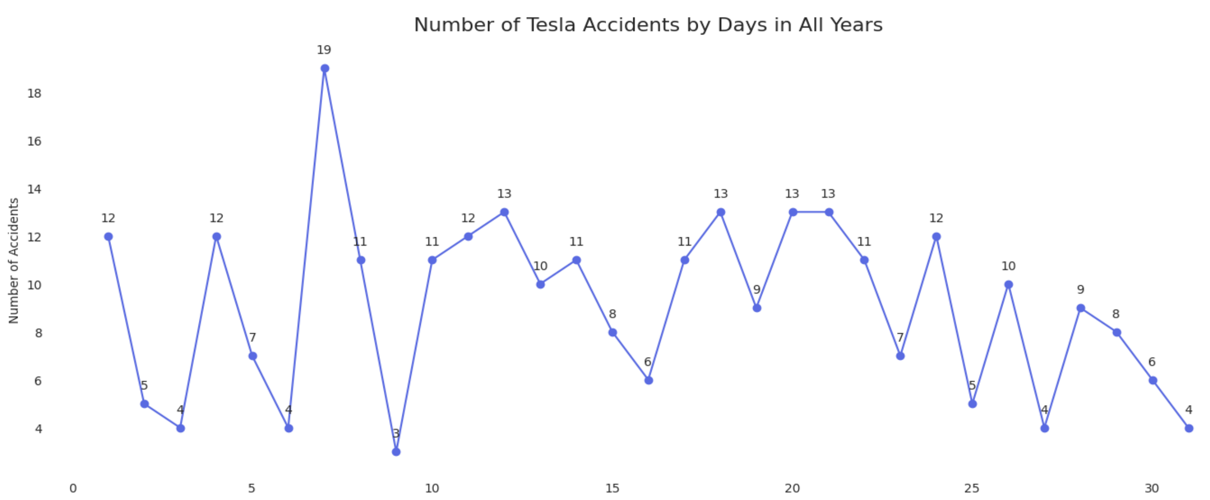
Appendix G


Correlation Heatmap of Tesla Fatal Crash Data
Deaths 1.00 0.12 0.50 0.38 -0.05 0.40 0.39 0.02 0.08 -0.02 -0.01
Tesla_driver 0.12 1.00 0.09 -0.51 -0.35 0.78 0.60 -0.08 0.10 -0.13 0.04
Tesla_occupant 0.50 0.09 1.00 -0.25 -0.14 0.69 0.63 -0.03 0.06 0.05 -0.06
Other_vehicle 0.38 -0.51 -0.25 1.00 -0.28 -0.53 -0.71 0.10 -0.07 0.02 0.02
Cyclists/Peds -0.05 -0.35 -0.14 -0.28 1.00 -0.34 0.24 -0.01 0.02 0.06 -0.03
Tesla_In-Vehicle 0.40 0.78 0.69 -0.53 -0.34 1.00 0.83 -0.08 0.11 -0.07 -0.01
TSLA+cycl/peds 0.39 0.60 0.63 -0.71 0.24 0.83 1.00 -0.09 0.13 -0.03 -0.02
Autopilot_Deaths 0.02 -0.08 -0.03 0.10 -0.01 -0.08 -0.09 1.00 0.01 -0.02 0.11
Year 0.08 0.10 0.06 -0.07 0.02 0.11 0.13 0.01 1.00 -0.11 -0.02
Month -0.02 -0.13 0.05 0.02 0.06 -0.07 -0.03 -0.02 -0.11 1.00 -0.01
Day -0.01 0.04 -0.06 0.02 -0.03 -0.01 -0.02 0.11 -0.02 -0.01 1.00
Deaths Tesla_driver Tesla_occupant Other_vehicle Cyclists/Peds Tesla_In-Vehicle TSLA+cycl/peds Autopilot_Deaths Year Month Day
1.0 0.8 0.6 0.4 0.2 0.0 −0.2 −0.4 −0.6

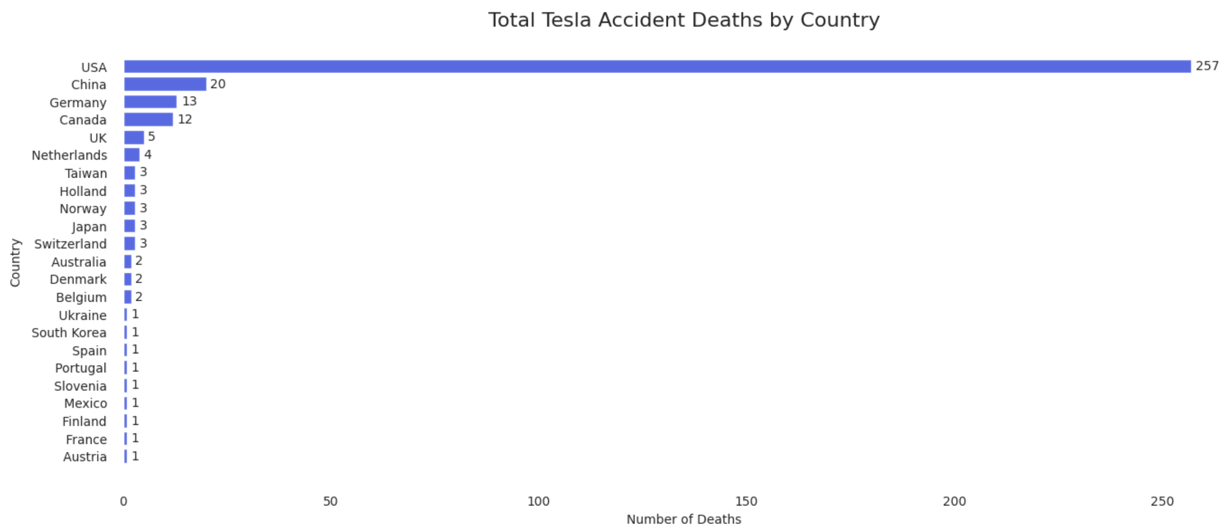
Appendix H


Number of Tesla Accidents by Year
Number of Accidents
Year
0
20
40
60
80
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
2
4
5
15
11
18
45
39
54
90

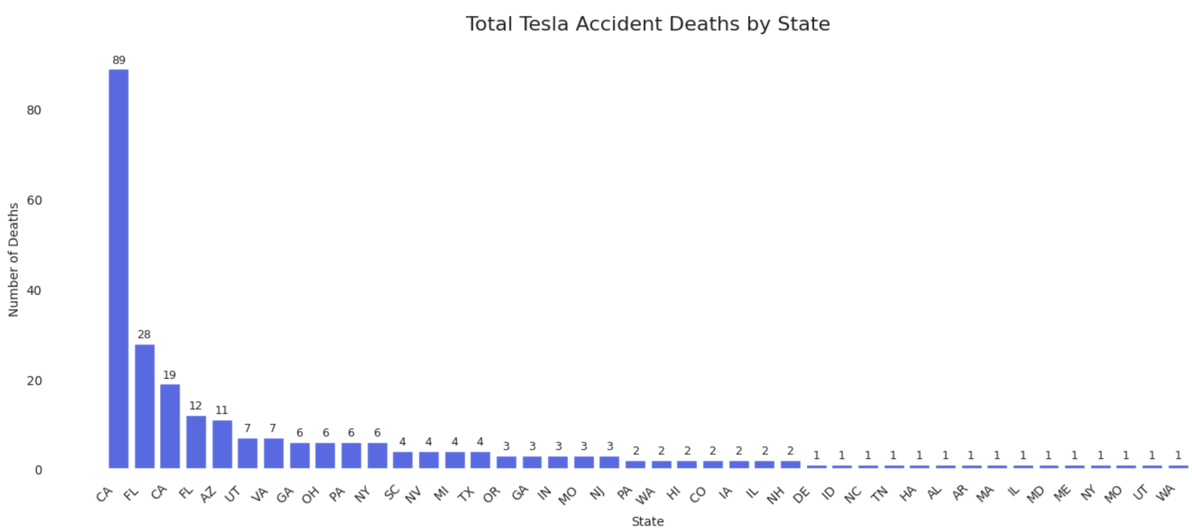

Number of Tesla Accidents by Month in All Years
Number of Accidents
Months
10
15
20
25
30
January
February
March
April
May
June
July
August
September
October
November
December
18
9
23
20
28
28
26
23
26
16
33
33


Number of Tesla Accidents by Days in All Years
Number of Accidents
Days
4
6
8
10
12
14
16
18
0
5
10
15
20
25
30
12
5
4
12
7
4
19
11
3
11
12
13
10
11
8
6
11
13
9
13
13
11
7
12
5
10
4
9
8
6
4

Appendix I

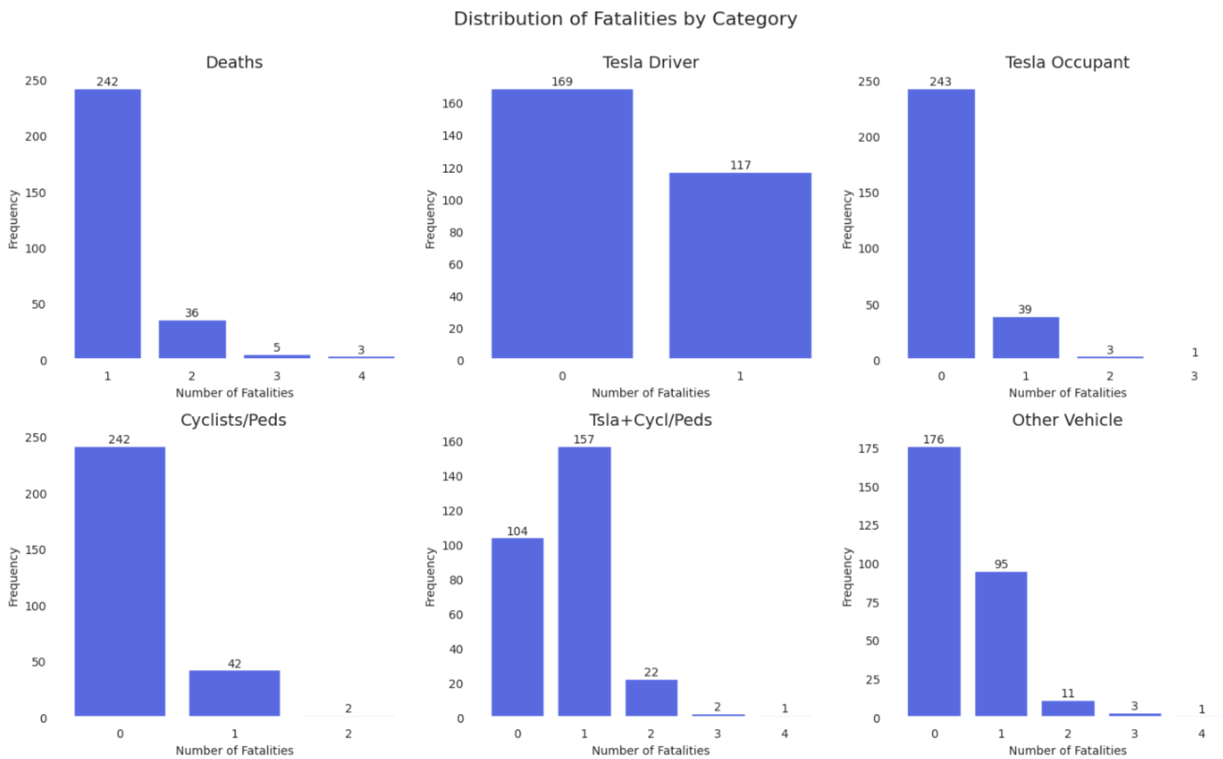


Total Tesla Accident Deaths by Country
Country
USA
China
Germany
Canada
UK
Netherlands
Taiwan
Holland
Norway
Japan
Switzerland
Australia
Denmark
Belgium
Ukraine
South Korea
Spain
Portugal
Slovenia
Mexico
Finland
France
Austria
257
20
13
12
5
4
3
3
3
3
3
2
2
2
1
1
1
1
1
1
1
1
1
0
50
100
150
200
250
Number of Deaths

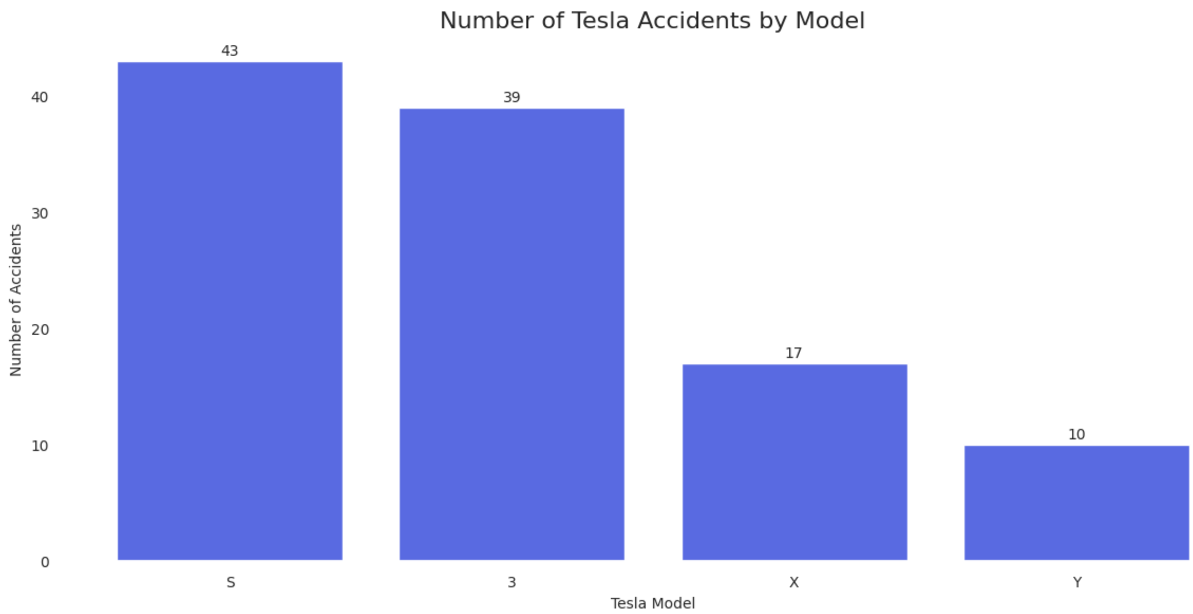


Total Tesla Accident Deaths by State
Number of Deaths
0
20
40
60
80
89
28
19
12
11
7
7
6
6
6
6
4
4
4
4
3
3
3
3
3
2
2
2
2
2
2
2
1
1
1
1
1
1
1
1
1
1
1
1
1
1
1
CA
FL
CA
FL
AZ
UT
VA
GA
OH
PA
NY
SC
NV
MI
TX
OR
GA
IN
MO
NJ
PA
WA
HI
CO
IA
IL
NH
DE
ID
NC
TN
HA
AL
AR
MA
IL
MD
ME
NY
MO
UT
WA
State

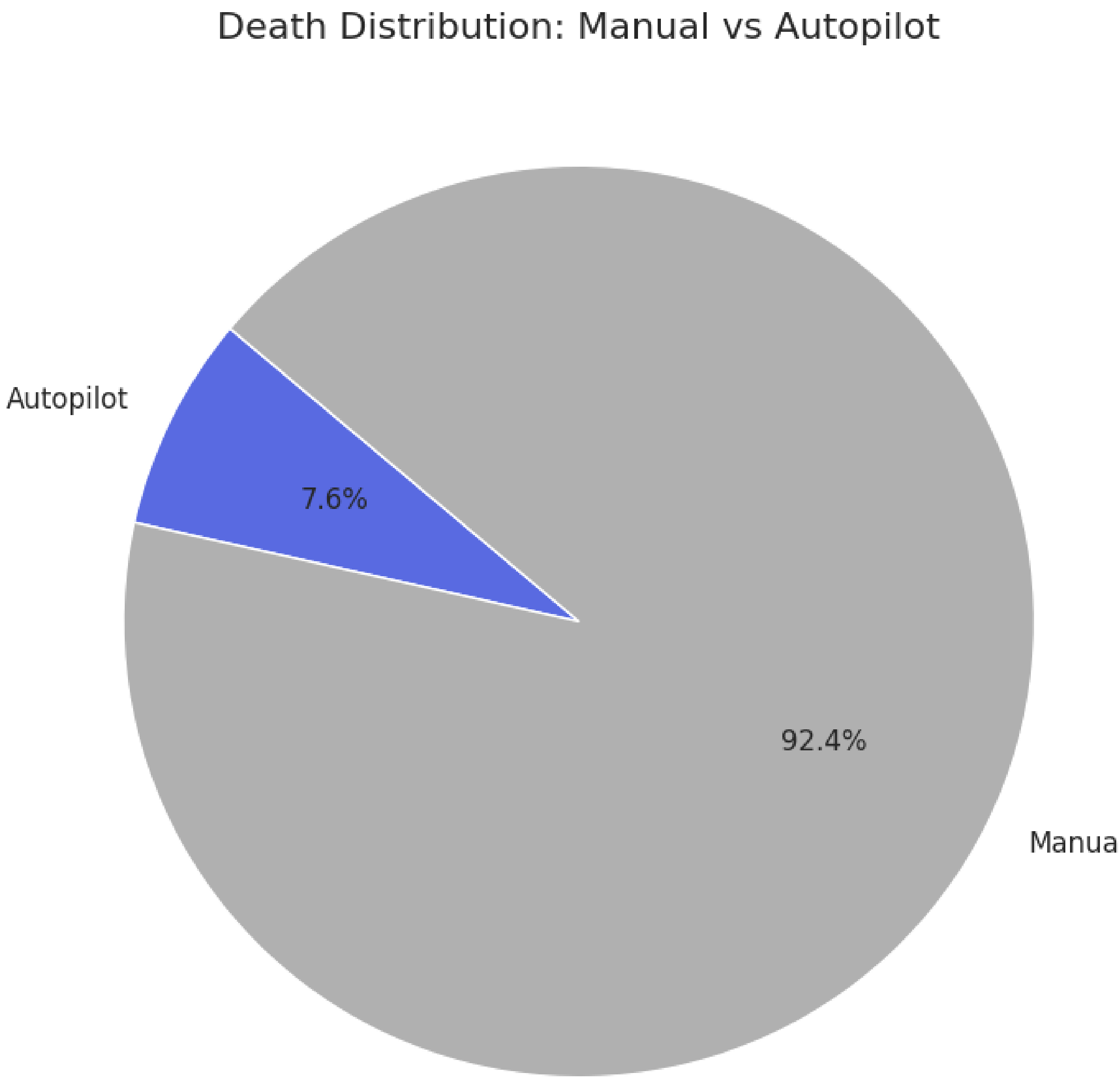
Appendix J


Distribution of Fatalities by Category
Deaths
Tesla Driver
Tesla Occupant
Cyclists/Peds
Tsla+Cycl/Peds
Other Vehicle
Frequency
Number of Fatalities
242
36
5
3
169
117
243
39
3
1
242
42
2
104
157
22
2
1
176
95
11
3
1

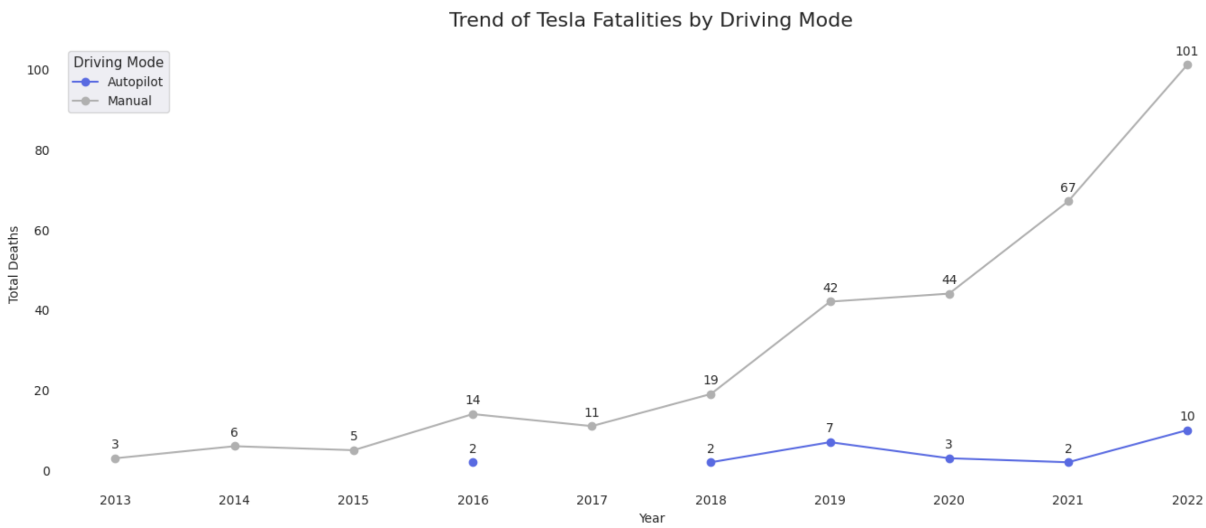
Appendix K


Number of Tesla Accidents by Model
43
39
17
10
Number of Accidents
0
10
20
30
40
S
3
X
Y
Tesla Model

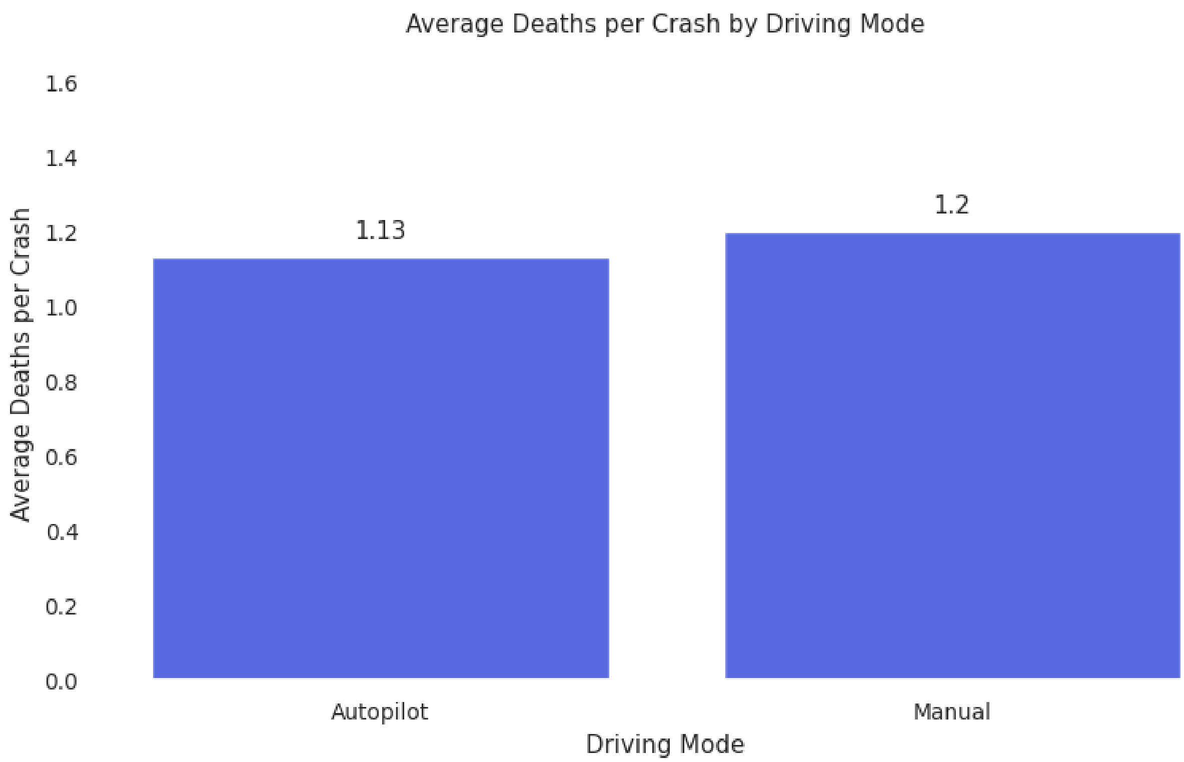
Appendix L


Death Distribution: Manual vs Autopilot
Autopilot
7.6%
92.4%
Manual

Appendix M


Trend of Tesla Fatalities by Driving Mode
Driving Mode
Autopilot
Manual
Total Deaths
Year
0
20
40
60
80
100
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
3
6
5
14
11
19
42
44
67
101
2
2
7
3
2
10

Appendix N

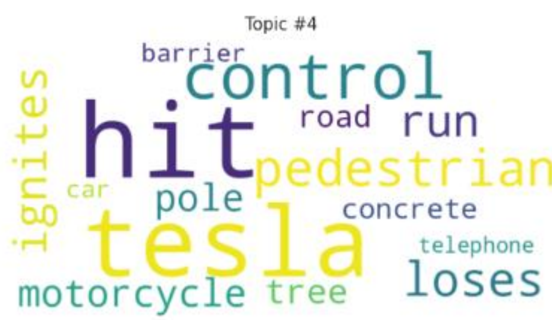

Average Deaths per Crash by Driving Mode
Average Deaths per Crash
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
1.13
1.2
Autopilot
Manual
Driving Mode

Appendix O


Topic #1
crash
tesla
car
driver
killed
red
light
injury
duo
died
later
hospital
run
tree
dy

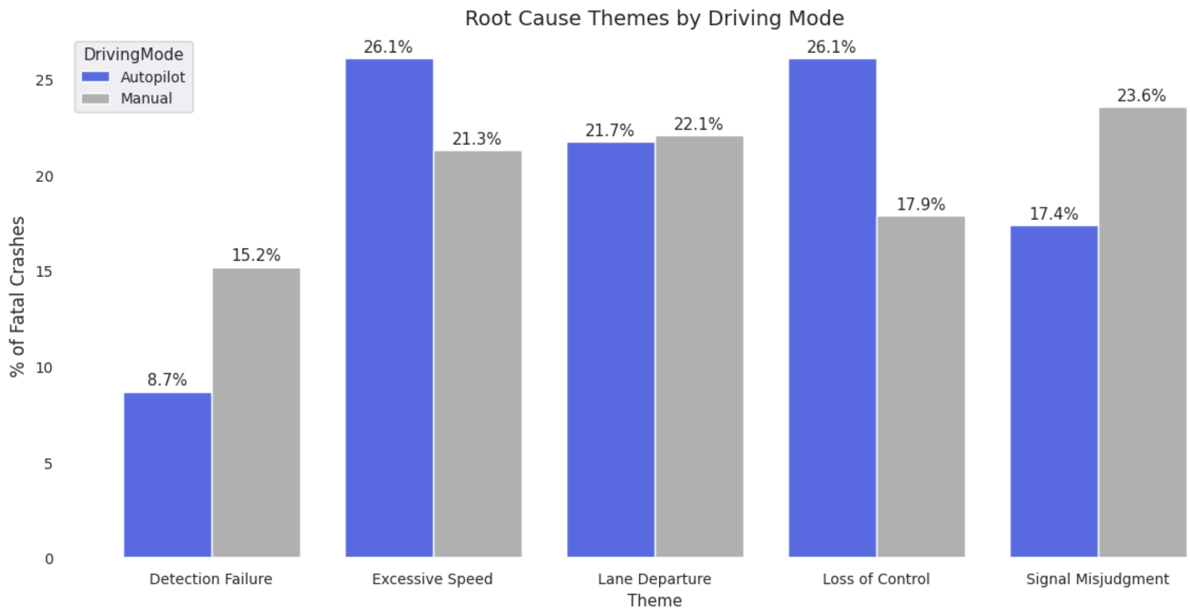

Topic #2
collision
tesla
autopilot
hit
two
wrong
accident
driver
catch
highway
multicar
involving
car
fire
intersection


Topic #3
tesla
kill
drive
road
motorcyclist
sudden
cliff
pedestrian
unintended
go
flame
high
speed
acceleration
wall


Topic #4
hit
tesla
control
barrier
road
run
ignites
pedestrian
car
pole
concrete
telephone
loses
motorcycle
tree


Topic #5
tesla
strike
rear
car
traffic
headon
end
lane
oncoming
ford
burn
stopped
collides
vehicle
veers

Appendix P



Root Cause Themes by Driving Mode
DrivingMode
Autopilot
Manual
% of Fatal Crashes
0
5
10
15
20
25
8.7%
15.2%
26.1%
21.3%
21.7%
22.1%
26.1%
17.9%
17.4%
23.6%
Detection Failure
Excessive Speed
Lane Departure
Loss of Control
Signal Misjudgment
Theme