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What Can We Learn from Fatal Automated Vehicle Crashes? A Closer Look at Crash Narratives in Media

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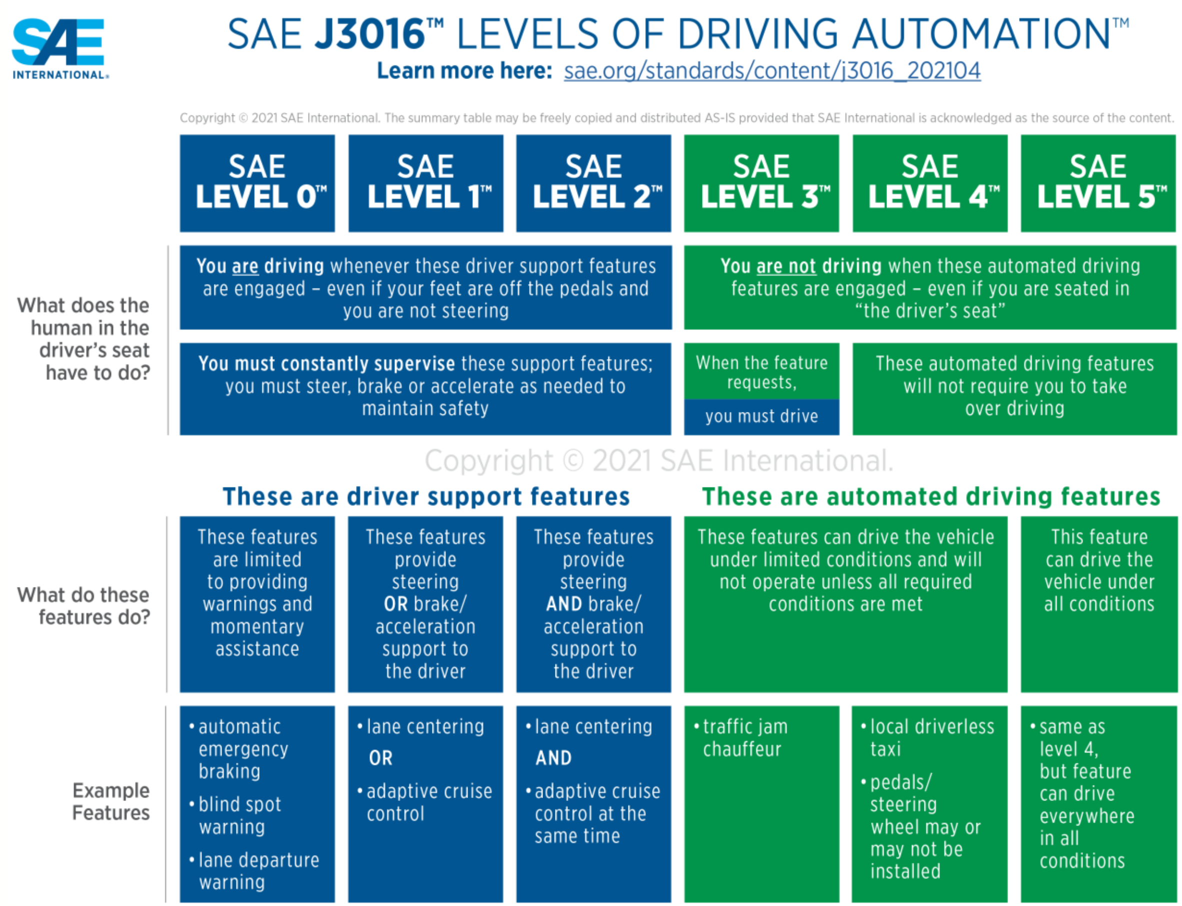
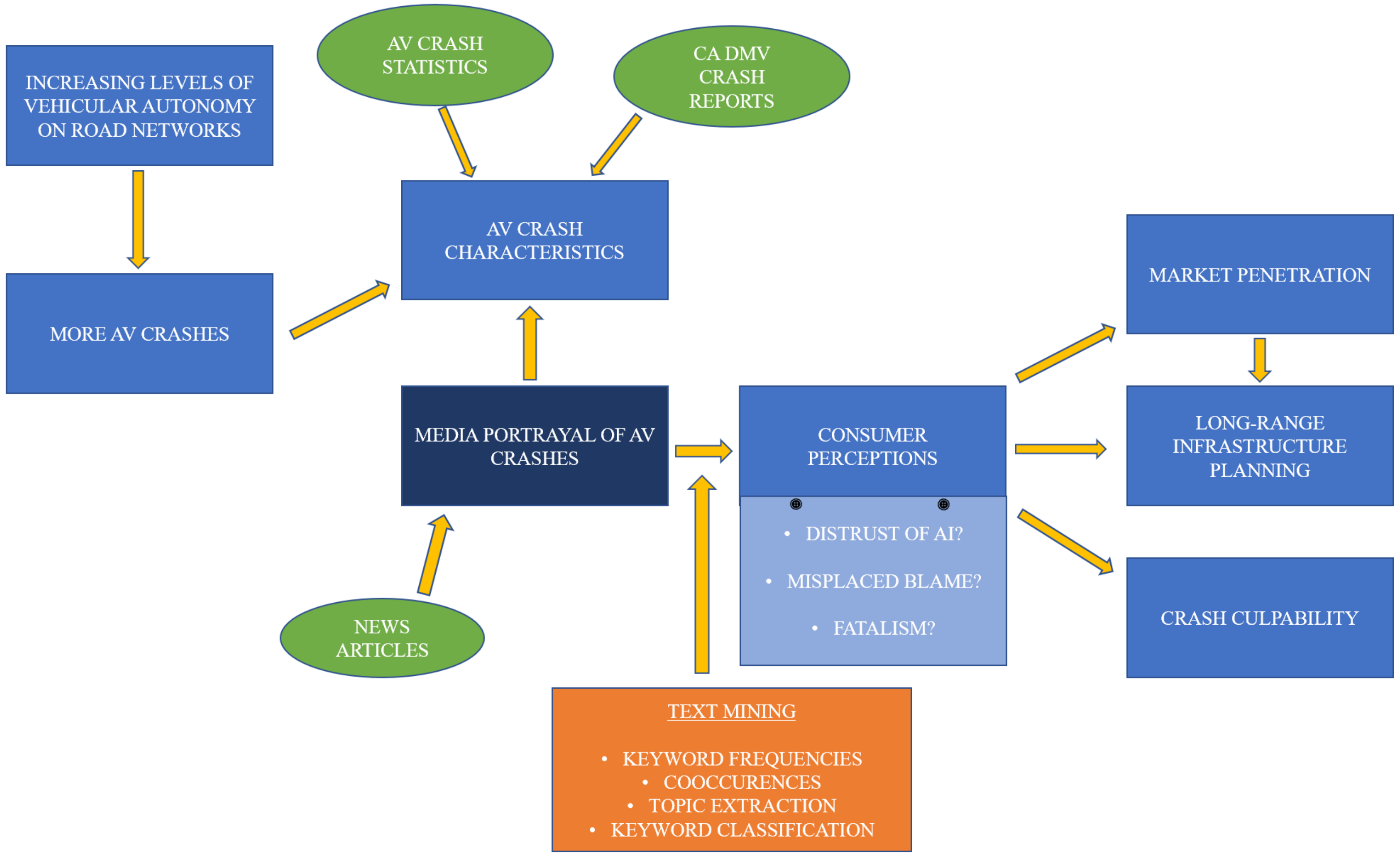
Background

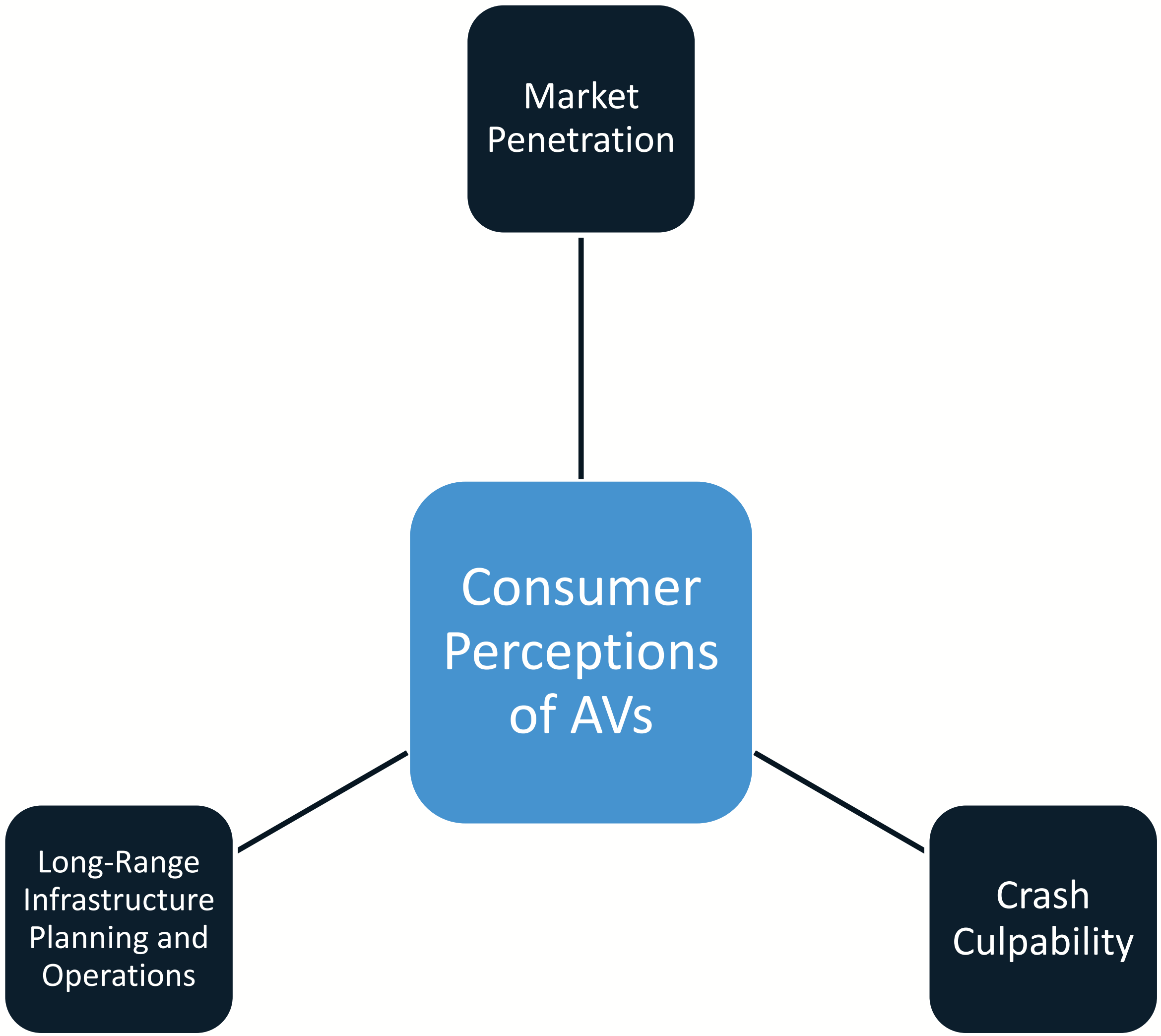
- Vehicles with increasing levels of automation are entering our roadways
- Many manufacturers such as Tesla, GM, Ford, Honda, and Toyota have introduced cars with at least level 2 automation
- Production of level 3 vehicles predicted within next 5 years



Conceptual Framework



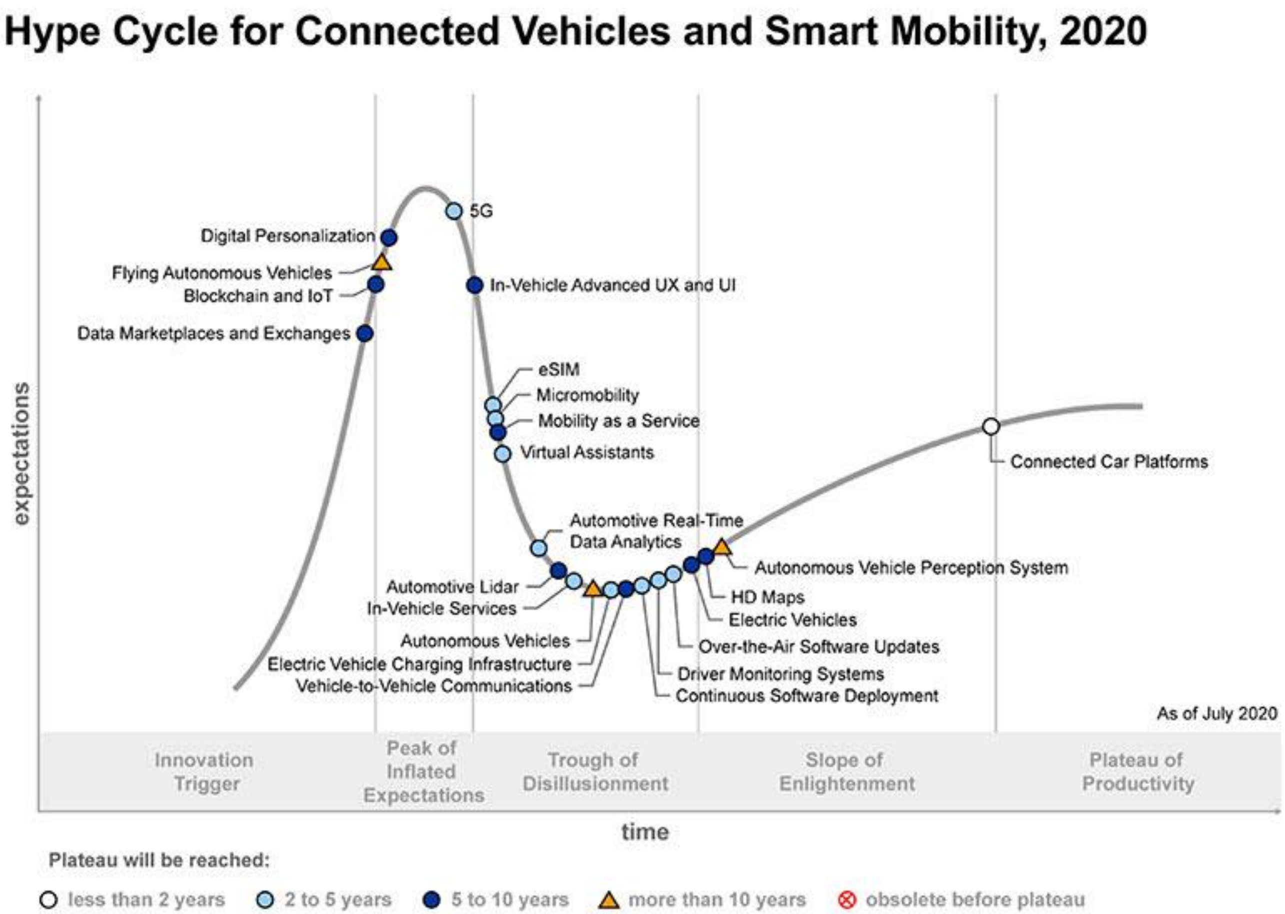
Why Study Media?



Market Penetration

- Reporting of high-profile AV crashes can negatively impact the reputation of AVs
- Language used by journalists impacts public sentiment

Figure 1. Hype Cycle for Connected Vehicles and Smart Mobility, 2020



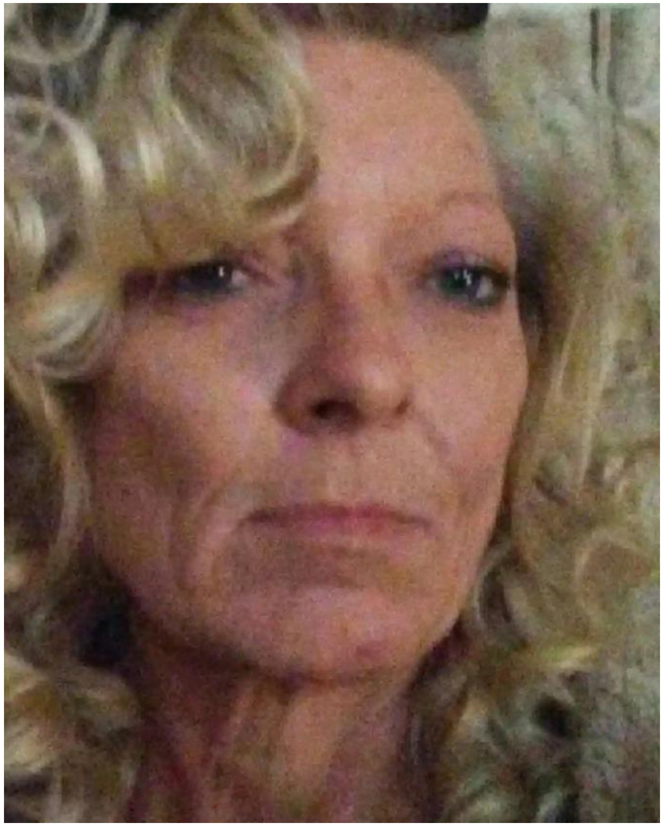
Source: Gartner
ID: 450205

Long-Range Planning and Operations

- Road networks will need to be prepared for the expected emergence of AVs
- Intelligent Transportation System (ITS) Technologies may be deployed
    - 5G towers, road-side units, real-time adaptive traffic signals, V2X communications

Crash Culpability

- It is not always clear who should bear the legal responsibility in the event of an AV crash
- Death of Elaine Herzberg – First recorded case of pedestrian fatality involving self-driving vehicle (Uber)
  - Vehicle was operating autonomously
  - Vehicle driver was charged with negligent homicide; Uber not held criminally responsible
  - Camera footage from vehicle reveals that the pedestrian detection system failed when the pedestrian was clearly visible
- Media narratives can shape whether manufacturers or drivers are blamed in AV crashes



In Memoriam

Elaine Herzberg (August 2, 1968 – March 18, 2018)

Literature Review - Automated Vehicle Crash Studies

- AV fatal crash data is still limited in early stages of deployment
- California DMV AV Testing Program
  – Primary source of AV narrative data in literature (N = 9)

Year	Author	Study approach		Study Quality
		Method	Location and Sample size	
2021	Ashraf, et al.	Decision tree, Association rule data mining (CART model)	CA; N=198	High
2021	Liu et al.	Pre-crash scenario typology	CA; (AV, N=122) (Conventional : N=2084)	High
2021	Sinha et al.	Crash severity models (Bagging/DT)	CA; N=259	
2020	Boggs, Wali, Khattak	Text Mining (WordStat), Bayesian Model	CA; N=113	High
2020	Boggs, Arvin, Khattak	Fixed and Random Parameter Binary logistic regression	CA; N=159,840	High
2020	Alambeigi et al.	Probabilistic topic modeling	CA; N=114	High
2019	Wang et al.	Ordinal logistic regression modeling, Classification and regression tree (CART) modeling	CA; N=113 (CA DMV, N=107; News Reports, N=6)	High
2019	Xu et al.	Bootstrap-based binary logistic regression	CA; N=72	High
2017	Favaro, et al.	Descriptive statistics, Linear regression	CA; N=26	High

Source

CA DMV Manufacturer-Reported Traffic Collision Reports

→

Methods

Text Mining

Frequentist Methods

Machine Learning Methods

Bayesian Modeling

→

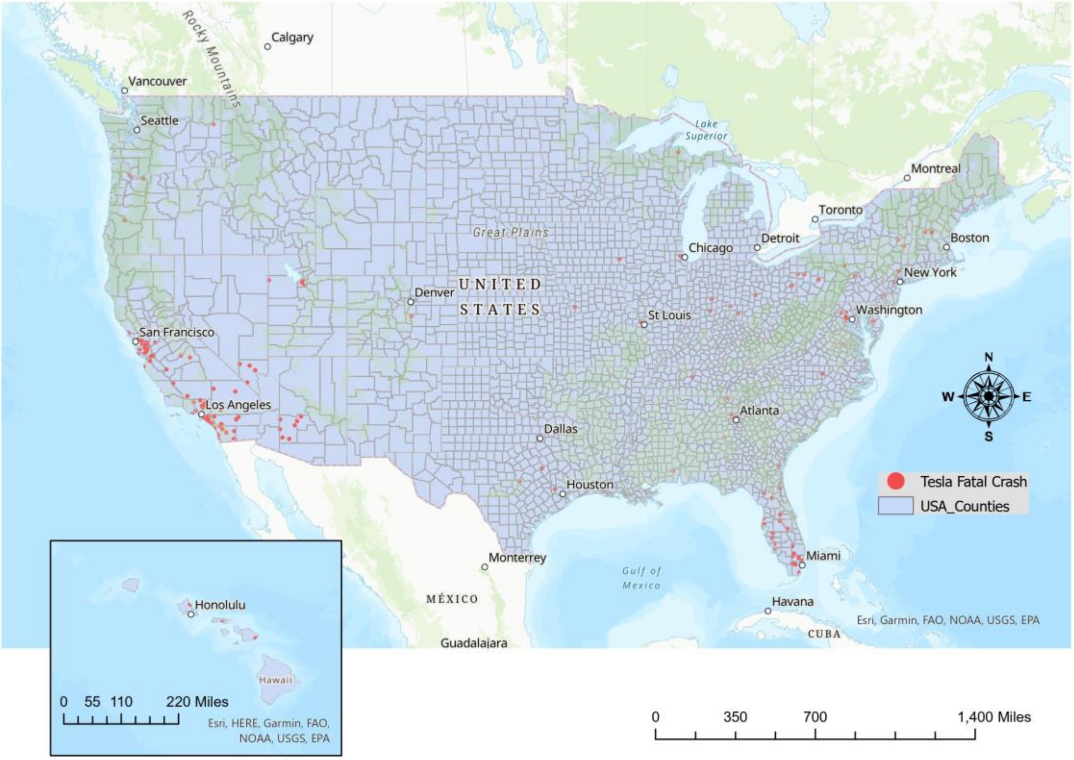
Findings

- Rear-end most frequent type of crash due to perception discrepancy with conventional vehicles

- Most AV crashes occur on highway segments

Study Area

- News articles from local stations related to fatal Tesla crashes
- This study: 202 fatal crashes
  - USA (155)
  - China (9)
  - France (2)
  - Germany (9)
  - Canada (5)
  - UK (3)
  - Norway (4)
  - Portugal (1)
  - Finland (1)
  - Belgium (1)
  - Taiwan (2)
  - Slovenia (1)
  - Austria (1)
  - Spain (1)
  - Holland (1)
  - Denmark (1)
  - Japan (2)
  - Switzerland (3)

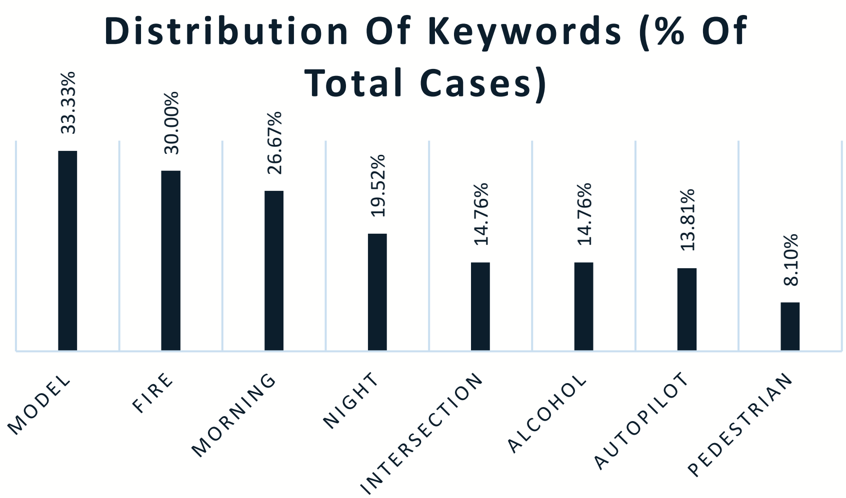


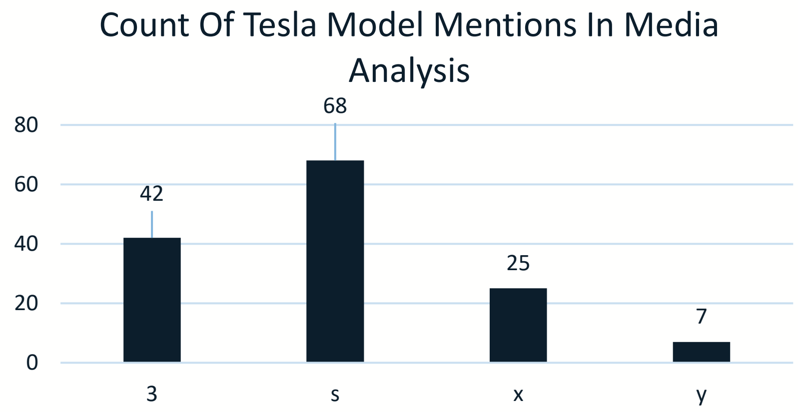
CASE DISTRIBUTION ACROSS USA

Data Extraction

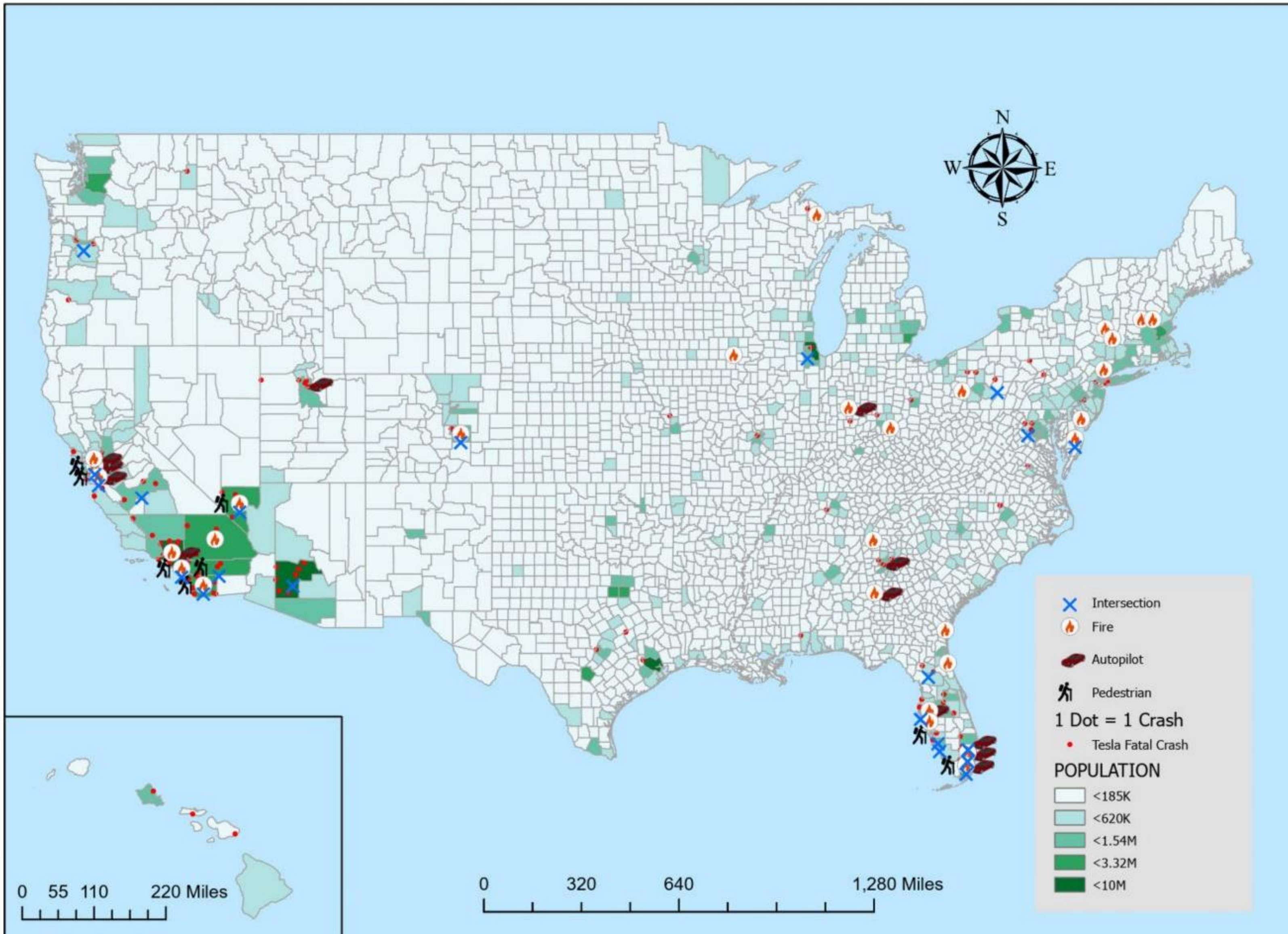
Narratives from local news stations' websites

Results - Frequencies





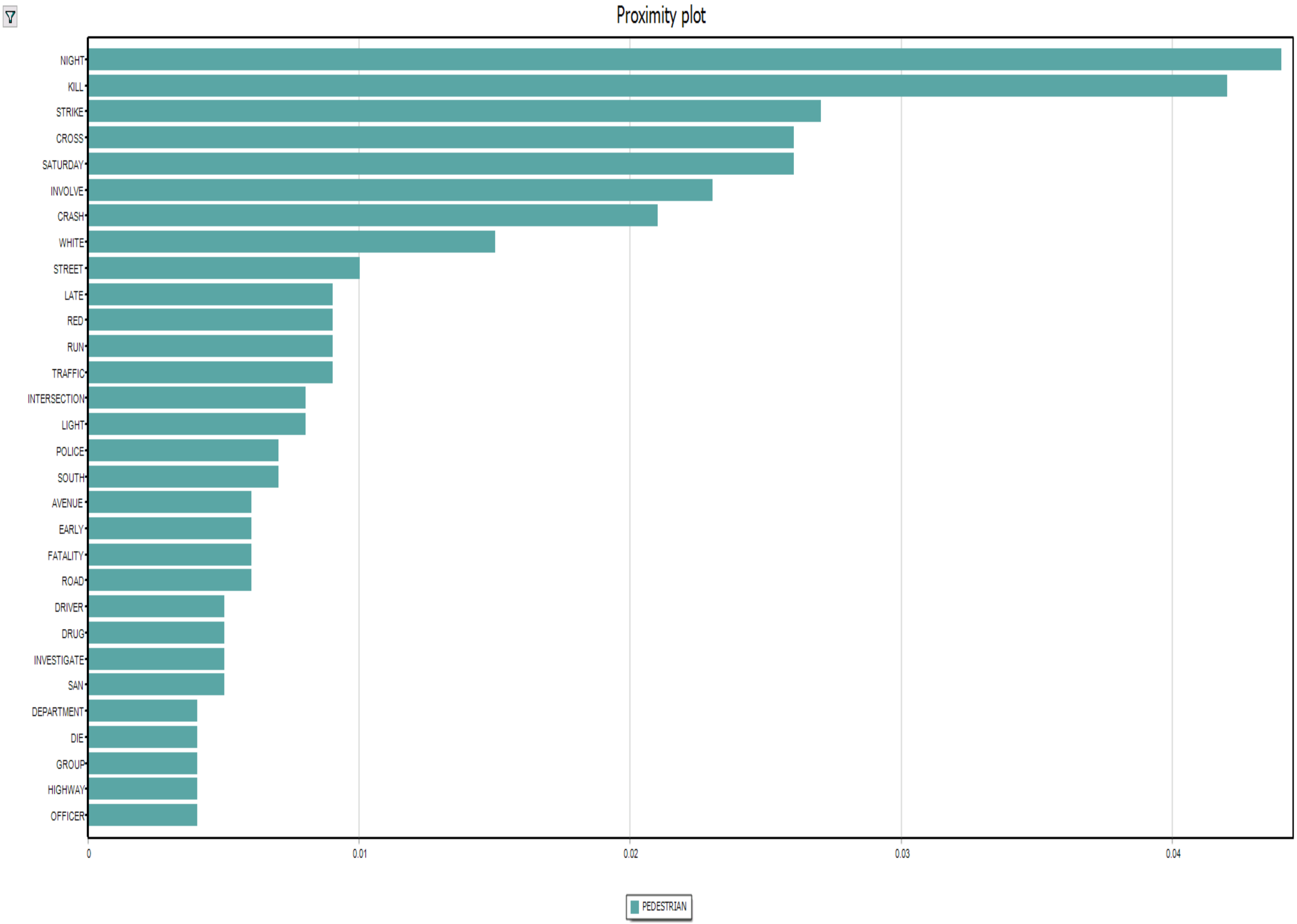
Keywords in Articles Discussing Fatal Tesla Crashes Along with 2020 Population Data



Note: No cases were documented in Alaska or any other U.S. territories not shown on this map.

Results – Topic Extraction

TOPIC	KEYWORDS	COHERENCE (NPMI)	FREQ	CASES	% CASES
VEHICLE BEHAVIOR	LANE; TRAVEL; NORTH; DRIVE; LOSE; CONTROL; SIDE; STRIKE; REAR; TURN; COLLIDE; LEAVE; SOUTHBOUND; FRONT; LOSE CONTROL; SOUTHBOUND LANE; TRAVEL LANE; TRAVEL NORTH; GUIDE RAIL; FINAL REST;	0.254	439	150	71.43%
CRASH INVESTIGATION AND CONTRIBUTING FACTORS	PATROL; HIGHWAY; EARLY; MORNING; SATURDAY; CRASH; KILL; CALIFORNIA; CROSS; SUNDAY; COUNTY; HIGHWAY PATROL; CALIFORNIA HIGHWAY PATROL; FLORIDA HIGHWAY PATROL; SUNDAY MORNING; EARLY SATURDAY; EARLY SUNDAY MORNING; ATTEMPT TO CROSS UNIVERSITY BOULEVARD; CAR EARLY THAT MORNING; FIERY CRASH; MAN DIE SATURDAY; ORANGE COUNTY; STATE PATROL; MAN DIE; KILL EARLY;	0.241	534	175	83.33%
CASUALTIES AND INJURIES	PRONOUNCE; DEAD; HOSPITAL; INJURY; SCENE; PASSENGER; SUFFER; DIE; PRONOUNCE DEAD; PRONOUNCE DEAD AT THE SCENE; CRASH REPORT; INJURE IN THE CRASH; REMAIN ON SCENE; DECLARE DEAD AT THE SCENE; SCENE OF THE ACCIDENT;	0.226	370	163	77.62%



Proximity plot
NIGHT
KILL
STRIKE
CROSS
SATURDAY
INVOLVE
CRASH
WHITE
STREET
LATE
RED
RUN
TRAFFIC
INTERSECTION
LIGHT
POLICE
SOUTH
AVENUE
EARLY
FATALITY
ROAD
DRIVER
DRUG
INVESTIGATE
SAN
DEPARTMENT
DIE
GROUP
HIGHWAY
OFFICER
0
0.01
0.02
0.03
0.04
PEDESTRIAN

Results – Single vs Multi-Vehicle Classification

$$x^2 = \sum \frac{(O_i - E_i)^2}{E_i}$$

$$x^2 = chi\ squared$$
$$O_i = observed\ value$$
$$E_i = expected\ value$$

Name	Global Chi²	P	Max Chi²	P	Biserial	Predict
COLLIDE	26.30	0.00	26.30	0.00	7.2214	multiple
TREE	24.17	0.00	24.17	0.00	8.7388	single
DRIVER	13.49	0.00	13.49	0.00	4.6031	multiple
LANE	13.39	0.00	13.39	0.00	4.8759	multiple
HONDA	12.43	0.00	12.43	0.00	6.4916	multiple
REAR	10.50	0.00	10.50	0.00	5.0434	multiple
FREEWAY	10.05	0.00	10.05	0.00	5.1910	multiple
INJURY	9.84	0.00	9.84	0.00	4.0823	multiple
MOTORCYCLE	9.80	0.00	9.80	0.00	5.7637	multiple
ONCOMING	9.80	0.00	9.80	0.00	5.7637	multiple
TRUCK	8.77	0.00	8.77	0.00	5.1054	multiple
HEAD	8.58	0.00	8.58	0.00	4.1045	multiple
CAR	8.13	0.00	8.13	0.00	3.6950	single
CATCH	7.93	0.00	7.93	0.00	5.0072	single
FLA	7.53	0.01	7.53	0.01	5.3847	single
TRAFFIC	7.13	0.01	7.13	0.01	3.6058	multiple
SHERIFF	7.08	0.01	7.08	0.01	4.9946	single
TURN	6.83	0.01	6.83	0.01	4.2792	multiple
EARLY	6.59	0.01	6.59	0.01	3.9285	single
FIRE	6.25	0.01	6.25	0.01	3.7379	single
FIREFIGHTER	6.12	0.01	6.12	0.01	4.8551	single
REST	6.10	0.01	6.10	0.01	4.7370	multiple
MOTORCYCLIST	6.10	0.01	6.10	0.01	4.7370	multiple
MONDAY	6.00	0.01	6.00	0.01	3.9681	single
ELECTRIC	5.79	0.02	5.79	0.02	4.4314	single
COLLISION	5.66	0.02	5.66	0.02	3.2231	multiple
SET	5.37	0.02	5.37	0.02	4.5470	multiple
DAILY	5.20	0.02	5.20	0.02	4.7179	single
RESULT	5.13	0.02	5.13	0.02	3.5265	multiple
RED	5.10	0.02	5.10	0.02	4.2406	multiple

Single

Multiple

Findings – Media study

- Of pre-selected keywords, " "fire" appears in 30% of cases
  - Motivated us to examine further
- Three topics: vehicle behavior, crash investigation and contributing factors, and casualties and injuries
- "Pedestrian" and "night" exhibit frequent co-occurrence
- Single vs multiple vehicle classification reveals certain keywords are more associated with single vehicle crashes, such as "tree," whereas other keywords are associated with multiple-vehicle crashes, such as "driver"
- Limitations
  - Small sample size
  - Automated translations may not be truly representative of original language used
  - Asymmetric geospatial distribution - predominantly U.S. cases

Further Study

- Tesla fatal death database assembled (n = 71)
- Fire reported in this dataset (26%) in a higher percentage of crashes than in conventional vehicle crashes (3.3%) (FARS dataset)
- 13% of vehicles in single vehicle crashes caught fire
- Sommer's D Probability Test
  - Autopilot engagement not shown to correlate with driver survivability

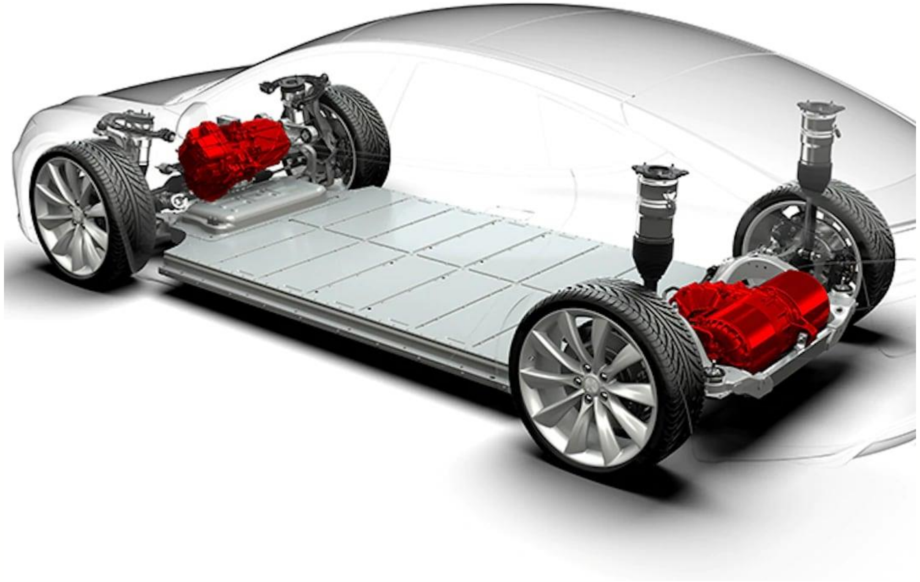
$$pA = Pr\,(Y = 1 | X = 1)$$

$$pB = Pr\,(Y = 1 | X = 0)$$

- Two pairs (Xi, Yi) and (Xj, Yj) are said to be concordant if ranks of both the elements agree
- Two pairs (Xi, Yi) and (Xj, Yj) are said to be discordant if the ranks of both elements do not agree

It Starts in the Battery…

- A Tesla battery pack is composed of 2,976 lithium-ion cells
    - Anode, cathode, liquid electrolyte
    - Cased in titanium or other strong material
- When one or more lithium-ion cells short-circuit, the battery heats up, and anodes and cathodes can become exposed to the highly flammable liquid electrolyte
- Stored energy in battery → 5,000-degree Fahrenheit fires



Firefighting EVs

Crane lifting EV into water (discouraged by manufacturers)

Battery Extinguishing System Technology – Piercing nozzle penetrates battery from a safe distance

<u>Recommendations</u>

- Evaluate and improve fire safety mechanisms in Tesla (and other electric) vehicles
  - Solid-state batteries
- Improve firefighter/EMS response to electric battery fires
  - Training
  - Update standards

Closing

- What we have learned from the narratives:
  - “Fire” is used in 30% of articles
  - “Pedestrian” and “Night” exhibit frequent cooccurrence
- Heavy reporting of these crash details can negatively impact public perception of Tesla vehicle safety
- Next steps: Perform sentiment analysis by using text-mining tools and developing a domain-specific dictionary

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