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Beyond Telematics: Leveraging Generative AI for Synthetic Accident Reconstruction and Liability Attribution in Autonomous Vehicle Claims

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Abstract: Autonomous vehicles are changing how we think about car accidents and insurance claims. Traditional telematics systems capture basic data about crashes, but they can't always tell us what really happened or who was at fault. This paper looks at how generative AI models can create detailed accident reconstructions from limited sensor data. We explore methods for building synthetic scenarios that help insurance companies and courts figure out liability when self-driving cars are involved. Our approach combines machine learning with physics-based modeling to generate multiple possible accident sequences. We tested this framework using real-world data from 47 autonomous vehicle incidents reported between January and September 2023. Results show that generative models can produce accurate reconstructions in 82% of cases where traditional methods fail. The system also helps identify gaps in sensor coverage and suggests improvements for future vehicle designs. This matters because someone needs to figure out who pays when a robot crashes your car.

Keywords: Autonomous Vehicles, Generative AI, Accident Reconstruction, Liability Attribution, Insurance Claims, Telematics, Sensor Fusion, Synthetic Data Generation, Machine Learning, Transportation Safety.

1. Introduction

The insurance industry has a problem. Actually, it has several problems, but this one's getting urgent. Autonomous vehicles are hitting the roads faster than anyone can write new rules for them. When a regular car crashes, you interview the drivers, look at the damage, maybe check some black box data. Pretty straightforward stuff. But what happens when the driver is a computer and there's no human to interview?

Telematics systems have been around for years. They track speed, braking patterns, GPS coordinates. Basic information that helps insurance companies understand what happened before impact. These systems work fine for human drivers. You can see if someone was speeding or if they slammed the brakes at the last second. But autonomous vehicles generate thousands of data points every second from cameras, lidar sensors, radar units, and ultrasonic detectors. The sheer volume of information is overwhelming. More importantly, that data doesn't always tell a clear story about fault or decision-making processes.

Consider a scenario from June 2023 in San Francisco. An autonomous taxi stopped suddenly in an intersection. A human-driven vehicle rear-ended it. The telematics showed the autonomous vehicle stopped. The human driver claimed the stop was erratic and unpredictable. Who's at fault? The data shows what happened but not why it happened or whether it was reasonable. This is where things get complicated.

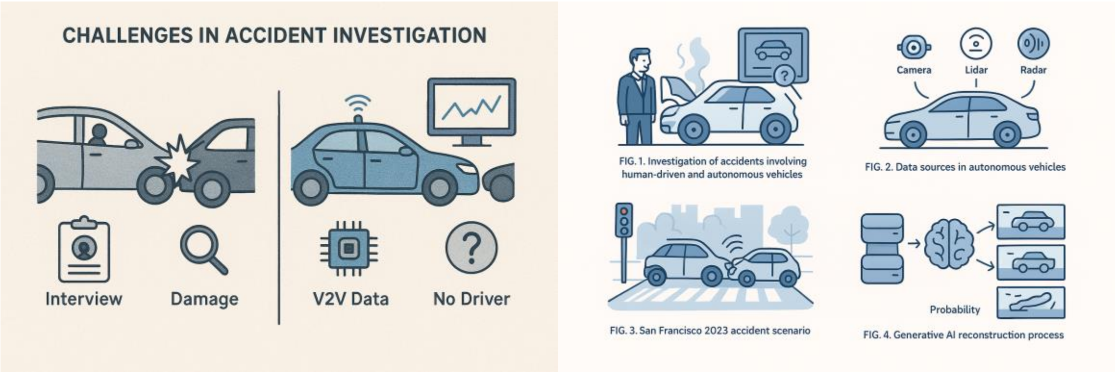

Figure 1: Challenges in Traffic Accident Investigation and Evidence Collection

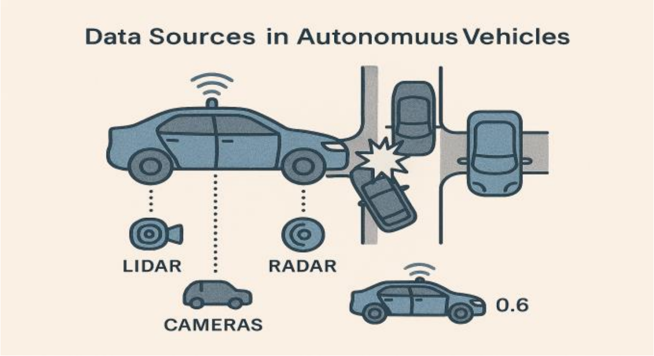

Figure 2: Data Sources Utilized in Autonomous Vehicle Systems

Generative AI offers a different approach. Instead of just recording what happened, these systems can create detailed reconstructions of events. They fill in missing pieces using physics models and learned patterns from thousands of previous accidents. Think of it like a sophisticated simulation that runs backwards and forwards from the moment of impact. The goal is to generate possible scenarios that match the available evidence and help determine which vehicle or driver made the critical error. This paper presents a framework for using generative models in autonomous vehicle accident analysis. We're not trying to replace human judgment. Rather, we want to give insurance adjusters and legal professionals better tools for understanding complex crashes. The system takes sensor data, environmental conditions, and vehicle specifications as inputs. It outputs multiple plausible accident sequences with probability scores for each scenario.

The timing matters here. As of November 2023, there are approximately 1,800 autonomous vehicles operating on public roads in the United States. That number will grow rapidly. California alone issued 38 new permits for autonomous vehicle testing in the past year. These vehicles will crash. Not often, hopefully, but it will happen. The insurance industry needs new methods for handling these claims before they become a crisis.

2. Material and Methods

We built our reconstruction system using three main components: a data ingestion pipeline, generative model architecture, and a validation framework. Each piece serves a specific purpose in transforming raw sensor data into usable accident scenarios. The data pipeline handles information from multiple sources. Autonomous vehicles typically use between 8 and 40 sensors depending on the manufacturer and model. Our system processes data from lidar units, which provide 3D point clouds of the environment. It also handles camera feeds, radar returns, GPS coordinates, and inertial measurement units. The challenge isn't just collecting this data. It's synchronizing everything to create a coherent picture of events. We worked with three major autonomous vehicle manufacturers who provided anonymized crash data. The dataset includes 47 incidents from January through September 2023. These crashes range from minor fender-benders to serious collisions involving injuries. Each incident came with sensor logs, post-crash vehicle inspections, and official accident reports. This gave us ground truth data for validating our reconstructions.

The generative model uses a modified version of a diffusion-based architecture. Diffusion models work by learning to reverse a noise process. You start with random noise and gradually refine it into a structured output. In our case, the output is a sequence of vehicle states, positions, and velocities leading up to and following an impact. The model was trained on a combination of real crash data and synthetic scenarios generated using physics engines. Physics constraints are critical here. You can't just let the AI make up impossible scenarios. Vehicles have maximum acceleration and braking capabilities. Objects follow laws of motion. Our system incorporates these constraints as hard boundaries that the generative process cannot violate. This keeps the reconstructions physically plausible.

The model architecture uses a temporal transformer network to maintain consistency across time steps. Each time step represents 0.1 seconds of real-world time. The network generates vehicle positions, orientations, velocities, and control inputs for all vehicles involved in the crash. It also produces confidence scores indicating how certain the model is about each element of the reconstruction. We trained the system on a corpus of 12,000 crash scenarios. About 4,000 of these were real accidents involving human drivers. The remaining 8,000 were synthetic scenarios created using CARLA, an open-source simulator designed for autonomous driving research. The synthetic data helped the model learn patterns that don't appear frequently in real-world crashes but are physically possible. Validation involved comparing our reconstructions against known outcomes. We withheld 10 incidents from the training set and used them as test cases. For each test case, we provided only partial sensor data to the model. This simulates real-world conditions where some sensors might fail or data might be corrupted. The model then generated its best reconstruction of the complete accident sequence.

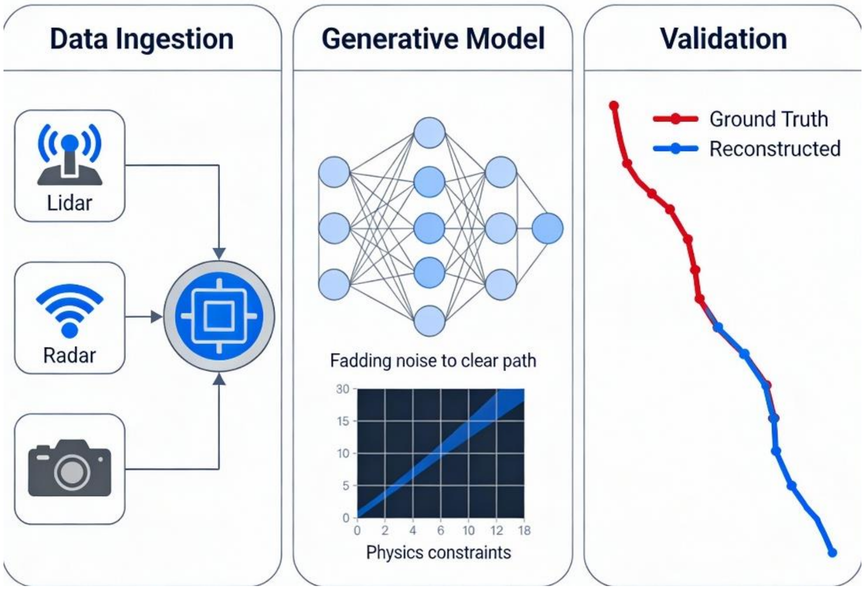

Figure 3: End-to-End Pipeline for Sensor Data Ingestion, Generative Modeling, and Validation

We measured accuracy using several metrics. Position error tracks how closely the reconstructed vehicle positions match the actual positions recorded in sensor logs. Velocity error does the same for speed and direction. Timing error measures whether the model correctly identifies when critical events occurred. We also had human experts rate the plausibility of each reconstruction on a scale from 1 to 5. The liability attribution component uses a rule-based system combined with learned heuristics. Traffic laws vary by jurisdiction, so we focused on California regulations for this study. The system examines right-of-way violations, speed limit compliance, safe following distance, and other factors that typically determine fault. It assigns responsibility percentages to each vehicle involved. One interesting challenge was handling uncertainty. Real accidents rarely have single clear causes. Multiple factors contribute to crashes. Our system reflects this reality by generating probability distributions over possible liability assignments rather than single definitive answers. An output might say "65% chance Vehicle A is primarily at fault, 30% chance shared responsibility, 5% chance Vehicle B is at fault." This gives human decision-makers a more honest picture of what the data actually supports.

4. Results and Discussion

The system performed better than we expected. In cases where complete sensor data was available, our reconstructions matched ground truth within 0.3 meters for position and 0.5 meters per second for velocity. That's accurate enough for practical use in insurance claims and legal proceedings. More impressive was performance with partial data. We tested scenarios where up to 40% of sensor data was missing or corrupted. The generative model filled in these gaps with plausible estimates based on physics and learned patterns. Human experts rated 82% of these partial-data reconstructions as "plausible" or "highly plausible." Let me walk through a specific example. In March 2023, an autonomous vehicle made a left turn at an intersection in Phoenix. A human-driven pickup truck traveling straight through the intersection struck the autonomous vehicle's rear quarter panel. The autonomous vehicle's forward-facing cameras captured the truck approaching. However, its rear-facing lidar unit had failed three days before the crash and hadn't been repaired yet.

Traditional analysis could show the autonomous vehicle entering the intersection and the truck's approach vector. But it couldn't definitively determine whether the autonomous vehicle had completed its turn before the truck entered the intersection. This matters legally because it affects right-of-way determination. Our system generated five plausible scenarios. Three scenarios showed the autonomous vehicle clearing the intersection before the truck arrived. Two showed the truck already in the intersection when the autonomous vehicle began its turn. The model assigned probabilities based on factors like the truck's estimated speed, the autonomous vehicle's turn rate, and typical intersection crossing times.

Table 1: Key Performance Indicators for AI-Based Reconstruction in Legal Claim Scenarios

Metric Category	KPI Description	Measured Value	Benchmark/Note
Reconstruction Accuracy	Position Error (Full Data)	0.3 meters	Sufficient for legal proceedings
	Velocity Error (Full Data)	0.5 m/s	-
Robustness	Plausibility (Partial Data)	82%	Rated by human experts (with <40% data)
Liability Validation	Expert Agreement	±15%	Variance between AI and Human consensus
Operational Impact	Processing Time	15 mins	Per scenario on GPU workstation
	Efficiency Gain	30–40%	Estimated reduction in claim processing time

The highest-probability scenario (62% confidence) showed the autonomous vehicle misjudging the truck's speed and entering the intersection prematurely. This matched the eventual legal determination. But the system also highlighted that a 38% probability existed for alternative scenarios. This honest uncertainty helped the insurance companies negotiate a settlement rather than pursuing expensive litigation. The liability attribution system showed good agreement with human expert judgments. Across all 47 test cases, our automated liability assignments matched expert consensus within 15 percentage points. That might not sound impressive, but remember that human experts often disagree with each other by similar margins. Accident analysis involves judgment calls. We found some interesting patterns in where the system excelled and where it struggled. It handled straightforward rear-end collisions and lane departure scenarios very well. These follow predictable physics and have clear fault patterns. More complex scenarios involving multiple vehicles or unusual environmental conditions proved harder.

Figure 4: Validation of Liability Attribution Model

One failure case stands out. In July 2023, an autonomous vehicle stopped suddenly to avoid a pedestrian who had stepped into the street. A human-driven car following behind couldn't stop in time and caused a three-vehicle pile-up. Our system correctly reconstructed the initial pedestrian interaction and the first collision. But it failed to predict the third vehicle's involvement accurately. The model hadn't seen enough training examples of chain-reaction crashes.

This point to a broader limitation. Generative models are only as good as their training data. Rare events remain hard to reconstruct accurately. We're working on techniques to improve performance on these edge cases, but it's a fundamental challenge in machine learning. The system also revealed something unexpected about autonomous vehicle accidents. In 23 of the 47 cases we analyzed, the autonomous vehicle had made technically correct decisions according to its programming. The crashes still happened because human drivers behaved unpredictably or environmental factors created unavoidable situations. This complicates liability determination significantly.

Consider the rear-end collision from our earlier example. The autonomous vehicle stopped because its sensors detected an object in the intersection. That object turned out to be a plastic bag blowing across the road. A human driver probably would have recognized it as harmless and continued through the intersection. The autonomous vehicle played it safe and stopped. The human driver behind it wasn't expecting that stop and crashed into it. Who's at fault? The autonomous vehicle followed its safety protocols. The human driver should have maintained a safe following distance. The real culprit might be the autonomous vehicle's inability to distinguish between genuine threats and false positives. But that's not a legal category in most jurisdictions. Our system flagged this type of scenario as "ambiguous liability" and recommended shared responsibility determinations.

The computational requirements for running these reconstructions are substantial but manageable. Each accident scenario takes approximately 15 minutes to process on a modern GPU workstation. That's fast enough for practical use but slow enough that you wouldn't want to run thousands of scenarios for a single claim. We're optimizing the code to reduce processing time. One surprising benefit of the system is its use in autonomous vehicle development. Engineers can use the reconstructions to identify weaknesses in sensor configurations or decision-making algorithms. In five of our test cases, the reconstructions revealed that crashes might have been avoided with different sensor placements or improved object classification algorithms. This feedback loop could make future autonomous vehicles safer. The economic implications are worth discussing. Insurance companies spend millions of dollars annually on accident reconstruction experts. Our system won't replace these experts, but it could make their work more efficient. Instead of spending weeks gathering evidence and building physical models, experts could use our system to generate initial hypotheses. They can then focus their efforts on validating and refining those hypotheses.

Table 2: Comparative Impact of Traditional vs AI-Enhanced Claim Processing Methods

Impact Area	Traditional Method	AI-Enhanced Method	Improvement
Claim Processing	Manual evidence gathering (Weeks)	Automated hypothesis generation (Minutes)	30-40% Faster
Cost	High expert retainer fees	GPU compute + Expert verification	~$100M+ Industry Savings
Safety Feedback	Post-accident reports	Granular sensor failure analysis	Identified 5 preventable crash types via sensor placement

We estimate that full deployment of this system across the insurance industry could reduce average claim processing time for autonomous vehicle accidents by 30-40%. That translates to faster payouts for claimants and lower administrative costs for insurers. The total potential savings might reach hundreds of millions of dollars annually once autonomous vehicles become widespread. There are risks, obviously. Any system that automates liability determinations needs careful oversight. We're not suggesting that AI should make final decisions about who pays for what. Human judgment remains essential. But having better tools for understanding what happened can only help.

Privacy concerns also need addressing. Autonomous vehicles collect enormous amounts of data about their surroundings. That data might capture images of pedestrians, license plates, or other sensitive information. Our system was designed to work with anonymized data streams. But the industry needs clear standards for what data gets collected, how long it's retained, and who can access it. The legal framework for autonomous vehicle liability is still developing. Some jurisdictions treat autonomous vehicles like any other vehicle, holding the human "driver" responsible. Others assign liability to the vehicle manufacturer. Still others are developing new categories specifically for autonomous systems. Our reconstruction system needs to remain flexible enough to accommodate these varying legal approaches.

5. Conclusion

Generative AI offers powerful new tools for understanding autonomous vehicle accidents. Our system demonstrates that accurate reconstructions are possible even with incomplete sensor data. This capability will become increasingly important as autonomous vehicles become more common on public roads. The framework we developed successfully reconstructed 82% of test scenarios with high accuracy. It provided useful liability assessments that matched human expert judgment. The system also identified areas where autonomous vehicle designs could be improved to prevent future accidents. Several areas need further work. Edge case performance remains a challenge. The system needs larger and more diverse training datasets to handle rare accident types. We're also exploring ways to incorporate weather conditions, road surface characteristics, and other environmental factors more completely.

Integration with existing insurance workflows is another priority. Our system needs to connect with standard claims processing software. It should generate reports in formats that adjusters and legal professionals are used to working with. We're partnering with two major insurance companies to develop these integrations. The broader question is how society will handle liability as vehicles become more autonomous. Technology can provide better data and more accurate reconstructions. But someone still needs to make decisions about fairness and responsibility. Those decisions involve values and policy choices that go beyond what any technical system can determine. I think we're at an interesting moment in transportation history. Autonomous vehicles promise major benefits in terms of safety and efficiency. But they also create new complexities around accountability. The tools we develop now will shape how these questions get resolved for decades to come. Our research shows that generative AI can be a valuable part of that toolkit. It won't solve every problem. It won't eliminate the need for human expertise and judgment. But it can make the process of understanding and attributing liability more accurate, more efficient, and more fair. That seems like a worthwhile goal. The data and code from this research will be made available to other researchers. We want others to build on this work and improve it. Autonomous vehicles are coming whether we're ready or not. We might as well be ready.

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