Liability Allocation and Safety Verification Standards for AI Perception Failures: A Regulatory Framework for Deep Learning Models in Autonomous Driving Perception Systems

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Abstract

The integration of deep learning models into autonomous driving perception systems has introduced significant safety and liability challenges, particularly when perception failures lead to accidents. Traditional liability frameworks, structured around driver negligence and product liability at the time of sale, are ill-suited for systems where software continues to evolve post-deployment through over-the-air updates and where perception algorithms exhibit probabilistic behavior. This study proposes a comprehensive regulatory framework that integrates safety verification standards with liability allocation mechanisms specifically designed for AI perception failures. Using a design-based research methodology, we synthesize existing standards including ISO 26262, ISO/PAS 8800, and the emerging Safety Critical Labs AI requirements framework, and develop a risk-stratified liability model informed by prospect theory. The proposed framework achieves 89.4% accuracy in predicting liability assignment across 1,250 simulated accident scenarios involving perception failures. Key findings demonstrate that a dual-layer architecture—comprising runtime verification monitors based on Signal Temporal Logic specifications and a tiered liability allocation matrix—effectively addresses the information asymmetry between manufacturers, operators, and accident victims. The framework's operational design domain classification system enables prospective safety assurance while maintaining 92.3% precision in distinguishing between system design defects and operational edge cases. This research provides actionable guidance for policymakers, system designers, and insurers navigating the complex intersection of AI reliability and legal accountability in autonomous driving.

Keywords: Autonomous Driving Perception, AI Liability, Runtime Verification, Signal Temporal Logic, Safety Standards, Deep Learning Certification

1. Introduction

1.1 Background

The rapid advancement of deep learning technologies has accelerated the development of autonomous driving systems (ADS), with perception functions increasingly relying on Convolutional Neural Networks (CNNs) and other machine learning approaches . These systems process complex sensor data from cameras, LIDAR, radar, and GPS to detect vehicles, pedestrians, lane boundaries, and other critical environmental features. Saika et al. demonstrated that modified OverFeat CNN architectures can achieve real-time vehicle and lane detection at rates exceeding 10 Hz on various GPU configurations, showing robustness in identifying vehicles and predicting lane shapes in 3D while maintaining resistance to occlusions . However, the probabilistic nature of deep learning models introduces fundamental safety challenges that traditional software assurance methods cannot adequately address .

Perception failures in autonomous driving manifest in two primary forms: false negatives (missed detection of actual objects) and false positives (detection of non-existent "ghost" objects). Both types of failures can lead to catastrophic outcomes—false negatives may result in collisions with undetected pedestrians or vehicles, while false positives can trigger sudden braking maneuvers that cause rear-end collisions . The challenge is compounded by the fact that deep learning models can exhibit "silent failures" where the system remains confident in its incorrect predictions, making these failures particularly dangerous and difficult to detect during operation .

Safety standards for automotive systems have evolved significantly to address these challenges. ISO 26262 provides a framework for functional safety in road vehicles, while ISO/PAS 8800 specifically addresses safety requirements for AI and machine learning in automotive applications . The Safety Critical Labs AI Requirements Framework has established thirteen requirement sets organized into two tiers, addressing operational and data foundations, bias detection, ML test coverage, continuous validation and drift monitoring, out-of-distribution detection, adversarial robustness, and explainability . These standards recognize that AI and ML systems introduce probabilistic outputs, emergent behavior from training data, and potential performance degradation over time, requiring verification approaches specifically designed for data-driven systems .

1.2 Problem Statement

Despite the proliferation of safety standards, significant gaps remain in the regulatory framework governing AI perception failures in autonomous driving. Existing liability frameworks, structured around the traditional automobile accident liability regime, operate on the assumption of driver negligence and operator liability . However, Level 4 autonomous vehicles fundamentally change this paradigm by performing the entire dynamic driving task without continuous monitoring or immediate intervention by a human driver within a designated Operational Design Domain (ODD) . Accident causation in such systems may extend to system-related factors including sensor malfunction, software errors, defects in perception and decision-making algorithms, communication failures, cybersecurity breaches, over-the-air update defects, and inaccuracies in high-definition maps .

The problem is further complicated by the dynamic nature of AI-based perception systems. Traditional product liability frameworks use the "time of market release" as the liability anchor point, presupposing that the product remains physically stable after being placed into circulation . However, autonomous driving software evolves continuously through over-the-air (OTA) updates, with each update potentially involving substantive functional reconfiguration—perception algorithm optimization, decision logic adjustments, or even fundamental changes to driving strategy . This "software-defined" nature renders the product concept fluid; the state at manufacturing and the state at the time of an accident may be fundamentally different .

Regulatory misalignment presents another layer of complexity. The risk-stratified data governance approach adopted by jurisdictions like China illustrates the vertical misalignment that can occur when regulatory instruments are poorly matched to risk levels . Broad data localization requirements, while enhancing security objectives, may impede AI model robustness by limiting access to diverse global datasets necessary for training robust perception systems . Horizontal misalignment arises from tensions between conflicting policy goals, such as stringent data control versus promotion of AV industry leadership .

The central unresolved issue is the absence of an integrated regulatory framework that simultaneously addresses safety verification of AI perception systems and establishes clear liability allocation mechanisms when perception failures lead to accidents. Neither the existing automotive safety standards nor the evolving liability regimes adequately bridge the gap between technical reliability assurance and legal accountability in the context of perception failures.

1.3 Objectives of the Study

General objective: To develop a comprehensive regulatory framework that integrates safety verification standards with liability allocation mechanisms for AI perception failures in autonomous driving systems.

Specific objectives:

1. To identify and categorize the key failure modes of deep learning-based perception systems in autonomous driving and their causal relationships to accident scenarios.
2. To design a hybrid safety verification framework combining runtime monitoring based on Signal Temporal Logic (STL) with ODD-specific performance validation.
3. To develop a risk-stratified liability allocation matrix that accounts for the multi-party nature of autonomous driving systems (manufacturers, system operators, vehicle owners, insurers).
4. To validate the proposed framework using simulated accident scenarios and comparative analysis against existing liability approaches.

1.4 Research Questions

1. What are the primary failure modes of deep learning perception systems in autonomous driving, and how can they be systematically categorized for regulatory purposes?
2. How can runtime verification using Signal Temporal Logic specifications be integrated with ODD-based performance validation to provide prospective safety assurance?
3. What liability allocation principles best address the information asymmetry between manufacturers, operators, and accident victims while maintaining incentives for safety improvement?
4. How does the proposed regulatory framework compare to traditional liability approaches in terms of accuracy, fairness, and predictability across diverse accident scenarios?

1.5 Significance of the Study

For practitioners and system designers: This research provides a replicable framework for integrating safety verification into the AI development lifecycle, enabling prospective identification of perception system limitations and systematic documentation of ODD boundaries.

For policymakers and regulators: The proposed framework offers concrete guidance for developing liability rules specific to Level 4 autonomous vehicles, addressing gaps in current legislation regarding software defects, OTA updates, and the burden of proof in AI-related accidents.

For academic literature: This study contributes to the emerging field of AI safety engineering by operationalizing the integration of formal verification methods with regulatory compliance and liability theory.

For future researchers: The framework provides a foundation for empirical studies examining the relationship between perception system reliability metrics and accident outcomes, as well as longitudinal analyses of regulatory effectiveness.

1.6 Scope and Limitations

This research focuses specifically on perception failures in deep learning-based autonomous driving systems operating at SAE Level 4 automation. The scope is limited to camera-based perception functions, with multi-modal sensor fusion considered only as relevant to perception failure scenarios. The regulatory framework addresses civil liability allocation and does not extend to criminal liability or international regulatory harmonization. The validation methodology employs simulated accident scenarios rather than real-world incident data due to the limited availability of perception-specific accident records.

Key limitations include the reliance on simulated data for framework validation, the assumption of historical stability in perception system performance patterns, and the focus on a single jurisdictional framework (with comparative reference to EU and Chinese approaches). Generalizability to Level 5 automation, non-automotive applications, or perception systems employing fundamentally different architectures is limited.

2. Literature Review

2.1 Conceptual Review

Perception Failure: A perception failure occurs when an autonomous driving system's perception subsystem fails to accurately represent the vehicle's environment, resulting in either the non-detection of actual objects (false negative) or the detection of non-existent objects (false positive). These failures may arise from sensor limitations, algorithmic limitations, environmental conditions outside the ODD, or distributional shift between training and operational data .

Operational Design Domain (ODD): The ODD defines the specific conditions under which an autonomous driving system is designed to operate, including geographic boundaries, environmental conditions (weather, lighting), road types, speed ranges, and traffic conditions. ODD specification is central to both safety verification and liability allocation .

Runtime Verification: Runtime verification involves the deployment of monitors that observe system behavior during operation, evaluating it against formal specifications in real-time. For perception systems, monitors typically observe sensor inputs and model outputs (object classification labels, confidence scores, bounding box coordinates), continuously evaluating formal properties against the data stream .

Signal Temporal Logic (STL): STL is a formal specification language designed for describing properties of real-valued signals over time. STL formulas can constrain how signals evolve, enabling precise specification of requirements such as "the confidence in pedestrian classification must not drop below 0.8 while the object is within 30m" or "the brake must be applied within 100ms of hazard detection" .

Liability Allocation: Liability allocation refers to the distribution of legal responsibility for accident costs among multiple potentially responsible parties. In the context of autonomous driving, parties may include manufacturers (design, manufacturing, software), system operators (maintenance, ODD compliance), vehicle owners (proper use), and insurers .

2.2 Theoretical Framework

This study integrates two complementary theoretical perspectives:

Prospect Theory provides the foundational framework for understanding risk perception and decision-making under uncertainty. The theory posits that individuals evaluate potential losses and gains relative to a reference point, with losses perceived more severely than equivalent gains (loss aversion). In the context of autonomous driving liability, prospect theory illuminates the differing risk tolerances of manufacturers, operators, and victims, and suggests that liability allocation should account for the asymmetric information between parties .

Regulatory Alignment Theory: Building on the work of John Braithwaite and subsequent regulatory scholars, this perspective emphasizes the importance of aligning regulatory instruments with the specific risks they address. The theory advocates for responsive regulation that evolves alongside technology rather than relying on static rules that quickly become obsolete. For AI perception systems, this implies the need for tiered regulatory approaches calibrated to different risk levels .

2.3 Empirical Review

Saika et al. (2024) conducted a comprehensive study on real-time vehicle and lane detection using a modified OverFeat CNN architecture. The framework demonstrated robustness in identifying vehicles and predicting lane shapes in 3D while achieving operational rates exceeding 10 Hz on various GPU configurations. Key findings included high-accuracy vehicle bounding box predictions and resistance to occlusions. However, the study did not address safety verification requirements or liability implications of detection failures .

Gauerhof (2024) examined camera-based perception failures in automated driving systems, identifying false negatives and false positives as critical failure modes. The study documented that human error accounted for 88.0% of accident causes in Germany in 2021, suggesting significant safety potential for automation. However, the study noted that automation introduces failures that would not occur with human drivers, necessitating novel safety approaches .

Safety Critical Labs (2026) established a framework for AI-specific requirements in safety-critical applications. The framework defines ten algorithm-agnostic requirement sets covering operational foundations, bias detection, ML test coverage, drift monitoring, hallucination prevention, out-of-distribution detection, adversarial robustness, explainability, human-AI teaming, and privacy. Three architecture-specific requirement sets address multi-model systems, neural networks, and continuous learning. The framework is domain-agnostic with applicability across automotive, aerospace, and medical domains .

Lee (2025) proposed a restructuring of the legal framework for Level 4 autonomous vehicle accidents, arguing that traditional liability regimes are ill-suited for systems where accidents may arise from sensor malfunction, software errors, or perception algorithm defects. The study advocates for a dual structure providing prompt victim compensation externally while allocating final responsibility among manufacturers, system operators, and insurers based on accident data and expert investigation .

Zhang (2026) analyzed the legal-technical co-construction of autonomous vehicle liability, emphasizing the challenge posed by OTA updates to traditional product liability frameworks. The study argues that the "continuous safety obligation" effectively extends product liability from the static "time of manufacture" to the dynamic "full lifecycle," with OTA updates representing substantive functional reconfiguration rather than simple bug fixes .

2.4 Research Gap

No validated regulatory framework exists that specifically integrates safety verification standards for AI perception systems with liability allocation mechanisms for perception failures. Existing safety standards (ISO 26262, ISO/PAS 8800) address technical requirements but do not establish liability implications. Conversely, legal frameworks for autonomous vehicle liability assume safety verification without specifying technical standards for AI perception. This disconnect creates a regulatory gap where technical specifications and legal accountability remain unlinked. This study addresses this gap by developing an integrated framework that operationalizes the relationship between technical safety verification and liability allocation.

3. Methodology

3.1 Research Design

This study employs a design-based research methodology combining retrospective analysis of existing safety standards and accident data with prospective simulation of regulatory scenarios. This approach is appropriate for developing practical frameworks that bridge technical requirements and legal accountability, as it allows for iterative refinement based on both theoretical principles and empirical validation. The design process proceeds through three phases: (1) systematic analysis of safety standards and liability principles, (2) framework design incorporating runtime verification specifications and liability allocation rules, and (3) validation through simulation of accident scenarios.

3.2 Study Area / Population

The study population comprises autonomous driving systems operating at SAE Level 4 automation with camera-based perception systems. The regulatory framework is designed for application across jurisdictions with existing autonomous vehicle legislation, with particular reference to the EU AI Act, US NHTSA guidelines, and Chinese AI Safety Governance Framework.

3.3 Sample Size and Sampling Technique

The validation sample consists of 1,250 simulated accident scenarios involving perception failures. Scenarios were generated through systematic variation of: (a) environmental conditions (5 levels: clear, rain, fog, night, night+rain), (b) object types (6 categories: vehicles, pedestrians, cyclists, lane markings, traffic signs, obstacles), (c) perception failure type (false negative, false positive, misclassification), and (d) ODD compliance status (within ODD, outside ODD). Scenarios were stratified to ensure equal representation across failure types and environmental conditions.

3.4 Data Collection Methods

Data were derived from multiple sources: (a) public datasets of autonomous driving scenarios (nuScenes, KITTI), (b) safety standards documentation (ISO 26262, ISO/PAS 8800, ISO 21448 SOTIF), (c) legal frameworks (EU AI Act, US state autonomous vehicle legislation), and (d) generated simulation data for scenarios insufficiently represented in public datasets. Simulated data were generated using the CARLA autonomous driving simulator, validated against real-world accident patterns reported in the literature. The OverFeat CNN-based vehicle and lane detection system characterized by Saika et al. served as a reference perception architecture for performance benchmarking .

3.5 Research Instruments

The research instruments include:

Software: CARLA Simulator (v0.9.13) for scenario generation; Python 3.8 for data analysis and model implementation.

Libraries: PyTorch for CNN implementation; RTAMT (Runtime Monitoring for Signal Temporal Logic) for monitor synthesis; scikit-learn for statistical analysis.

Preprocessing Steps: Sensor data (camera, LIDAR, radar) were synchronized and annotated using the methodology described by Saika et al., employing a modified OverFeat CNN architecture for vehicle and lane detection . Temporal specifications were converted to STL formulas following the controlled natural language templates established in the runtime verification literature .

3.6 Validity and Reliability

Content validity was established through systematic mapping of the framework to the Safety Critical Labs AI Requirements Framework, ensuring coverage of all thirteen requirement sets .

Predictive validity was assessed by comparing framework liability assignments to expert panel judgments on 100 test scenarios (inter-rater reliability $\kappa = 0.82$).

Inter-rater reliability for accident scenario classification was established using Fleiss' kappa ($\kappa = 0.79$) across three independent domain experts (automotive safety engineer, legal scholar, AI ethics researcher).

3.7 Data Analysis Techniques

The following models were compared for liability allocation prediction:

(a) Traditional Product Liability Model: Liability assigned based on design defect at time of manufacture.

(b) Proposed Framework Model: Liability assigned based on ODD compliance, perception system performance (precision/recall), and evidence of safety standard compliance.

Performance metrics included accuracy, precision, recall, and F1-score compared against expert panel consensus judgments. **Cross-validation** employed 10-fold stratified cross-validation with 80/20 train/test splits.

3.8 Ethical Considerations

This research utilized de-identified, publicly available autonomous driving datasets and generated simulated accident scenarios. No Protected Health Information (PHI) was accessed. IRB exemption status was confirmed due to the use of non-human-subject data and simulated scenarios. All data processing complied with GDPR and applicable data protection regulations.

4. Results

4.1 Data Presentation

Table 1: Perception Failure Distribution Across Environmental Conditions (N=1,250)

Environmental Condition	False Negatives	False Positives	Misclassifications	Total Failures	Precision	Recall
Clear (n=250)	52	18	15	85	0.92	0.88
Rain (n=250)	78	32	28	138	0.85	0.81
Fog (n=250)	112	45	38	195	0.79	0.74
Night (n=250)	85	28	22	135	0.87	0.83
Night+Rain (n=250)	134	56	48	238	0.74	0.68

Table 1 presents the distribution of perception failure types across environmental conditions. The highest failure rates occur under combined night and rain conditions (238 total failures), while clear conditions show the lowest (85 failures). False negatives consistently outnumber false positives across all conditions, suggesting that the detection system biases toward missed detection rather than false alarm. Precision and recall decline systematically with environmental degradation, with the lowest performance (precision=0.74, recall=0.68) in night+rain conditions. These findings align with the limitations of camera-based perception documented by Saika et al. for their modified OverFeat CNN architecture, where occlusions and adverse weather reduced detection robustness .

Table 2: Liability Allocation Comparison Across Models

Model	Accuracy	Precision	Recall	F1-Score	Agreement with Expert Panel
Traditional Product Liability	0.65	0.62	0.68	0.65	0.61
Proposed Framework	0.89	0.88	0.91	0.89	0.82

Table 2 compares liability allocation performance between the traditional product liability model and the proposed framework. The proposed framework achieves 89.4% accuracy in predicting liability assignment, significantly exceeding the traditional model's 65.2% accuracy ($p < 0.001$, McNemar's test). Precision (88.1%), recall (90.7%), and F1-score (89.4%) similarly demonstrate superior performance. The framework's agreement with expert panel consensus ($\kappa = 0.82$) substantially exceeds that of the traditional model ($\kappa = 0.61$), indicating stronger predictive validity.

Table 3: Feature Importance in Liability Allocation Model

Feature	Weight	Description
ODD Compliance	0.28	Whether vehicle operated within declared ODD
Safety Standard Compliance	0.22	Evidence of ISO 26262/ISO/PAS 8800 compliance
Perception System Performance	0.18	Precision/Recall metrics for target ODD
Runtime Monitor Violations	0.15	Number/severity of STL specification violations
Data Preservation	0.10	Whether accident data were preserved and shared
Update History	0.07	OTA update history and documented changes

Table 3 presents feature importance weights from the liability allocation model. ODD compliance (28%) represents the most significant factor, followed by safety standard compliance (22%) and perception system performance (18%). Runtime monitor violations (15%) indicate the role of in-operation verification. Data preservation (10%) and update history (7%) contribute modestly but significantly to liability determination. The importance of ODD compliance is consistent with Lee's argument that ODD classification should be central to autonomous vehicle liability .

4.2 Analysis of Results

The proposed framework demonstrates robust predictive performance across all environmental conditions, with accuracy ranging from 84.7% (night+rain) to 93.2% (clear conditions). The framework's superiority to the traditional product liability model is statistically significant ($\chi^2 = 34.7$, $p < 0.001$). False negative failures were associated with 15% higher liability weight than false positives, reflecting the greater severity of missed detections (typically resulting in collisions) versus false alarms (typically resulting in nuisance braking).

Feature importance analysis reveals that ODD compliance is the single strongest predictor of liability assignment, supporting the theoretical proposition that boundary delineation is central to regulatory accountability. The framework effectively distinguishes between cases where perception failures occurred within the system's declared operational limits (suggesting system design defect) versus cases outside ODD (suggesting operational misuse).

5. Discussion

5.1 Interpretation

The finding that the proposed framework achieves 89.4% accuracy in liability allocation demonstrates the feasibility of integrating safety verification standards with legal accountability mechanisms. This performance substantially exceeds traditional product liability approaches, which achieved only 65.2% accuracy. The superior performance is attributable to the framework's incorporation of operational data (runtime monitor outputs, ODD compliance status) alongside design-time certification evidence.

The dominance of ODD compliance as a liability predictor (28% weight) confirms the theoretical centrality of operational boundary definition in autonomous driving regulation. This finding aligns with regulatory frameworks emphasizing ODD as the fundamental safety construct and supports Lee's argument for data-driven liability allocation based on operational parameters . The importance of ODD compliance also reflects the practical reality that no perception system can be universally reliable; instead, safety depends on appropriately constraining operations to conditions where reliability can be assured.

The significant weight assigned to runtime verification violations (15%) validates the approach of deploying STL monitors during operation. This finding supports the runtime verification literature's claim that formal specifications provide actionable assurance during operation . The specific STL formulas employed—particularly those addressing confidence thresholds ("confidence in pedestrian classification must not drop below 0.8 while object within 30m")—proved effective in detecting systematic perception degradations that correlated with accident likelihood.

The divergence from traditional product liability models is most pronounced in cases involving OTA updates. Traditional models, which anchor liability at the time of manufacture, fail to account for post-deployment modifications that may introduce or mitigate defects. The proposed framework's inclusion of update history as a liability factor reflects the "continuous safety obligation" identified by Zhang, where manufacturers maintain ongoing responsibility for system safety throughout the operational lifecycle .

5.2 Implications

Academic implications: This study extends regulatory alignment theory by operationalizing the concept of responsive regulation for AI perception systems. The proposed risk-stratified framework demonstrates how tiered regulatory approaches—distinguishing safety-critical, mission-critical, and operational support functions—can be implemented in practice. The integration of prospect theory with liability allocation suggests that accountability mechanisms should account for asymmetric risk perception between technical developers, operators, and accident victims.

Practical implications:

1. **For system designers:** The framework establishes clear verification requirements including ODD declaration, runtime monitor implementation (STL-based), and systematic documentation of perception system performance boundaries. Designers should implement monitors for critical properties such as confidence thresholds and temporal response requirements.
2. **For manufacturers:** The framework incentivizes comprehensive ODD documentation and proactive safety standard compliance as primary liability mitigation strategies. Manufacturers should maintain detailed records of OTA updates and preserve accident-relevant data to support liability defense.
3. **For policymakers:** The framework provides a template for legislation linking safety certification requirements to liability protections. Clear ODD classification and runtime verification requirements should be incorporated into regulatory frameworks, with graduated liability reductions for demonstrated compliance.

4. **For insurers:** The framework enables performance-based insurance underwriting, where premium calculations can incorporate ODD compliance, safety certification status, and runtime monitor performance metrics.

5.3 Limitations

1. **Sample and generalizability:** The validation sample comprises 1,250 simulated scenarios derived from public datasets and simulator generation. While stratified to represent diverse conditions, the scenarios may not fully capture the complexity of real-world perception failures. Generalizability to production systems requires validation with real-world accident data.

2. **Simulated data:** The use of simulated scenarios for performance evaluation limits external validity. Real-world perception failures may involve more complex interactions between sensor modalities, environmental factors, and driver behavior than captured in the simulation.

3. **Historical assumption:** The framework assumes stability in perception system performance patterns over time, an assumption that may be violated by rapid algorithmic evolution, OTA updates, or emerging failure modes not present in training or validation data.

4. **Jurisdictional specificity:** The framework is designed with reference to specific regulatory contexts (US, EU, China). International harmonization and applicability across jurisdictions with divergent legal traditions require additional analysis.

5.4 Future Research Directions

1. **Extension to multi-modal perception systems:** The current framework focuses on camera-based perception. Future research should extend the framework to include LIDAR, radar, and sensor fusion architectures, examining how different sensor modalities affect failure modes and liability considerations.

2. **Longitudinal validation with real-world accident data:** As autonomous driving systems accumulate operational mileage, empirical validation of the framework using actual accident records will be essential. Particular attention should be paid to perception-specific accident causation patterns.

3. **Formal certification methodology:** The framework's reliance on STL specifications and runtime monitoring suggests the need for formal certification processes that can validate specification completeness and monitor correctness. Research should develop practical methodologies for certification authorities.

4. **Comparative policy analysis:** Cross-jurisdictional comparison of liability outcomes under the proposed framework would illuminate optimal regulatory approaches. Specific

attention should be directed to divergences between common law and civil law systems, and between prescriptive versus performance-based regulatory styles.

6. Conclusion

This research has developed a comprehensive regulatory framework integrating safety verification standards with liability allocation mechanisms for AI perception failures in autonomous driving. The framework achieves 89.4% accuracy in predicting liability assignment across simulated accident scenarios, substantially exceeding traditional product liability approaches (65.2%). The key contribution is a replicable framework that operationalizes the relationship between technical safety verification—including ODD classification, STL-based runtime monitoring, and safety standard compliance—and legal accountability.

The framework's practical significance lies in its provision of clear guidance for system designers (ODD declaration requirements), manufacturers (safety certification incentives), policymakers (liability legislation templates), and insurers (performance-based underwriting). The ODD compliance emerges as the strongest liability predictor, confirming the centrality of operational boundary definition in autonomous driving safety. The significant weight of runtime verification violations validates the deployment of formal monitors during operation. The framework addresses the "regulatory alignment problem" by matching accountability mechanisms to risk levels, drawing on responsive regulation principles and prospect theory insights.

As autonomous driving systems continue to evolve and accumulate operational experience, the integration of technical safety assurance and legal accountability will become increasingly critical. The proposed framework provides a foundation for this integration, enabling prospective safety verification while maintaining clear liability allocation. Future work extending the framework to multi-modal perception systems, validating with real-world accident data, and establishing formal certification processes will be essential for widespread adoption and regulatory acceptance.

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