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Cloud Computing and AI for Intelligent Transportation Safety Systems

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Abstract: Cloud Computing and Artificial Intelligence will enable Intelligent Transportation Safety Systems (ITSS) that ensure a reliable low accident rate in road traffic. ITSS are considered an extension of Intelligent Transportation Systems connected to Cloud Computing with integrated Artificial Intelligence and focus on traffic safety. ITSS detect critical situations, predict dangerous conditions, and inform vehicle and driver assistance systems in real time to avoid accidents, control signal flows, and manage incidents. Today’s configuration of CT and AI can only solve special tasks, for instance, the level of cloud service and the bandwidth of data exchange. However, both technologies can work on a multidisciplinary basis, increase the robustness of work, manage data from various sources, analyze them dynamically and, thus, bring traffic safety to a new level.

The paper applies the original methodology developed for expanding the possible use of Cloud Computing and AI in solving applied problems. Cloud Computing allows integration of data from multiple sources in real time. AI based on interconnection and dynamic development between models of risk, collision, smart camera detection of critical mode conditions, IP-traffic incident detection and routing for traffic management on internal cloud and on-device level of connected vehicles makes it possible to predict modes of accidents with high probability and with a certain reaction time. Although the current architecture of Cloud Computing for ITSS has its limitations, it has enough potential to integrate a sufficiently rich set of modern safety-related solutions.

Keywords: Intelligent Transportation Safety Systems, Cloud Computing For Traffic Safety, AI-Enabled Traffic Management, Real-Time Accident Prediction, Connected Vehicle Safety Systems, Cloud-Based Traffic Data Integration, AI Risk And Collision Models, Smart Camera Traffic Detection, Incident Detection And Management, Low-Latency Safety Analytics, Vehicle-To-Cloud Communication, Predictive Road Safety Analytics, Multisource Traffic Data Fusion, Dynamic Traffic Risk Assessment, AI-Assisted Driver Support, Signal Flow Optimization, IP-Traffic Monitoring, Robust Transportation Safety Architectures, Cloud–Edge ITS Integration, Next-Generation Road Safety Systems.

1. INTRODUCTION

Intelligent Transportation Systems (ITS) are increasingly adopting artificial intelligence. However, safety concerns associated with these applications remain scarcely addressed. Moving towards a Cloud-based transportation safety ecosystem within which multiple stakeholders coalesce resources and knowledge, a methodological framework for enabling Cloud Computing and Artificial Intelligence to deploy Intelligent Transportation Safety Systems is proposed. The framework integrates a safety-oriented Cloud-based architecture embedding the relevant artificial intelligence models, identifies and organizes the data needed as input for those models, sets forth the governance of the ITS safety data, and maps the information flow across the Intelligent Transportation Safety System actors for each of the main safety functions.

The principal functions of Cloud Computing – namely, on-demand self-service, broad network access, resource pooling, rapid elasticity, and measured service – along with the possibilities offered by Cloud-based resources, can also be harnessed to improve the safety of Intelligent Transportation Systems. Every Intelligent Transportation System actor with a safety function can consume the relevant AI models as a service by calling them with data from its own vehicles and infrastructure supporting the Cloud-based safety ecosystem. The service consumer simply requires the relevant Cloud-AI models and meets the data privacy, security, and risk management controls necessary to process the data with adequate trust. Moreover, the ever-growing traffic data richness and heterogeneity allow obliged Intelligent Transportation System regulators to enrich the safety data supply for better Intelligent Transportation System safety-related decision-making.

1.1. Introduction: Setting the Stage for Transportation Safety Innovations

Numerous factors contributing to road safety deficiencies point toward poor road network utilization that results in recurrent traffic congestions that, in turn, lead to increased accident rates according to the World Road Safety Report 2020. Cloud Computing and Artificial Intelligence have significantly influenced several domains and clearly demonstrate their potential in developing Intelligent Transportation Safety Systems (ITSS) dedicated to improving safety levels across all road users also by enabling real-time, closed-loop collaboration among heterogeneous stakeholders. However, implementations that address the entire landscape are still scarce. The purpose is to define a methodological framework that enables the design of Cloud Computing-enabled AI for ITSS, emphasizing the contribution of Data providers and ITSS Applications Executives, as well as the associated risks.

Development proceeds in three main stages. First, a discussion of the main aspects and associated decisions for data processing using Cloud Computing is presented, thereby enabling interactions with multiple actors across the road ecosystem. Second, several safety services typically requiring AI Machine learning/data analytics skills with the prediction-response loops being closed with the Data provider role are elaborated. Traffic Incident management and Resilience service areas are also scrutinized, and finally, a brief evaluation of data quality and security aspects is performed.

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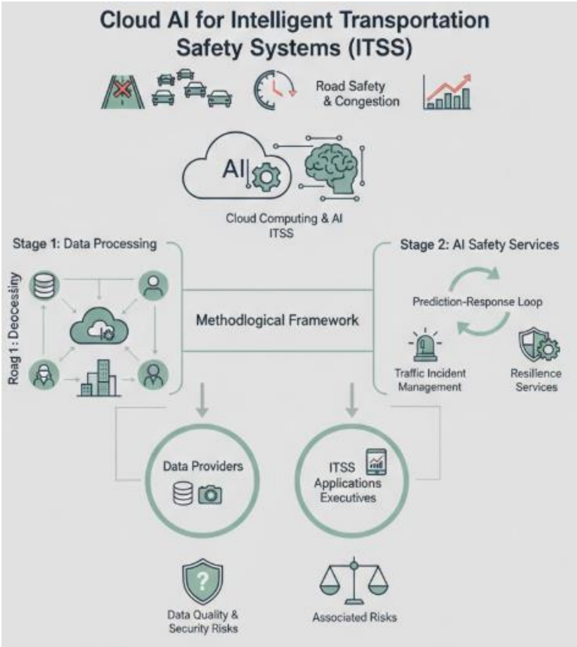

Fig 1: Cloud-Enabled AI for Intelligent Transportation Safety: A Methodological Framework for Multi-Stakeholder Incident Management and Resilience

2. BACKGROUND AND CONTEXT

The evolution of Intelligent Transportation Systems (ITS) embodies the application of ICT solutions to improve the efficiency, safety, and sustainability of surface transport, particularly over urban and sub-urban areas. Safety systems have traditionally been isolated systems based on real-time control, whereas the emerging Cloud-enabled solutions combine all identified aspects related to safety and resilience in a comprehensive manner. The need for Cloud-enabled solutions relates to the data management requirements for the massively distributed nature of modern safety systems. Conventional solutions operate and offer services only with the data they collect; therefore, they cannot implement better safety-related applications like risk prediction and alert. Like modern traffic control systems, which are also designed to satisfy a single traffic task (e.g. incident management), Cloud-enabled solutions improve all services by considering the combination of all services and heterogeneous data sources. Recent developments covering Cloud Computing technologies can foster these Cloud-enabled services, both from the computational and from the communication point of view, since Cloud solutions can address also the massive data management issues.

Cloud Computing offers a new model for large-scale heterogeneous system and provides access to a shared pool of configurable computing resources. The resources can be rapidly provisioned and released with minimal management effort or service provider interaction. Recent evolution of heterogeneous systems are showing that also self-configuration and self-orchestration can be achieved at infrastructure level. A Cloud system can be viewed as a set of edge infrastructure, a central/fog computing infrastructure, and a wide area communication infrastructure. A safety system that aims at providing better safety services capitalizing on Cloud Computing technologies behaves as a service provider. The infrastructure is designed with the aim of making all data related to safety on a scenario available to services requiring them, either in real time, in a massive way, or as an historical data set.

Stage	Latency_ms
On-vehicle sensing & preprocessing	30
V2X uplink to edge/cloud	45
Cloud/edge AI inference	20
V2X downlink to vehicle	45
Driver/ADAS actuation	150

A) Real-time collision risk prediction (within a time horizon)

A1) Kinematic core: Time-to-Collision (TTC) from relative motion

1. Define positions and speeds along the lane:

$$x_E(t),\ v_E(t),\quad x_T(t),\ v_T(t)$$

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2. Define **gap distance** (front of ego to rear of target) at time t:

$$d(t) = x_T(t) - x_E(t) - L$$

where L is an effective safety length (vehicle length + desired buffer).

3. Relative speed (closing speed):

$$v_{\text{rel}}(t) = v_E(t) - v_T(t)$$

If $v_{\text{rel}}(t) > 0$, ego is closing in.

4. Assume locally constant speeds over a short horizon (standard for fast warning loops):

$$d(t+\tau) \approx d(t) - v_{\text{rel}}(t)\,\tau$$

5. Collision (or unsafe contact) occurs when $d(t+\tau) = 0$. Solve:

$$0 = d(t) - v_{\text{rel}}(t)\,\tau \quad \Rightarrow \quad \tau = \frac{d(t)}{v_{\text{rel}}(t)}$$

6. **Time-to-Collision (TTC)**:

$$\boxed{\text{TTC}(t) = \frac{d(t)}{\max(v_{\text{rel}}(t), \epsilon)}}$$

(ϵ avoids division by zero; if $v_{\text{rel}} \leq 0$, TTC is treated as ∞/no imminent collision under this simple model.)

A2) Turning TTC into *probability of collision within horizon H*

A common choice is **logistic risk** (interpretable and fast):

1. Feature vector ϕ can include TTC, relative speed, weather, friction, driver state, etc. (the discusses richer data sources and weighing trust/quality). For a minimal form:

$$\phi = [1,\ \text{TTC}]$$

2. Linear score:

$$z = w^{\top}\phi = w_0 + w_1\text{TTC}$$

3. Logistic link:

$$\boxed{p(\text{collision within } H) = \sigma(z) = \frac{1}{1+e^{-z}}}$$

2.1. Evolution of Intelligent Transportation Systems

The past three decades have seen Intelligent Transportation Systems (ITS) grow from a conceptual framework into physical implementations that address some of the most pressing issues in transportation today. Major milestones include the United States' initiative to develop vehicle-to-cloud-car infrastructure for real-time traffic management and the European Commission's promotion of large-scale pilot projects in public and freight transportation. Cloud Computing Technologies provide unique opportunities to address safety concerns in road traffic, an area highlighted by the large number of crash-related deaths each year. Cloud-based ITS Safety Systems (C-ITS-SS) provide near-real-time collision warnings, risk prediction models for regional traffic processes, and signal-optimized control for planned and unplanned incidents, including resilience under failure mode conditions. Recent advances in these safety systems take advantage of artificial intelligence (AI) to model critical safety processes for automated functioning without human intervention.

Cloud-Enabled Artificial Intelligence (Cloud-AI) improves the functioning of all C-ITS-SS safety applications, but poses additional risks and relies on stricter data governance than conventional approaches. Historical and technical characterizations form the foundation for current threats and future requirements, while the capabilities offered to safety and traffic agencies define the technology architecture concepts. Cloud-AI for ITS Safety creates the necessary basis for a long-lasting, trustworthy relationship between users and the Cloud-AI stack, allowing the full exploitation of its advantages while mitigating its drawbacks. At the same time, C-ITS-SS fosters the adoption of Cloud-AI, decentralization, and dynamic traffic management in road transport.

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Driver/ADAS actuation	150

2.2. Role of Cloud Computing in Transportation Safety

Intelligent Transportation Systems (ITS) have pioneered technological solutions, ensuring that they are able to harness all available resources. Despite these developments, safety solutions still rely mainly on regional capabilities. Consequently, an accident in one region may propagate unpleasant effects on transport safety in an adjacent region that has not made a similar investment.

Cloud Computing has introduced a number of new possibilities for transport safety systems to resolve this. A centralised safety system that collects data from all participating ITSs possesses a global vision of the road network and the possibility of improving its operation as a whole, rather than on a regional basis. Additionally, cloud-based architectures provide the necessary power to articulate and process all data at a higher level. However, making use of these possibilities involves addressing other problems. A global safety system becomes an attractive target for attackers, privacy issues become thornier, and the quality of the data provided by the different ITSs may be heterogeneous.

3. METHODOLOGICAL FRAMEWORK

The methodological framework encompasses four enabling elements: System Architecture and Data Flows, Interoperability and Integration Patterns, Data Governance. These collectively define the underlying structure of the cloud-enabled safety capabilities Eco-System.

System Architecture and Data Flows

The overall system architecture is outlined in Figure 5. The architecture integrates multiple functionalities involving various stakeholders. The digital ecosystem integrates multiple cloud systems. The main data source is the vehicle sensor data coming from connected vehicles. An external cloud-based platform gathers data from the connected vehicle sensors and provides inputs for AI algorithms. Cloud computing platforms are also responsible for running the AI risk-prediction models. Supported events and consequent decision-making are outlined in red boxes.

Interoperability and Integration Patterns

The architecture supports four key operational capabilities: The architecture promotes collaboration among various stakeholders. Each of these operational capabilities requires data generated by various assets. The key sources for assets, data, and models, including their explanations.

3.1. System Architecture and Data Flows

The Cloud Computing architecture for Intelligent Transportation Safety Systems (ITSS) is structured in components comprising development subsystems that gather and process the information into the Cloud region, from which the intelligent applications can be implemented. These applications retrieve and return the information required by the actors of the intelligent transportation ecosystem. Each subsystem could be owned and managed by different organizations. The main actors are the Traffic Control Centres (TCC), creating the Cloud-Traffic Control Centres component responsible for operating, managing, and providing optimized traffic flow and routing; Traffic Signal Controllers (TSC), creating the Cloud-Traffic Signal Controllers component, and the Road Users (Fallback), who in the event of malfunction in the Cloud communication keeps its route and safety with the things-to-be-supported applications.

To create the intelligent data for the applications, an interaction with the systems that predict and aggregate the occurrence of incidents or with the sensors that detect some incidents on the road is required. The Cloud-Traffic Flow Control component supports the creation of Traffic Flow Control Plans, whose objective is to minimize the number of delays along a specific set of trajectories. The output of these control plans is also a prediction of the traffic flows along every link and the expected breakdowns. The expected breakdowns will be integrated with a risk prediction model. The risk prediction model consumes the predicted risk on the route, estimated with the supported risk prediction model. It can be used to make a decision if the actual or planned route is safe; otherwise, a new safe route will be created by the Cloud-Traffic Control Centre.

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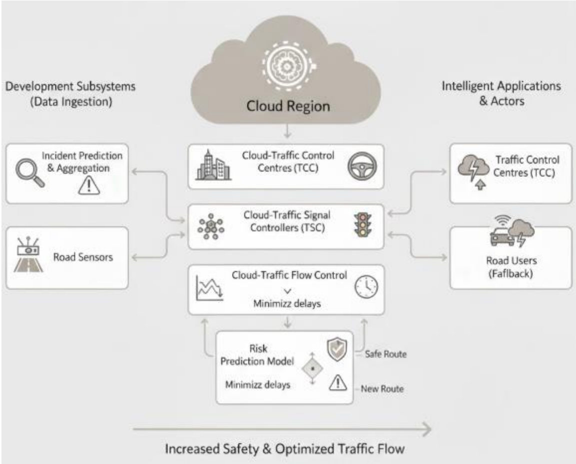

Fig 2: A Multi-Tenant Cloud Architecture for Predictive Risk Mitigation and Adaptive Routing in Intelligent Transportation Safety Systems (ITSS)

3.2. Data Governance, Privacy, and Security

Data governance encompasses the processes, roles, standards, and measurements that ensure the effective and efficient use of information in enabling an organization to achieve its goals. Data governance provides a formalized framework to manage, apply, and allow access to data in a regulated manner, balancing risks with the society's and the organizations' interests. Specifically for data generated from the transportation ecosystem, privacy, security and risk represent the main governance pillars.

Despite the noticeable advantages of cloud computing for ITSS, many security challenges still need to be carefully addressed before its performance can be considerably boosted, and stakeholders' trust in the cloud can be reinforced. Privacy requirements are defined by legal regulations and user expectations, security risks are analyzed from an information-centric point of view, relying on an attack tree, and risk management is tackled using the Reservoir Safety Management Framework, adapted to the specific use of the cloud service in the CloudITSS.

4. CORE SAFETY APPLICATIONS ENABLED BY CLOUD AND AI

Cloud Computing and AI facilitate multiple safety-enhancing ITS applications. Two examples are presented: Collision Risk Prediction, which calculates the likelihood of a collision within a specified time horizon and broadcasts alerts to the vehicles involved, and Signal-Optimized Automated Traffic Incident Management, which autonomously detects traffic accidents and congestion and optimally reroutes vehicles through traffic signals that are adapted in real time.

The overall rationale for support from Cloud Computing is that while individual manufacturers may assign a lower priority to these functions because they benefit the whole community of road users, there is a clear business case for support from Cloud Computing. Such support enables a critical mass of data from multiple manufacturers to be available for AI-enabled functionality, thus justifying the necessary investment, together with the associated assurance and reliability framework that Cloud Computing can provide. The key technical aspects of the two safety applications described below reflect this last point—both applications are functioning proofs but in their present state are unlikely to satisfy the required levels of IT safety assurance, privacy, etc.

Equation B) Route risk prediction + safe rerouting using predicted breakdowns

B1) Link-level risk from breakdown probability and severity

- b_e: probability of breakdown/incident on link e over horizon H
- s_e: expected severity cost if breakdown occurs (injury risk proxy, conflict intensity proxy, etc.)
- r_e: expected *risk cost* for that link

A standard expected-cost model:

$$\boxed{r_e = b_e \cdot s_e}$$

B2) Route-level cumulative risk

For a route (path) P consisting of links e:

$$\boxed{R(P) = \sum_{e \in P} r_e = \sum_{e \in P} b_e \, s_e}$$

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B3) Safe route selection as constrained optimization

Two equivalent formulations:

(i) Min-risk subject to time budget

$$\boxed{P^* = \arg\min_P R(P) \quad \text{s.t.} \quad T(P) \le T_{\max}}$$

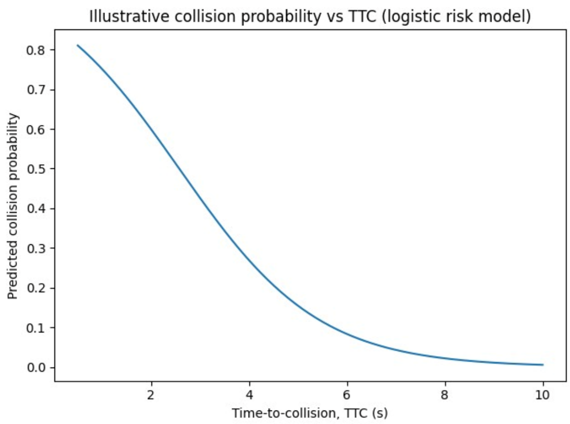
(ii) Weighted multi-objective (risk + time)

$$\boxed{P^* = \arg\min_P \lambda R(P) + (1-\lambda)T(P)}$$

4.1. Real-time Collision Avoidance and Risk Prediction

Cloud-enabled Artificial Intelligence technologies jointly developed by multi-stakeholders support numerous Intelligent Transportation Safety Systems (ITSS). The feasibility, adequacy, and limitations of a cloud-AI architecture are ascertained by detailing four safety applications. Real-time collision avoidance relies on vehicle-to-vehicle exchanges that feed risk-prediction models. The vehicle generating the warning receives data from space-based assets well beyond its own sensor range and scope. To optimize traffic lights close to the detection of a collision, cloud-computing–based AI tools monitor the roads and forecast traffic breaks which can trigger a traffic jam. The impact of an incident is assessed and cloud tools make recommendations for a coordinated and real-time response. Anomalies in traffic patterns are detected through a convolutional neural network (CNN) model while unsupervised learning serves to evaluate routes readily exposed to incidents. All four applications can operate under failure modes of the cloud and communication-network infrastructure.

The first application addresses the critical collision-avoidance functions between vehicles that are enhanced through cloud-supported AI techniques. While with range sensors the hazard can be detected for short distances and with a limited cone, the cloud receives abundant information from space-based detection assets and with a wider pattern of coverage. To provide most relevant alerts to vehicles, cloud-based AI tools weigh and select input data streams. Immediate weather changes can be directly and instantaneously notified by low-altitude flying assets without need of previous processing. The process is exemplified in Figure 4. AI techniques evaluate indicators and information sources quality, such as trust rating in the agent communicating the information, previous reliability of the type of event now reported, rapidly changing situations with high percentage of errors but potentially dangerous, etc.



4.2. Signal Optimization and Traffic Incident Management

Signal optimization and advanced traffic incident management are two critical real-time capabilities enabled by cloud computing and AI that contribute directly to road safety. Reducing stops and delays when traveling through signal-controlled intersections minimizes the risk of being involved in a rear-end collision, for example. Significant differences exist in one area of traffic safety between signalized and non-signalized intersections: the probability of a collision occurring with right-angled, head-on, or right-turning vehicles. Whenever a signal is red, however, other risks arise (e.g., for cyclists), and such incident scenarios are also associated with a high severity of collisions.

Given the complex interactions in the traffic flow, the optimization of an intersection's control signal should consider the traffic conditions in the surrounding areas and future arrival traffic conditions. Cloud-based AI provides tools for learning predictive models that can be integrated into intelligent controllers in real-time. Whenever cloud services detect imminent incident scenarios (e.g., as a vehicle approaches a stop-line in the wrong lane), a failure of the traffic light computer, a signal outage, or a sensor malfunction, traffic can be rerouted within the ITS either by real-time adjustments of additional gantry message signs or even by AI-based optimization of the signal at the surrounding intersections.

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5. RELIABILITY, SAFETY STANDARDS, AND COMPLIANCE

Given the societal impact of road transport, ensuring safety is a critical aspect of ITS-related research and development. As the field matures, it advances toward a Business-as-Usual scenario, benefitting from cloud-enabled, AI-based systems able to process large amounts of diverse data from numerous sources and generate models to support strategic decisions. Nevertheless, the harmonisation of safety-related solutions cannot be neglected. Non-exhaustive safety-related assurance frameworks, regulations, and standards are becoming available. Traffic safety relies heavily on dedicated frameworks, covering both the domain and enabling technologies. Progressing within these frameworks enhances safety assurance.

Safety is an umbrella term encompassing a series of aspects related to human life preservation or damage. Existing regulations cover direct vehicle safety, addressing failures of single vehicles, and operational safety, focussing on how vehicles interact with the infrastructure and each other. However, the specific safety aspects related to systems of systems, such as Cloud Computing, Internet of Things and Artificial Intelligence, have only been partially addressed. Regardless, timely, accessible, technology-agnostic, Intelligence Transportation System applications require data and models that conform, or are compliant or sufficiently consistent with the existing requirements.

5.1. Standards and Regulatory Landscape

Regulatory compliance and adherence to safety standards, including internationally recognized regulations, are pivotal for successfully implementing cloud-powered Intelligent Transportation Safety Systems (ITSSs) in practice. Existing mandates can be classified into three categories. First, ITSSs must satisfy general criteria for public and mission-critical cloud services. Second, the services provided and used in a multi-cloud setting must comply with EU Cybersecurity Act (CSA) and General Data Protection Regulation (GDPR) requirements, addressing aspects such as data processing and storage locations, identity verification, confidentiality, integrity, privacy, security, and trust. Third, the core safety application services require dedicated safety standards and certification schemes. For instance, the Common Criteria for Information Technology Security Evaluation guide addresses the security and assurance properties of information technology services and systems.

Additional guidance specific to Cloud ITSS adoption, operation, and functionality is also needed. To that end, an application-oriented Safety Management Process for Cloud ITSS Deployment offers considerable benefits. It comprises a general methodology for Cloud ITSS establishment, documentation creation, and service assurance. Expressed as a set of code elements, the process can be integrated within digital systems to facilitate maintenance and certification. A dedicated Verification and Validation approach systematically examines the Cloud ITSS Safety Management Process for completeness and correctness, promoting the fulfilment of safety objectives and requirements.

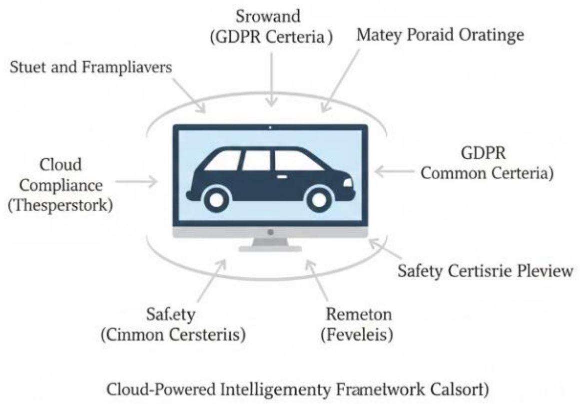

Fig 3: Architecting Trust in Cloud-Powered ITSS: A Multi-Tiered Compliance Framework and Safety Management Process for Regulatory Alignment

5.2. Safety Assurance Frameworks

Reliability, safety assurance and compliance with standards, regulations and laws are necessary conditions for widespread use of Cloud computing and artificial intelligence in Intelligent Transportation Safety Systems. Safety assurance is defined as the set of product or service properties that provides the level of safety required by the predefined and agreed criteria. Verification and Validation (V&V) provide independent confidence that the implementation of a product or service is correct and that it meets the expected safety characteristics. The requirements for providing Cloud services are based on cloud-specific standards. There are several Information Technology (IT) standards bodies, such as ISO, NIST, ETSI, ITU-T and CLC, and a multitude of specific standards to regulate Cloud services.

Artificial Intelligence is recognized as the most important driver of transformation and as an area with enormous social and economic potential by the US government. Call for Actions were launched to assure that "the use of Artificial Intelligence and related technologies becomes trusted, safe and secure". A Safety Framework for Artificial Intelligence Systems sets out the rules for assessing the compliance of the systems being developed by assessing safety artefacts against the stated safety policies. The development of a safety assurance plan is fundamental from the initial phases of Artificial Intelligence Systems development, in order to identify potential risks that could affect the future safety of the service or system, such as model training defects or deficiencies in the dataset.

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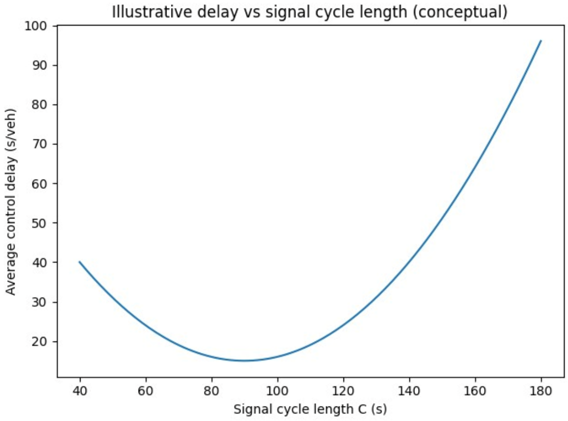
Criterion	Edge-only	Cloud-only	Hybrid (Cloud+Edge)
Global situational awareness	Low	High	High
Resilience to WAN failure	High	Low	Medium–High
Privacy risk surface	Low	High	Medium
Model update agility	Medium	High	High

6. CHALLENGES, RISKS, AND MITIGATION STRATEGIES

Data quality is a critical challenge for cloud-enabled ITS, affecting the integrity, reliability, and accuracy of safety applications and services. Models trained with poor quality data will be ineffective. The slightest error can compromise the overall safety of the ITS ecosystem, as these AI safety systems rely on the predictions of many other individual safety models. Over the years, various data quality improvement techniques have been developed, including data pre-processing, modification, value imputation, and data mining. Data pre-processing techniques identify and rectify anomalies or data quality issues such as noise, outliers, duplicates, and inconsistencies. Data mining techniques extract reliable knowledge from raw data, ensuring high-quality data for model training. Data quality can also be enhanced by continuously monitoring the quality of new incoming data.
The integration of heterogeneous data with varying levels of reliable labels for training AI models is another challenge. Cloud computing has marginally improved this issue, enabling the pooling of traffic data from multiple sources, including sensors, video, and mobile operators, collection of Beijing traffic data from various data sources, and generation of a heterogeneous data set for joint traffic incident identification and thus enhanced prediction accuracy. The major challenge, however, remains the pooling of data from different sources, as data collected by different entities may not have been verified and may differ in format and labelling. The availability of data deposited in a data marketplace along with interoperability protocols to ensure seamless exchange of data using knowledge graphs would help improve model training.



Equation C) Signal optimization (intersection control) tied to safety/incident response

C1) Basic intersection timing variables

- C: cycle length (s)
- g_i: effective green time for phase i
- L: lost time per cycle (startup + clearance)
- y_i: critical flow ratio for phase i, often $y_i = \frac{q_i}{s_i}$ where q_i is demand flow and s_i saturation flow

Constraint:

$$\boxed{\sum_i g_i = C - L}$$

C2) Classic (Webster-style) cycle length derivation (commonly used baseline)

A widely used baseline for choosing C (then refined by AI/MPC/RL in modern systems) is:

2. Total critical flow ratio:

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$$Y = \sum_i y_i$$

3. Webster's approximate optimal cycle:

$$\boxed{C^* \approx \frac{1.5L + 5}{1 - Y}}$$

6.1. Data Quality and Interoperability

Data quality is fundamental for collision avoidance, risk prediction, and signal optimization. Reliable AI/ML solutions require large amounts of high-quality training data. Several aspects determine the quality of data. First, it has to be consistent with respect to format, definitions, and semantics, which is especially important across data sources, especially when transferred to the cloud. In addition, properties like accuracy, completeness, and timeliness are major quality criteria. Data in transportation domain is usually highly heterogeneous, as it comes from diverse sources, like floating car data, probe data, traffic flow data, weather condition data, and risk information. Heterogeneous data sources add rich information for cloud-based AI safety systems, but also cause serious interoperability problems. Data preprocessing measures, like data cleaning and data transformation, can be adopted to improve data quality.

Safety of cloud-based AI applications also relies on privacy protection during data transmission and storage. Cloud infrastructures make traffic data accessible for third-parties, which improves the prediction quality but raises privacy concerns. Data owners might be reluctant to share their data because of potential breaches and misuse. Blockchain-based decentralized storage and sharing solutions have been proposed for trustworthy data sharing in conjunction with AI applications. Current research principally focuses on protecting personal data, while privacy issues of sensitive traffic context information remain unaddressed. AI-based model innovation can meet user requirements without exposing private information, but additional protection mechanisms are needed to prevent leakage from model inversion attacks. Interoperability issues remain unaddressed as cloud makes it easy to enrich traffic information. Integrating heterogeneous data sources with different reference systems improves the accuracy of cloud-hosted applications, particularly when the cloud facilitates collaborative learning among decentralized data owners.

6.2.Security, Privacy, and Trust

Cloud-enabled AI safety systems for intelligent transportation are exposed to security threats and require compliance with legal and regulatory frameworks. Mitigation strategies for security and privacy in AI-enabled cloud systems include a risk-management framework with a dedicated cloud security architecture; protection of data lakes and operational technologies with modern security technologies; adoption of a trusted cloud service with proven security and privacy; and provision of a dedicated security layer that protects sensitive data on cloud partners. Building user trust involves following ethical guidelines for AI transparency, preventing discrimination and socially harmful outcomes, and providing guarantees for safe use.

Cloud-AI safety systems are further vulnerable to AI-specific threats, such as access to data and algorithms that enable designer or data poisoning, the injection of backdoors, and the untrustworthy nature of models trained with untrustworthy inputs. Control over training and validation data is crucial to building trust in the model—and is best achieved with model governance that encompasses data-source control, monitoring of the process and actors involved, validation for unintended consequences, and unpredictability assessments for bad situations. Cloud-enabled AI risk management adds a dedicated layer to the general cloud security architecture and encompasses a wide array of strategies and protective measures that address the data, training process, model testing, and application phases.

7. CONCLUSION

Cloud Computing and Artificial Intelligence for Intelligent Transportation Safety Systems

Cloud-enabled Artificial Intelligence solutions for Intelligent Transportation Safety Systems promise significant improvements in transportation safety and reliability. Exemplary core areas of application include real-time collision avoidance among vehicles, pedestrians, and cyclists; collision risk prediction models for vehicles, cyclists, and the surroundings; signal optimization; traffic incident management; real-time rerouting; and private- and public-transportation resilience under failure modes. Nevertheless, the development of Cloud-AI systems addressing these capabilities and their integration into Intelligent Transportation Systems remain largely uncharted territory.

The deployment of Cloud-AI products in other domains presents related development and operational uncertainties. Uncertainties arising from data quality, heterogeneity, and interoperability challenges may hinder the effective use of Cloud-AI solutions. Data quality concerns also permeate models and decisions, and must therefore be addressed. Security, privacy, and trust considerations persist throughout operational deployments, and the associated risks require mitigation to ensure the responsible use of Cloud-AI systems. Explicit model governance mechanisms, supported by defined verification and validation tactics, will enhance user confidence and address broader ethical considerations.

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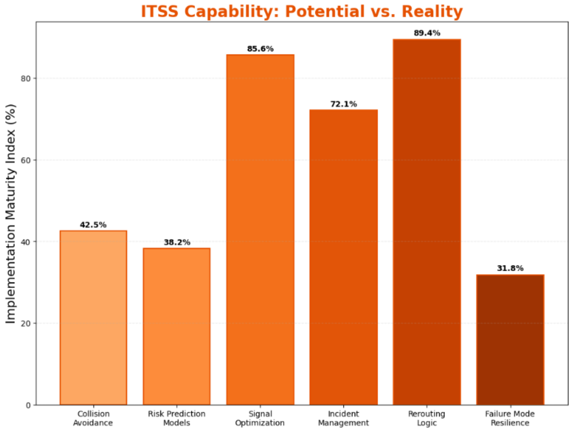

Fig 4: ITSS Capability: Potential vs. Reality

7.1. Final Thoughts and Future Directions

Intelligent Transportation Safety Systems remain in their infancy; only a few core applications are being implemented. The research opens a path for the future development of cloud-enabled Artificial Intelligence technologies to address multiple safety problems in an interoperable manner across all types of users. Cloud computing allows smaller stakeholders to share data, enhancing AI model quality and relevance. Enriched traffic data from various sources, including the private and public sectors, supports model training for real-time accident prediction. Such models can also be executed on edge devices, taking advantage of ML model compression techniques and providing collision-risk warnings to drivers ahead of a potentially dangerous situation. Using Open Travel Data standards enables higher accuracy in these applications.

With important cloud-security issues such as data sharing control and user-trust modelling considered, insufficient data quality – including completeness, accuracy, consistency, and temporal properties – remains a primary challenge. Addressing the inherent heterogeneity and potential lack of interoperability of the data is critical to improving model performance. In the absence of enough relevant data, ITS or transportation police data can be used to rebuild models. Furthermore, although AI provides tools for the assessment of dynamic data quality, promoting community or governmental initiatives for data sharing and management remains crucial.

The solutions offered by the Cloud-AI technology stack do not cover the full spectrum of modern Intelligent Transportation Systems but enable short-term sustainability. Expanding or building a Cloud-AI safety technology stack for any type of user calls for sustained investment and collaboration among national authorities, road agencies, universities, and the private sector and must address the weaknesses in the cloud-based approach. Despite their shortcomings, Cloud Computing technologies represent a unique tool for the development of Artificial Intelligence capabilities in smaller players.

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