From Data to Warnings: Challenges in Building in-Vehicle Data-Driven Hazard Warning Systems

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Abstract: Data offers a strong potential for advanced, data-driven services such as in-vehicle hazard warning systems. As data spaces and ecosystems mature, access to relevant assets for these applications will grow. This paper reviews the state of driver warning and reports on a project that developed a prototypical data-driven hazard warning system to alert drivers to potential route dangers. We present its architecture and key implementation challenges, including backend event generation, frontend warning mechanisms, data availability and integration, transformation of heterogeneous inputs into actionable warnings, definition of warning logics, handling of data validity and expiration, and human factors such as modality and user acceptance. By addressing these challenges through our prototype, the paper highlights technical and systemic requirements for dependable, data-driven warning applications in the evolving mobility data ecosystem.

1 INTRODUCTION AND MOTIVATION

The rapid digitalization of mobility and transport is generating vast amounts of data (Möller et al., 2024), now a key asset for stakeholders. This data enables new services (Zambetti et al., 2021) and business models (Stocker et al., 2024), as the automotive industry shifts from viewing vehicles as standalone products to connected ecosystem components (Nischak & Hanelt, 2019). This evolution supports data-driven, software-defined vehicles (Sterk et al., 2024; Otto et al., 2025) and services such as driver warning systems, especially when vehicle data is combined with contextual information and integrated into driver-facing systems (Kaiser et al., 2018, 2021).

Driver warning systems (Driver et al., 2021), a subclass of advanced driver assistance systems (ADAS), aim to enhance safety and situational awareness (Schömig & Metz, 2013). They include collision and lane departure warnings, blind spot detection (Kashevnik et al., 2021), drowsiness monitoring, speed and sign recognition, pedestrian and cyclist alerts, and hazard warnings.

In this paper, we focus on hazard warning systems (Xu et al., 2024; Ryder et al., 2016), a category of driver warning systems designed to alert drivers to emerging dangers based on external data and risk-relevant information. Such data may include weather conditions, accident hotspots, or signals from other vehicles (e.g., distracted drivers or stability control activation on slippery roads). We present the architectural design of our data-driven, in-vehicle hazard warning system and analyse key implementation challenges.

Despite advances in automated driving (Ebinger et al., 2024), driver warning systems remain essential (European Commission, 2025), as human drivers will continue to bear responsibility for vehicle operation (Stocker, 2025).

Our contribution offers insights into developing data-driven hazard warning systems, relevant for researchers, developers, and practitioners. The paper is structured as follows: Section 2 reviews the state of the art, Section 3 details our approach and architecture, Section 4 discusses implementation challenges, and Section 5 presents results, limitations, and an outlook for future research.

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2 RELATED WORK

2.1 Driver Warning Systems

The driver remains a central factor in road safety and a leading cause of accidents, with human errors such as speeding and risky driving (Sagberg et al., 2015; Kaiser et al., 2020), distraction (Regan et al., 2011), and misjudgement (Paker et al., 1995) contributing significantly. Driver warning systems address these risks by providing timely alerts to enhance awareness and support safer decisions.

As a subclass of driver assistance systems (Bengler et al., 2014), warning systems aim to prevent accidents by alerting rather than taking control. Examples include collision warnings (Jameson et al., 2008), lane departure warnings (Chen et al., 2020), blind spot detection (Liu et al., 2017), and drowsiness monitoring (Kashevnik et al., 2021). Other functions include speed limit and sign recognition, as well as pedestrian or cyclist alerts.

A key category is hazard warning systems (Xu et al., 2024; Ryder et al., 2016), which detect unexpected dangers like slippery roads, stationary vehicles, or accident hotspots (Ryder et al., 2016). Unlike traditional sensor-based systems, these increasingly integrate external data from vehicles, infrastructure, or cloud services, providing broader situational awareness. By combining vehicle and contextual data (Kaiser et al., 2018; Stocker et al., 2013), hazard warning systems enable earlier, proactive responses in complex traffic environments.

2.2 Factors Influencing Driving Safety

Driving safety is shaped by three categories: individual, route-related, and environmental factors. Individual factors involve the driver's state (Regan et al., 2011) and behaviour (Sagberg et al., 2015), including distraction, fatigue (Young et al., 2007), emotions, impairments (e.g., alcohol, medication), and risky driving. Route-related factors concern road characteristics (Intini et al., 2019; Bogenreif et al., 2012) such as layout, surface condition, signage, traffic density, and temporary hazards. Environmental factors include weather, lighting, visibility, other road users, and unexpected events (Maze et al., 2006; Malin et al., 2019).

Human behaviour is the dominant cause of accidents, accounting for over 70% of cases (McCarty & Kim, 2024). Risky actions such as speeding or aggressive manoeuvres directly contribute to crashes (Osafune et al., 2017), with young drivers (16–25) particularly vulnerable due to higher risk-taking (Jonah, 1986). Sagberg et al. (2015) propose a framework to better classify such driving styles.

Weather is another critical influence: snowstorms, low visibility, and wind increase accident risks (Maze et al., 2006), while rainfall and temperature also correlate with crash likelihood (Bergel-Hayat et al., 2013; Malin et al., 2019). However, some datasets suggest weather is not always significant (Theofilatos, 2017). Road geometry also matters, including curvature, lane width, shoulders, and pavement. Narrow lanes, poor surfaces, and complex layouts are linked to higher crash risk (Rengarasu et al., 2009), with curves or bends especially hazardous (Bogenreif et al., 2012; Dantas et al., 2007).

3 SYSTEM ARCHITECTURE AND APPROACH

In this section, we present the architecture of our in-vehicle, data-driven hazard warning system (Figure 1 and 2), designed to alert drivers to potential dangers. The architecture follows a generic, technology-agnostic design for broad applicability. After this overview, Section 4 discusses implementation challenges and prototype-specific design decisions.

Our driver warning system operates as follows: an in-vehicle client (edge component) computes a Geo-Spatial Key (GSK) from the vehicle's position and speed, transmitting it to the central hazard warning platform. The platform queries internal and external data sources for relevant safety events, which are then cleaned, consolidated, enriched, and sent back to the client. The client compares this data with real-time driving conditions (e.g., position, speed, heading) and, if risk is detected, triggers a warning—adaptable to driver preferences. As the vehicle reaches the boundary of a GSK, a new one is generated, and the process repeats. The following subsections describe each system component (Figure 1).

3.1 In-Vehicle Client

The in-vehicle client, such as a smartphone app or embedded infotainment application, serves as the driver's interface to the hazard warning platform. It fulfils three main roles: (1) providing the user interface for login, warning configuration, and connectivity, while delivering warnings visually, acoustically, or haptically; (2) acting as an edge-computing node that evaluates received events against real-time driving conditions to decide whether

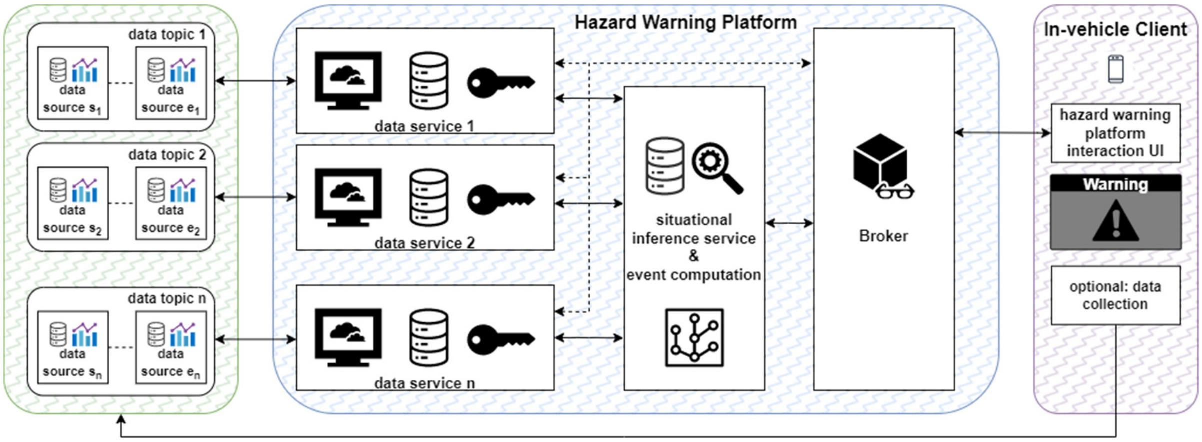

Figure 1: System Architecture.

to issue a warning; and (3) serving as a data source by sending safety-relevant events or issued warnings back to the platform, supporting the refinement of driving risk models..

3.2 Data Source and Data Topic

A data source is any device or service providing safety-relevant information, such as in-vehicle sensors, data from other vehicles, third-party weather services, or government accident statistics. Since sources often lie outside the core platform and may incur access costs, minimizing requests is essential. The platform must also remain flexible to integrate new feeds or retire obsolete ones.

A data topic, by contrast, is a logical grouping of related sources (e.g., all weather feeds). While not physical components, topics simplify management, querying, and aggregation of multiple feeds on the same subject.

3.3 Data Service

A data service encapsulates a single data topic, providing a unified interface to all its underlying sources. Each topic has exactly one data service, making it a core platform component. When queried with a Geo-Spatial Key (GSK), it returns relevant events, re-indexing incoming data and merging overlapping or redundant feeds for consistency.

The service also maintains a local cache of incoming data (e.g., weather), reducing repeated external calls, improving response times, and abstracting the complexity of heterogeneous sources. By normalizing, deduplicating, and caching feeds, it ensures higher-level components can access harmonized, up-to-date data without handling source-specific idiosyncrasies.

3.4 Situational Inference and Event Computation Service

This service is the core component, assembling and refining all relevant events for a given Geo-Spatial Key (GSK). It queries all data services to retrieve their event collections, then reconciles cross-topic conflicts to produce a unified dataset.

Expert-defined rules are applied to infer additional risk-relevant events and enrich existing ones. For instance, a sharp curve may be considered more hazardous in rain or snow, generating a composite event with a condition-specific safe speed. The service outputs a consolidated set of observed and inferred events, ready for transmission to the in-vehicle client.

3.5 Broker

The Broker acts as the communication hub between the platform and the in-vehicle clients. As a core component of the system, it manages and maintains client connections, receives Geo-Spatial Keys (GSKs) transmitted by the clients, and ensures that the corresponding sets of computed events are reliably routed back to the appropriate originating vehicles.

By handling message coordination and delivery, the broker enables timely, bidirectional communication between the edge and backend components of the hazard warning system.

4 IMPLEMENTATION CHALLENGES

4.1 Backend and Event Generation

A major implementation challenge is ensuring that all data services can process and respond to queries within a bounded, fast timeframe, allowing the system to generate timely and relevant warnings for the driver. This requires orchestrating asynchronous requests, efficient data retrieval and caching, and robust timeout mechanisms to handle slower or temporarily unavailable sources.

In our prototype, multiple independent data services run in Docker containers, including external weather data, vehicle crash and traffic data, accident hotspots, harsh braking, and road geometry. The event inference service queries these services within a defined GSK (currently 4 km²), allocating about 20 seconds per service and one second for final merging. Related events, such as curves combined with adverse weather, are merged into single, meaningful events with safe speed recommendations, improving warning coherence while reducing event volume.

Importantly, highly relevant information—like weather—must not be filtered out, as it can serve both as standalone spatial events or as context for other warnings, enabling early alerts for drivers in hazardous conditions such as snow, ice, or heavy precipitation.

4.2 Frontend and Warning Mechanism

A major implementation challenge lies in designing how data is accessed, processed, and transformed into actionable warning events that reach drivers in a timely manner. While drivers expect prompt alerts to react appropriately to potential hazards in near to real-time, the reality is that not all relevant data may be immediately available to generate such warnings. Additionally, low or unstable internet connectivity can further delay data transmission to the vehicle.

To address the challenge of timely and reliable driver warnings under variable connectivity and data availability, we implemented a two-step mechanism. Warning-relevant events are first generated on the server side using a Geo-Spatial Key (GSK), which defines a broader area of potential relevance. These events are then validated on the in-vehicle client using a driving corridor-based mechanism that focuses on the vehicle's real-time trajectory. This dual architecture is shown in figure 2 and balances data efficiency, connectivity limitations, and warning relevance.

In our prototypical implementation, the GSK is represented as a configurable square region (in our case currently a 4 km² area) surrounding the vehicle's current GPS position. The in-vehicle client sends a GSK to the server, which queries all relevant data services for potential warning events in that area. Aggregated warning events are returned and cached locally on the in-vehicle client for low-latency access.

On the client side, a dynamic driving corridor is constructed as a triangle aligned with the vehicle's position, speed, and heading. This corridor is used to filter the cached events in real time. If a relevant event falls within this corridor, and certain local conditions are fulfilled (e.g. vehicle speed is above a threshold for a particular event), a warning is issued.

To ensure uninterrupted service, the in-vehicle client proactively requests data for the next GSK region before exiting the current one, allowing seamless preloading of warning events. Key parameters - including GSK size, driving corridor geometry, and update intervals - are configurable to support different operational scenarios and allow more frequent updates in high-risk areas, such as during evolving weather conditions or traffic incidents.

4.3 Availability and Use of Data

Accessing relevant data for driver warning is challenging, and a key implementation issue is how to use limited, costly sources efficiently to generate timely, actionable warnings. Queries to third-party data, such as weather or vehicle telemetry, must be minimized to reduce cost while ensuring relevant events are delivered to the vehicle.

In our prototype, weather data is collected from 100 spatially distributed points across a defined driving region, each treated as a virtual weather station representing localized conditions including precipitation, temperature, wind, visibility, and severe weather alerts.

Vehicle telemetry is ingested in real time via a Kafka-based stream from a connected vehicle data marketplace, providing position data and risk-relevant events such as crash detections or activation of safety systems like ABS or ESP. The incoming streams are filtered and cached for rapid access by the event inference service, allowing enrichment, merging, or generation of new hazard events.

In addition, historical vehicle trip data is leveraged to generate curve information, including radius and maximum recommended safe speeds under various surface conditions. Sudden braking events are clustered to identify brake hotspots, while historical accident data is clustered to define accident hotspots. These dedicated data services, together with the curve data service, enrich the platform with both real-time and context-aware, locally derived insights, supporting more accurate and actionable hazard warnings for drivers.

4.4 Event Data Processing: Balancing Between Server and Client

Another key implementation challenge is deciding where data processing should take place—on the server or in the in-vehicle client—and how warning events should be structured and delivered. This requires careful coordination of data availability and timing to ensure the system remains performant, fault-tolerant, and capable of generating warnings even if certain data services are temporarily unavailable. Balancing the division of labor between platform and client is critical for maintaining responsiveness, reliability, and overall system robustness.

A typical scenario illustrates this approach: warning a driver approaching a curvy curve too quickly during adverse weather. The server independently queries weather and curve data, then combines them to adjust the recommended safe speeds for each curve under current conditions, such as lowering speeds due to rain. These updated curve events are sent to the in-vehicle client, which continuously monitors the vehicle's speed, position, and driving corridor. If the vehicle exceeds the safe speed for the curve and weather conditions, a warning is issued.

Decision-making is distributed across components based on data availability. The in-vehicle client has access to real-time vehicle data, enabling it to infer higher-level events, such as hazardous driving behavior, locally. Meanwhile, external data like weather, accident hotspots, or icy road conditions can be processed server-side and either merged with curve data or issued as standalone warnings. This distributed approach ensures warnings are timely, context-aware, and resilient to delays or temporary unavailability of individual data services.

4.5 Warning Logics Defined by Experts

Many types of meaningful warnings can, in principle, be generated using existing data sources—ranging from infrastructure and weather information to real-time vehicle telemetry—as well as future sources. A key challenge is translating these diverse data points into effective warnings, designing logic that converts raw data into actionable, context-aware alerts without causing overload or false alarms. This requires robust methods and algorithms capable of interpreting heterogeneous inputs and triggering clear messages that enhance driver awareness and safety.

In our prototype, we focused on relatively simple warning logics to validate core functionality. Experts initially create "warning stories," fictional but plausible hazardous events at specific locations—such as distracted drivers or high-risk intersections—which serve as a foundation for designing and testing alert logic in real-world or simulated scenarios.

For example, a warning for drivers approaching a tight curve too fast under adverse weather merges static road geometry (curve radius and location), dynamic weather data (rain or snow), and real-time vehicle speed to determine if a warning is necessary. General weather-based alerts, like icy road warnings, are implemented using geographic overlays. If historical accident data or real-time vehicle signals—such as ESP activation, distraction, or an ongoing accident—are present, the hazard level increases, but even a single additional risk signal may suffice to classify the curve as hazardous.

The central challenge is designing hazard logic flexible enough to incorporate a broad, dynamic range of input signals, both historical and real-time, without relying on a fixed rule set. At the same time, the system must generate meaningful warnings even with limited data, e.g., using only curve geometry or weather, while remaining robust against false positives. Balancing richness and robustness requires careful, data-aware design of event fusion and decision logic, supported by heuristics and expert knowledge, to weigh signals and determine urgency and warning necessity.

4.6 Data and Event Invalidation

Another key implementation challenge is the handling of data and event invalidation. Not all safety-relevant data remains valid indefinitely: Weather conditions evolve, distraction events are transient, and incidents such as accidents or roadworks have limited temporal and spatial relevance. The system must therefore continuously assess the validity period of each event and ensure that outdated or no longer applicable information is removed or updated in a timely manner to avoid misleading or unnecessary warnings.

In our current prototype, many events span the full duration of the evaluation period and are derived from

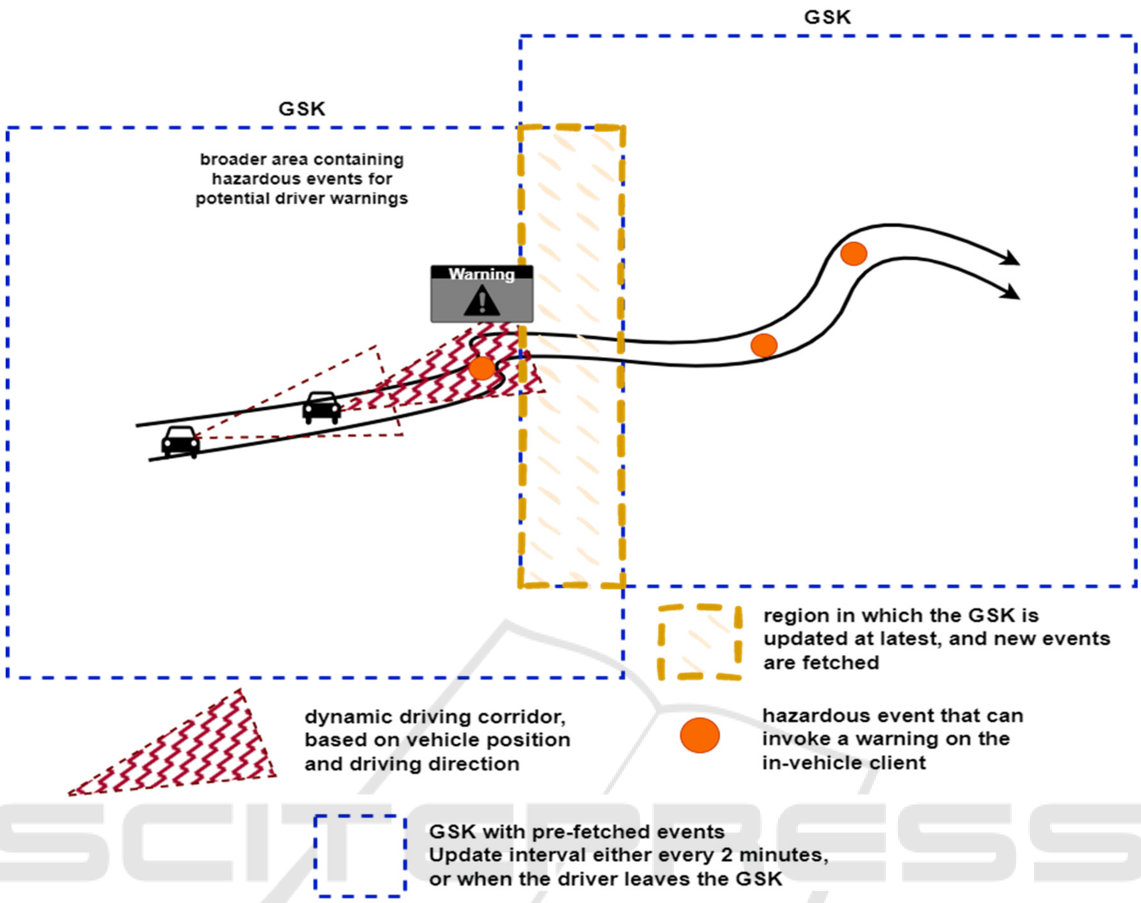

Figure 2: GSK, Driving Corridor, Hazardous events and warnings.

historical datasets, explicit deletion or expiration has not been required. However, for few dynamic data types such as weather and vehicle-related events, we have implemented basic invalidation strategies. Weather data is refreshed hourly, while vehicle-related events are streamed continuously. Events from the vehicle stream are cached in a database for the data service and invalidated after a maximum of two hours, ensuring that only recent, potentially relevant incidents are retained for warning evaluation.

4.7 Human Factor: Vehicle Integration and Warning Modality

As the platform scales, handling more data sources or time-sensitive use cases like real-time driver distraction detection, effective data and event invalidation becomes crucial. One approach is to timestamp each event and assign a type-specific validity period after which it's excluded from processing. While simple in concept, choosing appropriate expiration intervals is challenging. For instance, a distraction alert may be valid for seconds, weather data for up to an hour, while events like road construction lack predictable durations, requiring adaptive or manual invalidation strategies.

Another key implementation challenge is how to integrate the warning mechanism into the vehicle in a way that does not distract the driver. The system must alert drivers to hazards while minimizing cognitive load and avoiding any increase in distraction.

This implementation challenge involves deciding whether to use a mounted smartphone or integrate the system into the in-vehicle infotainment system, as well as determining the most effective modality for delivering warnings, visual, acoustic, haptic, or a combination. The challenge lies in striking a balance between providing timely and relevant information and ensuring the warning mechanism remains subtle and non-intrusive, so that it genuinely improves safety rather than undermines it.

For simplicity, our prototype uses a smartphone as the in-vehicle client, displaying visual warnings via an on-screen triangle and brief message. We also explored integration as an Android Automotive OS

(AAOS) app to show alerts within the infotainment system. To reduce distraction, we considered alternative modalities like ambient lighting, haptic feedback (e.g., steering wheel vibrations), or audio cues, leveraging in-vehicle actuators for more intuitive driver alerts.

5 DISCUSSION & CONCLUSION

We introduced hazard warning as a category of driver warning systems, presented our architectural and procedural approach, and discussed the implementation challenges and solutions in our prototypical system. We acknowledge several limitations: the system is a prototype and not a fully operational solution with guaranteed availability or formal service-level agreements.

Our prototype is tailored for rural areas and not yet optimized for urban settings, where limited positioning precision and overlapping events near intersections or roundabouts make hazard detection more challenging. Highways and urban roads also require wider driving corridors for timely warnings at higher speeds, increasing the risk of false positives. Connectivity gaps, such as long tunnels or areas with poor internet, can cause update failures. Large update areas (GSKs) add computational overhead, increase data transfer, and lengthen update intervals, reducing the accuracy and timeliness of soft real-time warnings. The system is intended as a driver-assistance or comfort feature rather than a safety-critical component. Barriers to large-scale deployment include high costs of accessing and licensing diverse data sources, which require continuous streaming and high-volume API requests for many connected vehicles. Privacy is also a key concern (Lechte et al., 2023): the in-vehicle client transmits only a generalized Geo-Spatial Key (GSK), with no speed or direction data sent to the backend. GSKs are cached temporarily and processed locally, and all speed and direction computations occur within the vehicle. This privacy-by-design approach minimizes transmitted PII and ensures sensitive data remains within the vehicle.

In conclusion, we presented the architecture and workflow of a data-driven, in-vehicle hazard warning system. Our prototype highlighted key challenges, including data acquisition, integration, real-time processing, warning logic, and client-side evaluation. These insights guide researchers and offer practical value for automotive OEMs and Tier-1 suppliers. Unlike commercial solutions focused on static events, our approach demonstrates how dynamic, situationally enriched warnings can better enhance driver awareness and road safety.

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