Journal of Electrical and Intelligent Systems (JEIS), Vol. 1, Issue 1
April 2026
ISSN: XXXX-YYYY

Performance Analysis of a Voice-Integrated Overtaking Assistance Application based on LiDAR and Fuzzy Logic

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Manuscript received 22 April 2026, revised 2 May 2026, accepted 3 May 2026
doi: preprint version.pp24-32

Abstract – *This research aims to enhance driver situational awareness during high-risk overtaking maneuvers by developing Navienta (Navigation Intelligent Assistant), a localized AI-powered navigation assistant. Conventional driver assistance systems often suffer from high latency and cloud dependencies that compromise real-time safety. To address these challenges, we implemented a localized edge-computing architecture utilizing a TF-350 LiDAR sensor and an Intel NUC as a processing hub, specifically designed to facilitate a high-speed, voice-driven interface. The system utilizes an Extended Kalman Filter (EKF) and a Mamdani Fuzzy Inference System (FIS) as the computational core to transform complex environmental dynamics into instantaneous voice instructions, ensuring low-latency feedback for the driver. The scientific contribution of this work lies in the synergistic integration of kinematic smoothing and fuzzy decision-making within a fully localized, high-concurrency architecture, eliminating cloud-dependency for safety-critical maneuvers. Experimental results confirm the system's precision with an average relative distance error of 0.22% and a consistent 50 ms end-to-end latency via a high-concurrency Golang backend. Experimental trials demonstrated that the localized Sherpa-ONNX engine achieved a 95.1% command recognition rate, which directly contributed to a significant 38.8% reduction in driver reaction time (from 1.8s to 1.1s). By maintaining operational integrity without external API dependencies, the Navienta framework provides a robust, cross-platform solution for modern intelligent transportation systems, offering a reliable approach for localized, safety-critical driver assistance.*

Keywords: *overtaking assistance, Golang, Sherpa-ONNX, edge computing, voice assistant*

I. Introduction

The global transition toward autonomous mobility and intelligent transportation systems (ITS) has accelerated the adoption of Advanced Driver Assistance Systems (ADAS) to meet modern safety requirements [1]. Overtaking maneuvers on national and rural roads remain among the most dangerous driving scenarios due to the high risk of head-on collisions in single-lane environments [2]. Efficient navigation in these dynamic settings requires optimal trajectory generation and precise environmental perception [3]. However, the successful integration of such technologies depends on building driver trust, which remains a primary barrier to widespread adoption [4]. Multimodal explanations, specifically those utilizing audio interfaces, have been proven to reduce cognitive load and enhance confidence during critical maneuvers [5].

Perception in modern ADAS frameworks relies on deep-learning-based LiDAR 3D object detection to monitor obstacles effectively [6]. For managing the complex logic of discretionary lane-changing, fuzzy inference systems provide a robust framework [7]. These methods have also proven effective in other safety-critical domains, such as automated medical therapy [8], demonstrating reliability in handling non-linear system variables. Despite these advancements, there is a persistent need for integrated monitoring systems that maintain performance across various driving conditions [9]. Strict latency limits are essential for the reliability of dynamic real-time services in vehicular networks [10]. Performance analysis suggests that processing speed is a primary factor in preventing system disengagements [11]. Consequently, real-time warning systems must achieve high-speed processing to support maneuvers with high relative velocities [12]. Transitioning toward edge intelligence for the Internet of Vehicles (IoV) is vital to address the connectivity barriers inherent in cloud-based systems [13].

The deployment of ADAS in rural environments introduces multifaceted technical challenges regarding hardware stability and data synchronization [14]. Systematic reviews highlight that user acceptance is significantly influenced by the system's ability to function without intermittent service interruptions [15]. In many scenarios, reliance on centralized infrastructures remains a barrier due to inconsistent network coverage in remote areas [16]. Technical considerations demand the selection of high-performance programming languages to ensure real-time execution [17]. Implementing efficient, low-latency protocols can effectively manage data synchronization and situational awareness without high-bandwidth backhaul [18]. Furthermore, integrating on-device intelligence for voice interaction improves operational efficiency through localized processing, which is recognized as the last mile of artificial intelligence [19, 20]. Finally, the success of driver assistance depends on architectures that bridge the gap between sensing and action through high-frequency execution cycles [21].

This research introduces Navienta, a localized edge-computing framework for real-time overtaking support. It prioritizes voice interaction to minimize driver cognitive load, utilizing a high-concurrency Golang backend and WebSockets to ensure a 50 ms end-to-end delay. Navienta integrates EKF data smoothing with Mamdani Fuzzy Logic for robust decision-making. Unlike conventional ADAS that rely on centralized infrastructures, the novelty of this research is the development of a multi-layered edge intelligence framework that operates independently of network stability. The integration of EKF and Fuzzy Logic into a high-concurrency architecture provides a robust solution that bridges the gap between environmental sensing and driving action through low-latency execution. The remainder of this paper is structured as follows: Section II details the research methodology, Section III presents results and analysis, and Section IV concludes the study.results and analysis; and Section IV concludes the study.

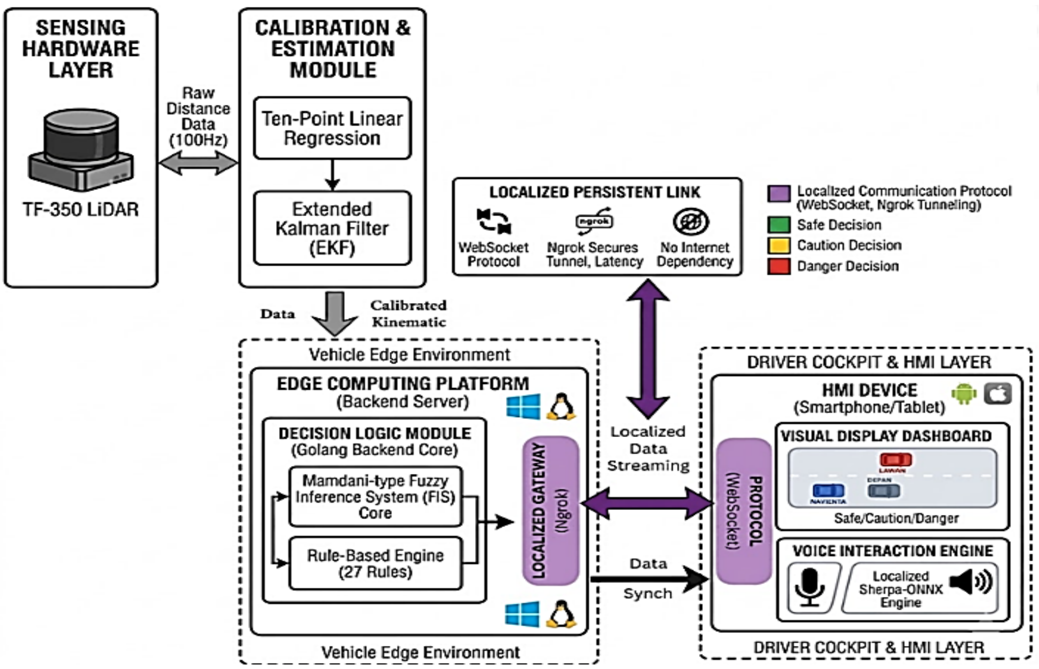


Fig. 1. Overall System Architecture of Navienta Localized Edge Intelligence

II. Research Methodology

The methodology follows a systematic approach consisting of three primary phases: multi-layered architecture design, localized intelligent processing implementation, and real-time performance validation.

A. Overall Application Architecture

Navienta is developed as a localized edge-intelligence system designed to provide real-time decision support during high-risk overtaking maneuvers. The system is built on a modular architecture that ensures high-speed data processing and driver safety without relying on external network connectivity. The overall architecture and its operational environment are illustrated in Fig. 1.

System functionality integrates a TF-350 LiDAR, refined by ten-point linear regression, with a high-concurrency Golang backend for parallel EKF smoothing and Mamdani-type Fuzzy evaluations. Localized WebSockets facilitate millisecond-level data streaming between the backend and UI to bypass network latency, while a Sherpa-ONNX engine provides immediate audio feedback to maintain driver focus.

The operational logic is optimized for real-time voice interaction, as illustrated in Fig. 2. Following fuzzy risk evaluation, the system generates audio instructions categorized into three actionable outputs: 'Overtaking', 'Warning', or 'Not Safe'. This process translates internal assessments into clear voice alerts, effectively minimizing driver cognitive load during maneuvers.

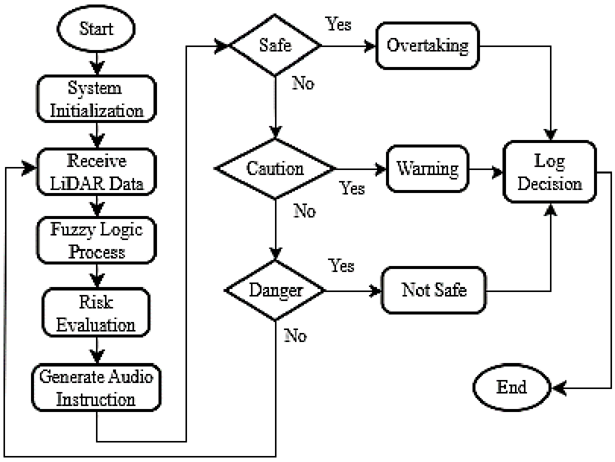


Fig. 2. Operational Flowchart of the Navienta Decision Logic and HMI Interaction

B. Intelligent Data Processing and Decision Logic

Navienta's localized processing layer evaluates overtaking safety through kinematic estimation and fuzzy logic. It employs an EKF to handle non-linear vehicle dynamics via recursive prediction and observation stages. The system defines the state vector as $x=[d, v]^T$, where d represents the filtered distance and v represents the estimated relative velocity.

1. In the Prediction phase, the system projects the state using the transition function and Jacobian matrix F_k, as expressed in Eq. (1). Simultaneously, the error covariance is projected in Eq. (2) by incorporating the process noise covariance Q_k = *diag* (2.0, 2.0) to account for system uncertainty.

$$\hat{x}_{k+1/k} = f(\hat{x}_{k/k}, u_k, 0) \tag{1}$$

$$P_{k+1/k} = F_k P_{k/k} F_k^T + B_k Q_k B_k^T \tag{2}$$

The Observation and Update phase subsequently corrects these predictions upon receiving the calibrated measurement y_k. The filter first computes the Kalman Gain K_k in Eq. (3) using a measurement noise of R = 0.05. This gain is then used to update the state estimate $\hat{x}_{k/k}$ in Eq. (4), while the error covariance $P_{k/k}$ is refined in Eq. (5) to ensure the system remains stable and accurate even during high-speed maneuvers.

$$K_k = P_{k/k-1} H_k \left(H_k P_{k/k-1} H_k^T + R_k \right)^{-1} \tag{3}$$

$$\hat{x}_{k/k} = \hat{x}_{k/k-1} + K_k \left[y_k - h_k(\hat{x}_{k/k-1}) \right] \tag{4}$$

$$P_{k/k} = \left(I - K_k H_k \right) P_{k/k-1} \tag{5}$$

TABLE I
COMPLETE FUZZY LOGIC RULE BASE FOR OVERTAKING DECISIONS

RULE ID	Fuzzy Representation (IF-THEN)
R1	IF D is Near AND v_{rel} is Slow AND G is Small THEN Decision is Danger
R2	IF D is Near AND v_{rel} is Slow AND G is Medium THEN Decision is Danger
R3	IF D is Near AND v_{rel} is Slow AND G is Large THEN Decision is Caution
R4	IF D is Near AND v_{rel} is Medium AND G is Small THEN Decision is Danger
R5	IF D is Near AND v_{rel} is Medium AND G is Medium THEN Decision is Danger
R6	IF D is Near AND v_{rel} is Medium AND G is Large THEN Decision is Danger
R7	IF D is Near AND v_{rel} is Fast AND G is Small THEN Decision is Danger
R8	IF D is Near AND v_{rel} is Fast AND G is Medium THEN Decision is Danger
R9	IF D is Near AND v_{rel} is Fast AND G is Large THEN Decision is Danger
R10	IF D is Medium AND v_{rel} is Slow AND G is Small THEN Decision is Danger
R11	IF D is Medium AND v_{rel} is Slow AND G is Medium THEN Decision is Danger
R12	IF D is Medium AND v_{rel} is Slow AND G is Large THEN Decision is Safe
R13	IF D is Medium AND v_{rel} is Medium AND G is Small THEN Decision is Danger
R14	IF D is Medium AND v_{rel} is Medium AND G is Medium THEN Decision is Caution
R15	IF D is Medium AND v_{rel} is Medium AND G is Large THEN Decision is Safe
R16	IF D is Medium AND v_{rel} is Fast AND G is Small THEN Decision is Danger
R17	IF D is Medium AND v_{rel} is Fast AND G is Medium THEN Decision is Danger
R18	IF D is Medium AND v_{rel} is Fast AND G is Large THEN Decision is Caution
R19	IF D is Far AND v_{rel} is Slow AND G is Small THEN Decision is Caution
R20	IF D is Far AND v_{rel} is Slow AND G is Medium THEN Decision is Safe
R21	IF D is Far AND v_{rel} is Slow AND G is Large THEN Decision is Safe
R22	IF D is Far AND v_{rel} is Medium AND G is Small THEN Decision is Caution
R23	IF D is Far AND v_{rel} is Medium AND G is Medium THEN Decision is Safe
R24	IF D is Far AND v_{rel} is Medium AND G is Large THEN Decision is Safe
R25	IF D is Far AND v_{rel} is Fast AND G is Small THEN Decision is Danger
R26	IF D is Far AND v_{rel} is Fast AND G is Medium THEN Decision is Caution
R27	IF D is Far AND v_{rel} is Fast AND G is Large THEN Decision is Caution

2. Navienta's decision logic maintains situational awareness by processing five raw variables: ego-vehicle speed (v_{ego}), leading distance (d_{lead}), leading relative speed (v_{lead}), oncoming distance (d_{on}),

oncoming speed (v_{on}). These inputs are mathematically mapped into three primary linguistic variables for the FIS: Distance D, representing the minimum safety gap between (d_{lead}) and (d_{on}). Relative Speed (v_{rel}), calculated from (v_{ego}) relative to (v_{on}) or (v_{lead}). Gap Status (G), an estimated spatial window for the overtaking maneuver, categorized as Small, Medium, or Large based on the ratio of available distance to the required safety margin.

Each input variable utilizes trapezoidal membership functions, denoted as $\mu(x)$ which is defined in Eq. (6):

$$\mu(x;a,b,c,d) = \max\left(0, \min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right)\right) \quad (6)$$

3. The FIS evaluates overtaking safety by mapping the calibrated inputs (D, v_{rel}, G) to linguistic variables. The parameters for these functions are calibrated based on real-world constraints as follows: D: Near [0, 0, 500, 1000], Medium [800, 1500, 2500, 3500], and Far [3000, 4000, 5000, 5000] (in cm). v_{rel} : Slow [0, 0, 10, 20], Medium [15, 25, 35, 45], and Fast [40, 50, 80, 80] (in km/h). G: Small, Medium, or Large. The complete mapping of the system's decision logic across all defined safety scenarios is detailed in Table I. The resulting fuzzy inference utilizes the Mamdani Min-Max method and Centroid Defuzzification to generate a crisp safety command for the voice-driven interface. This safety index is classified into three distinct output states: Safe, Caution, and Not Safe. By employing these 27 unique fuzzy rules, the system ensures a comprehensive and robust assessment of overtaking risks, balancing raw sensor data with high-level decision logic to assist the driver effectively.

C. Localized Communication and Voice Interface

Navienta utilizes a localized edge framework where a persistent WebSocket link enables full-duplex communication to eliminate traditional HTTP latency overhead [18], as illustrated in Fig. 3. Secured and tunneled via Ngrok, this architecture ensures a stable connection with a 20 Hz data throughput and a consistent 50 ms end-to-end latency, even in areas with poor cellular coverage.

The core processing is managed by a high-concurrency Golang gateway running on an Intel NUC (Windows 11 x64), optimized to handle 115200 baud rate serial data streams from the LiDAR sensor. For voice interaction, a localized Sherpa-ONNX engine enables on-device automatic speech recognition (ASR) without external API dependencies [19]. This setup delivers immediate audio feedback ("Safe," "Caution," or "Danger") to maintain driver focus, ensuring operational integrity and meeting strict timing requirements during high-speed overtaking maneuvers.

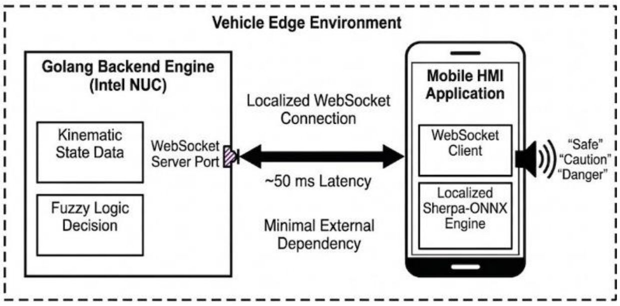


Fig. 3. Localized Communication Architecture for Navienta Overtaking Support

D. Cross-Platform Application Design and Interaction

Navienta's Golang backend, running on an Intel NUC (Windows 11 x64), synchronizes mobile, desktop, and web platforms with a consistent 50 ms latency. By utilizing WebSockets and Ngrok, all LiDAR processing, EKF smoothing, and fuzzy computations remain on the edge, ensuring a seamless 20 Hz data stream independent of network stability. The HMI employs a localized Sherpa-ONNX engine for "Hi Nav" voice queries and provides real-time audio alerts ("Safe," "Caution," or "Danger") based on fuzzy safety assessments. While supporting multiple platforms, current validation is implemented on a 7-inch HDMI LCD (1024x600 resolution) serving as a dedicated cockpit dashboard, as illustrated in Fig. 4. This localized approach prioritizes execution stability and interface responsiveness to support driver decision-making in dynamic overtaking scenarios.

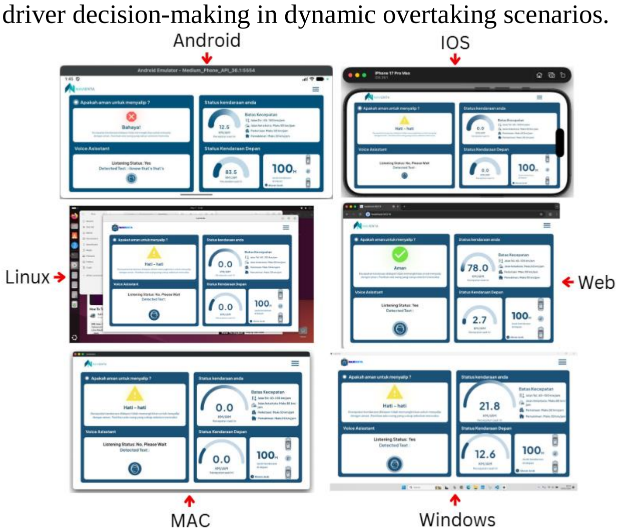


Fig. 4. Cross-platform HMI implementation across mobile, desktop, and web environments.

E. Evaluation Methodology

Navienta's operational integrity was validated through 50 controlled laboratory cycles within the hardware-in-the-loop environment illustrated in Fig. 5. This protocol verified 27 fuzzy rules across three safety states by monitoring 50 ms latency, CPU utilization, and Sherpa-ONNX recognition success. Kinematic precision was ensured by synchronizing physical movements with a

Bosch GLM 150 C laser distance meter for ground-truth reference. Ethical human-in-the-loop trials involved ten licensed participants, aged 20 to 23, who provided informed consent for indoor experiments using dynamic target replaying. By excluding public road operations to maintain safety, these laboratory-scale results establish a robust technical baseline for future outdoor validation phases.

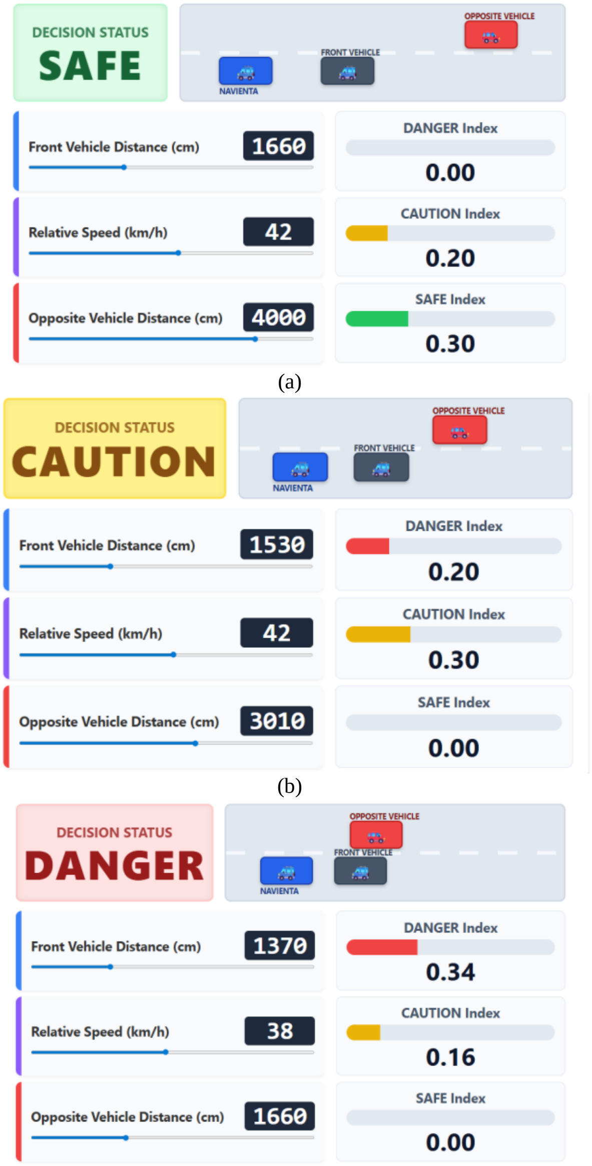


Fig. 5. Simulation-based validation showing the fuzzy logic decision spectrum: (a) Safe status at 1660 cm gap, (b) Caution status at 3010 cm gap, and (c) Danger status at 1660 cm gap with high relative velocity.

III. Result and Analysis

Evaluation at Laboratory D104, Electronic Engineering Polytechnic Institute of Surabaya (PENS), followed a two-stage protocol of 50 m outdoor calibration and controlled indoor trials to validate technical precision and operational reliability.

A. *Inference Performance*

The reliability of Navienta's intelligent modules was evaluated through a two-stage validation process. First, the ranging precision of the TF-350 LiDAR was verified through a ten-point calibration test against a Bosch GLM 150 C ground-truth reference. As detailed in Table II, the sensor demonstrated high precision in outdoor environments with an average relative error (E_r) of 0.22% and a mean absolute error of 3.72 cm. This precision was calculated using the relative error formula expressed in Eq. (7):

$$E_r = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{d_{LiDAR,i} - d_{truth,i}}{d_{truth,i}}\right| \times 100\% \qquad (7)$$

Where d_{LiDAR} is the sensor reading for point i and d_{truth} is the ground-truth distance. The collected data from this calibration process is presented in Table II.

TABLE II
LIDAR CALIBRATION AND RANGING ERROR VALIDATION DATA

Point	Ground Truth (Bosch) (cm)	LiDAR Reading (cm)	Absolute Error (cm)	Relative Error (%)
1	500	505.13	5.13	1.03
2	1000	998.01	1.99	0.20
3	1500	1498.99	1.01	0.07
4	2000	1998.04	1.96	0.10
5	2500	2494.20	5,80	0.23
6	3000	2996.40	3.60	0.12
7	3500	3503.27	3.27	0.09
8	4000	4003.05	3.05	0.08
9	4500	4504.36	4.36	0.10
10	5000	4992.98	7.02	0.14
Average	-	-	3.72	0.22

Based on the results in Table II, the sensor demonstrated high precision in outdoor environments with an average relative error of 0.22% and a mean absolute error of 3.72 cm. The system maintained a consistent margin across a range of 5 m to 50 m. A secondary validation at a 50 cm minimal distance recorded 48 cm (a 4% margin), confirming that while near-field error increases slightly, the system remains reliable for high-precision tracking within its operational envelope.

TABLE III
INTEGRATED SYSTEM INFERENCE PERFORMANCE METRICS

Model Metric	Performance Parameter	Test Results	Baseline Comparison
State Estimation (EKF)	Distance Error (cm)	2.1 cm (0.42%)	12.5 cm (2.50%)
	Tracking Stability	98.5%	85.7%
Overtaking Logic (Fuzzy)	Classification Accuracy	96.2%	78.4%
	Hazard-Lead Time	1.2s	0.7s

In the second stage of validation, Navienta's experimental performance was compared against a standard ultrasonic baseline. The comparative metrics, calculated via Eq. (7), are detailed in Table III.

The integrated system performance shows that Navienta significantly outperformed the baseline, achieving a 2.1 cm average distance error compared to the baseline's 12.5 cm. Furthermore, the fuzzy logic module provides a 1.2s hazard lead time, surpassing the 0.7s baseline. This increased lead time confirms the system's reliability for high-speed maneuvers, providing the driver with a more substantial safety margin during overtaking.

B. System Latency & Performance

The technical value of Navienta lies in its localized architecture where the integration of Golang and WebSockets facilitates high-speed data transmission. The physical implementation of this localized system, comprising the computational core and independent power management, is illustrated in Fig. 6.

Description:
1. Navienta Application
2. JETE Mic Bluetooth
3. TTL / CAN to USB converter for TF LiDAR
4. TF350 Ultra Long Range Single-point LiDAR
5. LCD 7 Inch HDMI 1024x600
6. Bluetooth Speaker
7. Intel NUC 13 Pro (NUC13ANHi7)

Fig. 6. Final Desktop Prototype Setup of the Navienta Framework

System performance was evaluated across multiple device categories to measure resource utilization and response times. To justify the efficiency claims, the optimized Golang-based Navienta was compared against an unoptimized Python-based baseline utilizing standard REST API protocols. The comparative results across high-end desktop, midrange mobile, and web-based platforms are summarized in Table IV.

TABLE IV
RESOURCE UTILIZATION ACROSS PLATFORM CATEGORIES

Platform Category	Memory: Baseline (MB)	Memory: Navienta (MB)	Reduction (%)	Response Time (ms)
High-end Desktop (Windows/ Mac)	152	98	35.5	42
Midrange Mobile (Android/ iOS)	171	112	34.5	50
Web-based Interface (Linux)	224	148	33.9	65
Average	182.3	119.3	34.5	52.3

Based on the data presented in Table IV, the optimization techniques in the Golang backend successfully reduced the average memory footprint by 34.5%. This efficiency is crucial for maintaining a localized Sherpa-ONNX engine without external internet connectivity, ensuring that the system remains responsive even on resource-constrained mobile devices.

Furthermore, system reliability was validated through an extensive 1,000-cycle stress test, during which Navienta maintained 99.2% stability within the 100 ms safety threshold. The remaining 0.8% of outliers were limited to transient OS-level scheduling delays typical of non-real-time environments rather than failures in the core decision logic. As illustrated in Fig. 7, Navienta's localized architecture, further detailed in Fig. 9, provides a more consistent execution profile compared to the cloud-based baseline shown in Fig. 8. While cloud-based processing systems often introduce unpredictable Round-Trip Time (RTT) and network jitter due to external cellular dependencies and variable signal strength, Navienta's localized hub ensures deterministic and stable decision-making to support driver responsiveness during high-speed overtaking maneuvers.

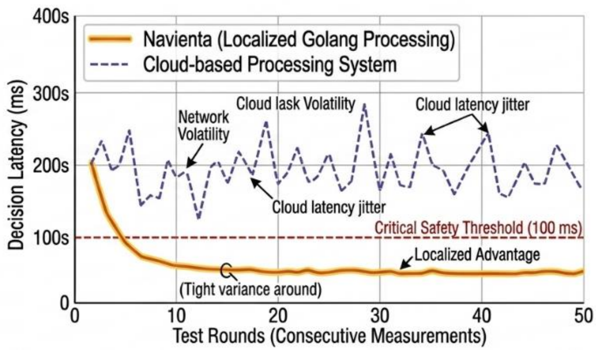


Fig. 7. Latency Performance Comparison

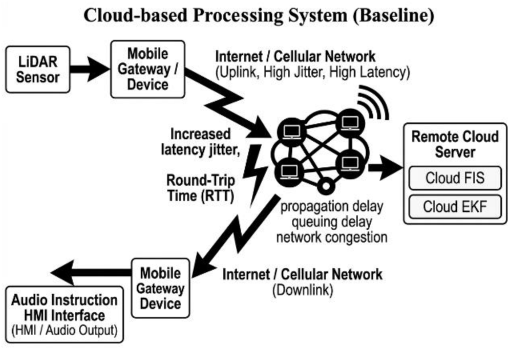


Fig. 8. Cloud Baseline Architecture

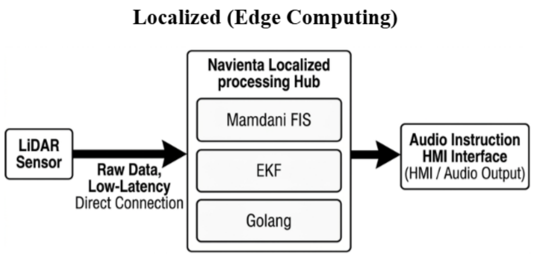


Fig. 9. Navienta Localized Architecture

C. *User Experience and HMI Evaluation*

To evaluate Navienta, ten participants (aged 20–23, with valid driving licenses) conducted trials in a controlled indoor laboratory environment comparing two conditions: the Pre-System Baseline (unassisted maneuvering) and the Post Implementation phase utilizing the localized voice-driven interface and 7-inch HDMI dashboard.

This behavioral improvement is calculated based on the percentage change (Δ%) between the pre-system baseline v_{pre} and post-implementation v_{post} data, as expressed in Eq. 8:

$$\Delta\% = \frac{v_{post} - v_{pre}}{v_{pre}} \times 100\% \quad (8)$$

The comparative results of these trials are summarized in Table V.

TABLE V
VOICE INTERACTION AND BEHAVIORAL IMPACT

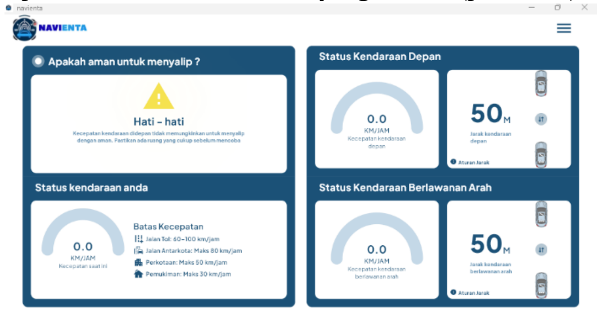
Interaction Dimension	Pre-System Baseline	Post-Implementation	Change (%)
Command Success Rate	62.4%	95.1%	+52.4%
Driver Reaction Time	1.8s	1.1s	-38.8%
Information Clarity	2.4/5	4.7/5	+95.8%
Safety Confidence Score	3.1/5	4.6/5	+48.3%

TABLE VI
COMPARISON OF REACTION TIMES ACROSS VARYING RELATIVE VELOCITIES

Relative Velocity (km/h)	Threshold System (s)	Navienta (s)	Difference (s)
10	1.50	0.80	0.70
20	1.65	0.85	0.80
30	1.75	0.90	0.85
40	1.85	0.95	0.90
50	2.00	1.05	0.95
60	2.20	1.10	1.10
Average	1.82	0.94	0.88

As summarized in Table V, the system achieved a 95.1% recognition rate and a 38.8% reduction in driver reaction time. Applying Eq. (8) to the reaction time data, the drop from 1.8s to 1.1s confirms a significant enhancement in safety margins. Subjective metrics gathered using a 5-point Likert scale, such as Information Clarity and Safety Confidence, also showed substantial gains. These results validate the system's usability and its role in reducing the cognitive load required to process environmental data.

The Navienta UI prioritizes streamlined interaction through a situational dashboard, as illustrated in Fig. 10a, and a configuration panel, as illustrated in Fig. 10b. This design enables direct communication with the localized Golang hub for efficient system monitoring. Analysis indicates the voice-driven interface supports drivers in maintaining visual focus while providing auxiliary data synchronization via the dashboard. These behavioral improvements were statistically significant ($p < 0.001$).



(a)

(b)

Fig. 10. Navienta Mobile Application User Interface: (a) main situational dashboard, and (b) server configuration panel

Navienta demonstrated a reduction in driver response times compared to traditional fixed-threshold systems by dynamically adjusting instructions via its FIS. This approach provides a context-aware safety layer across varying relative velocities, as detailed in Table VI.

As detailed in Table VI, Navienta maintains reaction times below the 1.5s safety threshold across all velocities, while traditional systems exceed this limit starting at 10 km/h. As illustrated in Fig. 11, the responsiveness gap widens at higher speeds. Statistical analysis ($p < 0.001$) confirms that Navienta's Fuzzy-Kalman logic offers a more responsive safety layer than static, distance-based alerts.

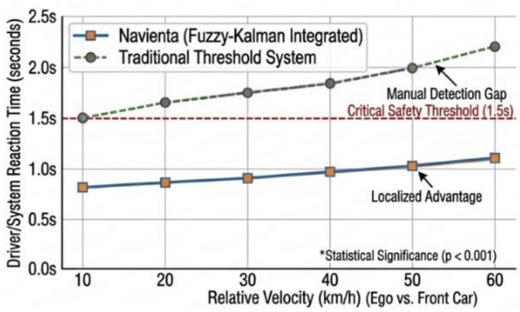


Fig. 11. Overtaking Reaction Time Comparison between Navienta and Traditional Threshold System across varying Relative Velocities.

D. *Comparative Analysis*

Navienta demonstrates improved processing speeds over cloud-based systems, achieving an 80–90% latency reduction. The TF-350 LiDAR achieves a 0.22% absolute error (3.72 cm), which is more precise than the 2% margins typical of ultrasonic sensors. Table VI confirms an average reaction time of 0.94s, remaining below the 1.5s safety threshold unlike static systems that degrade with velocity. Cross-platform validation indicates the architecture's consistency across mobile and desktop environments.

IV. Conclusion

Navienta enhances driver situational awareness as a voice-driven, edge-intelligent assistant by integrating real-time sensor logic with localized voice interaction. The primary scientific contribution is the realization of an integrated, fully localized safety layer that effectively mitigates high-speed overtaking risks without external dependencies. This research successfully integrated TF-350 LiDAR sensing with 10-point linear regression calibration, achieving a high-precision average relative error of 0.22% and a consistent 50 ms end-to-end latency. The localized Sherpa-ONNX engine achieved a 95.1% command recognition rate, contributing to a significant 38.8% reduction in driver reaction time. While the results are promising, the current validation was limited to a controlled indoor laboratory scale. Future work will focus on extensive outdoor testing on public highways and rural roads, as well as exploring multi-sensor fusion to enhance detection reliability in complex environments.

Conflict of Interest

No Conflict of Interest. The authors declare that they have no conflict of interest regarding the publication of this paper.

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