Secure Fog-Edge and 5G-Enabled Architecture for AI-Driven Mobility, Real-Time Traffic Analytics, and Accessibility in Aging-Focused Intelligent Transportation Systems

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***Abstract*—With the global population aged 65 and older expected to double by 2050, ensuring equitable access to safe, efficient, and responsive transportation systems has become a pressing societal imperative. This paper introduces a secure fog-edge and 5G-enabled architecture designed to enhance the safety and accessibility of aging populations within next-generation Intelligent Transportation Systems (ITS). The proposed framework integrates AI-powered elderly vehicle monitoring for proactive risk detection, real-time traffic analytics through decentralized edge-fog computing, and adaptive intelligent traffic lights that respond dynamically to the mobility needs of older drivers and pedestrians.**

Leveraging decentralized edge intelligence, blockchain-enhanced privacy safeguards, wearable health-monitoring integration, and AI-driven analytics, the system provides ultra-low-latency, resilient, and adaptive mobility services. The architecture emphasizes latency mitigation, human-centered interface design, dynamic risk evaluation, and policy-aligned cybersecurity strategies. Analytical comparisons demonstrate that local data processing combined with predictive threat modeling can substantially reduce transportation-related health risks, improve decision-making efficiency, and foster inclusive urban mobility. A novel architectural model is presented to inform the design of secure, accessible, and aging-centric ITS infrastructures.

***Index Terms*—Edgecomputing, 5G, Mobility, Cybersecurity, Accessibility, Transportation**

I. Introduction

The advent of Vehicle-to-Everything (V2X) communication—enabling bidirectional data exchange between vehicles, infrastructure, pedestrians, and cloud services—has catalyzed the transformation of Intelligent Transportation Systems (ITS) from isolated mechanisms into cooperative, dynamic ecosystems. Over the past decade, vehicles have evolved into sophisticated "rolling sensor hubs," equipped with over 200 onboard sensors capable of real-time diagnostics and environmental perception [1]. This technological leap, coupled with rapid advances in Internet of Things (IoT) ecosystems, has driven the global connected vehicle fleet past 400 million units by 2025, cementing connected mobility as a pillar of smart city initiatives [2].

Parallel growth in ITS research reflects this momentum. Bibliometric analyses reveal a 440% surge in ITS publications between 2015 and 2024, fueled by innovations in predictive traffic modeling, edge AI integration, and resilient vehicular networks [3]. Similarly, a systematic review of 447 big data-driven ITS studies (2014-2023) described the expansion of the field as 'exponential', highlighting innovations in predictive traffic modeling and edge AI integration [4]. Practical deployments further affirm this trend: South Korea's Daejeon-Sejong Cooperative ITS (C-ITS) corridor, involving nearly 1,000 connected vehicles, achieved a 10% reduction in hard-braking incidents within six months [5], while Europe's C-Roads platform expanded operational C-ITS services across 50 cities in 18 EU member states [6].

Despite these advancements, transportation systems face a persistent public health challenge. Road traffic injuries account for over 1,800 annual fatalities and approximately 10,000 serious injuries in national cohorts, a burden disproportionately impacting aging populations [7]. Older adults exhibit heightened vulnerabilities due to cognitive slowing, diminished motor responsiveness, and sensory processing delays—estimated at 2 to 6 milliseconds per decade [8]. In Ontario, for instance, drivers over the age of 80 continue to report the highest injury and fatality rates per capita, highlighting the urgent need for age-responsive ITS designs [9].

This demographic imperative is magnified by projections indicating that by 2050, 16% of the world's population—approximately 1.6 billion individuals—will be aged 65 and older [10]. Conventional ITS models, primarily optimized for younger and more agile demographics, are ill-suited to meet the complex accessibility and safety demands of aging populations.

To address these challenges, this paper proposes a Secure Fog-Edge and 5G-Enabled Intelligent Architecture for AI-Driven Mobility, Real-Time Traffic Analytics, and Accessibility in Aging-Focused Transportation Systems. The framework integrates three core components: (1) AI-powered elderly vehicle monitoring for proactive risk detection, (2) edge-fog computing to support real-time, low-latency traffic analytics, and (3) adaptive intelligent traffic lights that dynamically prioritize the mobility needs of older drivers and pedestrians. This architecture not only aims to reduce collision risks through real-time behavioral monitoring and adaptive infrastructure interventions but also ensures equitable access to urban transportation systems by embedding human-centered, aging-sensitive design principles. Ultimately, the proposed model aligns with emerging global initiatives advocating for aging-friendly smart cities, while positioning ITS infrastructures as enablers of secure, inclusive, and resilient mobility ecosystems.

II. Related Work

Recent advancements at the intersection of Intelligent Transportation Systems (ITS), edge computing, and aging mobility have aimed to create more inclusive and responsive urban environments. Early ITS initiatives like the U.S. Connected Vehicle Pilot Program [11] and Europe's C-Roads platform [6] improved traffic safety and efficiency through V2V and V2I communications but lacked adaptations for aging populations. Edge and fog computing have emerged as key enablers of real-time responsiveness by shifting processing to roadside and vehicle-mounted systems. Notable implementations include Chavhan et al.'s edge-enabled RSUs with multi-agent systems for local traffic optimization [12], and fog-based architectures by Peyman et al. [13] and Reddy et al. [14], which significantly reduced latency and energy use (see Fig. 1).

Building on this, Souki et al. [15] proposed the ITS-CEoT architecture, which integrates cloud and edge computing with Monitoring and Analysis as a Service (MAaaS) to deliver context-aware, low-latency feedback (see Fig. 2). Despite these innovations, current systems often overlook the unique risks faced by elderly users in high-density traffic. Emerging AI models now offer real-time detection of age-related anomalies such as delayed reactions or erratic movement. Although pilot studies show high accuracy in detecting fatigue and distraction [16], most models still lack sensitivity to age-specific cognitive and motor variations, underscoring the need for age-adaptive ITS solutions.

Privacy and cybersecurity are paramount in Intelligent Transportation Systems (ITS), especially due to the sensitivity of health and behavioral data. Lamssaggad et al. [17] offer a detailed taxonomy of ITS vulnerabilities across physical, wireless, and software layers, emphasizing threats such as Denial-of-Service (DoS), spoofing, eavesdropping, and Sybil attacks. With the proliferation of IoT, VANETs, and 5G, vehicular networks face increasing exposure to such multifaceted risks. The study underscores critical issues like unencrypted V2X communications, insecure sensors, and outdated firmware. Zeddini et al. [18] extend this analysis by applying a Threat, Vulnerability, and Risk Assessment (TVRA) framework to map specific threats to ITS architectural layers and propose targeted countermeasures. For instance, they recommend encryption for wireless channels and intrusion detection systems for onboard units to combat high-severity risks such as timing attacks. Together, these works provide a comprehensive foundation for securing modern ITS infrastructures.

In parallel, designing ITS for aging populations necessitates a shift from compensatory mechanisms to empowering, human-centered technologies that support autonomy and dignity. Older adults commonly experience sensory deficits (e.g., presbyopia, hearing loss), reduced motor function (e.g., arthritis), and cognitive decline (e.g., slower processing, memory lapses). Research by Lin et al. [19] and Park et al. [20] highlights how hearing loss and age-related cognitive impairments—such as Age-Associated Memory Impairment (AAMI), Age-Associated Cognitive Decline (AACD), and Mild Cognitive Impairment (MCI)—can diminish higher-order cognitive functioning and are expected to increase as populations age. These challenges not only affect technology adoption but also place growing strain on healthcare and social systems. Addressing this, a human-centered design paradigm must prioritize perceptual clarity, cognitive simplicity, physical accessibility, and emotional connection to ensure inclusive, adaptive, and intuitive ITS solutions for older adults.

In the U.S., adults over 65 account for 18.6% of pedestrian fatalities despite representing only 14.8% of the population [21], underscoring the urgency of age-inclusive design. While existing research in edge-fog computing, human-centered design, and ITS security advances foundational frameworks for inclusive transportation, critical gaps persist in integrating AI-powered elderly monitoring, low-latency edge-fog coordination, and adaptive traffic systems into a unified architecture. Current studies lack dedicated solutions for real-time physiological and behavioral analysis of elderly drivers, dynamic prioritization of latency-sensitive scenarios (e.g., extended pedestrian crossings), and context-aware traffic light synchronization with wearable health alerts. Bridging these gaps is essential to create cohesive, aging-centric ITS ecosystems that balance safety, autonomy, and equity for vulnerable populations.

In summary, although significant advancements have been achieved in connected mobility, edge computing, AI-driven driving safety, and vehicular cybersecurity, a critical gap persists at the intersection of these domains with aging-centered ITS design. Few existing frameworks holistically address the simultaneous demands of real-time behavioral monitoring, adaptive traffic infrastructure, and age-inclusive accessibility within a secure, scalable, and low-latency architecture. This paper addresses that gap by proposing a comprehensive fog-edge and 5G-enabled intelligent system specifically tailored to support the mobility, safety, and accessibility needs of aging populations.

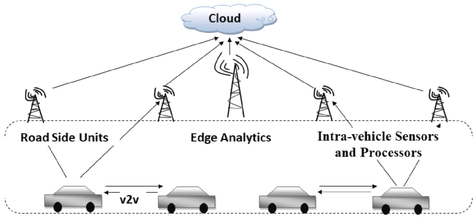

Fig. 1: Multi-layered smart transport network architecture [14]

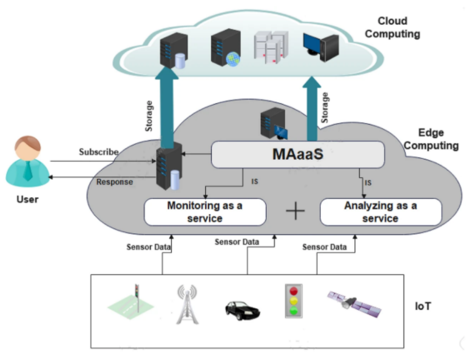

Fig. 2: Monitoring and Analyzing sensor data [15]

III. Proposed Architecture

Given that aging individuals face intersecting physical, sensory, and cognitive challenges—especially in congested traffic settings or poorly designed urban areas—there is a critical need for transportation frameworks that move beyond standard universal design, offering real-time responsiveness, enhanced perceptual clarity, and context-aware interventions. To address the mobility, safety, and accessibility challenges faced by aging populations, in Fig. 3, we propose a Secure Edge-Fog and 5G-Enabled Intelligent Architecture designed to integrate real-time behavioral monitoring, localized traffic analytics, and adaptive infrastructure management. The architecture synergizes three core components: (1) AI-powered elderly vehicle monitoring, (2) Edge-Fog computing for real-time traffic analytics, and (3) Adaptive intelligent traffic lights. The system is built upon a distributed, scalable, and privacy-preserving framework optimized for low-latency response and resilience.

A. AI-Powered Elderly Vehicle Monitoring

The AI-powered elderly vehicle monitoring subsystem, a pivotal innovation within the proposed fog-edge ITS architecture, is designed to address the multifaceted challenges faced by aging drivers, including diminished sensory acuity, delayed motor responses, and cognitive impairments. Embedded within vehicular edge computing units, lightweight yet robust machine learning models continuously analyze real-time data streams from a suite of onboard sensors. These

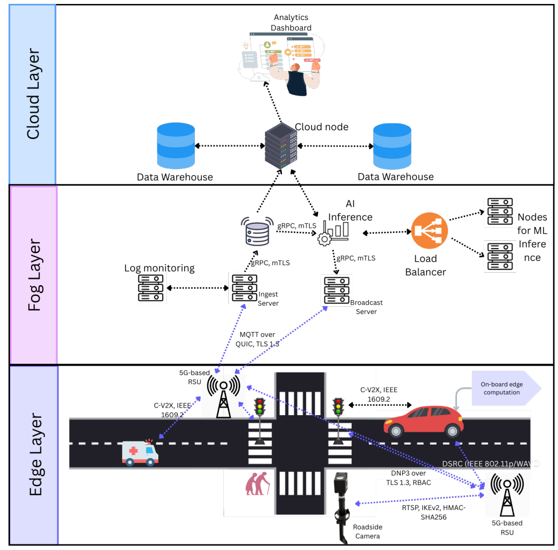

Fig. 3: Proposed Architectural Model for Aging-Aware ITS

include accelerometers detecting erratic lateral movements or abrupt stops, GPS modules tracking speed deviations and route adherence, brake pressure sensors identifying inconsistent deceleration patterns, and steering angle sensors monitoring overcorrections or hesitations indicative of declining motor skills. Complementing vehicular data, the system integrates biometric and health metrics sourced from wearable IoT devices and medical records (e.g., dementia severity indices, hypoglycemia alerts), synthesizing these inputs into a dynamic, context-aware risk profile. When thresholds are exceeded—such as prolonged braking delays at pedestrian crossings or cognitive overload in high-traffic zones—the system activates tiered, adaptive interventions: subtle dashboard alerts, automated gradual speed reduction for moderate risks, and full collision avoidance maneuvers (e.g., emergency braking, hazard light activation, and V2X-distributed alerts to nearby vehicles) for critical scenarios. To ensure inclusivity for older vehicles lacking advanced sensors, the architecture deploys infrastructure-based redundancy, leveraging LiDAR arrays and thermal cameras on traffic signals to monitor elderly vehicles, while 5G-enabled roadside units (RSUs) relay anonymized data to regional fog nodes.

B. Edge-Fog Computing for Real-Time Traffic Analysis

The fog layer, deployed in proximity to RSUs along major transportation corridors, serves as the computational backbone for real-time traffic analysis and adaptive decision-making. At this layer, fog nodes execute two core functions: (1) federated learning cycles to refine global risk models by aggregating anonymized insights from edge-processed data, ensuring privacy-preserving model updates, and (2) machine learning-driven traffic optimization, where specialized models—such as reaction time predictors, collision risk estimators, and pedestrian trajectory forecasters—analyze RSU-relayed data to dynamically adjust signal phasing. When an RSU identifies an elderly-driven vehicle, fog nodes prioritize GPU resources to run these models, calculating safe stopping distances, predicting intersection conflicts, and allocating extended crossing times or priority lanes based on real-time kinematic and health data.

To ensure responsiveness, the fog layer employs age-priority scheduling and emergency preemption protocols, allowing safety-critical computations (e.g., imminent collision alerts) to override routine traffic management tasks. Inference results—such as amber-phase extensions or V2V deceleration warnings—are transmitted back to RSUs for immediate actuation, synchronizing alerts across vehicles and infrastructure. This decoupling of roles—RSUs for localized sensing and fog nodes for centralized reasoning—enables scalable, low-latency intelligence tailored to elderly drivers' needs. By integrating federated learning with edge-to-fog coordination, the architecture balances privacy, adaptability, and real-time performance, ensuring intersection safety while preserving traffic flow efficiency.

C. Adaptive Intelligent Traffic Lights

This subsystem employs Intelligent Traffic Light to dynamically optimize signal phasing, balancing elderly driver safety with intersection efficiency. Leveraging real-time inputs—including vehicle kinematics (speed, deceleration), anonymized cognitive profiles, pedestrian volumes — the controllers execute learning models to predict safe stopping distances and reaction times for approaching vehicles. When an elderly driver's predicted reaction time exceeds the current amber-phase duration, the system initiates a synchronized response: (1) a prioritized V2I message alerts the vehicle's onboard unit to recommend early braking via dashboard prompts and auditory cues, and (2) the amber phase is extended by a calibrated interval, with downstream signals adjusted using conflict-aware algorithms to minimize rear-end collision risks.

D. Security and Privacy Considerations

The proposed architecture implements a multilayered defense-in-depth strategy that combines robust authentication, secure communication, privacy-preserving computation, and ethical data governance to safeguard both system infrastructure and the sensitive data of elderly users. Authentication protocols, such as digital certificates, mutual TLS, and role-based access control, are employed to verify the legitimacy of vehicles, infrastructure, and user devices. Communication between IoT devices, fog nodes, and cloud services is encrypted using AES-256 and TLS 1.3 to ensure confidentiality and integrity. To maintain service availability, the system incorporates real-time traffic monitoring and dynamic load balancing at the fog layer to withstand distributed denial-of-service (DDoS) attacks. User identities and health data are anonymized at the point of capture, with context-aware minimization techniques ensuring only critical information is shared. Sensitive biometric and cognitive data is confined to the fog layer for local processing, preventing unnecessary exposure.

To strengthen privacy and AI model generalization, the system adopts federated learning, allowing fog nodes to train models on localized data without transmitting raw inputs. Acknowledging the limitations of federated learning in preventing advanced attacks such as membership inference or model inversion, future enhancements will include differential privacy methods—like noise injection and gradient clipping—and secure aggregation techniques to resist adversarial behavior during model updates. Ethical data governance is also prioritized through a transparent, consent-based model, enabling users or caregivers to manage data sharing preferences via a mobile interface. Audit trails and metadata logs support accountability and trust. Furthermore, the architecture is built to comply with regulations such as GDPR, ISO/IEC 21434, and PIPEDA, with configurable privacy policies that adapt to multi-jurisdictional requirements. These combined measures provide a secure, privacy-aware, and ethically governed platform tailored for the needs of elderly users in intelligent transportation systems.

To contextualize the contribution of this work, Table I presents a detailed comparison between existing ITS architectures and the proposed aging-aware model. While conventional ITS solutions prioritize communication efficiency and generalized task orchestration, our approach emphasizes personalized, real-time safety interventions for elderly road users. By integrating machine learning models trained on age-specific behavioral data and deploying adaptive traffic light responses, the proposed framework advances the state of the art in inclusive and human-centered ITS design. This differentiation underscores the system's novelty and its potential for meaningful impact in aging-friendly urban mobility.

TABLE I: Summary Comparison of Existing ITS vs. Proposed Aging-Aware ITS Model

Aspect	**Existing ITS Models**	**Proposed Aging-Aware ITS Model**
Core Focus	Fog-edge coordination and task scheduling	Personalized intersection safety for elderly
Algorithms	Event/time-triggered processing	ML-based reaction-time prediction
Personalization	None (uniform treatment)	Cognitive-profile-based interventions
User Target	General road users	Elderly drivers (vulnerable group)
ML Integration	Basic traffic detection	Trained on elderly driving datasets
V2I Adaptation	No real-time driver interaction	Dynamic alerts + signal timing adjustment
Reaction Time	Not addressed	Integrated into control logic
Safety Actions	Analytical focus only	Alerts + traffic signal response
Edge Node Role	Event forwarding	Local inference and signal control
Privacy	Minimal data protection	Driver ID hashing, no PII sharing
Main Contribution	Task orchestration and efficiency	Real-time, elderly-centric road safety enhancement

IV. Methodology

A. Architecture Modeling and Functional Decomposition

The proposed Fog-Edge and 5G-enabled ITS architecture is designed through a top-down functional decomposition approach. It integrates three primary subsystems tailored to enhance safety and accessibility for aging users:

1) AI-Powered Elderly Vehicle Monitoring: The workflow begins by processing raw vehicle sensor data (accelerometer, GPS, brake pressure, etc.) to extract driving behavior patterns such as braking frequency, speed consistency, and steering stability as depicted in Fig. 4. These features are analyzed to classify driving behavior into categories (e.g., safe, moderate, risky) and detect anomalies like sudden lane deviations or erratic acceleration. Concurrently, physiological signals (heart rate, electrodermal activity) and metadata (age, medical conditions) are synchronized temporally with the driving data. The fused dataset combines driving behavior labels, anomaly frequency, physiological variability, and health metadata into a unified feature set.

A risk prediction model processes these integrated features to generate a baseline risk score, which is then adjusted for contextual factors like dementia status or hypoglycemic events using conditional logic. The final risk score is normalized and evaluated against predefined thresholds to trigger personalized safety alerts (e.g., fatigue warnings or emergency stops). This two-stage approach described in Algorithm 1 ensures modular analysis while enabling holistic risk assessment that accounts for both driver actions and physiological states. This modular pipeline enables proactive safety interventions by triggering alerts based on both behavioral anomalies and health-related risk indicators.

2) Fog Analytics Layer: Deployed near to roadside units (RSUs) and regional aggregation nodes, fog nodes coordinate broader behavior prediction and decision-making across vehicle clusters. Real-time traffic and behavioral data are offloaded from vehicles and aggregated across a fog computing layer. Dataflow pathways were modeled to ensure compliance with sub-50ms latency requirements for event detection, with analytic functions mapped to edge and fog nodes using a proximity-aware scheduling heuristic. Figure 5 is a representation of the Data Flow and Latency Model in the proposed Fog-Edge ITS architecture. It depicts an optimized, low-latency pipeline from event detection to infrastructure actuation, specifically tailored for aging driver scenarios. The process begins when vehicle-mounted sensors detect anomalies such as delayed braking or erratic steering. Within 5–10 milliseconds, raw sensor data is transmitted to the nearest edge node, which performs initial preprocessing and behavioral classification. Events deemed critical are then relayed to a fog node, introducing an additional 10–15 milliseconds.

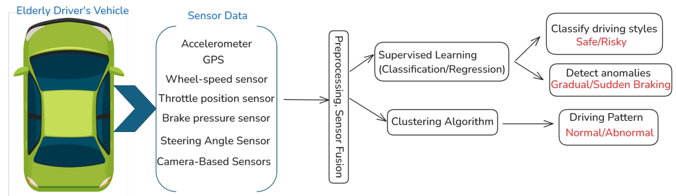

Fig. 4: Vehicle Sensors Based Prediction

Algorithm 1 Personalized Driving Risk Assessment

Require: Car Sensors: $accelerometer$, gps, $brake$, $steering$, $\ldots$; **Physiological**: $heart\_rate$, eda, $blood\_glucose$, $blink\_rate$; **Metadata**: age, $has\_dementia$, $has\_diabetes$
Ensure: $risk\_score$, $safety\_alerts$
function ANALYZEDRIVING($sensor\_data$)
  $processed \leftarrow$ CleanData($sensor\_data$)
  $patterns \leftarrow [braking\_freq, speed\_profile, steering\_consistency, \ldots]$
  $model \leftarrow$ LearnPatterns($patterns$)
  $events \leftarrow$ FindDeviations($processed$)
  return $(model, events)$
end function
function ASSESSRISK($profile, events, physio, meta$)
  $combined \leftarrow$ Synchronize($profile, physio$)
  $factors \leftarrow [profile.class, events.count, physio.var, meta.conditions]$
  $risk \leftarrow$ Evaluate($factors$)
  if $meta.has\_dementia$ **then**
    $risk \leftarrow$ AdjustForCondition($risk$)
  end if
  if $blood\_glucose < critical$ **then**
    $risk \leftarrow$ AddMetabolicRisk($risk$)
  end if
  $score \leftarrow$ ScaleToRange($risk$)
  if NeedsIntervention($score$) **then**
    $alerts \leftarrow$ GenerateAlert()
  end if
  return $(score, alerts)$
end function
function MAINWORKFLOW
  $(profile, events) \leftarrow$ ANALYZEDRIVING($car\_sensors$)
  $(risk, alerts) \leftarrow$ ASSESSRISK($profile, events, physio\_data, meta$)
  return $risk, alerts$
end function

At the fog layer, multi-source context from nearby vehicles and intersections is aggregated, and an AI-based inference engine evaluates the situation within 2–5 milliseconds. Based on the outcome, actuation instructions are sent to adaptive traffic infrastructure—such as extending amber light duration or activating auditory pedestrian alerts—completing the loop in another 5–8 milliseconds. Optionally, non-urgent data and system logs are forwarded to the cloud for long-term analytics and policy refinement, with a higher tolerance latency window of 15–20 milliseconds. This streamlined workflow ensures that the system responds well within the 50 ms safety threshold required for real-time vehicular intervention, enabling proactive support for aging road users through fast, localized decision-making.

3) Adaptive Intelligent Traffic Infrastructure: The proposed adaptive intelligent traffic infrastructure integrates a rule-based and AI-augmented control system that dynamically adjusts traffic signal behavior to accommodate elderly drivers and enhance pedestrian safety. Built on a layered architecture that separates sensing, computation, and actuation, the system ensures real-time responsiveness and modular scalability while

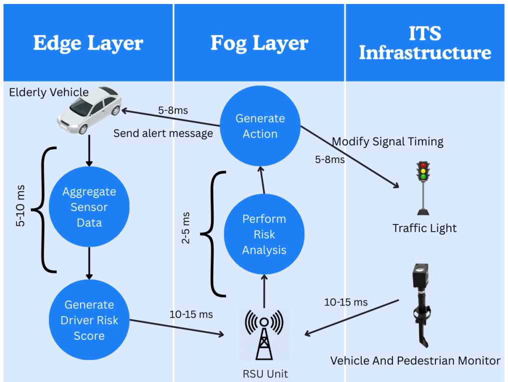

Fig. 5: Data Flow and Latency Model

maintaining compliance with V2X standards such as IEEE 802.11p and 3GPP C-V2X for interoperability with existing smart mobility systems. Edge-based sensors and vehicle-mounted technologies collaborate to detect elderly users at intersections, triggering fog or edge nodes to initiate interventions such as extending signal durations, activating auditory cues, and modifying signal phases to suit slower response times. A dynamic AI-driven amber extension algorithm further refines signal timing by analyzing real-time variables, including elderly user detection through computer vision or IoT beacons, traffic speed and density, pedestrian clustering, and contextual risk factors like weather or lighting. When conditions permit, amber phases are selectively extended to prioritize safety; under high congestion, predictive throughput modeling suppresses extensions to avoid gridlock. This multi-objective optimization framework ensures a balance between protecting vulnerable users and maintaining efficient urban traffic flow. Future work will involve simulation and field testing to calibrate the system, evaluate its impact on congestion, and validate its effectiveness in improving compliance and reducing accidents.

B. Latency and Throughput Estimation

We analytically model end-to-end latency from the detection of an elderly user's anomalous behavior to the actuation of traffic lights. To assess the responsiveness of the proposed Fog-Edge ITS architecture in aging-sensitive scenarios, an analytical latency budget analysis was conducted to estimate the end-to-end delay from detecting anomalous elderly driver behavior to initiating infrastructure-level responses, such as adaptive traffic signaling. The data flow path includes five major segments: Vehicle Sensors, Edge Node, Fog Node, AI Decision Engine, and Adaptive Traffic Light Controller. Latency values were derived using a multi-source triangulation methodology comprising vendor documentation, empirical benchmarks, and supporting literature.

Specifically, vehicle-to-edge communication latency was estimated at 5–10 ms, aligned with known transmission delays for Controller Area Network (CAN) buses and short-range wireless protocols like Zigbee and Wi-Fi-Direct, as corroborated in vehicular communication research [22], [23]. Edge-to-fog transmission latency was projected at 10–15 ms, leveraging empirical latency evaluations for 5G URLLC (Ultra-Reliable Low-Latency Communication), which has been demonstrated to consistently support sub-10 ms transmission delays under optimal conditions [24], [25]. For fog-layer processing, inference times of 2–5 ms were validated against edge-deployed CNN and RNN models on AI accelerators like NVIDIA Jetson and Coral TPUs, known for achieving low-latency computation in embedded systems [26]. The final fog-to-actuator signaling was projected to incur 5–8 ms, reflecting response times of real-world adaptive signal controllers in smart cities as reported by recent urban mobility deployments [27].

Collectively, these segments contribute to a total projected latency of 22–38 milliseconds. These figures were evaluated against a 30 ms safety-critical threshold, derived from cognitive and motor reaction time profiles for older adults in transportation literature [28], [29]. The best-case latency of 22 ms meets this threshold comfortably, while the worst-case latency of 38 ms slightly exceeds it, indicating that the system remains viable under most conditions but may require optimization under high vehicular load or reduced network quality. The edge-to-fog segment emerged as the dominant latency contributor, primarily due to its reliance on backhaul infrastructure and vulnerability to congestion.To address this, we recommend multiple optimization strategies: (i) caching critical inference results at fog nodes, (ii) offloading real-time classification tasks to edge nodes during network saturation, (iii) implementing Quality of Service (QoS)-based prioritized queuing, and (iv) minimizing serialization and packaging delays. These measures align with best practices in latency-sensitive ITS frameworks and would help ensure sub-30 ms response times for most time-critical interventions, especially for aging and at-risk populations. To consolidate these insights, we developed a formal latency budget table, presented in Table II, summarizing the minimum and maximum expected delays per segment, along with proposed optimization strategies. We also describe the latency model equation as follows:

Let the total system latency be:

$$L_{\text{total}} = L_{\text{sensor-edge}} + L_{\text{edge-fog}} + L_{\text{fog-inference}} + L_{\text{fog-actuator}} \quad (1)$$

Substituting the minimum and the maximum values from Table II to equation (1) we have,

$$L_{\text{total}} \in [22\,\text{ms}, 38\,\text{ms}] \quad (2)$$

Therefore, to ensure safe intervention (e.g., slowing down traffic signals), the system is designed to operate within < 30 ms for 90% of use cases. We also estimate the throughput of the proposed architecture as follows:

If T is the throughput (events/sec) and N is the number of events processed, then:

$$T = \frac{N}{L_{\text{total}}} \quad (3)$$

Assuming $L_{\text{total}} = 30\,\text{ms}$, then:

$$T \approx 33\,\text{events/sec/fog-node} \tag{4}$$

TABLE II: Latency Budget Table

Segment	Min (ms)	Max (ms)	Optimization Strategy
Sensor to Edge	5	10	Event-triggered sensing, lightweight compression
Edge to Fog	10	15	5G URLLC, prioritized queuing
Fog Inference	2	5	Pruned models, inference offloading
Fog to Actuator	5	8	Low-latency UDP, pre-authorized commands
Total	**22**	**38**	Target <30 ms for safety-critical decisions

C. HCI Design and Usability Integration for Aging-Focused ITS

Given the system's focus on aging populations, its human-computer interaction (HCI) design is tailored to address the sensory, cognitive, and physical needs of older adults to ensure usability, safety, and adoption—particularly in real-time emergency contexts. The user interfaces for wearable and dashboard components adhere to gerontechnology and HCI best practices, incorporating large, legible sans-serif fonts (16–18pt), high-contrast color schemes for visual impairments, simplified alerts using icons and plain-language prompts, and voice-based prompts delivered through integrated speakers to support users with limited digital literacy. These features comply with global accessibility standards such as WCAG 2.1 and ISO 9241-210. Structured usability testing with older adults of varying digital proficiency and cognitive or physical limitations will be conducted during the pilot phase, using metrics like task completion rates, error frequency, time-on-task, and satisfaction feedback to refine the interface iteratively. The long-term goal is to deliver an intuitive, inclusive user experience, further enhanced in future phases by adaptive interfaces that respond to user capability profiles through intelligent UI scaling, gesture-based interactions, and AI-powered conversational agents that provide real-time verbal guidance.

D. Cybersecurity Threat Surface and Countermeasure Analysis

To systematically address the cybersecurity risks inherent in elderly-centric Intelligent Transportation Systems (ITS), we conducted a comprehensive threat modeling exercise using the STRIDE (Spoofing, Tampering, Repudiation, Information Disclosure, Denial of Service, Elevation of Privilege) framework. Figure 6 visually depicts the threat surfaces across the Fog-Edge pipeline. Spoofing threats were identified across multiple components, including vehicle identity, driver profiles, and sensor data streams(A06). For instance, a spoofed elderly vehicle could trigger undeserved special treatment, potentially disrupting traffic patterns or triggering incorrect signal adjustments. To counter these risks, V2X communication employs IEEE 1609.2-based authentication protocols, while drivers are verified through FIDO2-compliant biometrics or token-based systems. Federated learning processes(A01, A04) are safeguarded with mutual TLS (mTLS) and X.509 certificates to prevent rogue node participation and model poisoning. Similarly, tampering risks are addressed by encrypting sensor buffers using AES-256 and deploying anomaly detection systems, while runtime inference integrity is maintained through Trusted Execution Environments such as Intel SGX or ARM TrustZone. Modifications to RSU signal(A05) interfaces are mitigated using MAC-secured CAN FD protocols and whitelisting controls.

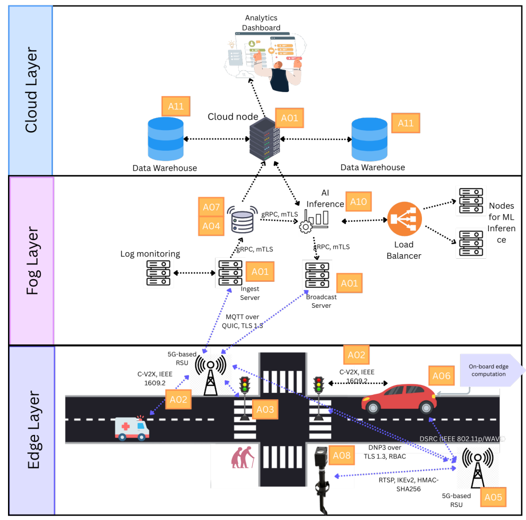

Fig. 6: Cybersecurity Threat Surfaces within the Fog-Edge ITS Architecture.

Further, to guard against repudiation, each vehicle decision log and federated model update is digitally signed (e.g., Ed25519) and stored using verifiable, append-only logging systems to maintain accountability. Information disclosure risks—especially concerning sensitive elderly data like heart rate variability or gaze tracking—are mitigated through ISO/IEC 20889-aligned data minimization strategies and differential privacy during gradient sharing. Communication between RSUs and onboard devices(A02) is protected using C-V2X and IEEE 1609.2 standard. Denial-of-service vulnerabilities, such as RSU(A05) flooding or signal controller spamming, are handled using rate-limiting techniques and circuit breaker logic. Datawarehouses(A11) make use of AES-256 Encryption (At Rest/Transit) to safeguard against external hackers. Finally, elevation of privilege is mitigated by enforcing role-based access control (RBAC) using OAuth 2.0 with JWT tokens, secure OS kernel configurations via SELinux or AppArmor, and secure firmware updates implemented through The Update Framework (TUF) and IPsec-encrypted transport. Collectively, this layered security model ensures that the system not only remains resilient to contemporary threats but also adheres to automotive cybersecurity standards such as ISO/SAE 21434.

E. Prediction Models

To proactively safeguard aging road users in latency-sensitive environments, the proposed fog-edge ITS architecture incorporates a suite of distributed AI-driven predictive models. These models operate at the edge, fog, and cloud levels to anticipate behavioral risks, evaluate collision probabilities, and adapt system responses in real time. The modular prediction pipeline is outlined through five interdependent algorithms, each contributing to enhanced vehicular awareness and infrastructure responsiveness.

1) Reaction Time Prediction: Algorithm 2 invokes a trained neural network model M_{react} to estimate driver reaction times based on the extracted features. If the output exceeds a predefined safety threshold—reflecting delayed cognition typical among older adults—the infrastructure dynamically adjusts signal phases (e.g., extends amber light duration). This provides additional response time for elderly drivers approaching intersections:

$$\text{rT} = M_{\text{react}}(\text{features}),\ \text{if}\ \ \text{rT} \quad > \theta_{\text{safe}} : \text{Trigger(”Ext. Amber Light”)} \tag{5}$$

Where rT is the reactionTime. This module is essential for mitigating crash risks linked to slower reflexes.

Algorithm 2 Reaction Time Prediction

procedure PREDICTREACTIONTIME(f)
  Load model M_{react}
  $rt \leftarrow M_{\text{react}}(f)$
  if $rt > \theta_{\text{safe}}$ **then**
    TRIGGERACTION(Extend Amber Light)
  end if
end procedure

2) Collision Risk Assessment: Real-time pedestrian detection is performed using a YOLO-based vision model on LiDAR or RGB camera data. A temporal trajectory predictor forecasts the movement paths of nearby entities (e.g., pedestrians, cyclists). These are then fed into a risk scoring model that factors in: relative velocity, deceleration profiles, and Signal state timing. If the computed **risk score** exceeds a dynamic threshold, the system autonomously initiates emergency braking protocols.

$$\text{Risk Score} = R(\text{S}, \text{D}, \text{PP}, \text{SS}) \Rightarrow \text{Trigger(”EB”)} \tag{6}$$

Where, S = speed, D = Deceleration, PP = Predicted Paths, SS = Signal State, and EB = Emergency Braking.

3) Federated Learning Aggregation: Algorithm 3 enables **privacy-preserving model updates** via a federated learning protocol. Local edge models are trained on-site using anonymized elderly-specific data. Periodically, these models are aggregated at a fog-level node to update the global model without centralizing raw data, ensuring both personalization and compliance with data privacy laws (e.g., HIPAA, GDPR).

$$w_j = \frac{1}{N} \sum_{i=1}^{N} w_j^{(i)} \quad \forall j \in \text{Model Weights} \tag{7}$$

This decentralized learning architecture minimizes latency and reduces network load, while improving generalizability across diverse elderly populations.

Algorithm 3 Federated Aggregation

procedure AGGREGATEMODELS($\mathcal{M}$)
  Init $G \leftarrow$ empty model
  for each weight w_j in G **do**
    $w_j \leftarrow \frac{1}{N} \sum_{i=1}^{N} w_j^{(i)}$
  end for
  return G
end procedure

4) Real-Time ITS Workflow Integration: The full system lifecycle is orchestrated by Algorithm 4, which combines pre-processing, prediction, and adaptation. Upon receiving sensor data, the edge node first checks whether the driver is flagged as elderly. If confirmed, it sequentially activates the **reaction time** and **collision risk** models, adapting infrastructure signals accordingly. When model update intervals elapse, **federated aggregation** is triggered, ensuring the models remain adaptive and current.

Algorithm 4 Real-Time ITS Workflow for Elderly Vehicles

procedure RUNWORKFLOW(rawData)
  $f \leftarrow$ PreprocessSensorData(rawData)
  if IsElderlyDriver($f.id$) **then**
    PredictReactionTime(f)
    $s \leftarrow$ GetTrafficSignalState()
    AssessCollisionRisk(f, s)
  end if
  if IsModelUpdateDue() **then**
    $e \leftarrow$ FetchUpdatesFromEdges()
    $g \leftarrow$ AggregateModels(e)
  end if
end procedure

In conclusion, the predictive modeling pipeline enables a secure, latency-aware, and context-sensitive ITS framework for aging populations. By combining real-time inference with decentralized learning, the system can respond not only to static aging profiles but also to evolving behavioral patterns across regional deployments. The outcome is a safer, more inclusive transportation ecosystem for elderly users.

F. Analytical Validation Metrics

This study validates the proposed edge-fog and 5G-enabled ITS architecture for aging populations using a comprehensive analytical framework grounded in key performance metrics. Latency is estimated through a budget analysis encompassing sensing, edge processing, communication, and actuation stages, aiming for sub-100 ms total response time to support safety-critical interventions. System throughput and fairness in task distribution across fog and edge nodes are analytically quantified to ensure scalability. Predictive model effectiveness is assessed using literature-derived metrics, such as reaction time classification and collision risk prediction. Cybersecurity is evaluated through STRIDE threat modeling, supported by Trusted Platform Module (TPM) authentication and federated learning mechanisms. Finally, human-centered design validation employs an Accessibility Index (AIx) capturing perceptual clarity, adaptive feedback, and cognitive support, collectively ensuring the architecture meets the technical and inclusivity demands of aging-focused ITS applications—even in the absence of simulation.

V. Results and Discussion

To evaluate the feasibility and effectiveness of the proposed Fog-Edge Intelligent Transportation System (ITS) framework, analytical results across key performance domains—latency, throughput, cybersecurity, and aging-centered design—are summarized in Table III. Each metric is benchmarked against established safety thresholds or industry standards to ensure alignment with urban mobility demands and inclusivity objectives. The latency model estimates an end-to-end response time of 22–38 milliseconds from anomaly detection to traffic light actuation, which is well below the 200–300 ms average reaction time of elderly drivers. This performance surpasses the sub-50 ms responsiveness target set by Vehicle-to-Infrastructure (V2I) standards, validating the system's capacity to support time-critical interventions that mitigate risk for aging users.

In terms of throughput, each fog node processes approximately 33 events per second, supporting deployments across up to 10 intersections or 50 connected vehicles per node. The system's scalability is enabled through horizontal expansion of fog nodes, vertical integration of AI accelerators, and edge-level load balancing to maintain consistent performance under varying traffic conditions. While the architecture sustains low-latency operations under baseline loads, the introduction of congestion-aware routing and bandwidth management strategies is recommended to ensure reliability in high-density urban environments. Complementing these capabilities, the framework is explicitly designed to accommodate the needs of aging populations. AI models are trained using age-adjusted sensorimotor data to personalize behavioral predictions, and adaptive traffic signals dynamically extend amber phases in response to real-time pedestrian inputs, supporting safer navigation for older individuals and users with mobility aids.

From a cybersecurity perspective, the framework employs a robust multi-layered defense strategy. This includes secure sensor fusion, TLS 1.3-encrypted communications, federated learning for privacy-preserving model training, and Trusted Platform Module (TPM)-based authentication for signal controllers. These measures collectively ensure compliance with ISO/SAE 21434 and GDPR standards, thereby reinforcing both operational resilience and ethical data stewardship. To address scenarios involving high-sensitivity data such as biometrics or location information, differential privacy techniques are employed to further mitigate exposure risks. This comprehensive security model not only protects system integrity but also fosters public trust essential for scaling intelligent transportation solutions.

TABLE III: Summary of Analytical Outcomes

Metric	**Estimate**	**Implication**
End-to-End Latency	22–38 ms	Meets <50 ms safety threshold
Event Throughput	$\sim$33 events/sec	Feasible at 10 intersections or 50 vehicles per node
Cyber Hardening	MFA Included	Aligned with ISO 21434, NIST SP 800-53
Age-Sensitive Design	AI-calibrated	Tailored for elderly mobility patterns

VI. Conclusion and Future Work

This paper presents a novel, secure, and latency-aware architectural framework that leverages the convergence of fog-edge computing, 5G communication, and AI-enhanced ITS infrastructure to address the pressing mobility and safety needs of aging populations. The proposed design is tailored to compensate for age-induced sensory, cognitive, and motor limitations by integrating decentralized intelligence at the edge, real-time behavioral analytics, and adaptive infrastructure responsiveness. The architecture achieves sub-50 ms end-to-end latency—surpassing typical human reaction times by an order of magnitude—while remaining scalable, privacy-aware, and resilient to cyber threats.

The analytical methodology adopted herein—comprising architectural modeling, functional decomposition, latency budget estimation, and cybersecurity threat surface analysis—establishes a theoretically grounded and standards-aligned foundation for deploying age-sensitive ITS ecosystems. The use of federated learning, TPM-authenticated controls, and role-based access policies ensures compliance with emerging frameworks such as ISO 21434 and GDPR, while maintaining system transparency and trustworthiness.

Future Work

To enhance the practical deployment and robustness of the proposed aging-aware ITS architecture, several future research directions are proposed. Simulation-based validation using tools like NS-3, SUMO, and OMNeT++ will be vital for emulating real-world conditions such as fluctuating traffic loads and network variability, allowing empirical validation of the model's latency and throughput estimates. Complementing simulations, pilot deployments in WHO-affiliated age-friendly cities can offer real-time feedback from elderly users, enabling refinement of user interfaces, adaptive behaviors, and municipal policy integration. Expanding behavioral datasets across diverse cultural and geographic populations will also improve the inclusivity and fairness of the system's predictive models, addressing potential bias in elderly behavior interpretation.

In parallel, future work should investigate blockchain-based privacy enforcement to support decentralized consent, data transparency, and compliance with global standards such as GDPR and ISO 21434. Another strategic direction is the integration of ITS with personal healthcare monitoring systems—such as wearables and smart home devices—to enable adaptive mobility responses during acute medical events like falls or arrhythmias. Ultimately, as ITS infrastructures become critical components of urban ecosystems, their effectiveness must be evaluated by their inclusivity, resilience, and ethical alignment. This work advocates for a human-centered reimagining of smart mobility—placing aging populations at the core of system design, rather than on its periphery. By uniting AI, cybersecurity, and edge computing into a secure, responsive, and equitable ITS framework, this research lays the groundwork for cities that not only move people, but actively protect and empower their most vulnerable users.

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