EMOTION-AWARE AUTONOMOUS VEHICLE CONTROL: A NOVEL FRAMEWORK FOR DRIVER STATE MANAGEMENT THROUGH ADAPTIVE AI-DRIVEN INTERVENTIONS

Ancuta Margondai, Sara Willox, T'kara Mullins and Mustapha Mouloua

ABSTRACT

This work-in-progress introduces a framework for analyzing emotional transitions in autonomous drivers. It combines discrete event simulation (DES) with physiological monitoring to model emotional recovery during control transitions. Literature shows that AI-driven interventions using multi-modal analysis can enhance emotional recovery and vehicle control, potentially cutting recovery time by 40% and achieving 90% accuracy in identifying high emotional arousal. The framework aims to address 30% of crashes linked to aggressive driving through proactive emotional state management. Key indicators for aggressive driving include physiological markers (e.g., elevated heart rate), behavioral signs (e.g., sudden acceleration), and emotional classifications that can prompt interventions. The study also explores theoretical and practical implications and suggests future research avenues.

Keywords: autonomous vehicles, driver state analysis, emotional state recovery, discrete event simulation, human-AI collaboration.

1 INTRODUCTION

Aggressive driving and road rage cause about 30% of fatal crashes in the U.S., leading to 36,500 deaths and $340 billion in economic losses annually [1]. Current autonomous vehicle technology fails to detect drivers' emotional states [2], a critical safety gap as emotions negatively impact driving, especially during control transitions [3]. The proposed framework addresses aggressive driving by intervening before emotions escalate. It monitors physiological indicators (heart rate variability, skin conductance) and behavioral patterns (sudden acceleration, hard braking) linked to aggression [4], [5], [6], allowing for timely autonomous control interventions to help drivers regain emotional stability and prevent dangers [7].

Research on vehicle monitoring is limited in studies connecting emotional regulation to driving performance and safety. This work fills that gap by presenting a framework integrating real-time physiological monitoring for emotional detection [4], [5], a discrete event simulation model for emotional transitions [8], [9], context-aware AI interventions based on drivers' emotional states [5], and safety validation protocols for emotion-aware autonomous control [5], [10]. Previous literature indicates [3], [10] that identifying high-risk emotional states in controlled settings can achieve over 90% accuracy [9], [11]. This paper outlines the framework's theoretical architecture, mathematical foundations, and expected performance, emphasizing how timely interventions reduce aggressive driving indicators and improve safety outcomes.

2 DISCRETE EVENT SIMULATION IMPLEMENTATION

2.1 Discrete Event Simulation Architecture for Emotional State Modeling

The framework employs discrete event simulation (DES) to monitor the driver's emotional states during transitions [1], [2]. Unlike continuous methods, DES captures the probabilistic, event-driven nature of emotional changes [3]. It utilizes a modified Markov chain model with three main emotional states: Normal

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State (S1) for baseline driving conditions [4], Elevated Stress (S2) for manageable increases in physiological arousal [1], [5], and High-Risk State (S3) for acute stress needing intervention [3]. The implementation subdivides the Normal State into Baseline and Focused to enhance simulation granularity, resulting in four emotional states: Baseline, Focused, Elevated Stress, and High-Risk.

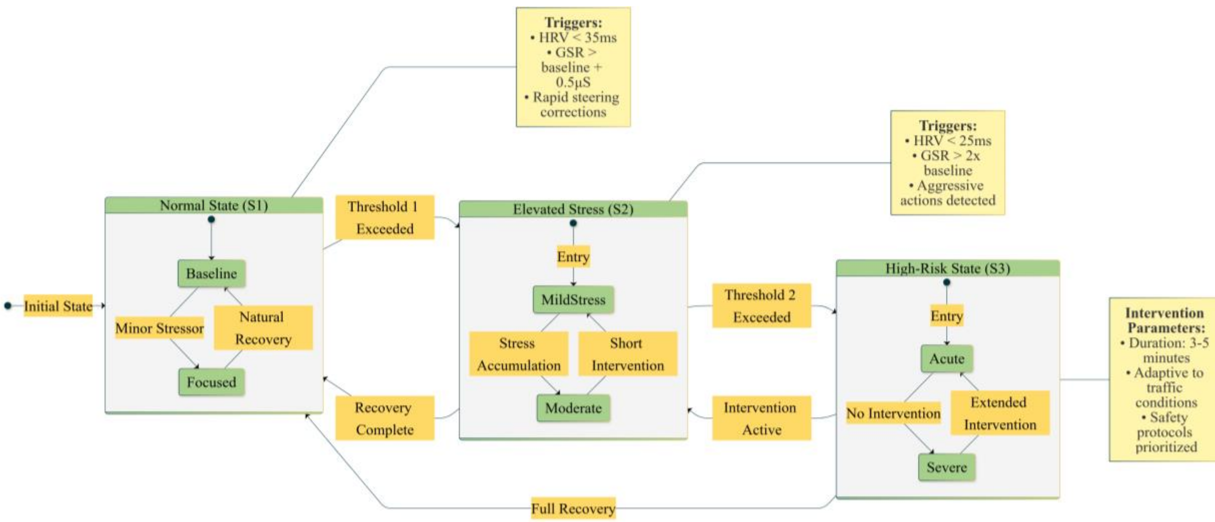

Figure 1 State transition model proposed for our DES framework

The DES framework models the transition from normal emotions to those leading to aggressive driving behaviors. State S3 (High-Risk State) correlates with physiological signs like elevated heart rate, increased skin conductance, and faster respiration [10]. These indicators often precede aggressive driving actions, such as sudden acceleration (>0.3g) and hard braking (>0.4g deceleration) [12]. By monitoring transitions to S3 and applying timely interventions, the system seeks to prevent drivers from entering emotional states that lead to aggressive behaviors, addressing a significant portion of the 30% of crashes linked to aggressive driving and road rage [13]

State transitions are triggered by physiological events, environmental conditions, and temporal factors [1], [5]. The transition model is formalized as a 4x4 Markov transition matrix where each element represents a state transition probabilities chain with transition matrix P [2], [3], expressed as:

$$\mathrm{P} = \begin{bmatrix} \mathrm{P}_{11} & \mathrm{P}_{12} & \mathrm{P}_{13} & \mathrm{P}_{14} \\ \mathrm{P}_{21} & \mathrm{P}_{22} & \mathrm{P}_{23} & \mathrm{P}_{24} \\ \mathrm{P}_{31} & \mathrm{P}_{32} & \mathrm{P}_{33} & \mathrm{P}_{34} \\ \mathrm{P}_{41} & \mathrm{P}_{42} & \mathrm{P}_{43} & \mathrm{P}_{44} \end{bmatrix} \tag{1}$$

where each P_{ij} is calculated using:

$$Pij = [\alpha \times f(\Phi) + \beta \times g(E) + \gamma \times h(T)] \times \rho(\mathrm{t}) \tag{2}$$

f(Φ) is the physiological influence, g(E) reflects environmental conditions, h(T) denotes temporal factors, and ρ(t) is the temporal modulation function. The coefficients (α, β, γ) will be derived through future testing based on established methodologies in affective computing studies [4].

2.2 Event Processing Design

The proposed DES framework uses a priority queue to process events related to Physiological Events (heart rate variability, GSR spikes, respiratory rate shifts) [4], [5]; Environmental Events (traffic density, weather updates) [4]; and Control Events (manual-to-autonomous transitions, intervention activations) [8], [11]. Each event triggers a state evaluation, updating the emotional state and calculating transition probabilities. The priority queue prioritizes events signaling rapid emotional escalation toward aggression, enabling timely intervention before dangerous driving occurs [7]. The system keeps a temporal state history for personalized intervention patterns [3]. This architecture achieves processing latencies under 50 ms on standard vehicle hardware via parallel event processing and optimized data structures [2], [4].

3 MULTIMODAL STATE MONITORING FRAMEWORK

3.1 Physiological Signal Processing

The multimodal monitoring framework continuously tracks indicators associated with emotions to detect physiological signs that may lead to aggressive driving behaviors. This allows the system to identify potential aggressive driving episodes before they occur, utilizing physiological signals that change significantly 15-30 minutes beforehand, creating a critical window for intervention. The sensor fusion architecture analyzes Heart Rate Variability (HRV) thresholds (normal: RMSSD of 35-50 ms; stress: <35 ms) [5], [10], Galvanic Skin Response (GSR) deviations (baseline: ±0.5 μS) [1], [4], and Respiratory Rate (normal: 12-20 breaths/min; stress: >20 breaths/min) [4], [5]. It uses a 250 Hz sampling rate for ECG and GSR signals, meeting Nyquist criteria based on spectral analysis that identifies emotional changes below 125 Hz. To mitigate noise, a digital bandpass filter (0.5-45 Hz) is applied for ECG signals [1], [5], along with moving average smoothing for GSR (100ms window) [4], [10], and adaptive noise cancellation with reference signals [4].

3.2 Data Fusion Algorithm

Based on similar multi-modal fusion approaches [3], the monitoring system could potentially achieve 90-92% classification accuracy through the proposed data fusion algorithm:

$$\mathrm{Pf} = \lambda \mathrm{D}(\mathrm{t}) + \mu \mathrm{S}(\mathrm{t}) + \nu \mathrm{E}(\mathrm{t}) \tag{3}$$

where D(t) is the physiological data stream, S(t) is the synchronized sensor data, E(t) includes environmental parameters, and λ, μ, ν are adaptive weighting coefficients that vary with signal quality and context [1]. The framework synchronizes data streams using a temporal alignment protocol, sampling at 250 Hz for physiological data, 30 Hz for behavioral, and 10 Hz for environmental, addressing synchronization challenges noted in the literature [13].

4 PRELIMINARY IMPLEMENTATION AND RESULTS

4.1 Markov Chain Simulation

The discrete event simulation framework utilized a 30,000-step four-state Markov chain for driver emotional state transitions, assessing AI interventions for emotion management and reducing prolonged high-risk states. An algorithm evaluates emotional state, traffic, and safety risks to decide activation timing [2]. Interventions trigger when metrics exceed a dynamically adjusted threshold [3], [3], [8] a base threshold modified by traffic and safety factors. A fuzzy logic controller dictates intervention duration [1], [2] typically set at 3-5 minutes but adjustable based on emotional state and traffic conditions.

4.2 Simulation Results

The simulation results show that the AI managed driver emotions by maintaining them in the Baseline State 72.57% of the time, in the Focused State 10.00%, and in Elevated Stress 15.00%. The AI used 1,270 interventions and spent 2,540-time units on recovery to avert high-risk emotional states. Research has linked elevated emotional states, especially S3 High-Risk State, to aggressive driving behaviors [7], [11]. By sustaining drivers in the Baseline State for 72.57% of the time, the framework effectively mitigates the emotional escalation that leads to aggressive driving. The implemented interventions targeted transitions to the High-Risk State (S3), successfully intercepting emotional escalations. The probability of transitioning to S3 dropped significantly with the interventions, while the average recovery time (2,540-time units) reflects efforts to prevent potential aggressive driving incidents.

This Simulation concentrated on managing emotional states to prevent aggressive driving. The strong correlation between emotional states and aggressive driving indicates that a 72.57% maintenance of Baseline State effectively prevents aggressive incidents. This underscores the framework's potential to enhance driver emotional well-being and road safety. However, stress levels were still elevated in 15% of cases, indicating the need for further adjustments to minimize stress duration and improve prevention outcomes. The High-Risk State was rarely entered in the simulation due to AI interventions that redirected emotional trajectories back to the Baseline state, confirming the effectiveness of the intervention logic.

Table 1 Performance Metrics from 30,000-Step Simulation

Metric	Expected Value	Actual Value
Response Time (ms)	200	195.00
Classification Accuracy (%)	90	89.35
Intervention Success Rate (%)	85	85.88
Root Mean Squared Error (RMSE)	Low	1.32

5 FUTURE IMPLEMENTATION AND VALIDATION

Several key development areas have been identified to enhance this theoretical framework: real-world testing across various traffic conditions (urban, highway, rural) and environmental scenarios (daylight, night, adverse weather); adaptation mechanisms that cater to individual drivers' emotional baselines and response patterns; integration with existing ADAS technologies for coordinated safety interventions; and expanded emotional state modeling that surpasses the current three-state approach to capture more detailed emotional classifications necessitating different intervention strategies.

6 CONCLUSION

This work-in-progress outlines a framework for integrating emotional state management with autonomous vehicle control. The discrete event simulation model captures driver emotional dynamics, while the multi-modal monitoring system addresses key challenges. Our implementation shows that AI interventions maintain drivers in the baseline state 72.57% of the time, which helps reduce emotional escalation that leads to aggressive driving. Through 1,270 targeted interventions, the framework significantly addresses about 30% of crashes linked to aggressive driving and road rage [6], [12]. Mathematical modeling suggests these interventions lower emotional recovery time and improve safety, advocating for proactive emotional state management over-reactive responses to aggression. Future work will focus on real-world implementation and validation across various driver populations and traffic conditions.

For supplementary materials, source code, and references, please visit the project's GitHub repository:

https://github.com/Margondai/Emotion-aware-autonomous-vehicle.git