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Neurocognitive and Experiential Evaluation of Autonomous Driving Strategies Using EEG and a Four-Dimensional Human Experience Model

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As autonomous driving technologies continue to evolve, understanding passengers' cognitive and experiential responses has become increasingly important for human-centered system design. However, the ways in which different autonomous driving decision-making paradigms influence passenger experience and underlying neurocognitive processes remain insufficiently explored. This study proposes an EEG-based evaluation framework grounded in a Four-Dimensional Human Autonomous Driving Experience Model (4D-HADEM), integrating comfort, tension, perceived control, and trust. Using the CARLA simulation platform, we conducted a within-subject experiment with 28 participants, in which three representative autonomous driving strategies—modular pipeline (MP), imitation learning (IL), and reinforcement learning (RL)—were adopted to model different levels of autonomous driving performance across three urban driving scenarios. Multimodal data, including EEG signals, vehicle-level metrics, and subjective evaluations, were analyzed with attention to their statistical hierarchy. Results showed that driving strategy and scenario significantly affected comfort, perceived control, and trust, with MP generally yielding the most favorable subjective profile. EEG analysis based on theta, alpha, and beta bands revealed significant model effects in occipital alpha and beta

power, a scenario effect in parietal alpha power, and a Model × Scenario interaction in occipital beta power after FDR correction. Vehicle behavior was examined condition level, and its associations with subjective ratings and EEG measures were therefore evaluated at the same level. Repeated-measures correlations further showed positive associations between alpha activity and comfort, trust, and perceived control, although these associations did not remain FDR-significant after controlling for model and scenario. These findings demonstrate the value of multimodal neuroergonomic evaluation and provide a basis for future adaptive autonomous driving systems that account for passengers' cognitive states, trust, and riding experience.

KEYWORDS: Automated Driving; Electroencephalography; Human Factors; Automation Trust; Neuroergonomics.

1. Introduction

With the rapid development of autonomous driving technology, autonomous vehicles (AVs) are gradually transitioning from controlled laboratory environments to real-world road deployment [4, 41]. Current research and development efforts in autonomous driving systems (ADSs) primarily focus on achieving safe, accurate, and efficient vehicle control through advanced perception, decision-making, and motion planning algorithms [19]. Most efforts are therefore centered on improving the vehicle's capability to perceive the external environment and execute reliable driving behaviors. While these advancements have significantly enhanced the technical performance of autonomous vehicles, the subjective experience and psychological responses of human passengers remain comparatively underexplored [29, 12]. Understanding how humans perceive and react to automated driving behavior has become increasingly important for promoting user acceptance and designing human-centered autonomous systems.

Autonomous driving decision-making architectures are generally categorized into three representative paradigms: Modular Pipeline (MP), Imitation Learning (IL), and Reinforcement Learning (RL). Modular pipeline architectures decompose the driving task into sequential functional modules such as perception, prediction, planning, and control, which provide strong interpretability and safety constraints but may lead to conservative or rigid driving behavior [32,35]. Imitation learning approaches learn driving policies from expert demonstrations and often generate smoother and more human-like driving behaviors, thereby potentially improving passenger comfort and predictability [11]. Reinforcement learning frameworks optimize driving strategies through interaction with the environment and reward feedback, enabling adaptive decision-making but often with reduced interpretability and occasional behavioral unpredictability [26]. These fundamentally different decision paradigms can produce distinct driving styles, ranging from cautious and rule-based behaviors to more exploratory and adaptive ones, which may significantly influence passengers' perceptions of safety, trust, comfort, and controllability.

Despite the importance of human perception in automated mobility, most existing evaluation methods rely heavily on subjective self-report measures. Widely used assessment tools include the NASA Task Load Index (NASA-TLX) for perceived workload [20], the Trust in Automation Scale [27, 40], and the Self-Assessment Manikin (SAM) for emotional valence and arousal [6]. Although these instruments provide valuable insights into human attitudes toward automation, they primarily capture explicit self-reported perceptions and may not fully reflect the dynamic and subconscious cognitive processes involved in experiencing autonomous driving. Moreover, traditional affective models such as the Valence-Arousal-Dominance (VAD) framework [9, 36] describe general emotional states but do not explicitly account for key experiential dimensions specific to automated driving, such as perceived control, predictability, and system reliability.

To complement subjective assessments, recent studies have increasingly explored physiological and behavioral indicators to objectively characterize passenger responses during automated driving [21]. Commonly used measures include heart rate vari-

ability (HRV), electrodermal activity (EDA), gaze behavior, and facial expressions, which are capable of reflecting variations in arousal, attention, and stress levels [18, 37, 30]. For example, Walker et al. demonstrated that gaze behavior and electrodermal activity can serve as continuous objective indicators of drivers' trust in automated vehicles, and that the combination of these signals provides a more reliable prediction of trust levels than either measure alone [37]. Similarly, Lohani et al. provided a comprehensive review of psychophysiological measures used in real-world driving studies and highlighted the potential of cardiac, electrodermal, and ocular metrics for assessing drivers' cognitive states such as workload, vigilance, and engagement [30]. In addition, physiological indicators derived from heart rate variability and electrodermal responses have been widely used to detect fatigue and stress during driving tasks, further demonstrating their sensitivity to changes in human cognitive and emotional states [22]. However, although these physiological signals provide objective measurements of human physiological states, they primarily capture peripheral manifestations of arousal or attentional responses. Consequently, they offer limited insight into the underlying neurocognitive processes that govern higher-level psychological constructs such as cognitive appraisal, perceived control, and trust formation during interactions with autonomous driving systems.

Electroencephalography (EEG) offers a promising alternative for investigating the neurocognitive processes underlying human interaction with autonomous systems [3]. EEG provides high temporal resolution and enables continuous monitoring of brain activity related to attention allocation, cognitive workload, and emotional regulation [10]. In autonomous driving research, EEG has been widely applied to study driver workload, takeover readiness, and trust calibration during human-automation interaction [23, 25, 28]. However, existing EEG studies often focus on specific driving tasks or automation levels and rarely examine how different autonomous decision-making paradigms influence passengers' neural responses across diverse driving contexts [13]. As a result, the relationship between algorithmic driving behavior and human neurocognitive experience remains insufficiently understood.

To address these limitations, this study proposes an EEG-based evaluation framework grounded in the Four-Dimensional Human Autonomous Driving Experience Model (4D-HADEM). The proposed framework characterizes passenger experience across four key dimensions, Comfort, Tension, Control, and Trust and integrates subjective evaluations with neurophysiological measurements. By systematically comparing passenger responses under three autonomous driving paradigms (MP, IL, and RL) across multiple driving scenarios, this study aims to uncover how different algorithmic driving strategies influence both neural activity and psychological perception.

Based on these objectives, the main contributions of this study are summarized as follows:

- We propose a theory-driven four-dimensional evaluation framework for passenger experience in autonomous driving, named 4D-HADEM.
- We provide a comparative evaluation of modular rule-based, imitation learning, and reinforcement learning driving strategies across multiple traffic scenarios, focusing on their effects on passenger experience.
- We jointly analyze subjective ratings, vehicle control behavior, and EEG spectral features to examine how different decision-making paradigms are associated with passengers' affective and neurocognitive responses.

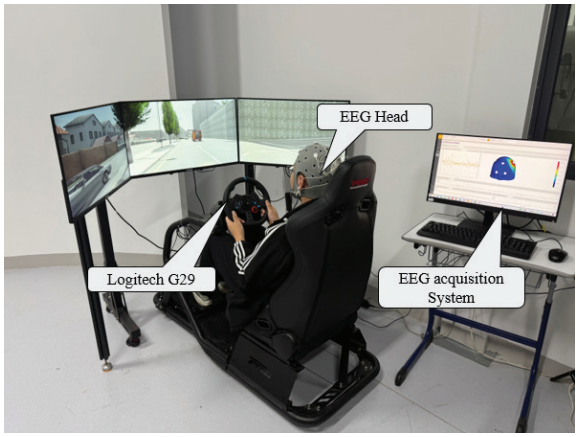
2. Materials and Methods

This section details the design of the simulation scenarios and the experimental procedures, including the hardware configuration and the setup of driving tasks. It further presents the experimental paradigms employed to accomplish the research objectives.

2.1. Participants

An a priori power analysis was performed using G*Power 3.1 [17] for a 3 (driving model) × 3 (driving scenario) within-subject repeated-measures ANOVA, with EEG indices as the primary outcome measures. Assuming a moderate effect size (f = 0.25), an alpha level of 0.05, statistical power of 0.80, a correlation among repeated measures of 0.50, and a nonsphericity correction of $\varepsilon = 1$, the minimum required sample size was estimated to be 24 participants.

Figure 1
Experimental platform for autonomous driving EEG acquisition.



A total of 28 healthy participants (15 males and 13 females), aged 21–32 years, completed the experiment and were included in the analysis. Their mean age was 23.14 years (SD = 2.55). All participants were informed of the experimental procedure, potential discomfort related to simulator exposure and EEG recording, and their right to withdraw at any time. Written informed consent was obtained from all participants before the experiment.

2.2. Apparatus

The driving simulation environment was developed using OpenAI Gym [7] and CARLA [15,1] (version 0.9.13), a high-fidelity urban driving simulator that supports realistic vehicle dynamics and traffic interactions. As illustrated in Figure 1, the simulation environment was presented through a driving simulator setup comprising three 32-inch displays, an adjustable racing seat, and a Logitech G29 manual control interface. An 8-channel Enobio EEG system was used to record participants' EEG signals during the experiment.

2.3. Data Acquisition

This section outlines the experimental conditions and data acquisition procedures used to evaluate participants' responses to automated driving. It describes the autonomous driving paradigms and traffic scenarios, as well as the acquisition and processing of EEG, subjective ratings, and driving-related variables.

EEG signals were recorded at 500 Hz from eight electrodes: F3, F4, Fz, P3, P4, Pz, O1, and O2. Specifically, frontal electrodes (F3, F4, and Fz) are sensitive to workload, vigilance, and executive monitoring, parietal electrodes (P3, P4, and Pz) are associated with visuospatial attention [8] and task engagement, and occipital electrodes (O1 and O2) reflect visual processing and environmental monitoring. This compact montage enables effective capture of neural dynamics associated with different automated driving conditions. The raw EEG data were notch-filtered at 50 Hz, band-pass filtered between 4 and 45 Hz, and then down-sampled to 128 Hz for spectral analysis. Independent component analysis (ICA) was applied to attenuate artifacts caused by eye blinks and horizontal eye movements. Given the low-density montage, ICA was used mainly for artifact reduction rather than neural source separation.

After preprocessing, the continuous EEG data were segmented into 60-s epochs corresponding to the automated driving period of each trial. In total, the 3 × 3 within-participant design produced 252 planned EEG epochs from 28 participants across 9 conditions. Each epoch was paired with four subjective ratings: Comfort, Tension, Perceived Control, and Trust. Power spectral density was estimated for each epoch, and band-power features were extracted for theta (4–8 Hz), alpha (8–13 Hz), and beta (13–30 Hz) bands over frontal, parietal, and occipital ROIs.

Within the CARLA platform, three representative autonomous driving paradigms – modular pipeline [15], imitation learning [11], and reinforcement learning [2] – were implemented under a unified control architecture. All models shared the same simulation environment, vehicle dynamics, perception inputs, and low-level control interface to ensure comparability. The MP model used rule-based lane-keeping, car-following, and obstacle-avoidance logic. The IL model learned control actions from expert demonstrations collected in the same environment, while the RL model used a reward function that encouraged waypoint tracking, smooth control, lane keeping, and collision avoidance.

In parallel, three representative traffic scenarios were designed in CARLA to emulate typical urban driving situations and to capture distinct driving demands. Scenario A consisted of straight driving with continuous right turns, primarily reflecting route-following

Table 1
Recorded driving-related variables during each autonomous driving simulation run.

Category	Recorded variables	Description
Ego Vehicle State	ego_x / ego_y	Ego vehicle global position (m).
	ego_yaw	Ego heading angle (rad).
	speed	Ego speed (m/s).
	ang_vel_z	Yaw rate around the z-axis (rad/s).
	acc_x	Longitudinal acceleration (m/s^2).
	acc_y	Lateral acceleration (m/s^2).
Leading Vehicle Information	front_vehicle_dist	Gap distance to the leading vehicle (m).
	relative_speed	Ego speed minus the lead-vehicle speed (m/s).
Lane Information	lane_width	Lane width (m).
	lateral_offset	Lateral deviation from the lane center (m).
Nearby Vehicle Information	nearby_distance	Distance to the nearest or target nearby vehicle (m).
Waypoint Information	wp_x / wp_y	Local waypoint coordinates in the ego frame (m).
	relative_yaw	Relative heading to the next waypoint (rad).
Ego Control Actions	throttle	Throttle command [0,1].
	steer	Steering command [-1,1].
	brake	Brake command [0,1].

and turning stability. Scenario B involved lane changing and a T-junction, introducing lateral maneuvering and intersection-related complexity. Scenario C represented straight car-following, emphasizing longitudinal following and headway control. Together, these scenarios covered different combinations of longitudinal control, lateral maneuvering, intersection negotiation, and car-following demands. During each simulation run, multi-source driving-related variables were continuously recorded to characterize vehicle dynamics, environmental interactions, control behaviors, and perception information. The recorded variables are summarized in Table 1.

2.4. Four-Dimensional Framework

Passenger experience in autonomous driving cannot be adequately characterized by general-purpose affective models alone. Although the classical VAD model effectively captures transient emotional states, autonomous driving represents a distinct interaction paradigm in which passengers are physically embedded in a safety-critical, continuously evolving system while lacking direct control authority. Consequently, passenger experience is shaped not only by momentary affect, but also by higher-order cognitive appraisal of system behavior [5, 38], including predictability, controllability, and reliability.

The proposed framework conceptualizes passenger experience as emerging from the interaction between autonomous driving system behavior, vehicle-level behavioral characteristics, and human neurocognitive processing (see Figure 2). At the system level, different decision-making and control strategies determine key behavioral properties of the vehicle [34, 21], such as smoothness, predictability, and stability, which are manifested through observable behavioral characteristics including speed variability, braking frequency, and lateral stability. These vehicle-level behaviors constitute the primary stimuli perceived by passengers and form the basis of subjective experience.

Within this structure, 4D-HADEM characterizes passenger experience along four complementary dimensions. Comfort corresponds to the valence dimension and reflects overall pleasantness and physi-

cal ease of the ride, while Tension aligns with arousal and captures heightened alertness or stress induced by dynamic driving behaviors. These two dimensions are retained from classical affective models because they represent the basic emotional responses most directly elicited by ride smoothness, acceleration, braking, and environmental uncertainty. Together, these dimensions form the affective layer of experience. Beyond affect, Control and Trust are introduced as system-oriented dimensions capturing higher-order cognitive evaluation. In autonomous driving, the dominance dimension of VAD cannot be interpreted as direct manual control, because passengers usually do not operate the vehicle. Therefore, it is translated into perceived Control, namely the extent to which passengers perceive vehicle behavior as predictable, coherent, and understandable.

Control represents passengers' perceived predictability and behavioral coherence of the vehicle, whereas Trust reflects confidence in the system's competence and safety assurance under uncertainty. Trust is further included because it is a central construct in human–automation interaction and directly affects passengers' acceptance and reliance on autonomous driving systems. Although related, these dimensions are conceptually distinct: perceived control emphasizes behavioral predictability, whereas trust reflects belief in system reliability and intent.

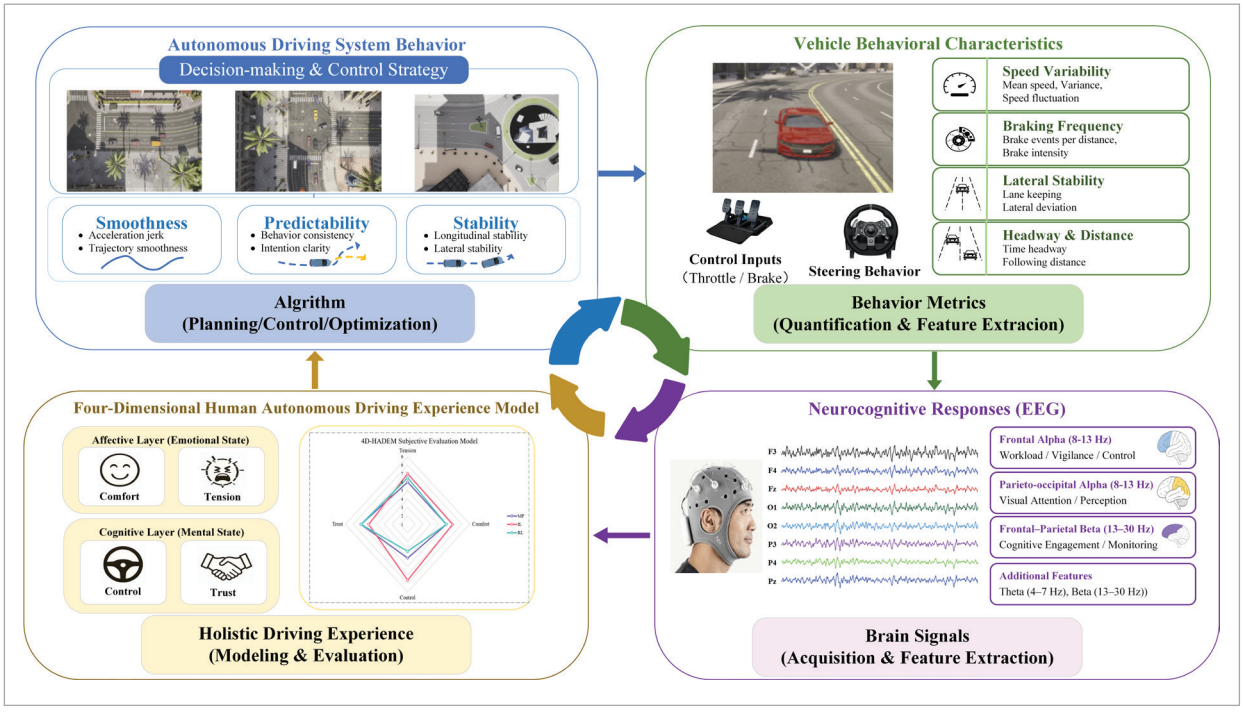
From a theoretical perspective, 4D-HADEM can be interpreted as a two-layer experiential model comprising an affective layer (Comfort and Tension) and a cognitive-evaluative layer (Control and Trust). This layered formulation enables a principled linkage between autonomous driving behavior, subjective experience, and neurocognitive responses [14, 33], thereby supporting the integration of subjective evaluations with vehicle-level metrics and EEG-based indicators within a unified neuroergonomic framework.

2.5. Experimental Paradigm

This study employed a within-subject experimental design that fully crossed three autonomous driving models with three representative driving scenarios,

Figure 2

Conceptual structure of the proposed 4D-HADEM framework. Autonomous driving strategies shape vehicle-level behavior and passenger experience across affective (Comfort, Tension) and cognitive-evaluative (Control, Trust) layers, with corresponding EEG-based neurocognitive responses.



yielding nine total trials per participant (3 models × 3 scenarios). This design enabled direct comparisons of participants' neural responses and subjective experiences across different algorithmic decision paradigms while minimizing inter-individual variability.

The three driving models were paired with three typical traffic scenarios: Scenario A (straight driving plus continuous right turns), Scenario B (lane changing plus T-junction), and Scenario C (straight car-following), arranged in the trial matrix shown in Figure 3.

Each trial comprised a 60-s automated driving task, followed by a 5-s simulation pause, a 20-s subjective rating phase using the 4D-HADEM scale, and a 30-s scenario-transition period for inter-trial washout and scenario resetting. Therefore, the interval between the end of one driving task and the beginning

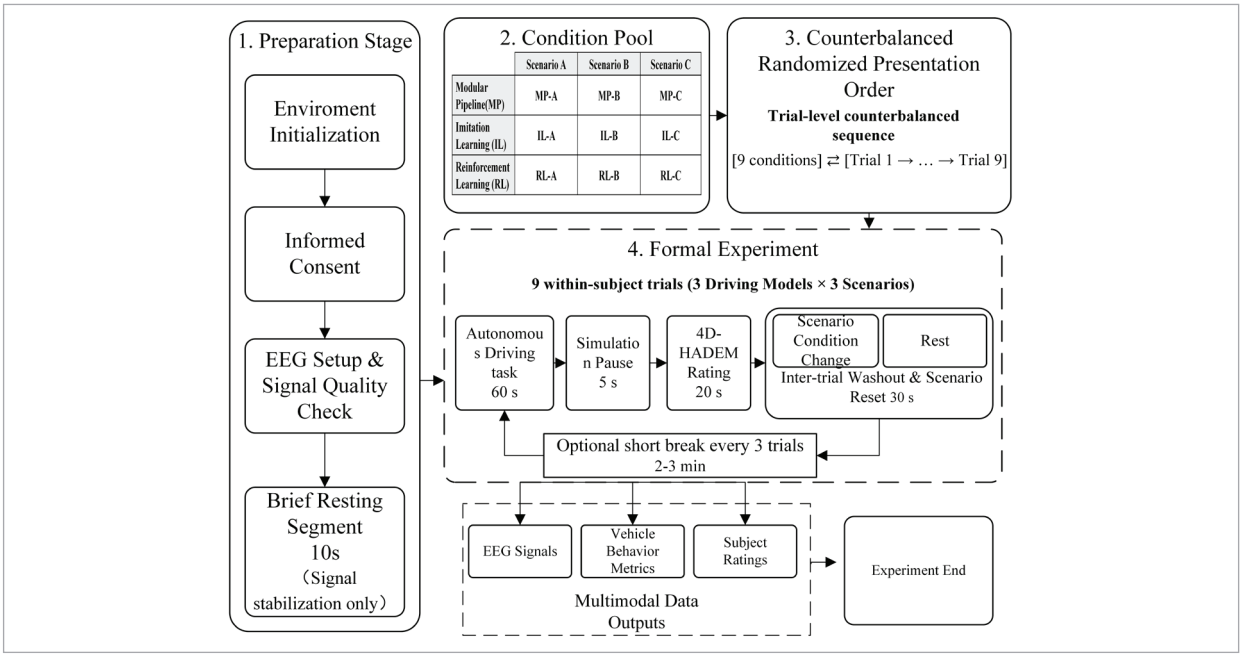
Table 2

Vehicle-level driving performance metrics across driving scenarios and autonomous driving models.

Scenario	Method	Speed (m/s) Mean	SD speed (m/s)	Jerk RMS (m/s3)	Steer-rate RMS (/s)	Brake ratio	Lateral offset P95 (m)
Scenario A	RL	8.88	3.23	13.64	0.309	0.187	0.346
	IL	6.43	1.65	17.19	0.233	0.318	0.317
	MP	6.33	2.64	16.12	0.239	0.348	0.283
Scenario B	RL	7.51	3.94	20.09	0.119	0.230	0.326
	IL	5.82	2.39	19.12	0.070	0.344	0.371
	MP	6.54	2.19	18.07	0.091	0.347	0.360
Scenario C	RL	6.98	2.03	18.43	0.054	0.377	0.403
	IL	6.61	1.41	14.74	0.060	0.325	0.370
	MP	6.95	1.87	17.39	0.059	0.295	0.366

Figure 3

Experimental procedure and counterbalanced presentation of the nine within-subject model–scenario trials.



of the next was approximately 55 s. An optional short break of 2–3 min was provided after every three trials. Before the formal experiment, a 10-s resting segment was recorded after EEG setup and signal-quality checking to confirm signal stabilization and provide a brief pre-task reference. This segment was not intended to serve as a comprehensive resting-state EEG recording.

2.6. Statistical Analysis

Subjective ratings and EEG ROI-by-frequency-band spectral features were analyzed using two-way repeated-measures ANOVA, with driving model and driving scenario as within-subject factors. For the EEG analyses, Greenhouse–Geisser correction was applied when the sphericity assumption was violated. The resulting p-values were subsequently adjusted using the Benjamini–Hochberg false discovery rate procedure across all ROI-by-frequency-band tests separately for each ANOVA effect. Vehicle-performance metrics were derived from the 10-Hz trajectory data for each participant under each Model × Scenario condition. Exploratory Spearman correlation analyses were conducted at the condition level to examine associations among vehicle-performance metrics, subjective ratings, and EEG features.

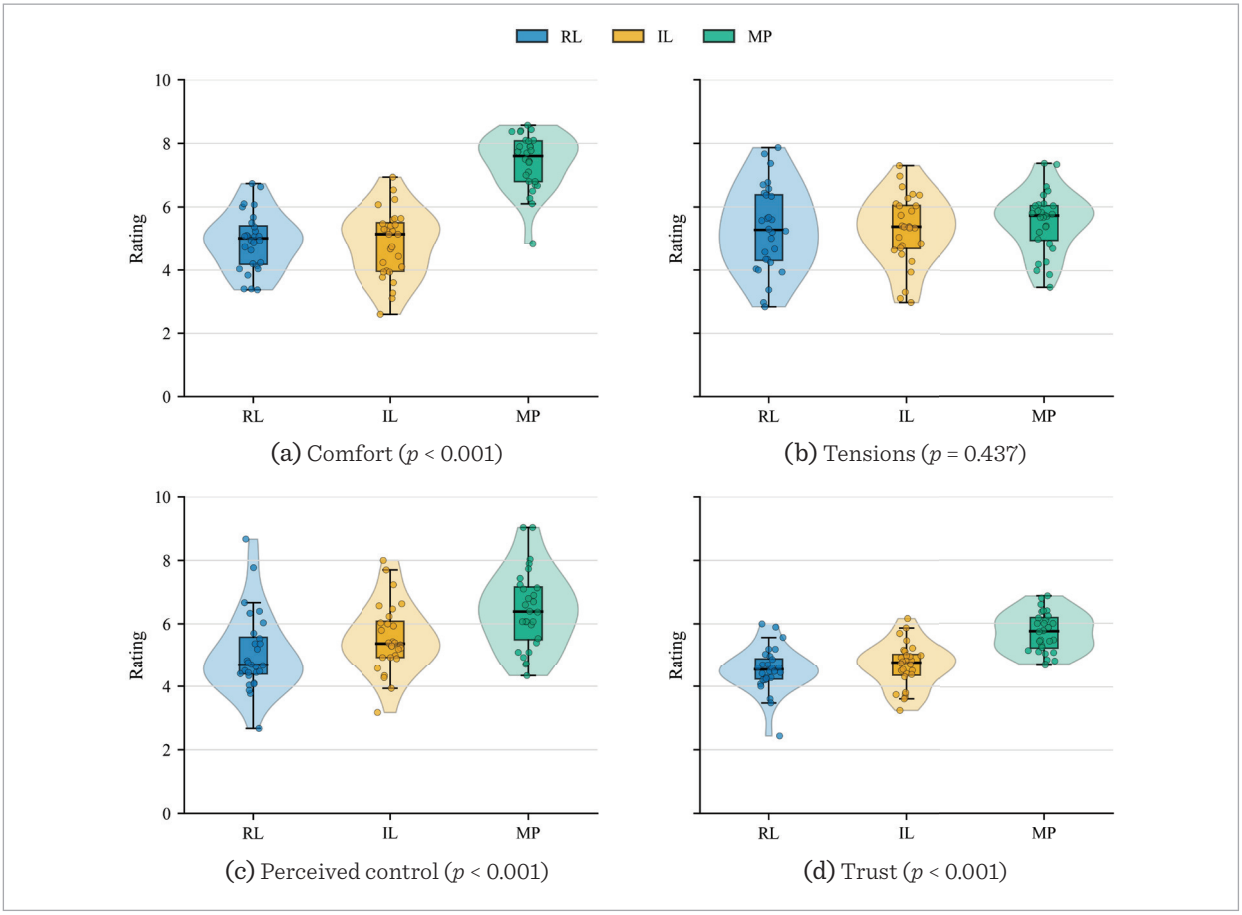
3. Results

3.1. Subjective Evaluation Results

Figure 4 summarizes the subjective ratings obtained across the 3 × 3 within-subject design. The result showed significant main effects of driving model and

Figure 4

Subject-level ratings of Comfort, Tension, Control, and Trust under the RL, IL, and MP driving models, averaged across driving scenarios. Each point represents an individual subject, and horizontal lines indicate median scores.



scenario for Comfort, Control, and Trust, together with significant Model × Scenario interactions. For Tension, the main effects of model and scenario were not robust, whereas the Model × Scenario interaction was significant, indicating that tension depended more on the specific combination of automation model and driving context than on either factor alone.

These results indicate that the choice of driving model is associated with marked differences in comfort, perceived controllability, and trust, while perceived tension is better interpreted as a context-dependent response. The subjective results are consistent with the 4D-HADEM framework, suggesting that affective and cognitive-evaluative ratings capture partially distinct aspects of passenger experience.

3.2. Vehicle Behavior Performance

3.2.1. Vehicle-level Driving Performance

We analysis examines the relationships among longitudinal dynamics, lateral control, braking behavior, and lane-keeping performance, complementing the descriptive statistics reported in Table 2. The three methods exhibited scenario-dependent driving characteristics, with the clearest differences emerging in braking usage and lane-keeping stability.

In Scenario A (straight driving plus continuous right turns), RL showed the highest mean speed (8.88 m/s) and the largest speed variability (SD = 3.23 m/s), whereas IL and MP drove at lower mean speeds of 6.43 m/s and 6.33 m/s, respectively. Brake usage was lowest for RL (0.187) and higher for IL (0.318) and MP (0.348). Because the RL trajectory in this scenario covered a longer path than the other two methods, this condition should be interpreted cautiously when comparing absolute speed-related metrics.

In Scenario B (lane changing plus T-junction), active driving duration differed across models (RL: 37.0 s; MP: 42.9 s; IL: 48.0 s), suggesting different progression speeds through the scenario. RL showed the highest mean speed (7.51 m/s) and speed variability (SD = 3.94 m/s), whereas IL and MP showed lower mean speeds of 5.82 m/s and 6.54 m/s, respectively. IL showed the largest lateral-offset P95 (0.371 m), while RL and MP showed comparable lateral-offset P95 values (0.326 m and 0.360 m).

In Scenario C (car-following), the three methods exhibited comparable mean speeds, ranging from 6.61 to 6.99 m/s. IL showed the lowest speed variability (SD = 1.43 m/s), while RL had the highest braking usage (0.377). MP achieved the lowest lateral offset RMS (0.199 m), although the differences among methods were relatively small.

Across scenarios, driving behavior was strongly scenario dependent. Scenario B produced shorter active durations and stronger progression differences among models, whereas Scenario C emphasized car-following stability and smoothness. Finally, no single model dominated all vehicle metrics across all scenarios: MP showed favorable subjective ratings, IL was smoother in some vehicle metrics, and RL was faster in some conditions but also more variable. These vehicle-level results provide behavioral context for the subjective and EEG results rather than a standalone ranking of model quality.

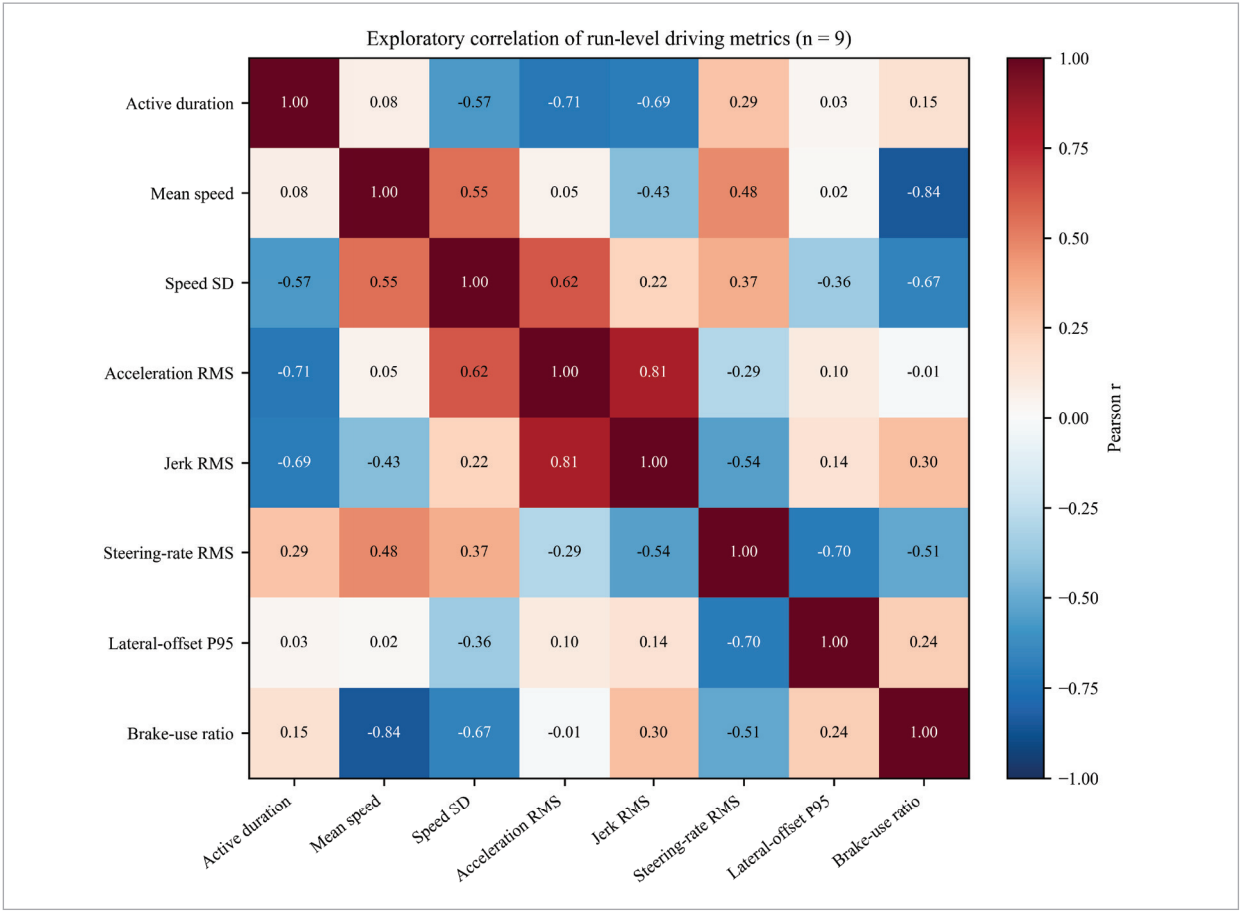
3.2.2. Relationships Among Vehicle-level Driving Metrics

To further examine interdependencies among vehicle-level driving metrics, Figure 5 presents the Pearson correlation matrix computed across the nine condition-level simulation runs. This correlation analysis was interpreted descriptively and reflects condition-level covariation rather than participant-level associations.

Several associations were observed. Brake ratio was negatively correlated with mean speed ($r = -0.84$) and speed variability ($r = -0.67$), suggesting that conditions with more frequent braking tended to involve slower and less variable longitudinal motion. Steering-rate RMS was negatively correlated with lateral-offset P95 ($r = -0.70$), indicating that conditions with greater steering activity generally showed smaller lateral deviations. Active duration was also negatively correlated with acceleration RMS ($r = -0.71$) and jerk RMS ($r = -0.69$), suggesting that shorter runs tended to involve more dynamic vehicle motion.

Lane keeping performance, quantified by lateral offset RMS, showed moderate positive correlations with braking usage rate and negative correlations with steering variability. This pattern indicates that increased braking activity and reduced steering smoothness were associated with larger lateral deviations, highlighting a coupling between longitudinal control instability and lane keeping performance.

Figure 5
Correlation matrix of run-level vehicle driving metrics, revealing interdependencies among longitudinal, lateral, and braking-related measures.



The correlation analysis suggests that longitudinal variability, steering activity, braking frequency, and lane-keeping performance covaried across the nine condition-level runs. These relationships provide behavioral context for interpreting the driving styles of the three autonomous driving models.

3.3. EEG Results

3.3.1. Descriptive EEG Spectral Patterns

Figure 6 presents representative ROI-band profiles for parietal alpha, occipital alpha, and occipital beta power across the three driving models and three driving scenarios. These ROI-band combinations were selected because they correspond to the main EEG effects identified in the FDR-corrected rm-ANOVA and provide interpretable examples of posterior spectral modulation.

For parietal alpha power, the three models showed relatively similar values in Scenario A, whereas RL and IL decreased more clearly in Scenario B and partially recovered in Scenario C. In contrast, MP showed a flatter profile across scenarios. This pattern is consistent with the scenario-related modulation of parietal alpha activity, suggesting that scenario complexity may influence posterior attentional or monitoring-related processes.

For occipital alpha and occipital beta power, clearer model-related differences were observed. RL generally showed higher occipital alpha and beta power than IL and MP, whereas IL tended to show lower power, particularly in Scenario B. The occipital beta profile also showed a more pronounced Model × Scenario pattern, with the difference among models varying across scenarios. These descriptive pat-

terns support the subsequent rm-ANOVA results, indicating that posterior alpha and beta activity were sensitive to both automation strategy and driving context.

3.3.2. ROI-band rm-ANOVA Effects

Figure 7 summarizes the statistical significance patterns of EEG spectral power across regions of interest (ROIs) and frequency bands, as assessed by a two-way repeated-measures ANOVA, together with representative band power comparisons for selected ROI band combinations.

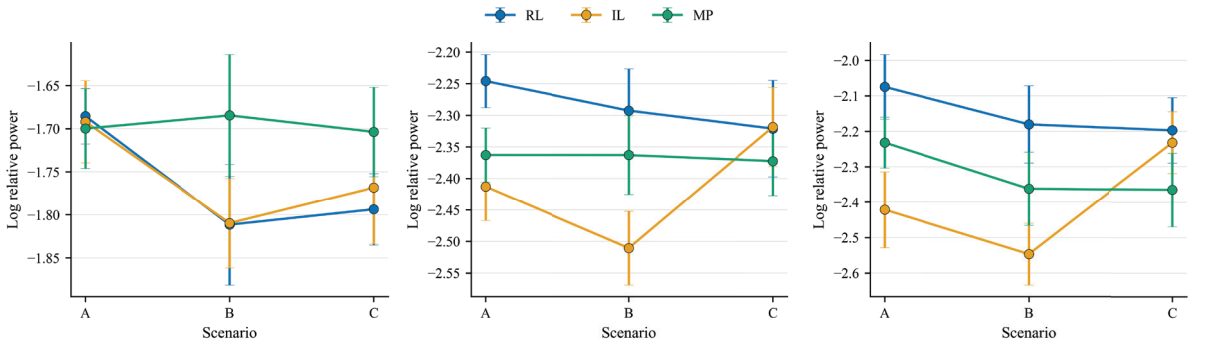
As shown in Figure 7(a), the FDR-corrected EEG analysis indicated significant main effects of driving model in occipital alpha and occipital beta power, rather than a model effect restricted to frontal alpha.

These posterior effects suggest that the visual-attentional and environmental monitoring components of passenger experience were sensitive to differences in automation strategy.

The main effect of driving scenario was most clearly expressed in parietal alpha power after FDR correction. This finding indicates that scenario structure and maneuver demands modulated posterior attentional or monitoring-related activity, consistent with the idea that different road contexts impose different levels of visual-spatial processing demand.

Figure 6

Representative EEG ROI-band interaction profiles for parietal alpha, occipital alpha, and occipital beta power. Points show condition means with confidence intervals, and q-values summarize the FDR-corrected model and Model × Scenario effects.



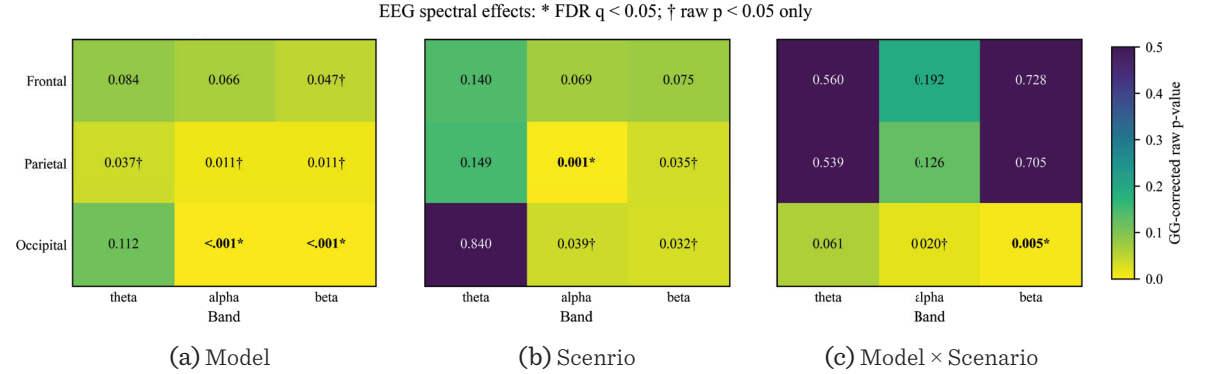
(a) Parietal α Model $q = 0.050$; interaction $q = 0.180$

(b) Occipital α Model $q < 0.001$; interaction $q = 0.077$

(c) Occipital β Model $q < 0.001$; interaction $q = 0.035$

Figure 7

EEG spectral-power rm-ANOVA probability maps for Model, Scenario, and Model × Scenario effects. Cell values show Greenhouse–Geisser corrected raw p-values; asterisks mark FDR q < 0.05 and daggers mark raw p < 0.05 only.



(a) Model (b) Scenrio (c) Model × Scenario

The interaction between driving model and driving scenario was significant for occipital beta power after FDR correction. This result indicates that the effect of automation strategy on posterior beta activity depended on the driving context, and therefore the model and scenario effects should not be described as purely additive.

To further illustrate the nature of these effects, the representative ROI-band comparisons should emphasize posterior alpha/beta activity and parietal alpha scenario modulation. Alpha activity can reflect reduced cortical excitability, visual-attentional inhibition, or lower monitoring demand, whereas beta activity may reflect sensorimotor or cognitive engagement. Therefore, these EEG effects should be interpreted as condition-sensitive neurophysiological correlates rather than direct one-to-one measures of workload.

In addition, repeated-measures EEG–subjective correlations showed that parietal alpha was positively associated with Trust, Comfort, and Control, and frontal alpha was positively associated with Trust and Comfort after BH-FDR correction. However, after controlling for Subject, Model, and Scenario fixed effects, these associations no longer survived FDR correction. Thus, alpha activity should be described as a candidate correlate of positive subjective experience, not as an independent biomarker.

3.3.3. EEG–subjective Associations

To further examine whether EEG spectral activity was related to passengers' subjective experience, repeated-measures correlations were computed between selected ROI-band EEG features and the four 4D-HADEM ratings. This analysis focused on within-participant covariation across the nine experimental conditions, thereby reducing the influence of stable between-subject differences.

The results showed that alpha-band activity was positively associated with favorable subjective experience. Parietal alpha power was significantly correlated with Trust ($r_{rm} = 0.256$, $p = 1.00 \times 10^{-4}$, $q = 0.0018$), Comfort ($r_{rm} = 0.263$, $p = 6.59 \times 10^{-5}$, $q = 0.0018$), and perceived Control ($r_{rm} = 0.205$, $p = 0.0020$, $q = 0.0177$). Frontal alpha power was also positively associated with Trust ($r_{rm} = 0.209$, $p = 0.0018$, $q = 0.0177$) and Comfort ($r_{rm} = 0.200$, $p = 0.0028$, $q = 0.0203$). These findings suggest that higher alpha activity tended to co-occur with higher comfort, trust, and perceived control within participants.

However, when Subject, Model, and Scenario fixed effects were included in the adjusted models, none of the EEG-subjective associations survived BH-FDR correction. The strongest adjusted trends were observed for occipital alpha with Trust and parietal alpha with Trust, but both remained non-significant after correction. Therefore, alpha activity should be interpreted as a candidate neurophysiological correlate of positive subjective experience rather than an independent biomarker. This distinction is important because part of the EEG-subjective association appears to reflect shared condition-level variation induced by driving model and scenario.

4. Discussion

This study investigated how different autonomous driving decision-making paradigms influence passengers' subjective experience and neurocognitive responses across multiple driving scenarios. By integrating subjective evaluations based on the proposed 4D-HADEM framework with vehicle-level behavioral metrics and EEG spectral features, the results show that algorithmic driving styles exert measurable and differentiated effects on human experience at both psychological and neural levels.

4.1. Interpretation of Subjective Experience Differences Across Driving Models

The subjective evaluation results revealed significant main effects of driving model on Comfort, Control, and Trust, while no significant differences were observed for Tension. This pattern suggests that passengers were able to clearly distinguish between autonomous driving strategies in terms of perceived smoothness, predictability, and reliability, but did not consistently report heightened emotional arousal or anxiety across models.

The MP model consistently received higher ratings in Comfort, Control, and Trust, which can be attributed to its conservative and predictable control logic. Rule-based systems prioritize safety margins, compliance with traffic rules, and stable control behaviors, which likely foster a sense of reliability and perceived controllability among passengers. These

findings are consistent with prior work showing that predictability and transparency are key contributors to trust in automation [31].

The IL model generally exhibited intermediate performance, suggesting that human-like driving behavior alone does not guarantee optimal subjective experience. While imitation learning can produce smoother trajectories [41] and more natural maneuvers, its performance is inherently constrained by the quality and diversity of training data, which may result in subtle inconsistencies or reduced robustness in unfamiliar situations. Passengers may perceive such behaviors as natural yet slightly less reliable than rule-based control.

In contrast, the RL model was associated with the lowest ratings in Comfort, Control, and Trust. Reinforcement learning agents often optimize long-term reward objectives [26] and may adopt exploratory or aggressive strategies, leading to higher speed variability and abrupt control actions, as reflected in the vehicle-level performance metrics. These characteristics likely reduce passengers' sense of predictability and controllability, even when objective safety is not compromised. This finding aligns with previous research indicating that aggressive or less interpretable automated driving styles can undermine user trust and acceptance.

The absence of a significant model effect on Tension suggests that, within the controlled simulation environment, none of the driving strategies consistently elicited strong emotional stress responses. This may indicate that tension is more sensitive to situational risk and environmental complexity than to driving style alone, a hypothesis further supported by the EEG scenario effects discussed below.

4.2. Linking Vehicle-Level Behavior to Subjective Experience

The vehicle-level analysis provides behavioral context for interpreting the subjective and EEG findings. Conditions with higher speed variability, braking differences, or larger lateral deviations tended to correspond to less favorable subjective profiles. However, because these associations were based on nine condition-level observations, they should be interpreted descriptively. Future studies should collect trial-level or participant-specific vehicle exposure measures to formally test vehicle–subjective–EEG coupling.

The correlation analysis further revealed that braking usage, speed variability, and lateral deviation are strongly interrelated. These coupled control characteristics likely contribute to passengers' perceptions of comfort and control. Frequent braking and unstable speed profiles were associated with poorer lane-keeping performance, which may be subconsciously perceived by passengers as reduced system competence or safety margin, even if no explicit hazards occur.

Taken together, these results suggest that subjective experience is not driven by isolated vehicle metrics [16] but rather by holistic control patterns that combine longitudinal smoothness, lateral stability, and predictability. This finding reinforces the importance of multi-dimensional evaluation frameworks when assessing autonomous driving systems from a human-centered perspective.

4.3. Neurocognitive Signatures of Driving Models and Scenarios

EEG analysis revealed that driving models significantly modulated posterior alpha and beta activity, with FDR-corrected model effects in occipital alpha and occipital beta power. This pattern suggests that differences among automation strategies were reflected primarily in posterior visual-attentional or monitoring-related oscillatory activity rather than only in frontal alpha activity.

The subjective advantage of MP was accompanied by EEG patterns that were physiologically plausible. Alpha power was positively associated with comfort and trust in repeated-measures correlations, which is consistent with lower monitoring demand or a more relaxed experiential state. However, these associations were weakened after controlling for model and scenario, indicating that part of the EEG–subjective coupling reflected shared condition-level structure.

Notably, driving scenario remained an important determinant of EEG activity, with a significant scenario effect in parietal alpha power. The significant Model ×Scenario interaction in occipital beta further indicates that automation strategy and road context jointly shaped posterior neural responses. These findings are consistent with the neurophysiological view that visual monitoring, attentional allocation, and cognitive engagement vary with both driving behavior and environmental demands [43, 12, 39].

Accordingly, the EEG results should not be summarized as purely additive model and scenario effects. Instead, the most defensible interpretation is that posterior alpha/beta activity captures condition-sensitive changes in passenger monitoring and visual-attentional processing.

4.4. Implications for Human-Centered Autonomous Driving Design

From a design perspective, these findings highlight the importance of aligning autonomous driving strategies with human cognitive expectations [44]. Although RL-based approaches offer strong adaptability and performance potential, their behavioral variability and limited interpretability may impose additional cognitive burden on passengers. Incorporating human-aware constraints, including smoothness regularization, predictability objectives, and trust-aware reward shaping, may help mitigate these effects.

The proposed 4D-HADEM framework further highlights the value of extending traditional affective models by incorporating trust and perceived control as domain-specific dimensions. These data support the integration of subjective ratings, vehicle behavior, and EEG features, while requiring attention to their different levels of analysis. Subjective ratings and EEG measures permit participant-level repeated-measures inference, whereas vehicle trajectories currently support only exploratory condition-level associations.

4.5. Limitations and Future Work

Several limitations should be acknowledged. First, the experiment was conducted in a simulated environment with relatively short driving trials, which may limit ecological validity and the assessment of long-term trust development. Future studies should extend this framework to longer-duration experiments and real-world driving contexts. Second, the EEG setup employed a low-density electrode configuration, which, while sufficient for monitoring global cognitive states, limits fine-grained source localization. Higher-density EEG or multimodal neuroimaging approaches could provide deeper insight into the underlying neural mechanisms.

Although the sample size was determined based on an a priori power analysis and was sufficient for detecting moderate within-subject effects, the final sample remained relatively small and consisted mainly of young healthy participants. Therefore, the generalizability of the findings to older adults, professional drivers, and passengers with different levels of autonomous vehicle experience may be limited. Larger and more diverse samples are needed to further validate the robustness of the present findings. Future work should examine how these neurocognitive patterns evolve in mixed-initiative or takeover situations, and whether adaptive driving policies informed by real-time physiological feedback can enhance user comfort, trust, and acceptance.

5. Conclusions

This study presented an EEG-based, human-centered evaluation framework for autonomous driving grounded in the proposed Four-Dimensional Human Autonomous Driving Experience Model (4D-HADEM). By comparing modular pipeline, imitation learning, and reinforcement learning strategies across three driving scenarios, the study demonstrated that autonomous driving paradigms and scenario contexts jointly shape passengers' subjective experience, vehicle-level behavior, and EEG spectral activity.

The subjective results showed that the MP model generally produced higher comfort, perceived control, and trust, whereas RL tended to receive lower ratings in several conditions. EEG analyses revealed FDR-corrected effects involving occipital alpha, occipital beta, parietal alpha, and the Model × Scenario interaction in occipital beta, indicating that posterior oscillatory activity was sensitive to both automation strategy and driving context. Repeated-measures correlations further suggested positive associations between alpha activity and favorable subjective experience, although these associations should be interpreted as candidate neurophysiological correlates rather than independent biomarkers.

Vehicle behavior analysis provided complementary descriptive evidence regarding speed, braking, smoothness, and lane-keeping characteristics, but these results should be interpreted as condition-level behavioral context rather than as evidence of participant-level multimodal coupling.

This work highlights the value of integrating subjective, behavioral, and neurophysiological measures for human-centered autonomous driving evaluation and provides a basis for future adaptive, trust-aware, and human-aligned autonomous vehicle design.

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Data Availability Statement

The data and code that support the findings of this study are available from the corresponding author upon reasonable request.

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