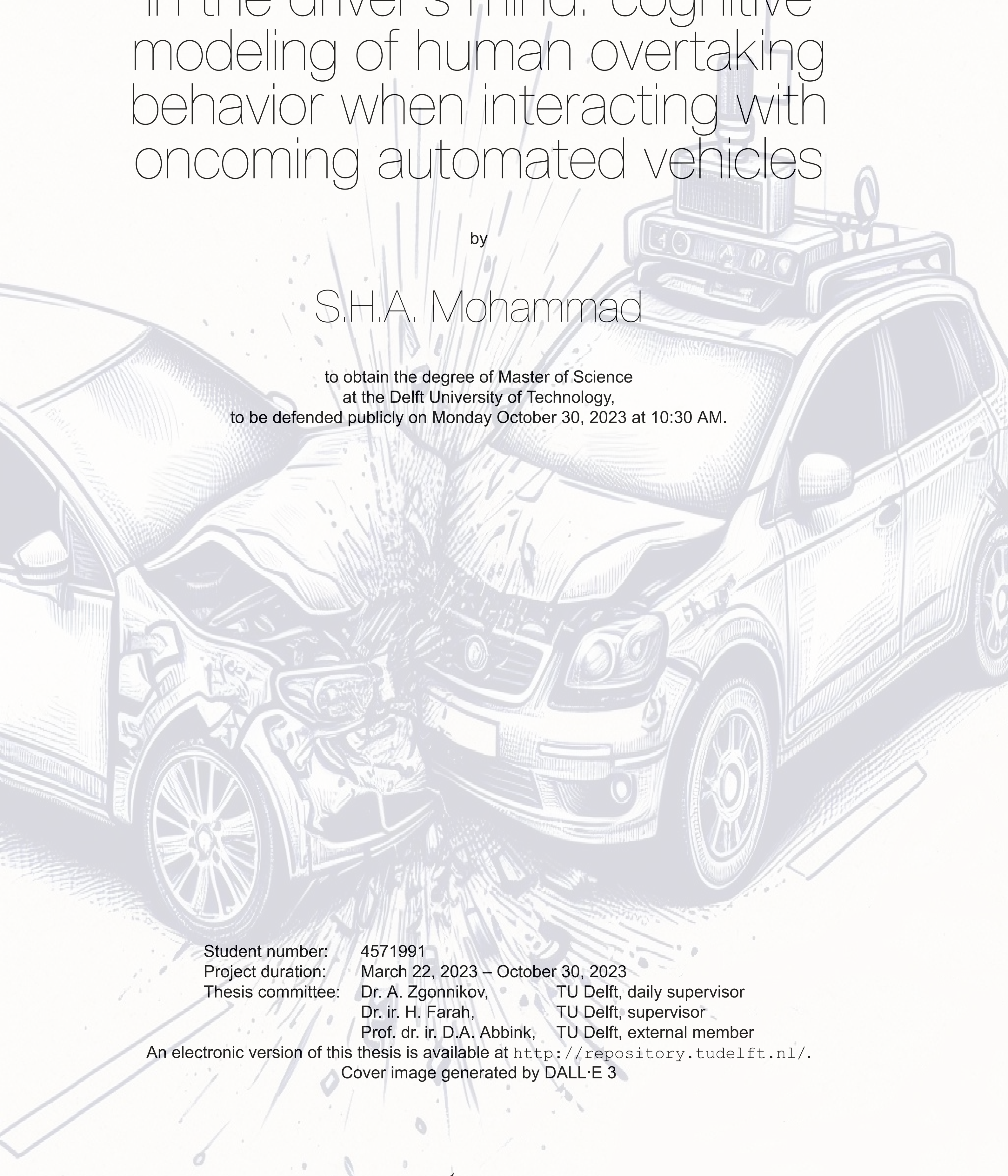
In the driver's mind: cognitive modeling of human overtaking behavior when interacting with oncoming automated vehicles



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Thesis committee:	Dr. A. Zgonnikov,	TU Delft, daily supervisor
	Dr. ir. H. Farah,	TU Delft, supervisor
	Prof. dr. ir. D.A. Abbink,	TU Delft, external member

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Paper

In the driver's mind: cognitive modeling of human overtaking behavior when interacting with oncoming automated vehicles

Samir H.A. Mohammad[1], Haneen Farah[2] and Arkady Zgonnikov[1]

Abstract— **Understanding human behavior in overtaking scenarios is crucial for enhancing road safety in mixed traffic with automated vehicles (AVs). Modeling plays a pivotal role in advancing our comprehension of human overtaking behavior in dynamically evolving scenarios. Currently, our understanding of overtaking behavior primarily revolves around straightforward interactions with human-driven vehicles (HDVs). To address this gap, we conducted a "reverse" Wizard-of-Oz driving simulator experiment with 30 participants interacting with both oncoming AVs and HDVs, featuring time-varying dynamics. We hypothesized that the type of oncoming vehicle (AV or HDV) does not significantly influence gap acceptance during overtaking, while we anticipated an increase in gap acceptance when the oncoming vehicle briefly decelerates during interactions with the human ego-vehicle driver. Our findings reveal that participants did not significantly alter their overtaking behavior when interacting with oncoming AVs compared to HDVs. Surprisingly, brief decelerations in the oncoming vehicle's velocity did not significantly affect the decision-making processes of overtaking. Moreover, our results reinforced previous insights into the significance of the initial distance and time-to-arrival to the oncoming vehicle, and the ego-vehicle velocity on participants' overtaking behavior. We highlight the potential of simple drift-diffusion models (DDMs), a subset of cognitive models, in understanding human overtaking behavior in dynamically evolving scenarios involving oncoming AVs. Our proposed model accurately captures qualitative patterns in gap acceptance during these intricate overtaking scenarios, further advancing the ongoing development of safer interactions between human drivers and AVs during overtaking maneuvers.**

I. Introduction

While driving automation offers promise for improving traffic safety [1], successfully managing interactions between automated vehicles (AVs) and human drivers in mixed traffic scenarios remains a substantial and ongoing challenge [2]. Overtaking maneuvers on two-lane rural roads, in particular, pose significant risks of head-on collisions at high speeds. Human drivers' inconsistent judgments of available gaps [3]–[5] underscore the need for a comprehensive understanding of human overtaking behavior to enhance road safety.

Advanced overtaking behavior models can play a pivotal role in enhancing road safety and the development of AV technology. These models can generate realistic overtaking scenarios, improving the accuracy of testing and validation during the early stages of AV development [6]. Equipped with these models, AVs can predict gap acceptance in real time and anticipate overtaking maneuvers by human-driven vehicles (HDVs), contributing to overall safety [7]. Moreover, integrating clear communication interfaces (e.g., [8], [9]) and effective behavioral cues (e.g., [10], [11]) between AVs and human drivers can further enhance human-AV interactions [2].

However, our current understanding of overtaking behavior predominantly focuses on instantaneous decision-making processes (e.g., [3], [12]–[20]), overlooking the dynamic nature of overtaking maneuvers. These interactions evolve over time, influenced by factors such as relative speeds, distances between vehicles, and possibly by the behavior of other road users [21], [22]. Neglecting these dynamic aspects can severely limit the predictive capabilities of AVs in overtaking scenarios.

Recent research has started to bridge this gap by employing cognitive process models to describe dynamic decision-making processes across various traffic situations, including pedestrian-crossing [23], unprotected left-turns [24], [25], and straightforward overtaking maneuvers [26]. Drift-diffusion models (DDMs), a subset of cognitive models, are grounded in the theory of bounded accumulation of evidence, where drivers integrate visual cues, such as distance and time-to-arrival (TTA) to oncoming vehicles, into their decision-making processes. These models have effectively captured the effect of interactions, such as an AV signaling yielding intent through deceleration or external human-machine interface signals, on gap acceptance behavior [23]. Furthermore, DDMs have demonstrated potential in describing how time-varying dynamics of oncoming AVs influence gap acceptance decisions and response times [25].

Despite this progress, DDMs have yet to be validated with data involving overtaking interactions with oncoming AVs featuring varying dynamics. Most notably, the study by Mohammad et al. [26] was based on data from Sevenster et al. [13], where oncoming vehicles exhibited constant acceleration. To better represent real-world scenarios, we propose two significant improvements: first, considering more intricate interactions, including time-varying dynamics of oncoming vehicles, and second, exploring how different vehicle types, AVs or HDVs, may affect gap acceptance. Recent studies have presented mixed results on the influence of vehicle type on gap acceptance. Notably, Soni et al. [27] and Trende et al. [28] reported that drivers significantly accepted more gaps when interacting with AVs compared to HDVs. However, it is worth noting that these studies influenced their participants' perceptions of AVs before their

[1]Samir H.A. Mohammad and Arkady Zgonnikov are with the Department of Cognitive Robotics, Faculty of Mechanical, Maritime and Materials Engineering, Delft University of Technology, Mekelweg 2, Delft, 2628CD, the Netherlands.

[2]Haneen Farah is with the Department of Transport and Planning, Faculty of Civil Engineering and Geosciences, Delft University of Technology, Stevinweg 1, Delft, 2628CN, the Netherlands.

experiments, potentially impacting their results. In contrast, studies that refrained from doing so (e.g., [29]–[31]) did not find a significant difference in gap acceptance. These mixed findings underscore the need for a more comprehensive investigation into the potential influence of vehicle type on overtaking behavior.

This study aims to address these gaps through a driving simulator experiment involving 30 participants who interacted with both oncoming AVs and HDVs with varying dynamics. We manipulated the acceleration profile of the oncoming vehicle in three different ways: maintaining a constant speed, brief and weak deceleration nudging, and brief and strong deceleration nudging, as detailed in Section II. Furthermore, we used a "reverse" Wizard-of-Oz experimental setup to increase the participants' belief that the two vehicle types are distinct. Our hypotheses are twofold: firstly, that human overtaking behavior remains consistent when interacting with AVs, and secondly, that gap acceptance increases when the oncoming vehicle briefly decelerates during interaction with the ego-vehicle driver – Section III. We collected decision outcomes and their respective response times to fit experimental data to cognitive models – Section IV. Our ultimate goal is to enhance our understanding of these intricate overtaking maneuver interactions and their implications for road safety and AV development, as discussed in Section V.

II. Methods

A. Participants

Approval for this study was granted by the Human Research Ethics Committee of Delft University of Technology. Our participant pool consisted of 30 individuals, evenly distributed by gender (15 males and 15 females), with an age range from 18 to 35 years (Mean: 24.2, SD: 3.1). On average, participants held a driver's license for 5.6 years, with a range from 0.3 to 17 years (SD = 3.7). Participants' self-reported familiarity with self-driving cars averaged 2.4 on a 5-point Likert scale, with a standard deviation of 1.3. Additionally, their self-reported perceived safety of self-driving cars on the road averaged 2.9 (SD: 0.8). In return for their participation, each participant received a 20-euro gift voucher.

B. Setup

Participants conducted the experiment within a fixed-base driving simulator located at the Cognitive Robotics Department of Delft University of Technology (Figure 1). The simulator featured a 65-inch screen and was equipped with a Logitech G923 steering wheel, along with an additional unconnected Logitech Driving Force GT steering wheel, and a secondary monitor. For data recording purposes, we used JOAN as an experiment manager [32], capturing data at a rate of 100 Hz. The simulator ran on CARLA, an open-source autonomous driving simulation platform [33]. The experimental environment, comprising a two-lane rural road, was designed in RoadRunner.

Figure 1: "Reverse" Wizard-of-Oz' experimental setup of the driving simulator. During sessions involving oncoming human-driven vehicles, the experimenter operated an unconnected driving simulator setup.

C. Experimental design

Participants were instructed to replicate their real-world driving behavior throughout the experiment. Each trial started with the ego-vehicle set to cruise control until the platoon of vehicles on the opposite lane passed it. Following an audible beep signal, participants gained full control over the pedals and were tasked with assessing the road situation. Participants always started driving with full control at a headway of approximately 1.5 seconds behind a lead vehicle (a truck). Subsequently, to induce a desire to overtake, the truck's speed was gradually reduced from 60 km/h to 45 km/h. During the driver's assessment of the road situation, a gap was presented, following a methodology akin to Sevenster et al. [13] (Figure 2). Participants then made an overtaking decision based on the presented gap.

Figure 2: Participants' perspective while performing the task in the driving simulator. As the participant moves to the opposing lane to assess the road situation a decision has to be made to either overtake the truck (accepting the gap) or stay behind the truck.

Each trial involved four controlled variables, including the initial distance between the ego-vehicle and the oncoming vehicle (240m and 280m), the initial time-to-arrival (TTA) (6s and 10s), the acceleration profile of the oncoming vehicle (constant speed, weak nudge, and strong nudge) and the oncoming vehicle type (AV and HDV) (Figure 3). The experiment followed a within-participant design with a 2 x 2 x 2 x 3 factorial structure, resulting in 26 unique conditions–24 plus one "impossible" condition ($d_0 \sim$ U(70m,150m), TTA = 2s) per vehicle type to discourage participants from performing blind overtaking maneuvers and to promote a careful assessment of the road situation.

To familiarize participants with the driving equipment and task, they underwent between 5 to 10 practice trials, ensuring their comfort with the experimental procedure. The 26 unique conditions were randomly repeated five times and split evenly into two sessions based on vehicle type, resulting in a total of 130 trials. To maintain participant concentration, a brief off-screen distracting task followed every 13 trials, and each session lasted approximately 45 minutes, including a 15-minute break between the sessions.

In the session featuring an oncoming HDV, we employed a "reverse" Wizard-of-Oz setup where the experimenter was situated behind another driving simulator setup (Figure 1). This setup created the illusion that the oncoming HDV was human-controlled. Furthermore, the HDV had an animated driver and no LiDAR (Figure 3). Participants were equipped with a noise-canceling headset throughout the experiment to prevent any auditory influence from the experimenter's pedal inputs. The session order was alternated among participants.

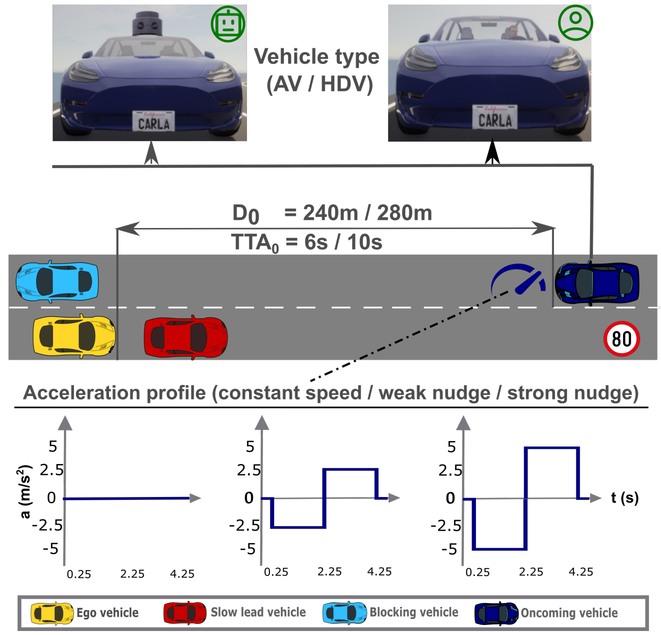

Figure 3: Experimental setup of the overtaking maneuver. The lead vehicle (red) slows down to induce an overtaking desire by the ego-vehicle (yellow). In each scenario, a distance and time-to-arrival gap to the oncoming vehicle (dark blue) is presented after the last platoon vehicle (cyan) passes. The oncoming vehicle, in half the cases an automated vehicle and in the other half a human-driven vehicle, drives with either of the three acceleration profiles.

D. Experimental conditions

Per vehicle type, the remaining conditions were equally distributed (Figure 3). Given the higher lead vehicle velocity in comparison to Sevenster et al.'s study (45 km/h vs. 30 km/h), the distance conditions were adjusted to 240 and 280 meters, allowing reasonably high-speed interactions with the oncoming vehicle. With TTA values of 6s and 10s and an average ego-vehicle speed of 45 km/h, the initial velocity of the oncoming vehicle ranged between 40 km/h (low distance, high TTA) and 120 km/h (high distance, low TTA). The oncoming vehicle either maintained a constant speed or executed a deceleration of either 2.5 m/s^2 or 5 m/s^2 for 2 seconds, followed by acceleration with the same respective value for another 2 seconds back to its initial speed.

To minimize variations in the initial ego-vehicle velocity and following distance to the lead vehicle, participants initiated each trial with cruise control and gained full control only upon hearing a beep (approximately 1.5 seconds of headway behind the truck). Following the beep, participants were tasked with assessing the road situation and subsequently deciding whether to overtake the truck or wait until the oncoming vehicle passed. The experiment recorded a total of about 3600 possible overtaking decisions.

E. Measures

To model overtaking behavior using the DDM framework, two primary dependent variables were measured: the decision outcome (Overtake or Stay) and its respective response time.

Response times for rejected gaps were calculated following the method proposed by Sevenster et al. [13] (see Figure 4). Their approach to measuring response times for accepted gaps specified that the decision-making process concluded when the ego-vehicle crossed the lane divider. In our experiment, the truck being overtaken was positioned more to the left of the lane compared to the setup in Sevenster et al.. As a result, the ego-vehicle was close to or already beyond the lane divider when assessing oncoming traffic in accepted gap scenarios. While an ideal generalized method for measuring the endpoint of decision-making in accepted decisions could have addressed this issue, it was beyond the scope of this study to conduct such an investigation. Instead, we compared three methods: 'crossing the lane divider', 'fully entering the opposing lane', and 'near full throttle' (see online supplementary information at https://osf.io/ya34n). We opted to use throttle data, later translated into acceleration data of the ego-vehicle, as a practical solution (Figure 4, 5). We justified this choice by the typical behavior observed in this experiment, where participants generally refrained from accelerating while assessing oncoming traffic due to their proximity to the slow-moving vehicle ahead.

Additionally, the decision outcomes—whether participants chose to "Overtake" (accepted gap) or "Stay" (rejected gap)—can potentially be further categorized into two subtypes: change-of-minds and aborted maneuvers [17].

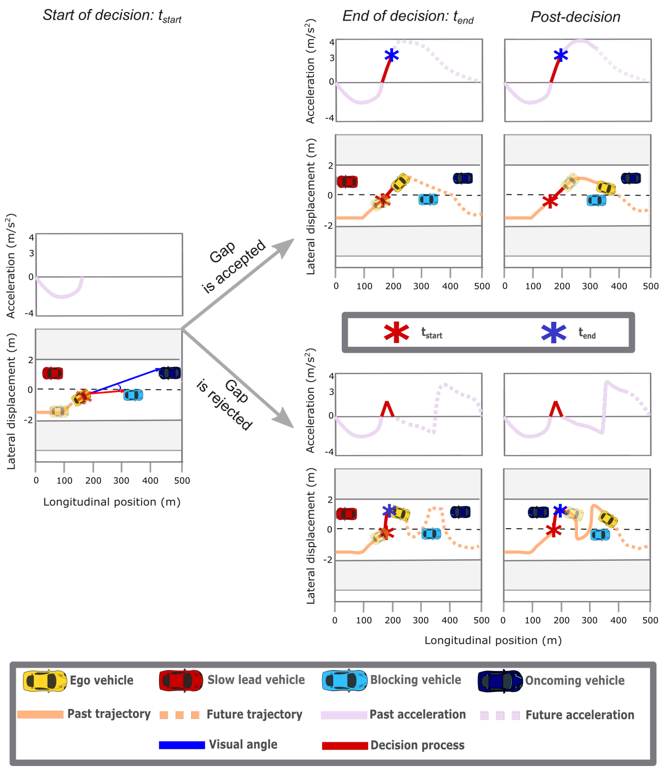

Figure 4: Response time measurement in rejected gaps [13] and our proposed measurement method in accepted gaps.

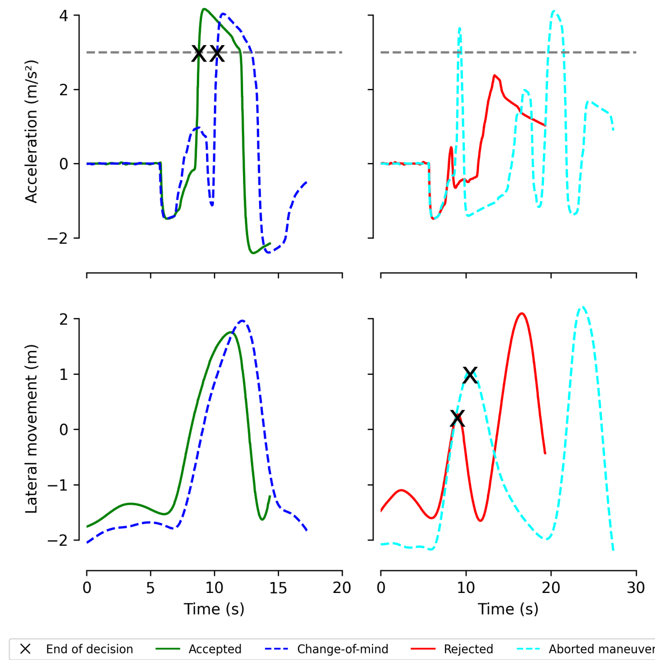

Figure 5: Comparison of decision outcomes: accepted gap vs. change-of-mind and rejected gap vs. aborted maneuver.

Change-of-minds are considered initially rejected gaps (braking i.e. acceleration $< 0m/s^2$) that participants later decided to accept, effectively converting them into accepted gaps. Conversely, aborted maneuvers represented scenarios where participants initially accepted a gap (near full throttle i.e. acceleration $> 3m/s^2$) but subsequently decided to reject it. We identified change-of-minds and aborted maneuvers based on acceleration data (Figure 5), but their analysis falls beyond the scope of this study, and therefore only final outcomes and their response times are further considered.

F. Exclusion criteria

We applied specific exclusion criteria to refine our dataset for analysis. We excluded trials in which the overtaking decision could not be determined due to vehicle crashes (N=19) and instances where the response time in accepted decisions could not be accurately measured (N=75) due to missing acceleration data. Additionally, we identified and removed instances of unrealistic response times, both excessively short ($< 0.5s$, N=225) and exceptionally long ($> 4s$, N=29). These exclusions were made in the context of statistical analyses involving response times and cognitive modeling but not in the statistical analyses of decision outcomes.

Unrealistically fast responses might be attributed to sensitivity in measurement equipment or instances where participants had already made their decisions before fully assessing the road situation. Distinguishing between these possibilities was not feasible; therefore, all unrealistically fast responses were excluded from further analysis.

Conversely, slow responses could be attributed to participants changing their decisions during the decision-making process. This is because the endpoint of the decision-making process is intricately linked to the final decision (Figure 5).

In total, our analyses were based on 3438 overtaking maneuvers to assess decision outcomes and 3184 decisions for analyzing response times and cognitive modeling.

G. Data analysis

We conducted statistical analyses using mixed-effect regressions for both decision outcomes (logistic) and response times (linear). Dummy coding was employed for vehicle types and acceleration profiles, using AV and constant speed as the respective reference groups. To address variations in baseline values of dependent variables across individuals, we included the vehicle type per participant ID as a random slope in all regression models.

Before proceeding with parameter estimation, we standardized all continuous variables (initial distance D_0, initial TTA TTA_0, and initial ego-vehicle velocity v_0^{ego}) through z-scoring. This standardization allowed us to interpret the coefficients (β) for each independent variable in terms of their relative contributions to the dependent variable.

In the case of the response time regression, we computed the Type-III sum-of-squares ANOVA table, utilizing the Satterthwaite approximation for degrees of freedom. To account for multiple comparisons in both decision and response time regression analyses, particularly concerning the acceleration profiles, we adjusted p-values using the Tukey method.

We used *pymer4* [34], a Python-based statistical analysis tool, to analyze decision outcomes and response times.

TABLE I: Coefficients of the mixed-effect logistic regression describing the final decision as a function of acceleration profile, vehicle type, session order, and z-scored variables D_0, TTA_0, and v_0^{ego}. The vehicle type per participant ID was included as a random slope.

	β	SE	z	p
(Intercept)	-0.056	0.28	0.20	0.85
D_0	0.99	0.06	15.48	< 0.001
TTA_0	0.56	0.06	9.18	< 0.001
v_0^{ego}	0.73	0.08	9.10	< 0.001
Acceleration profile 'weak nudge'	0.047	0.15	0.32	0.75
Acceleration profile 'strong nudge'	0.052	0.14	0.37	0.71
Vehicle type HDV	-0.26	0.40	-0.65	0.51
Session order second	-0.46	0.39	-1.18	0.23

III. Results

A. Decision outcomes

The probability of accepting the gap (expressed as the "Overtake" decision) was significantly positively affected by the initial distance D_0, initial time gap TTA_0, and initial ego-vehicle velocity v_0^{ego} (for details, see Table I and Figure 6). Post-hoc comparisons showed that there is no substantial evidence to suggest that the probability of overtaking differs between vehicle types AV vs. HDV (Δ = -0.11, z = -1.14, p = 0.25) in either the first ($p = 0.52$) or second session ($p = 0.21$). Likewise, there is no compelling evidence to indicate differences in overtaking probability across different acceleration profiles, such as 'constant speed' with 'weak nudge' (Δ = -0.071, z = -0.69, $p = 0.76$), 'constant speed' with 'strong nudge' (Δ = -0.057, z = -0.56, $p = 0.84$), and 'weak nudge' with 'strong nudge' conditions (Δ = -0.014, z = -0.14, $p = 0.99$).

B. Response times

In our analysis of response times (Table II, Figure 6), we observed significant influences of the decision outcome, initial distance D_0, and initial time gap TTA_0. Interestingly, there was no substantial evidence indicating that the initial ego-vehicle velocity v_0^{ego} significantly impacted response times (p = 0.23). Further post-hoc comparisons for response times revealed noteworthy patterns. Overtake responses exhibited significantly quicker response times than Stay responses (Δ = -1.16s, t = -60.0, $p < 0.001$). Moreover, no significant evidence emerged indicating differences in response times between vehicle types AV and HDV (p = 0.46). Furthermore, our analysis did not detect substantial differences in response times across different acceleration profile conditions. Specifically, for Overtake response times, between conditions 'constant speed' - 'weak nudge'(Δ = -0.01s, t = -0.29, $p = 0.95$), 'constant speed' - 'strong nudge' (Δ = -0.044s, t = -1.27, $p = 0.41$), and 'strong nudge' - 'weak nudge' (Δ = 0.034s, t = 1.01, $p = 0.57$). Likewise, Stay responses exhibited no significant differences in response times between the 'constant speed' - 'weak nudge' (Δ = -0.002s, t = -0.064, $p = 1.0$), 'constant speed' - 'strong nudge' (Δ = -0.020s, t = -0.76, $p = 0.73$), and 'strong nudge' - 'weak nudge' Δ = 0.019s, t = 0.69, $p = 0.77$) conditions.

TABLE II: ANOVA table based on the mixed-effect linear regression describing response time as a function of decision, acceleration profile, vehicle type, and z-scored variables D_0, TTA_0, and v_0^{ego}.

	SS	MS	df	F	p
Decision	641	641	1	3547	< 0.001
D_0	6.94	6.95	1	36.4	< 0.001
TTA_0	14.2	14.2	1	78.8	< 0.001
v_0^{ego}	0.26	0.26	1	1.46	0.23
Acceleration profile	0.39	0.19	1.07	1.05	0.34
Vehicle type	0.10	0.10	1	0.55	0.47
Session order	0.11	0.11	1	0.62	0.44

C. Post-experiment questionnaire

In the post-experiment questionnaire (Likert scale 1 to 5) participants reported a similar (t = -0.25, $p = 0.83$) sense of safe interactions in each session (AV: M = 3.9, SD = 0.76 and HDV: M = 3.9, SD = 0.64). Lastly, the belief that the self-driving and the human-driven car behaved differently varied substantially among the participants (M = 3.1, SD = 1.3).

D. Main findings

Based on the experimental findings, we can conclude the following.

- Initial distance, initial TTA, and initial ego-vehicle velocity significantly affected overtaking probability but response times showed only significant differences in initial distance and initial TTA.
- No evidence of a significant difference in overtaking probability between the oncoming vehicle types AV and HDV was found.
- Weak and strong nudges did not significantly impact overtaking probability compared to the constant speed acceleration profile of the oncoming vehicle.
- Response times exhibited no significant differences based on the oncoming vehicle type or its acceleration profile.

These key conclusions were also drawn when employing alternative methods to measure response times in accepted gaps, except for the initial ego-vehicle velocity *not* significantly affecting response times, as outlined in the supplementary information.

IV. Modeling

Modeling plays a crucial role in deepening our understanding of human overtaking behavior in dynamically evolving scenarios. Previous research demonstrated the effectiveness of cognitive modeling in comprehending and modeling straightforward overtaking interactions (as presented in the Thesis chapter on Preliminary Work). In this section, we aim to capture the complexities inherent in overtaking interactions when the oncoming vehicle exhibits varying dynamics. To achieve this, we employ the cognitive modeling framework and test variations of the drift-diffusion model. The model fitting and simulation code for this study is available online.

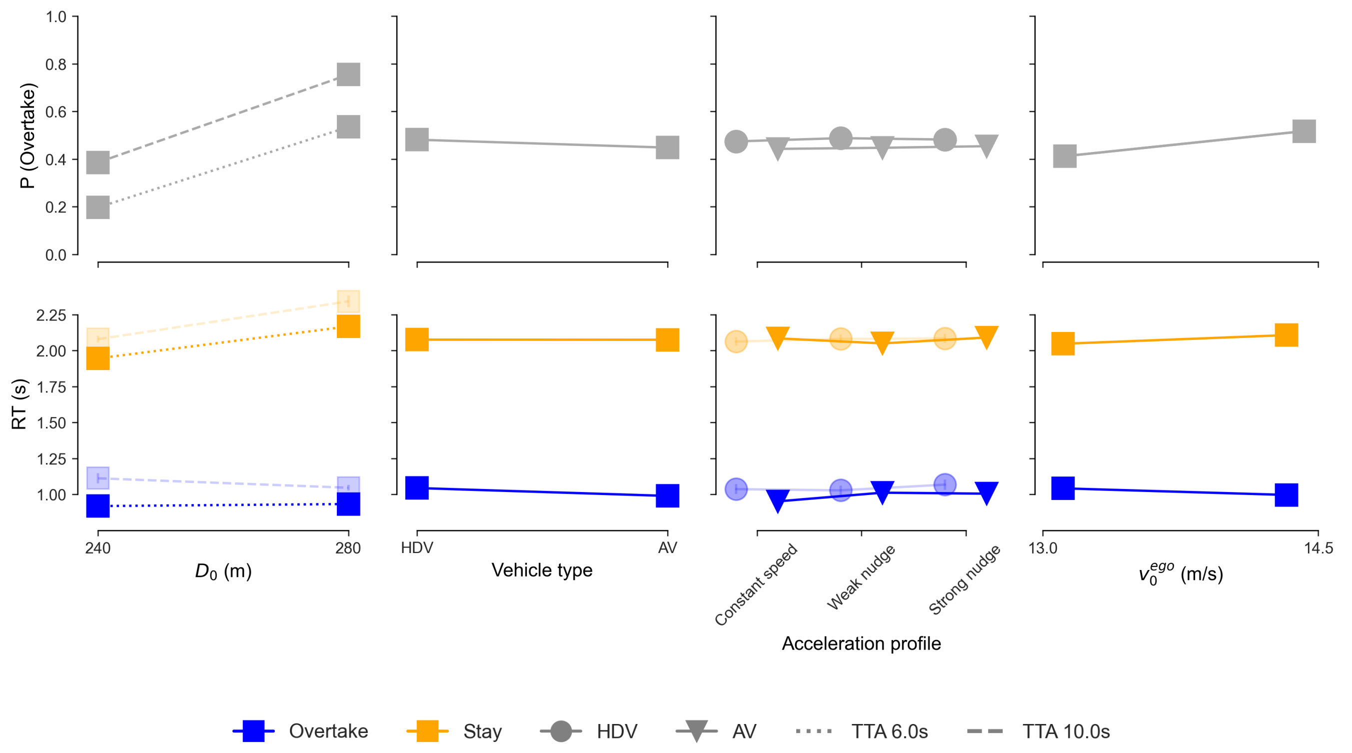

Figure 6: Overview of the average participant's behavior in overtaking decisions.

A. Dataset

We filtered this dataset by removing measures with unrealistic response times and missing values as described in Section II-F. The remaining data (N=3184) were used for further analysis. Additionally, we clustered the initial ego-vehicle velocities into two distinct groups for compatibility with existing fitting tools such as *pyddm* [35]. Our statistical analysis (Section III) of the dataset revealed relationships between the overtaking scenario's setup and human overtaking behavior (i.e. decisions and response times).

B. Cognitive modeling

1) Basic drift-diffusion model and its applications to traffic: We utilized the drift-diffusion modeling framework [36] to describe participants' decision-making processes in our experiment. This framework is based on the concept that when individuals are confronted with a decision, they engage in an ongoing process of integrating relevant perceptual information such as distance and TTA over time (Figure 7). Notably, Roitman and Shadlen [37] reported variations in neural activity within the LIP area (neurons associated with the visual sensory system) depending on the choice made, implying the continuous accumulation of evidence for each alternative.

Mathematically, the rate of evidence accumulation is denoted as the drift rate $s(t)$, while the diffusion process is characterized as a stochastic, noisy variable $\varepsilon(t)$. The momentary evidence x favoring one alternative emerges from integrating both drift and diffusion (Eq. (1)). This continuous process remains bounded, ceasing when the evidence favoring one alternative reaches a predetermined threshold ($x = \pm b(t)$). Despite its computational simplicity, DDMs have proven highly effective in modeling and comprehending a wide array of decision-making processes, encompassing perceptual judgments, choice behavior, and response times in experimental investigations [38].

$$\frac{dx}{dt} = s(t) + \varepsilon(t). \tag{1}$$

To address the potential element of choice urgency in traffic-related decisions, we explored extending the drift rate $s(t)$ and boundaries $b(t)$ to be contingent on dynamically evolving gap sizes. These extended DDMs successfully captured human gap acceptance behavior in scenarios like pedestrian crossings [23] and left-turns at unprotected intersections [24]. However, in contrast to these scenarios, overtaking maneuvers involve the human driver initiating the decision-making process with an initial velocity. The influence of this initial velocity on decision outcomes was evident in the overtaking experiment conducted by Sevenster et al. [13], where it positively influenced gap acceptance while negatively affecting response times in accepted gaps.

Drawing upon data from that study, Mohammad et al. [26] explored various iterations of the DDM where the initial velocity was integrated into different components of the model: drift rate $s(t)$, boundary $b(t)$, and the initial bias Z which is the starting point of the decision-making process. The simplest model capable of effectively capturing all qualitative patterns in their used dataset included the initial velocity within the initial bias Z. This indicated that higher initial velocities would initiate the drift-diffusion process closer to the 'Overtake' decision boundary, while lower initial velocities would position it nearer to the 'Stay' decision boundary.

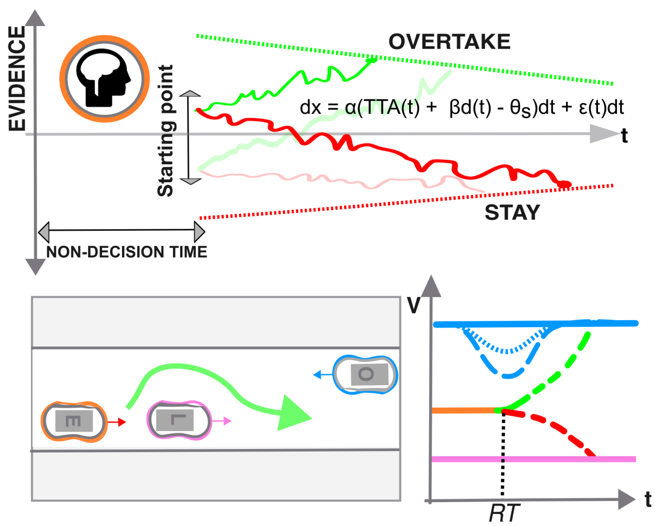

Figure 7: Gap acceptance visualization in overtaking scenarios using the drift-diffusion model. Purple represents the lead vehicle, blue is the oncoming vehicle, and orange characterizes the ego vehicle's human driver. Red indicates staying in the lane, and green represents overtaking, while blue velocity curves depict different dynamics of the oncoming vehicle.

2) *New candidate drift-diffusion models for dynamic overtaking scenarios:* Overtaking behavior in scenarios involving constantly accelerating oncoming vehicles was effectively modeled using an ego-velocity dependent starting point in a previous study [26]. The most effective model with the fewest parameters in that study had a drift rate dependent on both distance ($d(t)$) and TTA ($TTA(t)$), and the boundaries exhibited exponential collapse as distance and TTA decreased. We refer to this model as our baseline.

However, our experiment significantly differs from the one conducted by Sevenster et al. [13], with variations in the initial distance (160m and 220m vs. 240m and 280m) and additional controlled variables (initial TTA, and the oncoming vehicle's acceleration profile). Thus, we need to explore multiple models to find the one that fits our dataset best. To do this, we re-evaluate the four main components of the DDM framework used by Mohammad et al. [26] and propose four potential models to explain our experimental results.

2.1 Non-decision time

For all of our models, the non-decision time (the duration of cognitive processes unrelated to decision-making, such as perceptual and motor delays) is assumed to follow a normal distribution:

$$t^{ND} \in \mathcal{N}(\mu_{ND}, \sigma_{ND}), \quad \mu_{ND} > 0, \sigma_{ND} > 0. \tag{2}$$

Evidence accumulation begins after the non-decision time ends. Next, we consider the rate of accumulation i.e. the drift rate.

2.2 Drift rate

The drift rate $s(t)$ in all our four models is determined by parameters $\alpha > 0$, $\beta > 0$, and $\theta_s > 0$, and is a measure of relative evidence x favoring either the "Overtake" or "Stay" decision at any given moment t (Eq.3). As the gap between the ego-vehicle and the oncoming vehicle (comprising $d(t)$ and $TTA(t)$) increases, for example, when the oncoming vehicle decelerates in relation to a critical value θ_s (effectively representing the critical gap size in gap acceptance), the drift rate becomes more positive. This indicates a higher likelihood of the decision-maker leaning towards the "Overtake" decision. Conversely, a more negative drift rate suggests a greater probability of choosing the "Stay" decision.

$$s(t) = \alpha(TTA(t) + \beta d(t) - \theta_s) \tag{3}$$

The drift process ends upon reaching either boundary (positive or negative) with the height of each boundary representing how much evidence is required for choosing the respective alternative.

2.3 Boundary function

Intuitively, with lower values of $TTA(t)$ and $d(t)$, the decision-maker might experience a stronger sense of urgency to make a decision, which can potentially be reflected in the boundary $b(t)$ decreasing with gap size [24]. However, Zgonnikov et al. [25] showed that models with a constant boundary better described left-turn gap acceptance at unprotected intersections. Since initial TTA does affect response times in overtaking (Figure 6), it is worth examining whether decreasing TTA urges the driver to make a decision. We test two boundary functions: boundaries constant over time (Eq. 4) and boundaries exponentially collapsing with the kinematic variables $d(t)$ and $TTA(t)$ (Eq. 5)

$$b(t) = \pm B \tag{4}$$

$$b(t) = \pm \frac{b_0}{1 + e^{-k(TTA(t) + \beta d(t) - \theta_s)}}. \tag{5}$$

How fast drift rates reach a certain boundary can also be affected by the starting point of the evidence accumulation process.

2.4 Starting point initial bias Z

Despite the small differences in initial ego-velocity data (lower half: 13.1 m/s, upper half: 14.4 m/s), there is still a significant effect on the decision outcome (Figure 6). We will test two variations: a fixed starting point (Eq. 6) and one dependent on initial velocity-dependent (Eq. 7).

$$Z = C_z \tag{6}$$

$$Z = \frac{2b(t_0)}{1+e^{-b_z(v_{ego}^0-\theta_z)}} - b(t_0) \quad (7)$$

Here, a value of $Z < 0$ indicates an initial bias towards the "Stay" decision, while $Z > 0$ indicates a bias towards the "Overtake" decision. This bias can be represented by a constant value C_z or can vary based on the initial velocity v_{ego}^0. In the latter case, relatively higher and lower initial speeds correspond to a bias toward the "Overtake" and "Stay" decisions, respectively.

2.5 Fitting the drift-diffusion model variations

The four model variants, resulting from different combinations of boundary and initial bias functions, are presented in Table III. These models were fitted using the differential evolution optimization technique and Bayesian information criterion. We employed *pyddm*, a Python framework explicitly designed for fitting drift-diffusion models [35], to implement these methods. Our approach, similar to that of Mohammad et al. [26], aimed to assess whether our models effectively captured the behavior of the "average" participant, as discussed in Section III, rather than explaining individual differences, a topic explored in studies such as Zgonnikov et al. [24].

3) Comparing models and data: Since there was no significant distinction in overtaking behavior between oncoming AVs and HDVs, we excluded vehicle type considerations in all models.

Considering the rest of the findings, we found that the four tested models differed substantially in their qualitative alignment with the observed behavior of the average participant (Figure 8, Table IV).

All models exhibited consistent behavior regarding the probability of overtaking across various acceleration profiles with magnitudes of deceleration nudges ranging from 0 (Constant speed) to 5 m/s^2 (Strong nudge). However, models incorporating a constant starting point (M1 and M2) failed to account for the effect of initial velocity on gap acceptance probability. Conversely, models featuring an initial velocity-dependent initial bias (M3 and M4) successfully captured this effect.

Turning our attention to response times, models with constant boundaries (M2 and M4) provided a better fit for the observed increase in response times compared to their counterparts using exponentially collapsing boundaries. This suggests that there might not be a significant urgency effect under these experimental conditions.

The baseline model (M3) [26], which encompassed scenarios with shorter distances and greater variability in initial velocity, effectively described 6 out of 8 qualitative patterns. Model M4 comprehensively described all qualitative patterns of dynamic overtaking interactions by employing constant boundaries and including a velocity-dependent initial bias. The fitted parameters for M4 were as follows: $\alpha = 0.05$, $\beta = 0.52$, $\theta_s = 148$, $B = 1.4$, $b_z = 0.11$, $\theta_z = 8.48$, $\mu_{ND} = 0.53$, $\sigma_{ND} = 0.10$.

V. Discussion

We conducted a driving simulator experiment to determine the effect of a) the oncoming type AV as opposed to HDV and b) dynamic changes in the oncoming vehicle's velocity, and subsequently used the DDM framework to describe gap acceptance during these intricate interactions. Our experimental results revealed that gap acceptance in overtaking depends on the initial distance and TTA to the oncoming vehicle, and on the ego-vehicle's initial velocity. These findings resonate with other gap acceptance studies in overtaking such as Farah et al. [18] and Sevenster et al. [13]. Most importantly, our study reveals two new empirical findings and one advancement in the modeling part: Firstly, participants showed no significant difference in their gap acceptance when interacting with an AV as opposed to an HDV. This finding is rather reassuring as models do not need to increase their complexity by incorporating a vehicle-type-dependent bias. Secondly, the oncoming vehicle's acceleration profile did not affect overtaking behavior and this finding is both surprising and rather disappointing. Potentially, this limits the effectiveness of AVs in showing yielding behavior to other human-driven vehicles during overtaking maneuvers. Finally, we showed that a simplified version of earlier proposed DDMs using constant decision boundaries can adequately describe human overtaking behavior.

A. Oncoming automated and human-driven vehicles: two peas in a pod?

Studies of other gap acceptance situations showed conflicting results on whether humans change their behavior when interacting with AVs. Soni et al. [27] and Trende et al. [28] found that drivers were willing to accept shorter gaps at intersections with approaching AVs i.e. drivers significantly decreased their critical gaps when they interacted with AVs as opposed to HDVs. However, in both studies, drivers were given information with the intention of influencing their perception of AVs. Other studies that did not inform their participants about the AV's behavior (e.g., [29]–[31]) showed no significant difference in gap acceptance behavior. Our study contributed to investigating whether the presence of AVs impacts gap acceptance in overtaking by conducting a "reverse" Wizard-of-Oz experiment. We did not inform participants beforehand about the AVs behavior and we found no significant difference in human overtaking behavior between sessions with an oncoming AV and an oncoming HDV. Our finding is in line with those of previous studies that did not bias their participants' perception of AVs.

However, participants in our experiment were aware of the oncoming vehicle type (AV or HDV) before each trial. This prior knowledge could restrict capturing any potential bias *during* the decision-making process. Due to technical limitations in JOAN, we had to separate the experiment into sessions with each featuring always the same oncoming vehicle type. Future studies should consider randomizing the oncoming vehicle type across trials to mimic the uncertainty encountered in real mixed-traffic scenarios.

TABLE III: Four tested variations of the generalized drift-diffusion model (1) with varying boundary functions (4) (5) and initial bias functions (6) (7). The number of parameters in the last column includes the drift rate parameters α, β, θ_s and the two non-decision time parameters μ_{ND}, σ_{ND}.

Model	Decision boundary $b(t)$	Eq.	Initial bias $-b(t_0) < Z < b(t_0)$	Eq.	# parameters
M1	$\pm\frac{b_0}{1+e^{-k(TTA(t)+\beta d(t)-\theta_s)}}$	(5)	C_z	(6)	8
M2	$\pm B$	(4)	C_z	(6)	7
M3 (baseline [26])	$\pm\frac{b_0}{1+e^{-k(TTA(t)+\beta d(t)-\theta_s)}}$	(5)	$\frac{2b(t_0)}{1+e^{-b_z(v_{ego}^0-\theta_z)}} - b(t_0)$	(7)	9
M4	$\pm B$	(4)	$\frac{2b(t_0)}{1+e^{-b_z(v_{ego}^0-\theta_z)}} - b(t_0)$	(7)	8

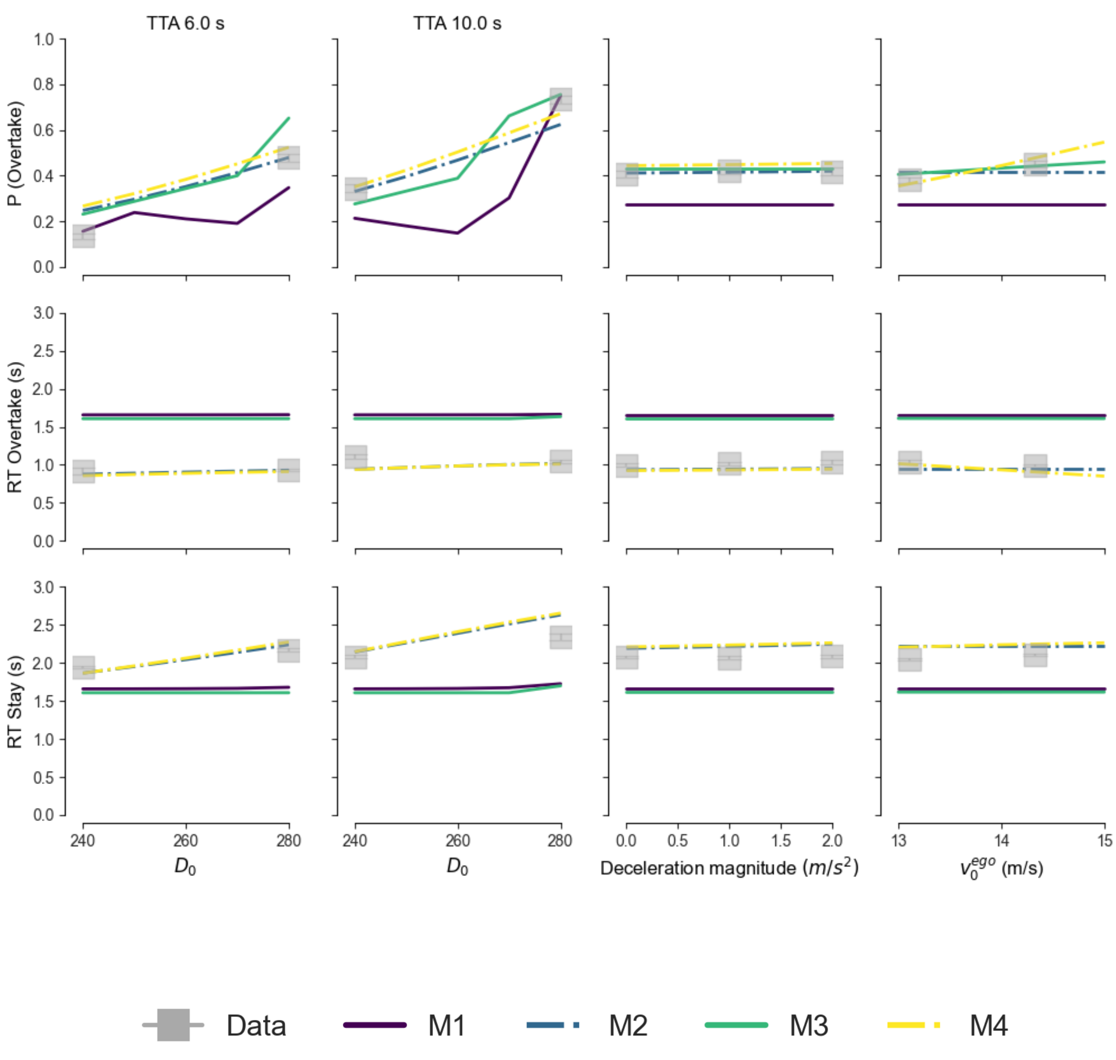

Figure 8: Simulated model results compared to the experimental data to show the effect of distance and TTA, deceleration magnitudes of acceleration profiles, and the initial ego-vehicle velocity on gap acceptance behavior. The error bars represent the standard error of the mean.

TABLE IV: Assessment of candidate drift-diffusion models according to the experimental findings.

Finding	M1	M2	M3	M4
The probability of accepting the gap increases with the initial distance to the oncoming vehicle.	X	✓	✓	✓
The probability of accepting the gap increases with the initial TTA to the oncoming vehicle.	X	✓	✓	✓
The probability of accepting the gap increases with the initial velocity of the ego vehicle.	X	X	✓	✓
The probability of accepting the gap remains constant regardless of the acceleration profile of the oncoming vehicle.	✓	✓	✓	✓
Response times in rejected gaps are on average higher than in accepted gap.s	X	✓	X	✓
Response times in rejected gaps increase with the initial distance to the oncoming vehicle.	X	✓	X	✓
Response times increase with the initial TTA to the oncoming vehicle.	X	✓	X	✓
Response times remain constant regardless of the initial velocity of the ego vehicle.	✓	✓	✓	✓
Response times remain constant regardless of the acceleration profile of the oncoming vehicle.	✓	✓	✓	✓
Total	**3/9**	**8/9**	**6/9**	**9/9**

B. Human overtaking behavior: robust to nudging?

Perhaps the most unexpected finding is that we observed no significant differences across the acceleration profiles of the oncoming vehicle. This outcome is contrary to Rettenmaier et al. [21] who found human drivers adapted their behavior when interacting with an oncoming vehicle with varying dynamics at a narrow passage. Consistent with this, Zgonnikov et al. [25] reported significantly higher gap acceptance in left-turn interactions with an oncoming vehicle exhibiting a deceleration nudge profile compared to a constant-speed profile. It could be argued that this phenomenon may be more prominent in interactions where changes in TTA are easier to perceive [39], such as those involving oncoming vehicles at relatively short distances (e.g., 50m [21] or 90m [25]) when compared to our experimental distances of 240m and 280m. The finding that even strong nudges (deceleration rate of $5m/s^2$) had no significant effect on response times suggests that our participants might not have perceived any change in TTA.

One possible explanation could be due to the fidelity of the driver simulator [40]. Participants perceived initial distance and TTA conditions discriminately but the field of view (i.e. screen resolution) of the simulator might not have been large enough to also capture subtle changes in spatial and temporal information [41]. Future studies should explore how these simulator-specific perceptual differences may influence decision-making during overtaking maneuvers.

Besides, it is noteworthy that participants in our study fell within the age range associated with increased risky behavior in driver simulators, potentially due to videogame experience [42]. Any increased risky behavior of participants might decrease their sensitivity to the oncoming vehicle's dynamics. Investigating the relationship between videogame experience and simulator behavior can help explain individual differences in driving decisions in simulators.

C. Simpler drift-diffusion model for more complex overtaking scenarios?

Behavioral models, particularly cognitive behavioral models, offer distinct advantages over purely statistical models when analyzing observational data. They provide a structured framework for comprehending the underlying mechanisms and causal relationships that drive observed behaviors. While statistical models can depict data correlations, behavioral models go a step further, allowing exploration into *why* drivers accept gaps, rather than merely describing *what* they do. Furthermore, cognitive behavioral models add insight into *how* human drivers process relevant perceptual information over time, emphasizing the decision-making process itself.

Our study demonstrated that the cognitive modeling approach is suitable for describing how time-varying interactions with oncoming vehicles affect the decision-making processes of human ego-vehicle drivers during overtaking maneuvers. Previous DDMs used to model gap acceptance behavior either included the acceleration of the oncoming vehicle separately [23] or integrated it into the TTA [25]. In our study, we streamlined the model by reducing the number of parameters and focused on models with drift rates that depend on both distance and TTA.

Out of the four tested DDMs, only M4 was capable of describing all the qualitative patterns in our overtaking dataset. Unexpectedly, the baseline model M3 proposed by Mohammad et al. [26], based on a dataset involving more straightforward overtaking maneuvers [13], failed to describe all patterns. The key difference between M3 and M4 is that the former incorporates time-varying decision boundaries, while the latter employs constant boundaries. Mohammad et al. reported a k value of 0.02, indicating only minor collapsing of boundaries over time. Contrary to our expectations, we did not find a global minimum during the fitting process, even with low values of k. Several factors could explain this behavior. Firstly, Mohammad et al. did not consider models with constant boundaries even though the low value of k indicated that time-varying boundaries might be redundant. Secondly, the lack of constant acceleration to close the gap [13] might explain why there was no urgency effect in our experiment. A note of caution is needed here since our dataset does not contain acceleration profiles with acceleration nudges hence we are not able to extrapolate our findings. Moreover, our results reinforced previous insights into the dynamics of the decision-making process during overtaking which emphasized the need to implement a velocity-dependent initial bias [26] despite small deviations in initial ego-vehicle velocity across our overtaking trials.

Finally, our study demonstrated that Mohammad et al.'s DDM [26] can be simplified by using constant decision boundaries, resulting in a better description of the decision-making processes in dynamic overtaking scenarios. Additional details can be found in the supplementary information, where we also show that our model effectively describes the overtaking dataset of Sevenster et al. [13].

However, our proposed model is limited to only account for response times of the final decision and not for the initial decision in case of an aborted overtaking maneuver or a change-of-mind [35]. This restricts the predictive power of the decision-making *process* and to a lesser extent the decision *outcome* [43]. Besides, our model does not consider all factors that affect the probability of aborting an overtaking maneuver such as the individual driver's age and gender [17]. We also note that our study is among the first to report change-of-mind decisions in overtaking maneuvers, and there is a need for further research to explore the underlying mechanisms leading to these changes in decision-making. Future studies should aim to extend DDM fitting tools to incorporate changed decisions.

D. Closing the gap: implications of cognitive modeling of intricate traffic decisions

In this paper, we introduce a cognitive modeling approach to describe human drivers' gap acceptance behavior during dynamic overtaking interactions with oncoming AVs. Our study extends the applicability of DDMs, enhancing our understanding of human behavior in AV interactions in dynamically evolving traffic scenarios.

Our findings underscore the versatility and generalizability of the cognitive modeling approach, in particular the DDM framework. DDMs effectively describe gap acceptance behavior in intricate, dynamic traffic scenarios, such as overtaking maneuvers involving AVs, and potentially in complex maneuvers like merging onto on-ramps or changing lanes on highways. This represents a significant step forward compared to previous models, which predominantly focused on less dynamic [26] scenarios, or simpler traffic situations without considering the initial velocity of the human decision-makers [23]–[25].

Understanding human behavior in more intricate interactions between AVs and human drivers is essential for safe road management [2]. AVs can significantly improve their trajectory planning by incorporating predictions of human gap acceptance behaviors exhibited by other road users [7]. AVs can adopt the perspective of human-driven vehicles and employ perceptual cues such as distance and TTA in the human drivers' evidence accumulation process. Yet, determining the exact initiation point of the decision-making process remains a complex task, as we currently assume that the desire to perform a particular maneuver already exists.

Furthermore, cognitive models like DDMs can contribute to more realistic microsimulations of human-AV interactions [44]. These models can be embedded in the trajectory control of other vehicles in simulations, allowing for rigorous testing of AV performance within highly realistic simulated environments. However, simulating the impact of individual differences and how human behavior changes over a long time, such as their critical gap or, more importantly, their perception of AVs in emerging mixed traffic, remains challenging in portraying realistic scenarios. On average, participants did not change their overtaking behavior when interacting with an AV in this study. However, it is conceivable that as human drivers become increasingly exposed to human-AV interactions on the road in the future, behavioral patterns may evolve. Therefore, it is important to continue investigating how humans interact with AVs on the road.

Cognitive models, reflecting naturalistic behavior in human-AV interactions, can enhance the training and validation of interactive-aware controllers for AVs [45]. This becomes particularly valuable when training and validation data are scarce or when certain scenarios are deemed too dangerous for data collection in real-world interactions with AVs like overtaking [46]. Interactive-aware controllers equipped with cognitive models can bridge this gap, simulating numerous times to predict human behavior and how humans would behave when the AV changes its dynamics. This development offers promise, emphasizing the potential of simple cognitive process models to not only enhance our understanding but also significantly improve human-AV interactions in a multitude of dynamically evolving traffic scenarios. Nevertheless, continued research is essential to address challenges related to the initiation of the decision-making process, individual differences, and evolving human perceptions of AVs, ultimately unlocking the full potential of these cognitive process models [47].

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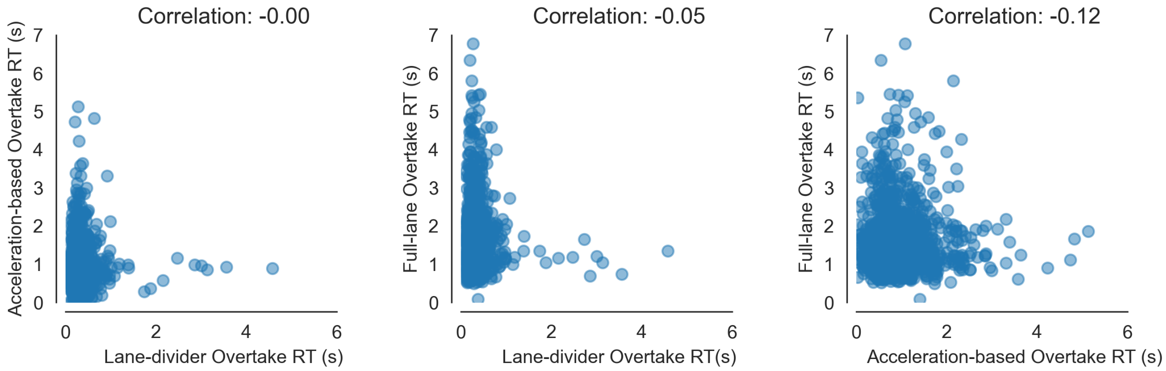


Figure 1.1: Correlation between response time measurement methods in accepted gap decisions

1.1. Supplementary information

A. Response time measurement for accepted gaps

This supplementary section provides insights into the comparison of three distinct methods (Figure 1.1) for measuring response times in accepted decisions, aiming to address the limitations of the original lane divider crossing approach and enhance response time accuracy in overtaking decisions.

Original method: crossing lane divider

The original method, as proposed by Sevenster et al. [1], defines the end of the decision-making process as the moment when the ego-vehicle crosses the lane divider (Figure 1.2). However, in our experiment, we faced challenges due to the lead vehicle's presence near the lane divider obstructing the driver's view of oncoming traffic. As a result, the ego-vehicle driver often crossed or was on the verge of crossing the lane divider before entirely assessing the road situation, leading to very short response times.

Alternative method 1: fully entering the opposite lane

In response to the limitations of the original method, we introduced an alternative approach where the end of the decision-making process is defined as when the ego-vehicle fully enters the opposite lane (Figure 1.2).

Alternative method 2: near full throttle

Another alternative method involved translating throttle data into acceleration and determining the end of the decision-making process as the moment when the ego-vehicle driver applies (or nearly applies) full throttle for overtaking, typically at an acceleration rate of 3 m/s^2. This method strikes a balance between the original lane divider crossing approach and the fully entering lane method, resulting in response times that more closely resemble natural behavior (Figure 1.2).

Effect on method choice on conclusions

We investigated whether the choice of response time measurement method would impact the conclusions drawn from our study. Figure 1.3 demonstrates that most qualitative patterns remain consistent across methods. Notably, the method 'near full throttle' differs from the other two methods in its observation of the effect of distance on accepted response times. However, key findings, such as similar response times when interacting with both autonomous vehicles (AVs) and human-driven vehicles (HDVs) and across various acceleration profiles of the oncoming vehicle, remain unaffected by the choice of measurement method.

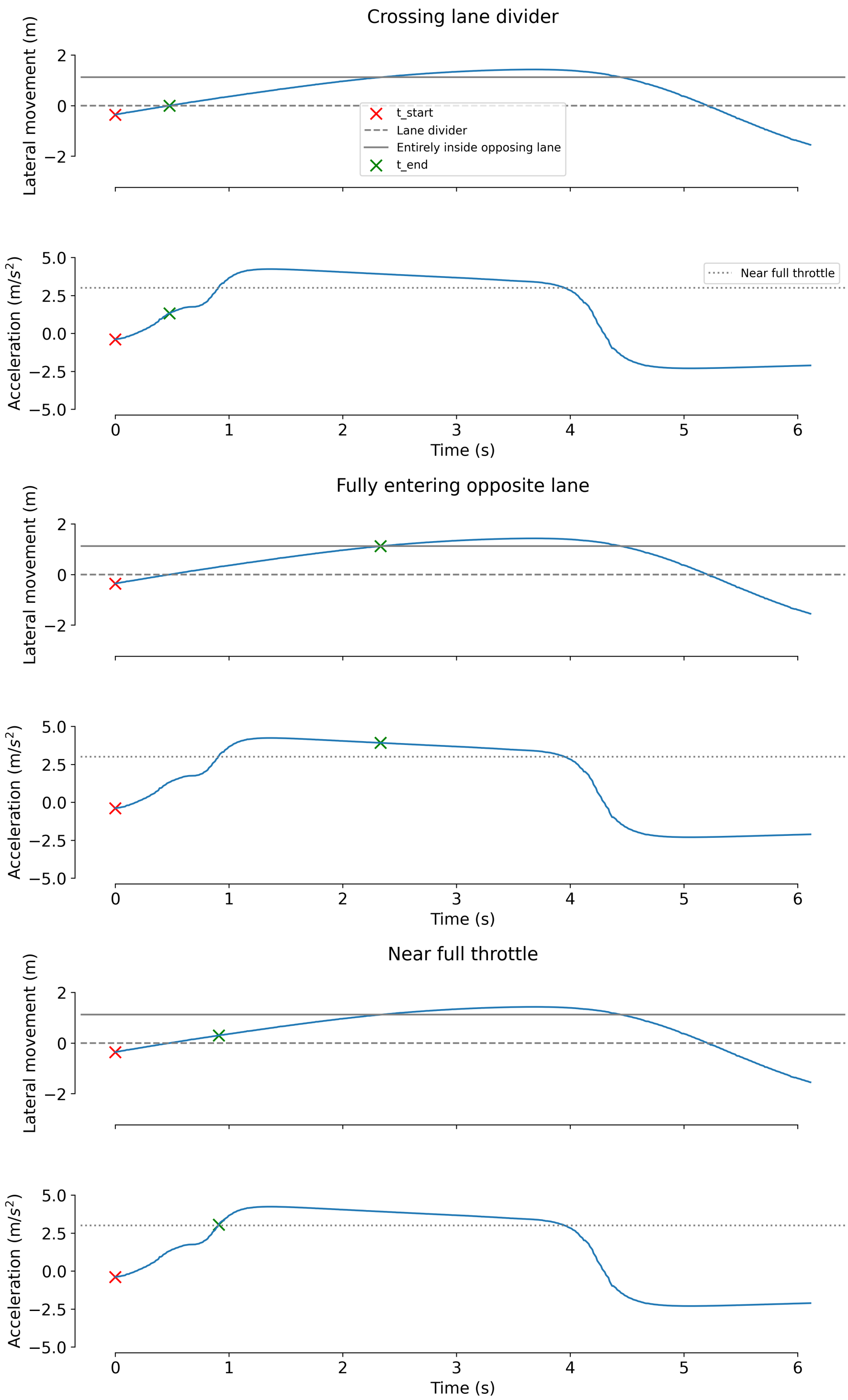
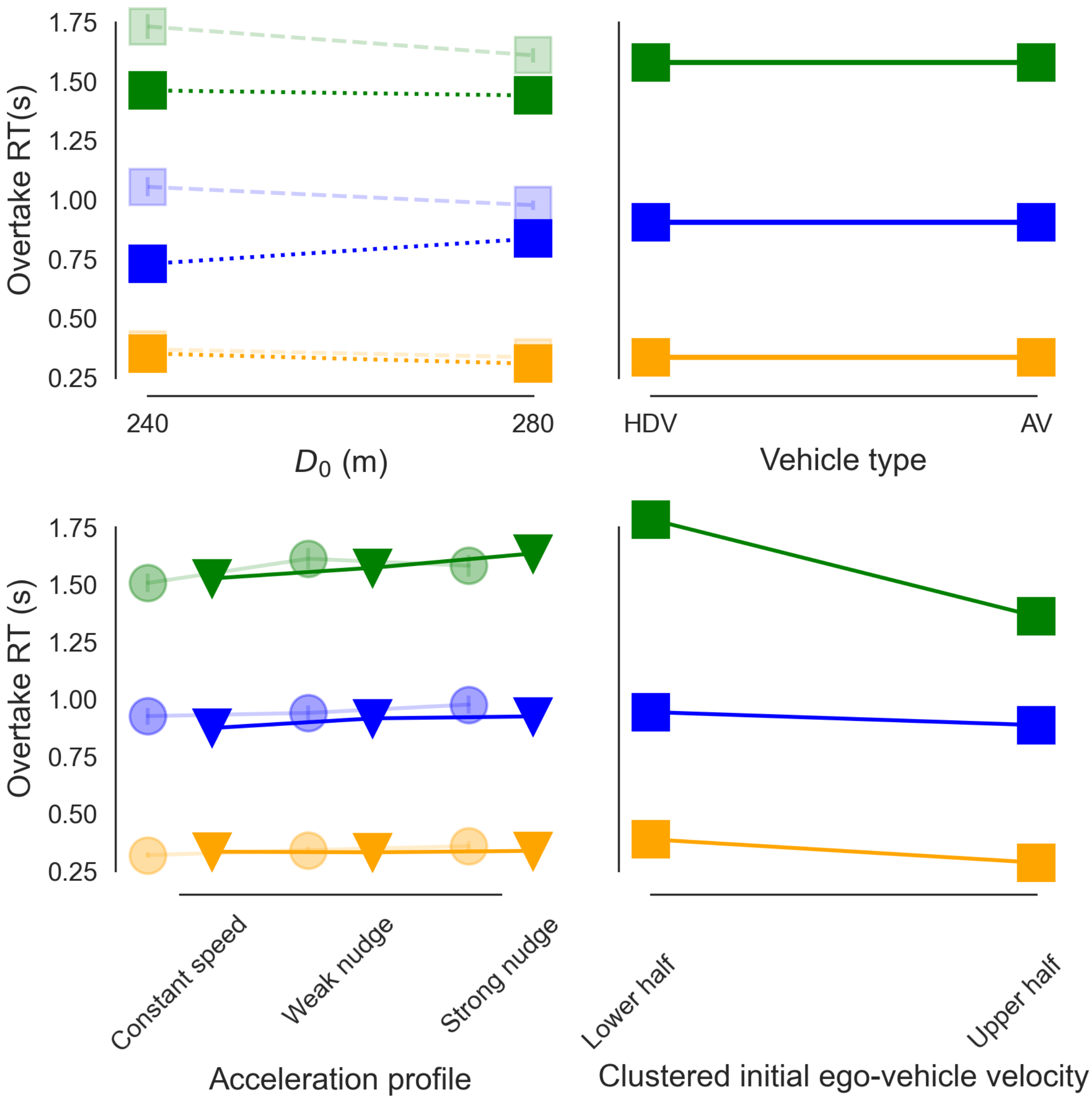


Figure 1.2: Comparison of response time measurement methods in accepted gap decisions, including the crossing lane-divider method proposed by Sevenster et al. [1] and two alternative approaches. Red and green crosses indicate the start and end of the decision-making process.



(a)

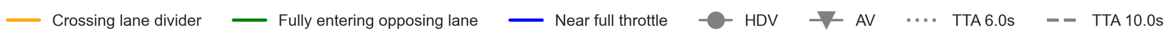


Figure 1.3: Experimental results showing the average participant's overtaking response times measured using the crossing lane-divider method by Sevenster et al. [1] and two alternative measurement methods

B. Simplification of the drift-diffusion model

Surprisingly, despite employing simpler boundary functions, our proposed model demonstrated a better capacity to capture the qualitative patterns of overtaking decisions in more complex scenarios compared to the earlier proposed DDM by Mohammad et al. [2]. To evaluate the robustness of our model, we fitted it to data on overtaking scenarios where the oncoming vehicle always accelerated at a constant rate, a setup described by Sevenster et al. [1]. Furthermore, we compared our model to the previously proposed model by Mohammad et al. Our findings reveal that our model, which incorporates a constant boundary function ($b(t) = \pm B$), performs on par with the earlier proposed model that utilizes an exponentially collapsing boundary function ($b(t) = \pm \frac{b_0}{1+e^{-k(TTA(t)+\beta d(t)-\theta_s)}}$), as depicted in Figure 1.4. This suggests the robustness and effectiveness of our simplified model in describing overtaking decisions in diverse scenarios.

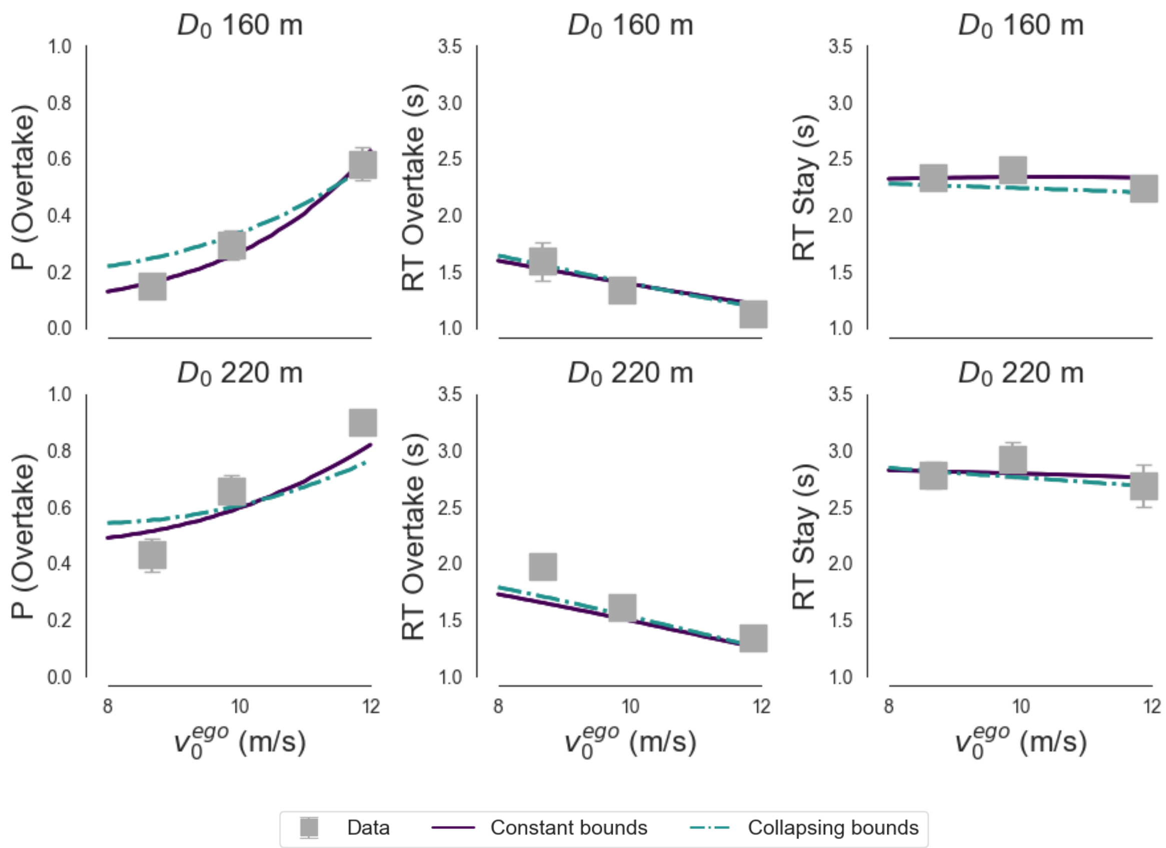


Figure 1.4: Simulated results of our model (Constant bounds) and Mohammad et al.'s [2] model (Collapsing bounds) compared to the data of Sevenster et al. [1]. The error bars represent the standard error of the mean.

2

Preliminary work: Cognitive modeling

The primary finding from my literature study, as presented in Sections II and III of Mohammad et al. [2] underscores the potential of cognitive models, particularly drift-diffusion models, as the most suitable framework for characterizing the dynamic decision-making processes involved in overtaking maneuvers. To assess the potentiality of the cognitive modeling approach, I investigated various drift-diffusion models to describe straightforward human overtaking behavior. The dataset for this study was derived from Sevenster et al. [1] and encompassed overtaking maneuvers with two different distances (160m and 220m) to the oncoming vehicle that was accelerating at a constant rate.

My findings revealed that a drift-diffusion model, incorporating an initial decision-making bias (defined as the starting point of the evidence accumulation process) dependent on the initial velocity, best replicates the qualitative patterns of overtaking gap acceptance observed previously. This analysis underscores the potential of the cognitive modeling approach in understanding and modeling human overtaking behavior, particularly in scenarios involving autonomous vehicles (AVs). This work forms the foundational basis for Chapter 1 of this thesis.

This chapter consists of the section ”Modeling human decision making in overtaking: a proof-of-concept” from my paper that has been accepted for publication ([2]).

MODELING HUMAN DECISION MAKING IN OVERTAKING: A PROOF-OF-CONCEPT

To investigate the feasibility of the cognitive modeling approach for overtaking, here we test several versions of the drift-diffusion model using the data on human overtaking decisions previously collected in a driving simulator [1]. The model fitting and simulation code used in this case study is available online.

A. Dataset

A prerequisite of cognitive process modeling using the drift-diffusion models is measuring the response time. Sevenster et al. [1] offered a simple way of measuring response times in overtaking, and explored the effect of two situation-specific factors (distance gap and ego-vehicle velocity) on the response times measured in a driving simulator experiment. The measures of Sevenster et al. ([1]) included 2097 overtaking decisions collected from 25 participants, with varying initial gaps to the oncoming vehicle (160 or 220 meters) and the initial ego-vehicle velocity as a free variable. It included the decision outcome and the corresponding response time as the dependent variables. To be able to model this dataset, we filtered it by removing any measures with unrealistic response times, missing values, and null values. The remaining data (N=1758) was used for further analysis.

The continuous nature of the free initial ego-vehicle velocity variable impedes model fitting using existing fitting tools such as *pyddm* [2]. Therefore, in this study, this variable has been clustered into three initial velocities, and by this transforming the problem to a 2x3 factorial design (2 initial distance conditions, 3 initial velocity conditions). We have opted to exclude measures relating to the lead vehicle such as following distance, since clustering these as well would significantly reduce the amount of data for each set of conditions.

Based on their data, Sevenster et al. [1] highlighted the following relationships between the initial setup of the overtaking scenario and the resulting human behavior and response times:

- The Probability of accepting the gap increases with the initial distance to the oncoming vehicle.
- The Probability of accepting the gap increases with the initial velocity of the ego vehicle.
- Response times in rejected gaps are on average higher than in accepted gaps.
- Response times in both accepted and rejected gaps increase with initial distance.
- Response times in accepted gaps decrease with initial velocity.
- Response times in rejected gaps remain constant regardless of the initial velocity.

In what follows, we evaluate how well different candidate cognitive models can capture human behavior according to these findings.

B. Cognitive modeling

1) Basic drift-diffusion model and its applications to traffic: We employed the drift-diffusion modeling framework [3] to explain participants' behavior and response times in our experiment. This framework is based on evidence accumulation, where humans integrate relevant perceptual information over time (Figure 1). Accumulation is a noisy process that continues until the evidence in favor of one alternative reaches a predetermined boundary. Despite its simplicity, DDMs have been successful in explaining various behavioral effects of decision context on outcomes and response times [4].

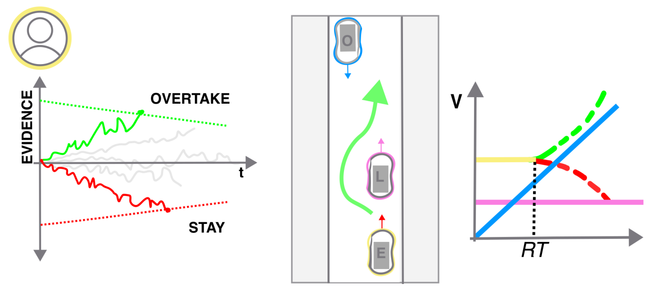


Fig. 1: Visualization of gap acceptance decision-making in overtaking. Depending on the gap to the oncoming vehicle (blue), the human driver of the ego vehicle (yellow) can decide either to reject the gap and stay in the lane (red trajectory) or to accept the gap (green trajectory) and overtake the slow lead vehicle. According to the drift-diffusion model, this decision can be represented as bounded accumulation of noisy evidence over time.

Mathematically, the drift-diffusion model represents the choice between two options as a random process, where evidence x accumulates based on a drift rate $s(t)$ (momentary evidence favoring one option over the other) and diffusion (random noise $\varepsilon(t)$):

$$\frac{dx}{dt} = s(t) + \varepsilon(t). \quad (1)$$

Accumulation stops when the accumulated evidence crosses an upper $x = b(t)$ or lower decision boundary $x = -b(t)$.

Recent applications of DDM to gap acceptance [5], [6] consider the drift rate $s(t)$ to capture dynamically changing gap sizes and time-varying decision boundaries $b(t)$ to reflect choice urgency. Such models were able to capture decision outcomes and response times of human decision-makers. However, they cannot be directly used for our overtaking scenario because they do not incorporate the initial velocity that the human driver has at the start of the decision. As previous studies have shown, this velocity affects the decision and therefore it needs to be incorporated in one of the components of the DDM.

2) Drift-diffusion model of overtaking: Here, we build upon the previously proposed left-turn gap acceptance model [6] by incorporating the initial velocity of the ego vehicle in the different components of the model (drift rate, decision boundary, initial decision bias). We then investigate which of the resulting 8 versions of the model better describes the data of Sevenster et al. [1].

Each of the tested models includes four main components. First, the drift rate $s(t)$ is a function of time-to-arrival (TTA) and distance d between the ego vehicle and the oncoming vehicle and possibly the initial velocity of the ego vehicle v_0

$$s(t) = \alpha(TTA(t) + \beta d(t) - \theta_s) \tag{2}$$

$$s(t) = \alpha(TTA(t) + \beta d(t) + \gamma v_0 - \theta_s), \tag{3}$$

where $\alpha > 0$, $\beta > 0$, $\gamma > 0$ and $\theta_s > 0$ are free parameters. We define x as a measure of *relative* evidence, with positive values indicating support for the "Overtake" decision and negative values favoring the "Stay" decision at a given moment t. Intuitively, as the gap between the decision maker and the oncoming vehicle (a combination of d and TTA) increases (e.g., when the opposing vehicle decelerates) relative to a critical value θ_s, the drift rate becomes more positive. This implies a higher likelihood of the decision maker leaning towards the Overtake decision. Conversely, they are more likely to arrive at the Stay decision when the drift rate becomes more negative. As the initial speed of the ego vehicle positively affects the probability of accepting the gap [1], these effects are amplified when including the initial velocity in the drift rate.

Second, the decision boundary collapses with either $TTA(t)$

$$b(t) = \pm \frac{b_0}{1 + e^{-k(TTA(t) - \tau)}}, \tag{4}$$

or with all the kinematic variables affecting the drift rate $s(t)$

$$b(t) = \pm \frac{b_0}{1 + e^{-k(TTA(t) + \beta d(t) - \theta_s)}} \tag{5}$$

$$b(t) = \pm \frac{b_0}{1 + e^{-k(TTA(t) + \beta d(t) + \gamma v_0 - \theta_s)}}. \tag{6}$$

Intuitively, with lower values of TTA and d the decision maker experiences stronger urgency to make the decision, which is reflected by boundary $b(t)$ decreasing with the gap size (similar to [6]).

Third, the initial bias Z defines the starting position of the evidence accumulation process (i.e. $x(t_0) = Z$)

$$Z = C_z \tag{7}$$

$$Z = \frac{2b(t_0)}{1 + e^{-b_z(v_0 - \theta_z)}} - b(t_0), \tag{8}$$

where a value of $Z < 0$ indicates an initial bias towards the Stay decision, while $Z > 0$ indicates a bias towards the Overtake decision. This bias can be represented by a constant value C_z (Eq. (7)) or can vary based on the initial velocity v_0 (Eq. (8)). In the latter case, relatively higher and lower initial speeds correspond to a bias toward the Overtake and Stay decision, respectively.

Fourth, for all models, the non-decision time (the duration of the cognitive processes unrelated to decision-making, such as perceptual and motor delays) is assumed to follow the normal distribution

$$t^{ND} \in \mathcal{N}(\mu_{ND}, \sigma_{ND}), \quad \mu_{ND} > 0, \sigma_{ND} > 0. \tag{9}$$

The eight model variants resulting from different combinations of the model components are shown in Table I. The odd-numbered models use a constant bias, while the even-numbered models use a bias depending on the initial speed. Models 1, 2, 5 and 6 have their drift rates depending on the $TTA(t)$ and $d(t)$, whereas Models 3, 4, 7 and 8 also include the initial speed in the drift rate. The decision boundaries of Models 1 to 4 decrease with the TTA, while Models 5 to 8 use decision boundaries depending on all kinematic variables affecting their respective drift rate functions. The simplest model (M6) contains 8 free parameters (α, β, θ_s, b_0, k, Z, μ_{ND}, σ_{ND}) and the most extensive model (M4) contains 11 free parameters (α, β, γ, θ_s, b_0, k, τ, θ_z, b_z, μ_{ND}, σ_{ND}).

3) Model fitting and evaluation: Our goal was to examine whether extended models could depict the behavior of the "average" participant in the dataset. Although it is possible to fit the model to each participant's data individually, providing insights into individual differences (see e.g. [6]), it requires a separate investigation beyond the scope of this study. Instead, we evaluated the models' qualitative match to the data reported in [1] according to the observations listed at the end of Section -A.

The fitting of the models involved utilizing the differential evolution optimization technique and Bayesian information criterion, as implemented in the *pyddm* framework, a Python package specifically designed for DDM fitting [2].

4) Comparing models and data: We found that the eight tested models differed substantially in regards to their qualitative match with the observed human behavior (Figure 2, Table II).

The models that did not include the ego vehicle's initial speed v_0 in any of the components (M1 and M5) predictably could not capture the increase of probability of accepting the gap with v_0. The other six models could all account for the probability of accepting the gap, making it essential to consider response time as the measure that can help distinguish between candidate models further.

For response times, the results differ considerably between odd- and even-numbered models (Table II). The odd-numbered models, i.e. models with a constant initial bias, struggle to consistently describe the effect of initial velocity on response times (in both accepted and rejected gaps). On the other hand, among the models that do include velocity-dependent initial bias, M8 captures 5 out of 6 qualitative patterns, and M2, M4 and M6 even describe them all.

The most successful models, M2, M4 and M6, contain respectively 10, 11 and 9 free parameters. The differences between these three models can be found in the decision boundary: decision boundaries of M2 and M4 collapse only with $TTA(t)$, while M6's boundary collapses with $TTA(t)$ and $d(t)$. Furthermore, in contrast to the drift rate used in M4, M2 and M6 do not have the initial velocity included in theirs. Lastly, M6 reuses parameters of the drift rate in the boundary

TABLE I: Tested variations of the generalized drift-diffusion model (1). The number of parameters in the last column includes the two non-decision time parameters μ_{ND}, σ_{ND}.

Model	Drift rate $s(t)$	Eq.	Decision boundary $b(t)$	Eq.	Initial bias $-b(t_0) < Z < b(t_0)$	Eq.	# parameters
M1	$\alpha(TTA(t)+\beta d(t)-\theta_s)$	(2)	$\pm\frac{b_0}{1+e^{-k(TTA(t)-\tau)}}$	(4)	C_z	(7)	9
M2	$\alpha(TTA(t)+\beta d(t)-\theta_s)$	(2)	$\pm\frac{b_0}{1+e^{-k(TTA(t)-\tau)}}$	(4)	$\frac{2b(t_0)}{1+e^{-b_z(v_0-\theta_z)}}-b(t_0)$	(8)	10
M3	$\alpha(TTA(t)+\beta d(t)+\gamma v_0-\theta_s)$	(3)	$\pm\frac{b_0}{1+e^{-k(TTA(t)-\tau)}}$	(4)	C_z	(7)	10
M4	$\alpha(TTA(t)+\beta d(t)+\gamma v_0-\theta_s)$	(3)	$\pm\frac{b_0}{1+e^{-k(TTA(t)-\tau)}}$	(4)	$\frac{2b(t_0)}{1+e^{-b_z(v_0-\theta_z)}}-b(t_0)$	(8)	11
M5	$\alpha(TTA(t)+\beta d(t)-\theta_s)$	(2)	$\pm\frac{b_0}{1+e^{-k(TTA(t)+\beta d(t)-\theta_s)}}$	(5)	C_z	(7)	8
M6	$\alpha(TTA(t)+\beta d(t)-\theta_s)$	(2)	$\pm\frac{b_0}{1+e^{-k(TTA(t)+\beta d(t)-\theta_s)}}$	(5)	$\frac{2b(t_0)}{1+e^{-b_z(v_0-\theta_z)}}-b(t_0)$	(8)	9
M7	$\alpha(TTA(t)+\beta d(t)+\gamma v_0-\theta_s)$	(3)	$\pm\frac{b_0}{1+e^{-k(TTA(t)+\beta d(t)+\gamma v_0-\theta_s)}}$	(6)	C_z	(7)	9
M8	$\alpha(TTA(t)+\beta d(t)+\gamma v_0-\theta_s)$	(3)	$\pm\frac{b_0}{1+e^{-k(TTA(t)+\beta d(t)+\gamma v_0-\theta_s)}}$	(6)	$\frac{2b(t_0)}{1+e^{-b_z(v_0-\theta_z)}}-b(t_0)$	(8)	10

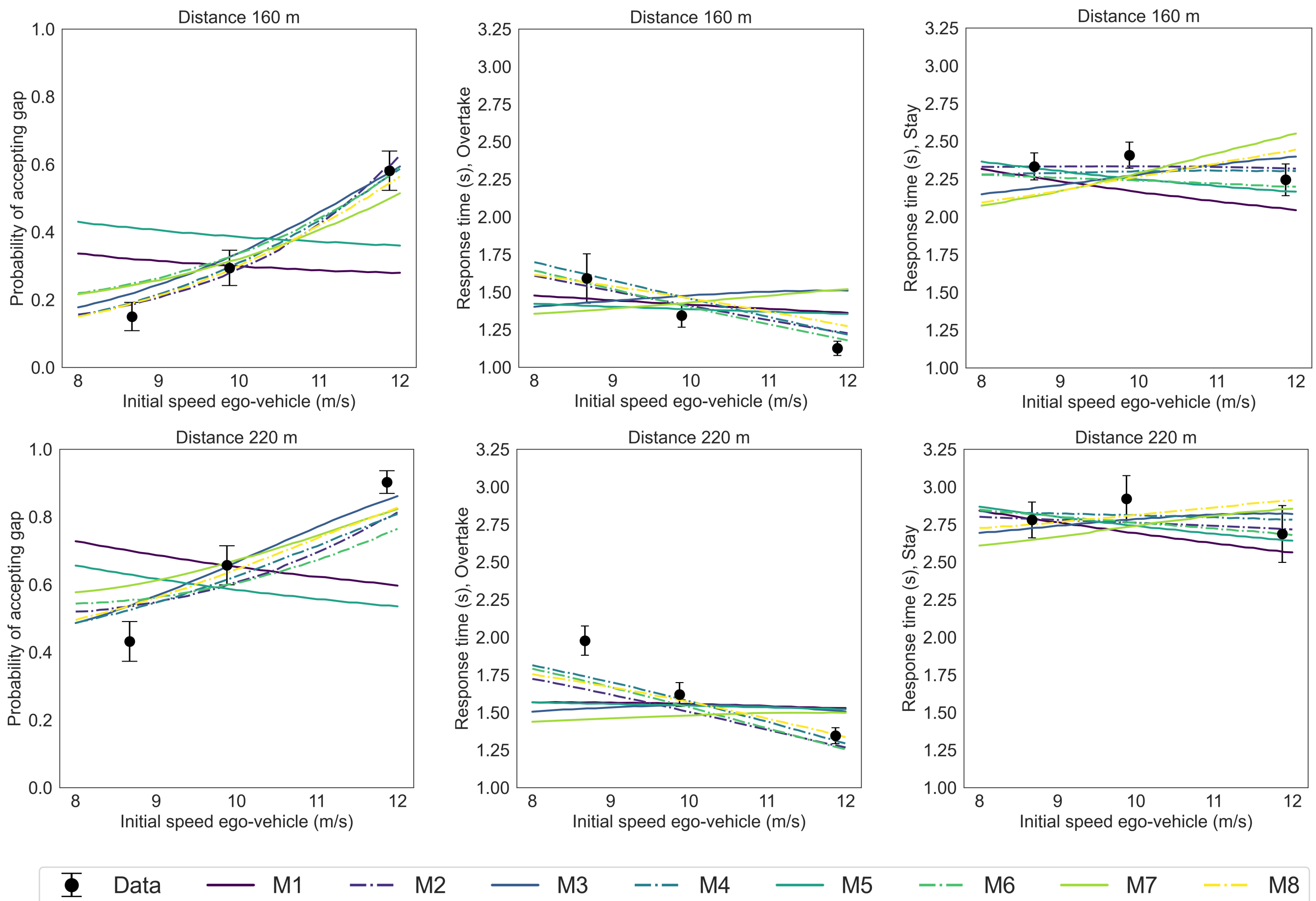


Fig. 2: Simulated model results compared to the data of Sevenster et al. [1]. The error bars represent the standard error of the mean.

TABLE II: Assessment of candidate drift-diffusion models according to the experimental findings of Sevenster et al. [1].

Finding	M1	M2	M3	M4	M5	M6	M7	M8
The probability of accepting the gap increases with the initial distance to the oncoming vehicle.	✓	✓	✓	✓	✓	✓	✓	✓
The probability of accepting the gap increases with the initial velocity of the ego vehicle.	**X**	✓	✓	✓	**X**	✓	✓	✓
Response times in rejected gaps are on average higher than those of accepted gaps.	✓	✓	✓	✓	✓	✓	✓	✓
Response time in both accepted and rejected gaps increases with initial distance.	✓	✓	**X**	✓	✓	✓	**X**	✓
Response times in accepted gaps decrease with initial velocity.	**X**	✓	**X**	✓	**X**	✓	**X**	✓
Response times of rejected gaps remain constant regardless of initial velocity.	**X**	✓	**X**	✓	**X**	✓	**X**	**X**
Total	**3/6**	**6/6**	**3/6**	**6/6**	**3/6**	**6/6**	**3/6**	**5/6**

function, therefore consolidating the total amount of free parameters. Therefore, we conclude that M6 is the simplest model that can describe all qualitative patterns previously observed in human behavior. This model hypothesizes drift rate and decision boundary that both depend on the same linear combination of TTA and distance, and the decision bias that scales with the initial velocity of the ego vehicle. The resulting fitted model parameters for M6 were $\alpha = 0.07$, $\beta = 0.11$, $\theta_s = 47$, $b_0 = 2.8$, $k = 0.02$, $b_z = 0.14$, $\theta_z = 5.8$, $\mu_{ND} = 1.0$, $\sigma_{ND} = 0.27$.

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3
Random effects of the regression models

In all regression models, the vehicle type per participant ID was included as a random slope. The forest plots below provide a visual representation of the individual variances between sessions involving human-driven vehicles (HDV) and automated vehicles (AV). Each session featured a consistent vehicle type. In Figure 3.1, positive estimate values indicate a higher gap acceptance rate in the HDV session compared to the AV session, while negative estimates indicate a relatively lower gap acceptance rate in the HDV session. Similarly, in Figures 3.2 and 3.3 positive estimate values indicate that participants exhibited longer response times in the HDV session when compared to the AV session.

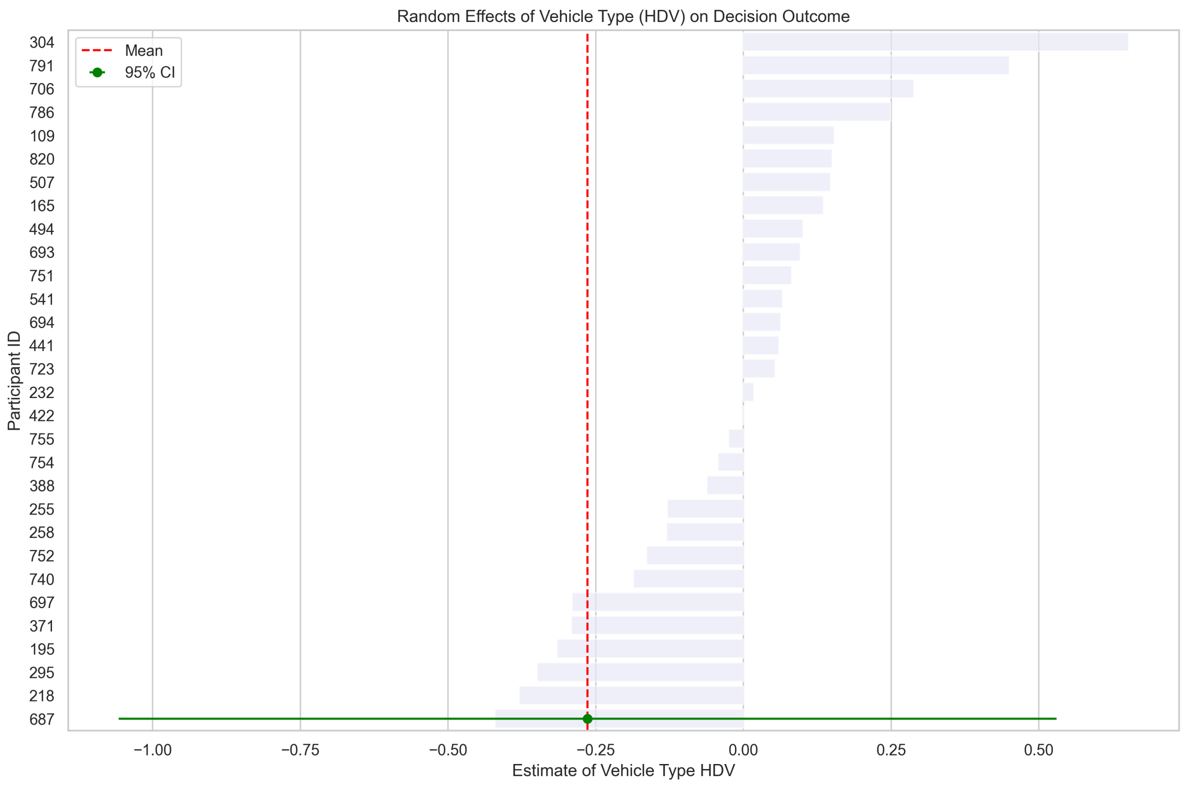


Figure 3.1: The vehicle type effect per participant as the random slope of the logistic regression model for the decision outcome.

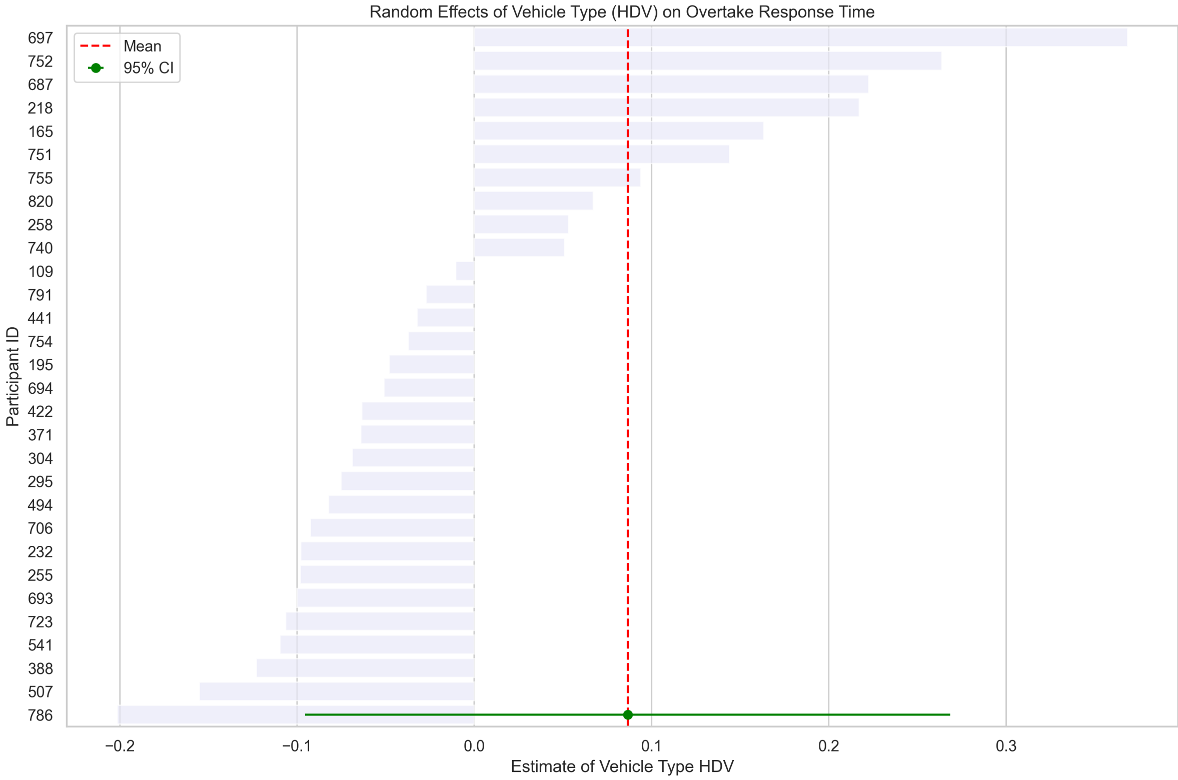


Figure 3.2: The vehicle type effect per participant as the random slope of the linear regression model for the response time in accepted gaps.

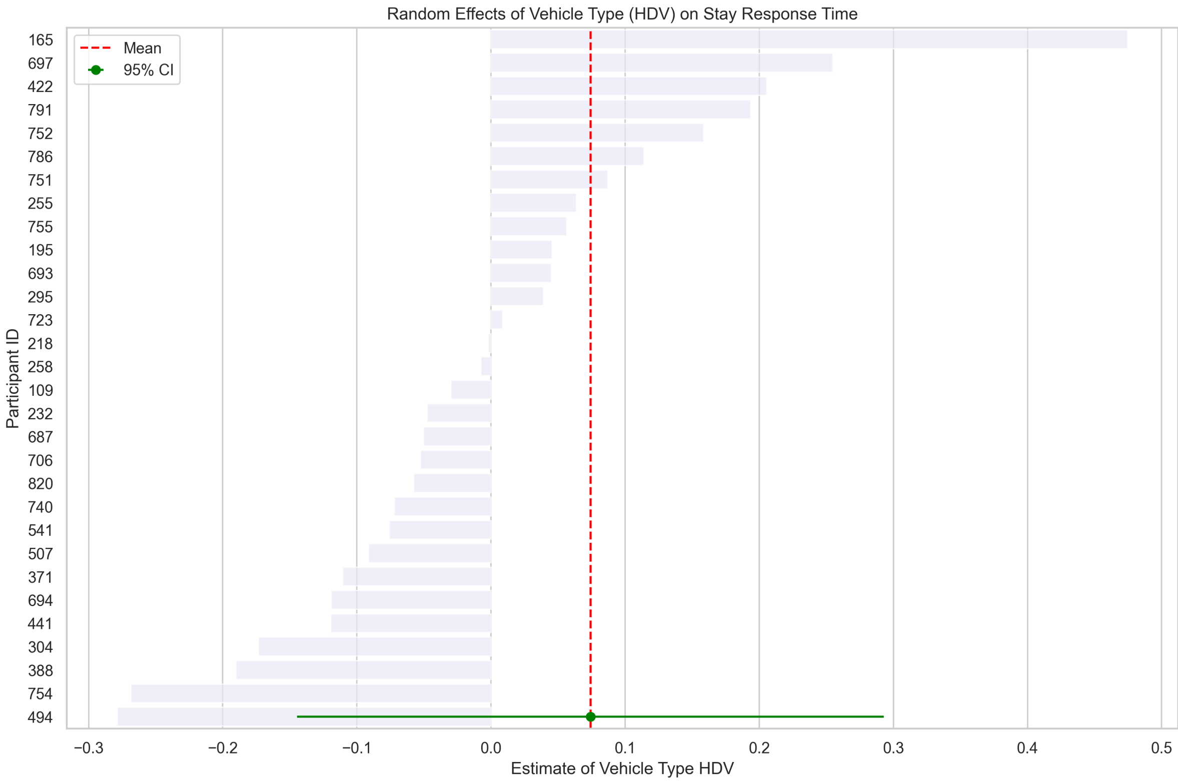
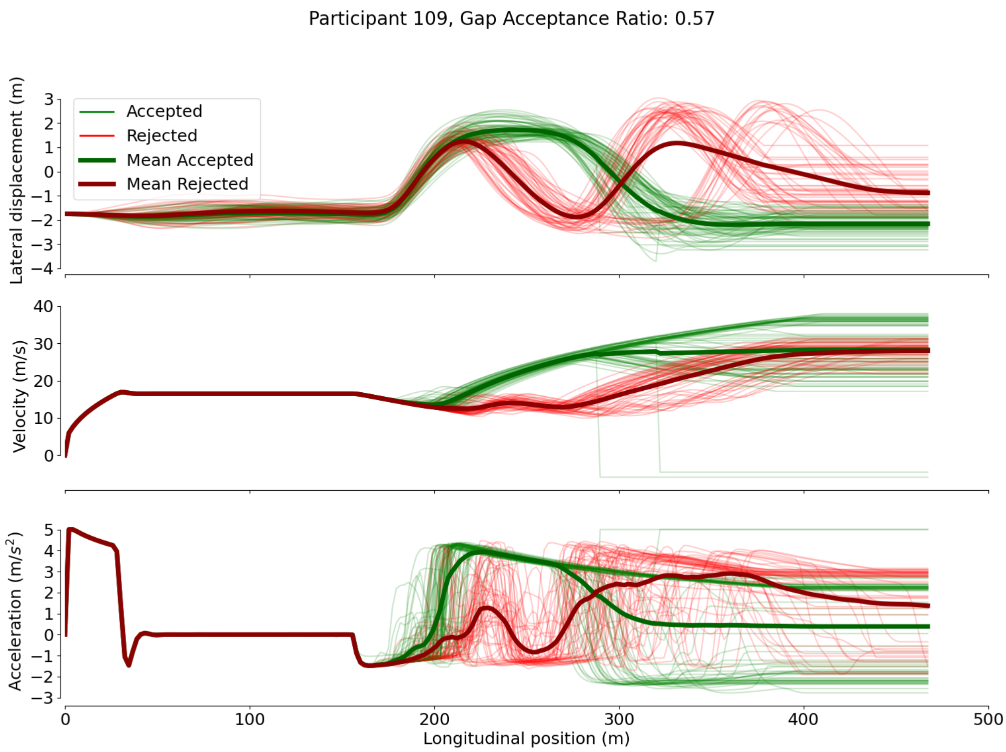
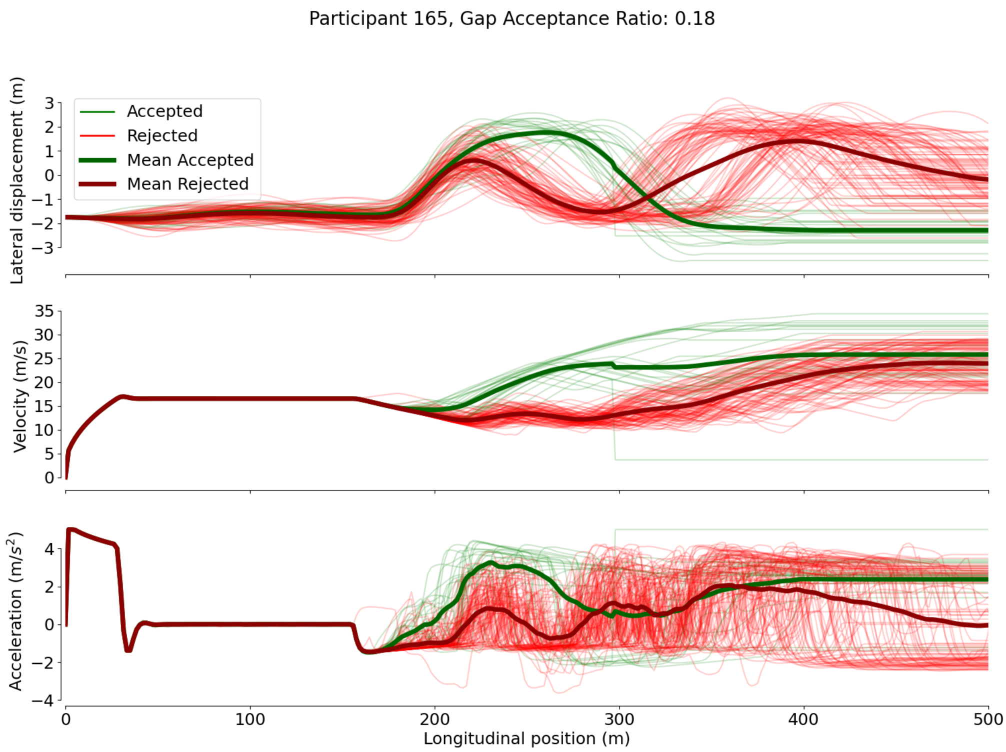


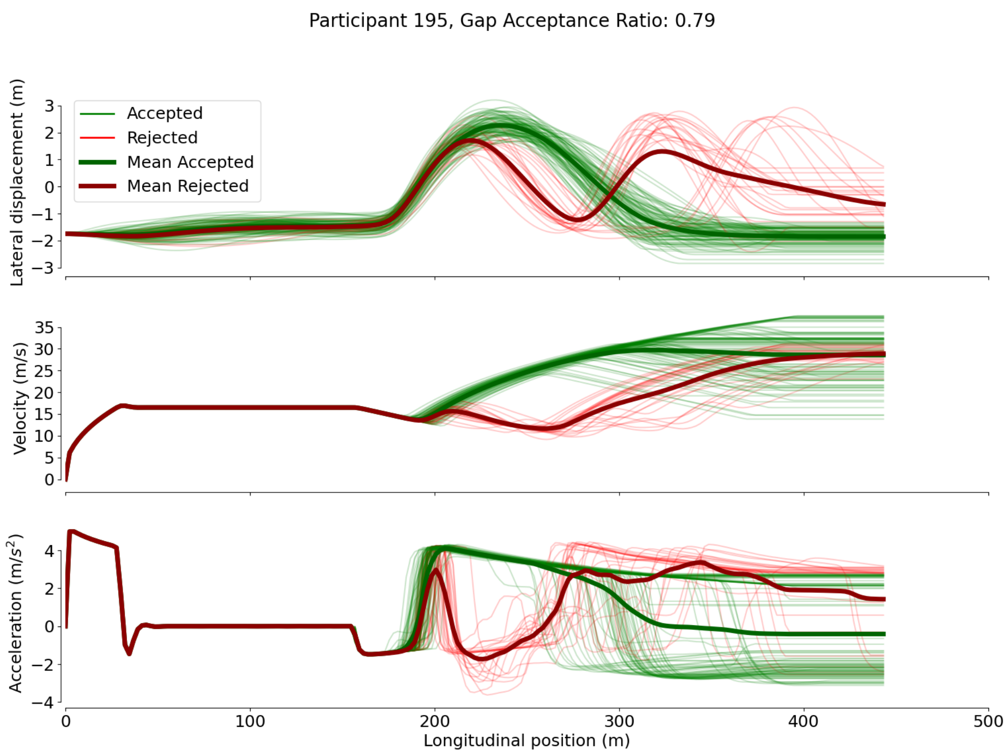
Figure 3.3: The vehicle type effect per participant as the random slope of the linear regression model for the response time in rejected gaps.

4 Extensive results

This chapter presents the participants' individual trajectories, velocities, and accelerations.




Participant 165, Gap Acceptance Ratio: 0.18
Accepted
Rejected
Mean Accepted
Mean Rejected
Lateral displacement (m)
Velocity (m/s)
Acceleration (m/s²)
Longitudinal position (m)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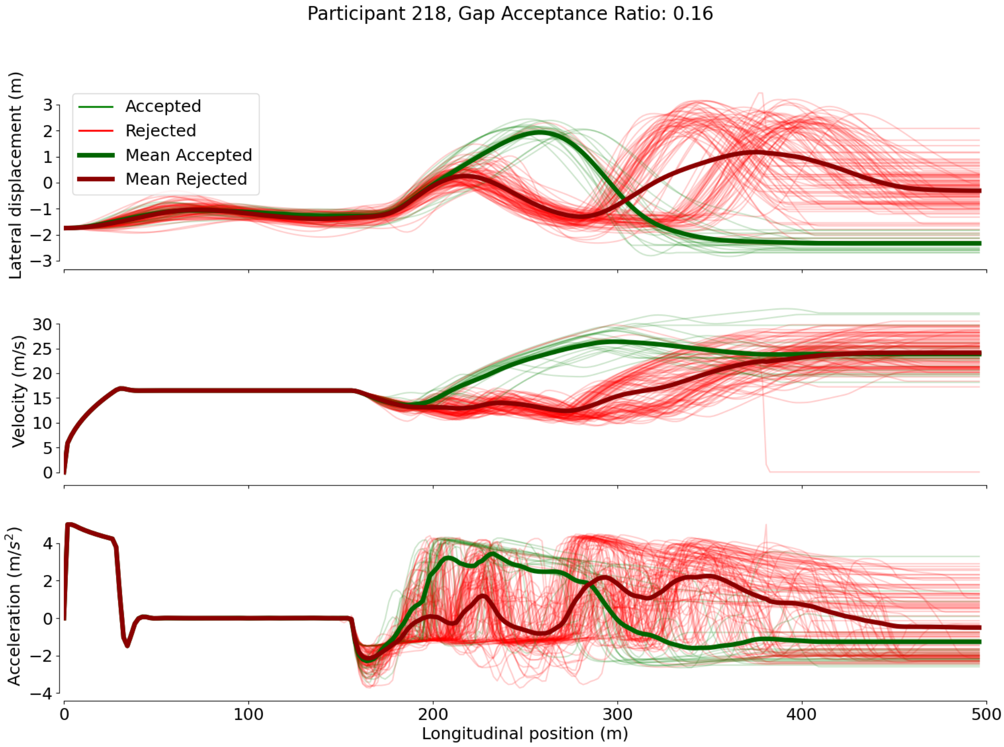
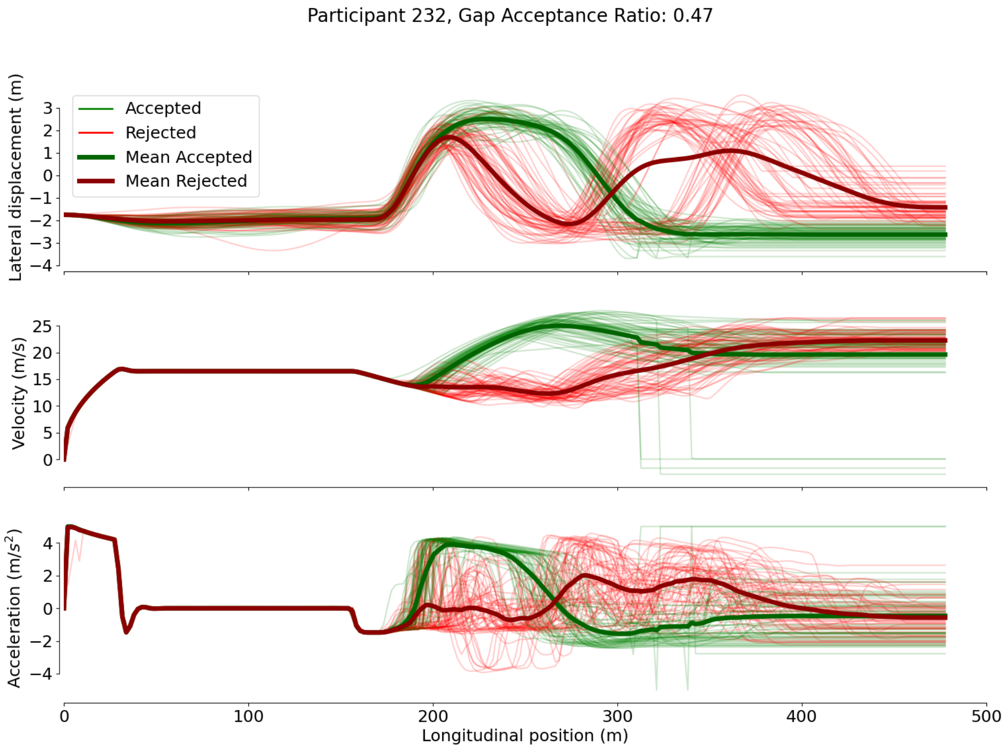
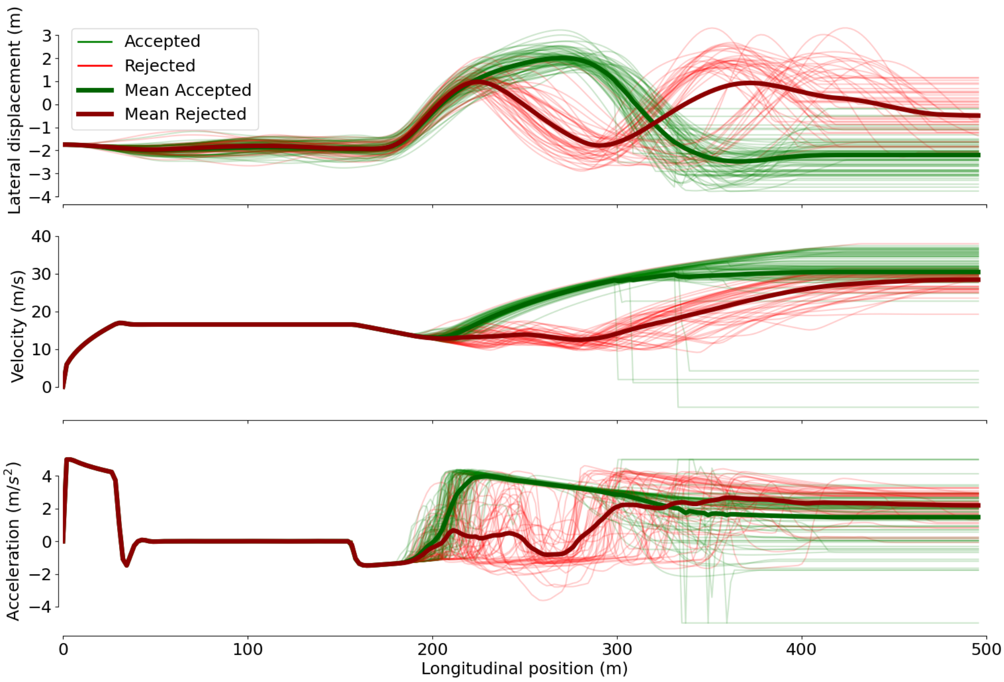
Accepted
Rejected
Mean Accepted
Mean Rejected
Lateral displacement (m)
Velocity (m/s)
Acceleration (m/s²)
Longitudinal position (m)

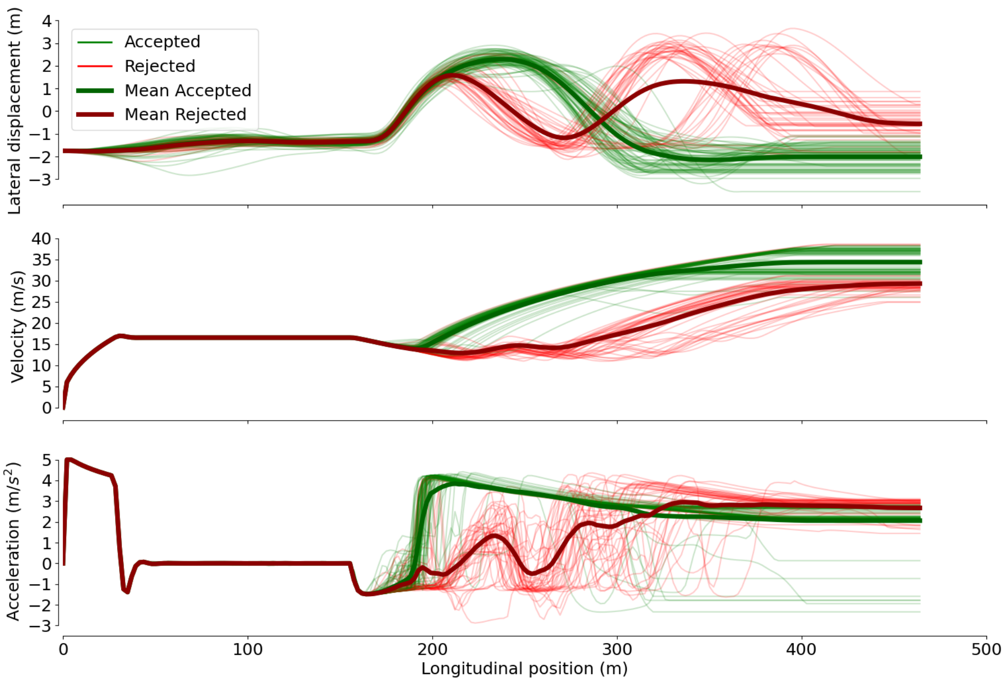

Participant 218, Gap Acceptance Ratio: 0.16
Accepted
Rejected
Mean Accepted
Mean Rejected
Lateral displacement (m)
Velocity (m/s)
Acceleration (m/s^2)
Longitudinal position (m)

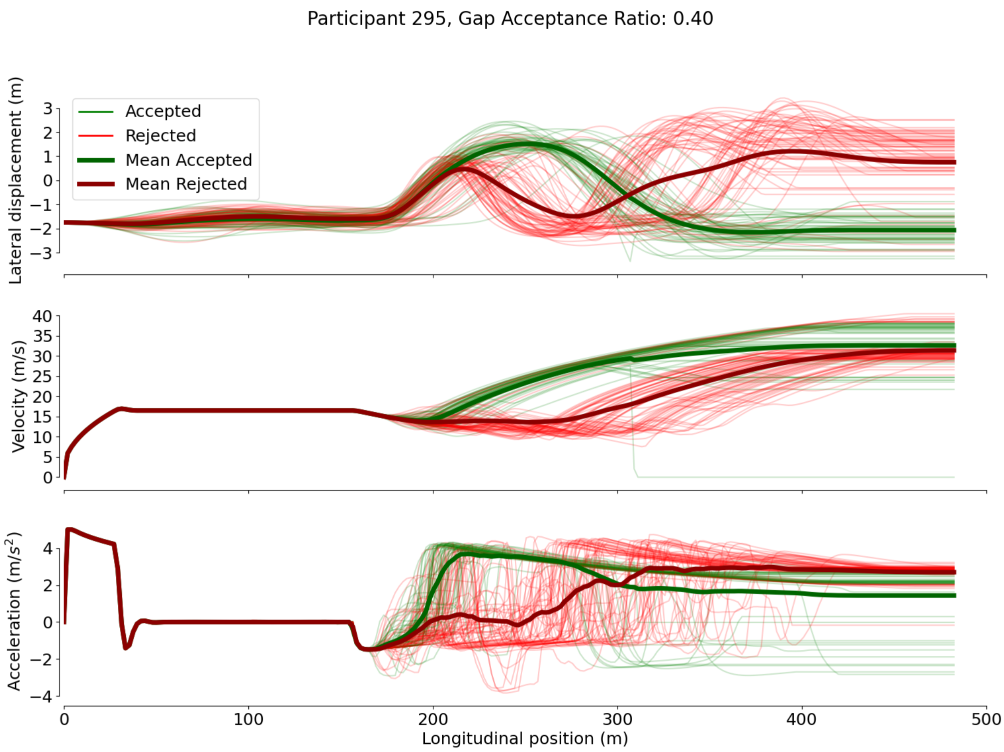

Participant 232, Gap Acceptance Ratio: 0.47
Accepted
Rejected
Mean Accepted
Mean Rejected
Lateral displacement (m)
Velocity (m/s)
Acceleration (m/s^2)
Longitudinal position (m)

Participant 255, Gap Acceptance Ratio: 0.61



Participant 258, Gap Acceptance Ratio: 0.64

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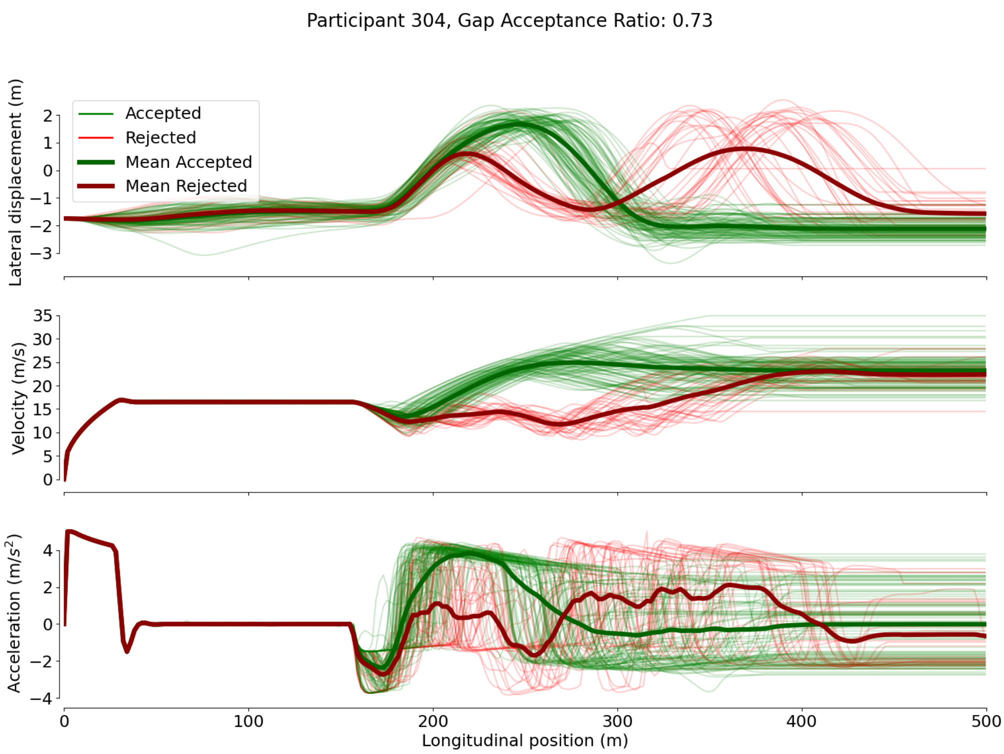
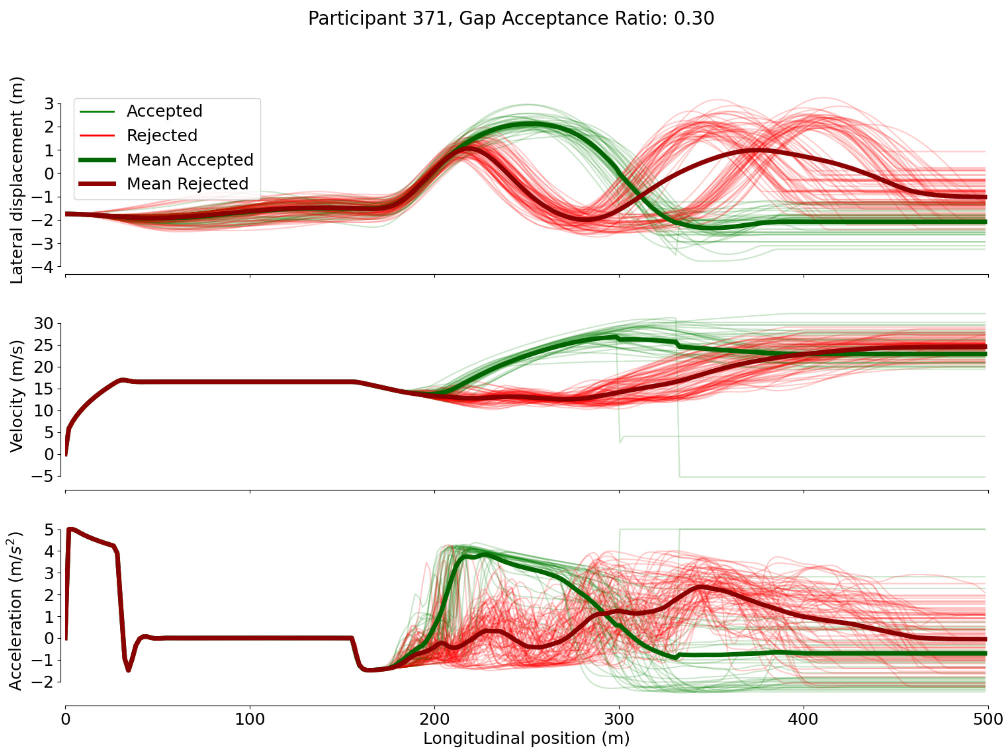
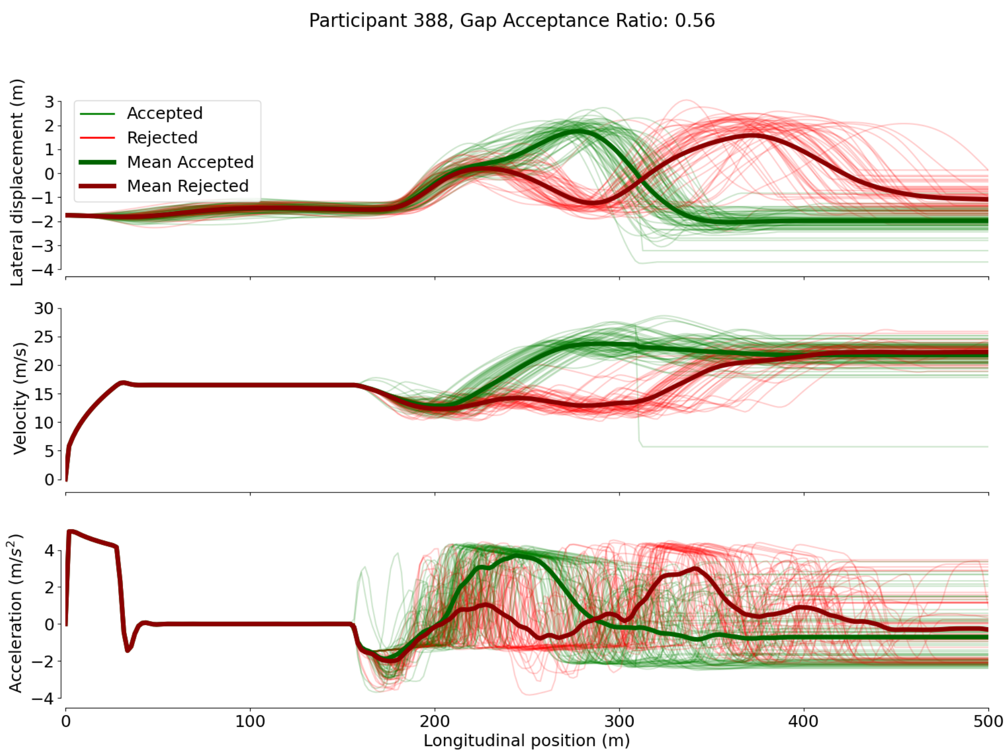
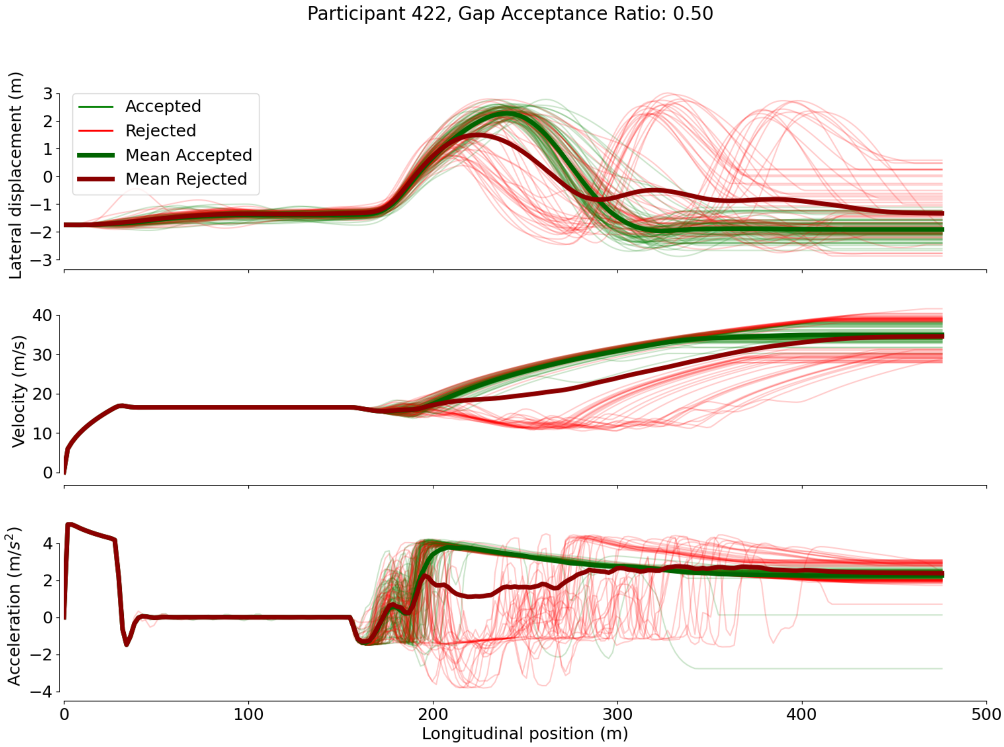
Accepted
Rejected
Mean Accepted
Mean Rejected
Lateral displacement (m)
Velocity (m/s)
Acceleration (m/s²)
Longitudinal position (m)


Participant 304, Gap Acceptance Ratio: 0.73
Accepted
Rejected
Mean Accepted
Mean Rejected
Lateral displacement (m)
Velocity (m/s)
Acceleration (m/s²)
Longitudinal position (m)


Participant 371, Gap Acceptance Ratio: 0.30
Accepted
Rejected
Mean Accepted
Mean Rejected
Lateral displacement (m)
Velocity (m/s)
Acceleration (m/s²)
Longitudinal position (m)


Participant 388, Gap Acceptance Ratio: 0.56
Accepted
Rejected
Mean Accepted
Mean Rejected
Lateral displacement (m)
Velocity (m/s)
Acceleration (m/s²)
Longitudinal position (m)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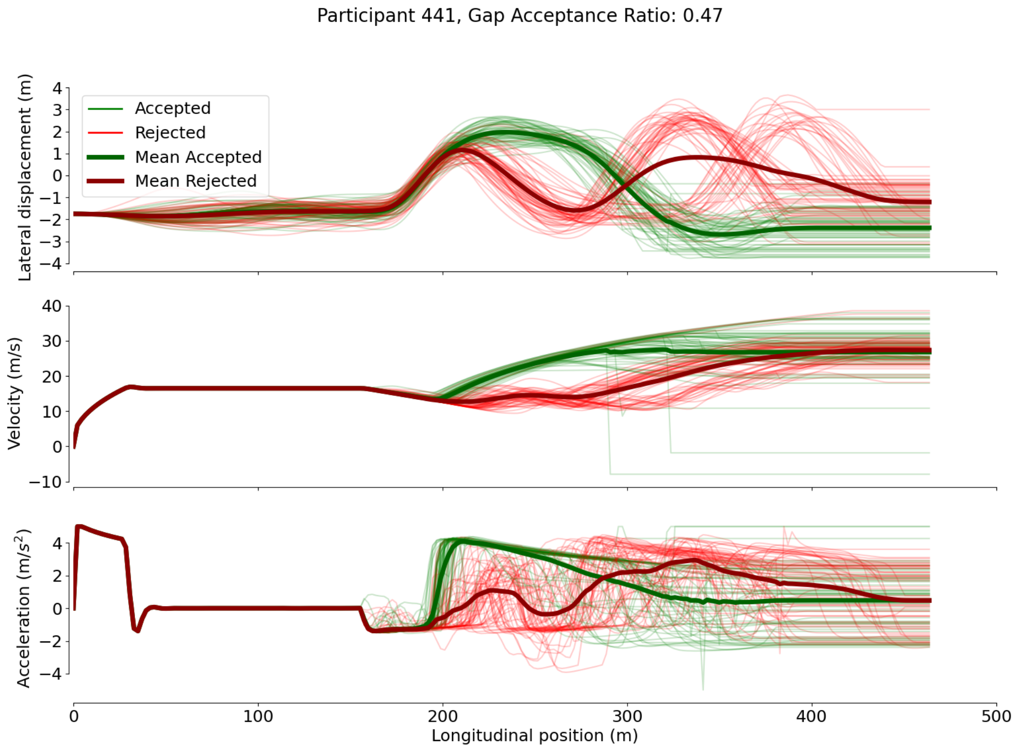
Accepted
Rejected
Mean Accepted
Mean Rejected
Lateral displacement (m)
Velocity (m/s)
Acceleration (m/s²)
Longitudinal position (m)
0
100
200
300
400
500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Accepted
Rejected
Mean Accepted
Mean Rejected
Lateral displacement (m)
Velocity (m/s)
Acceleration (m/s²)
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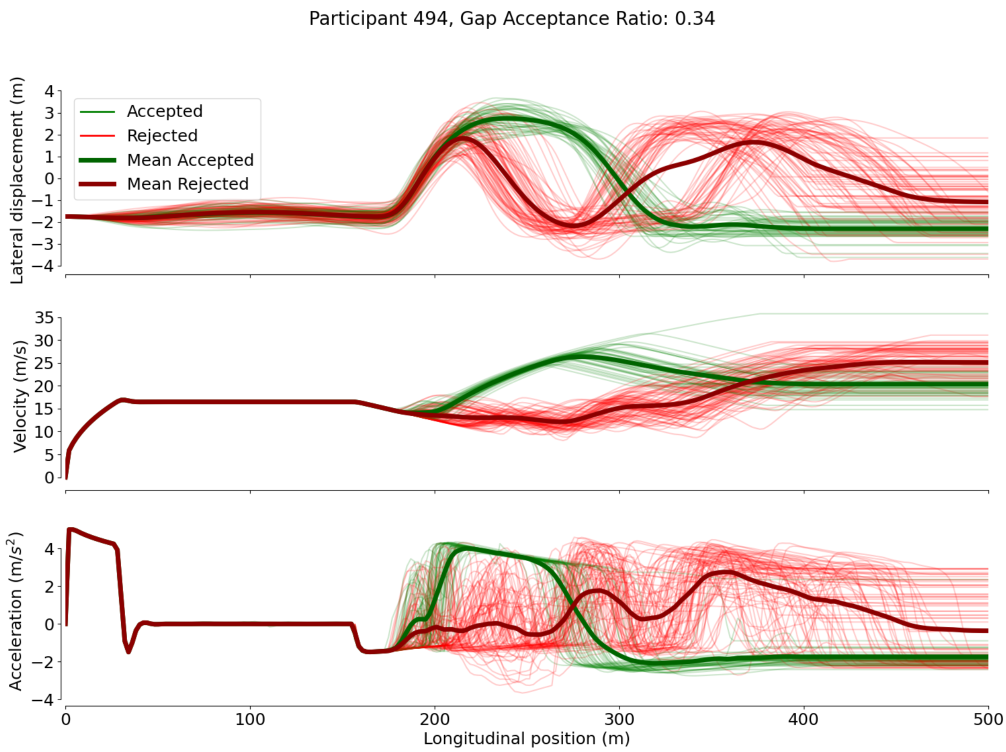
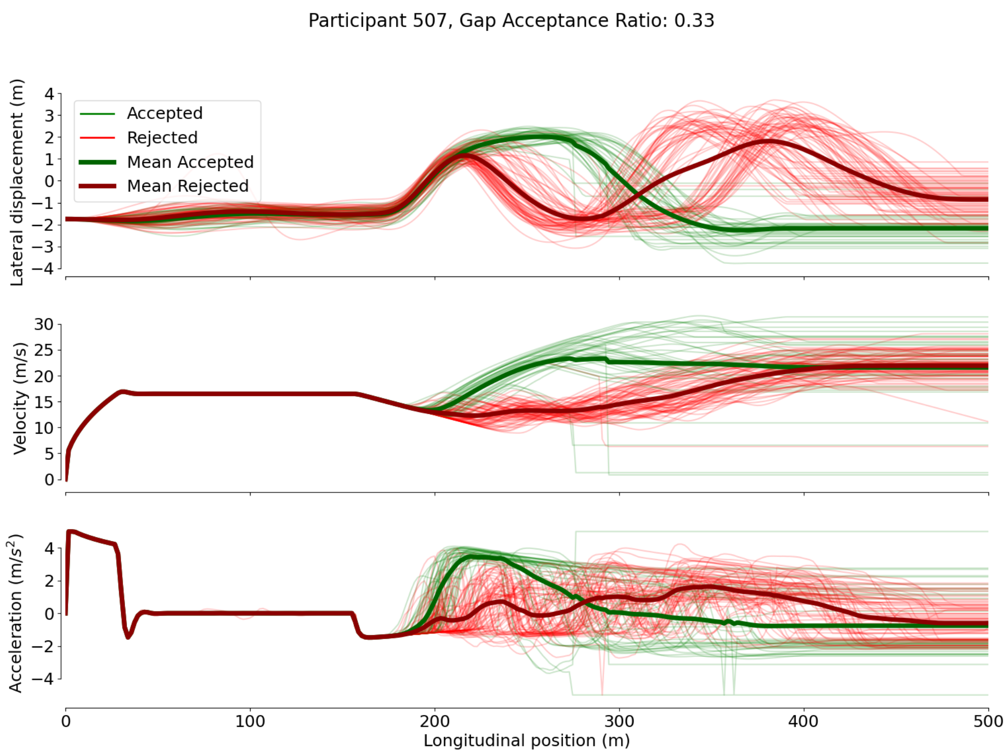
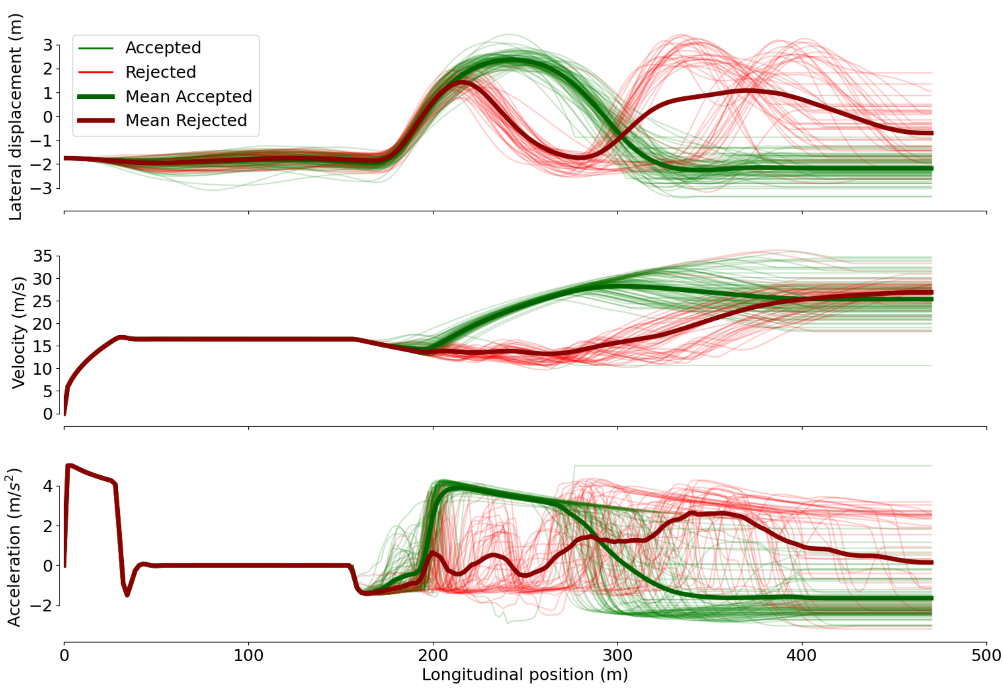
100
200
300
400
500

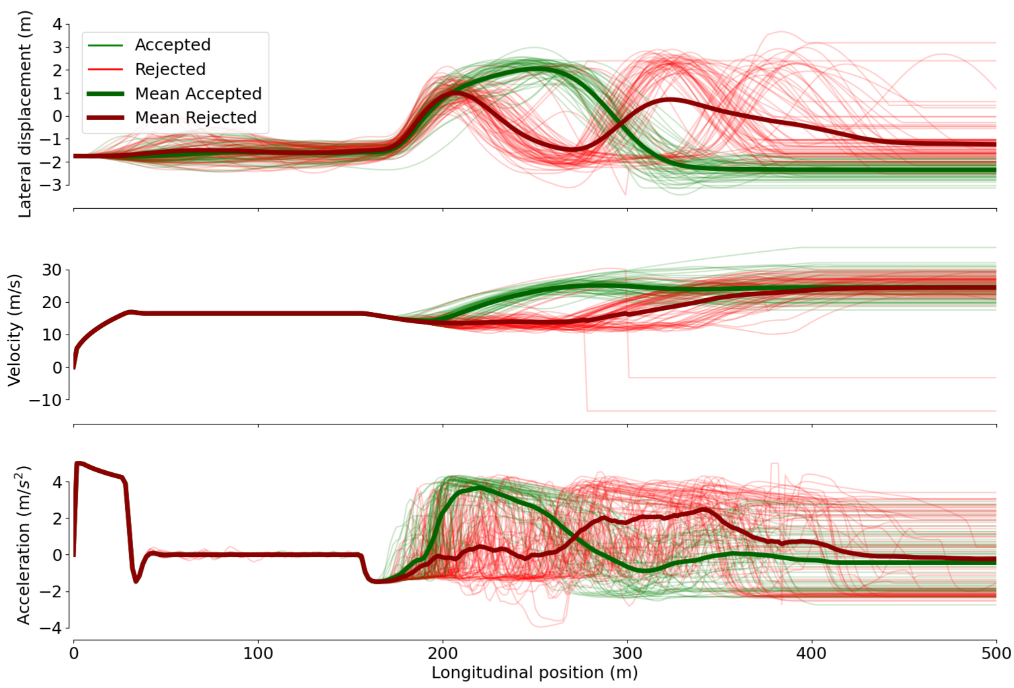

Participant 494, Gap Acceptance Ratio: 0.34
Accepted
Rejected
Mean Accepted
Mean Rejected
Lateral displacement (m)
Velocity (m/s)
Acceleration (m/s²)
Longitudinal position (m)

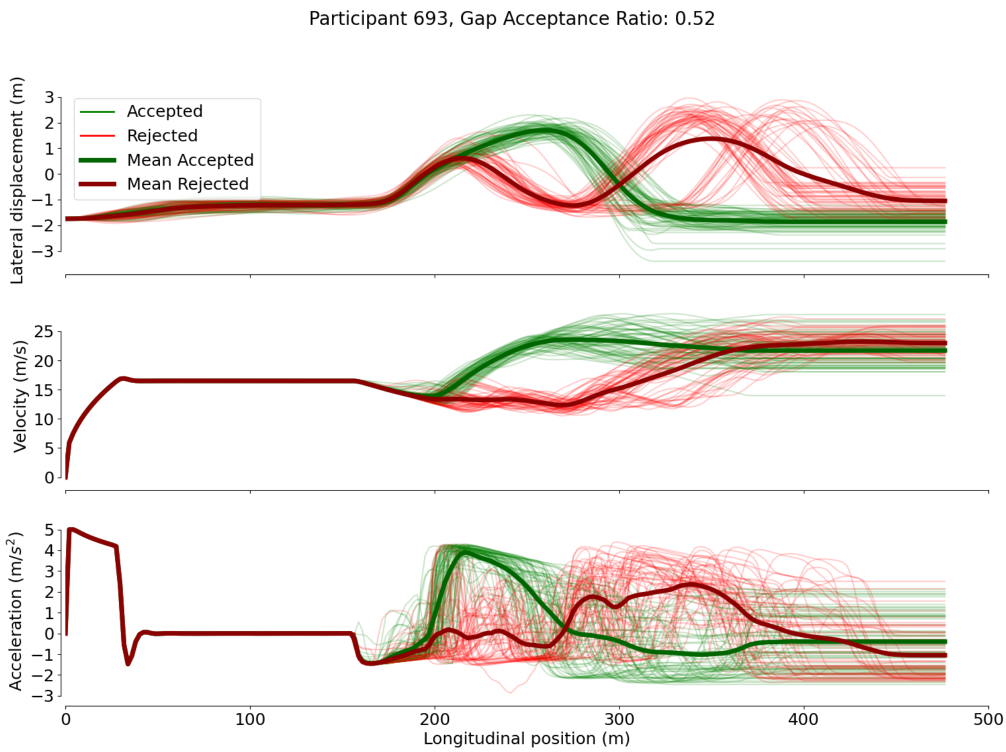

Participant 507, Gap Acceptance Ratio: 0.33
Accepted
Rejected
Mean Accepted
Mean Rejected
Lateral displacement (m)
Velocity (m/s)
Acceleration (m/s²)
Longitudinal position (m)

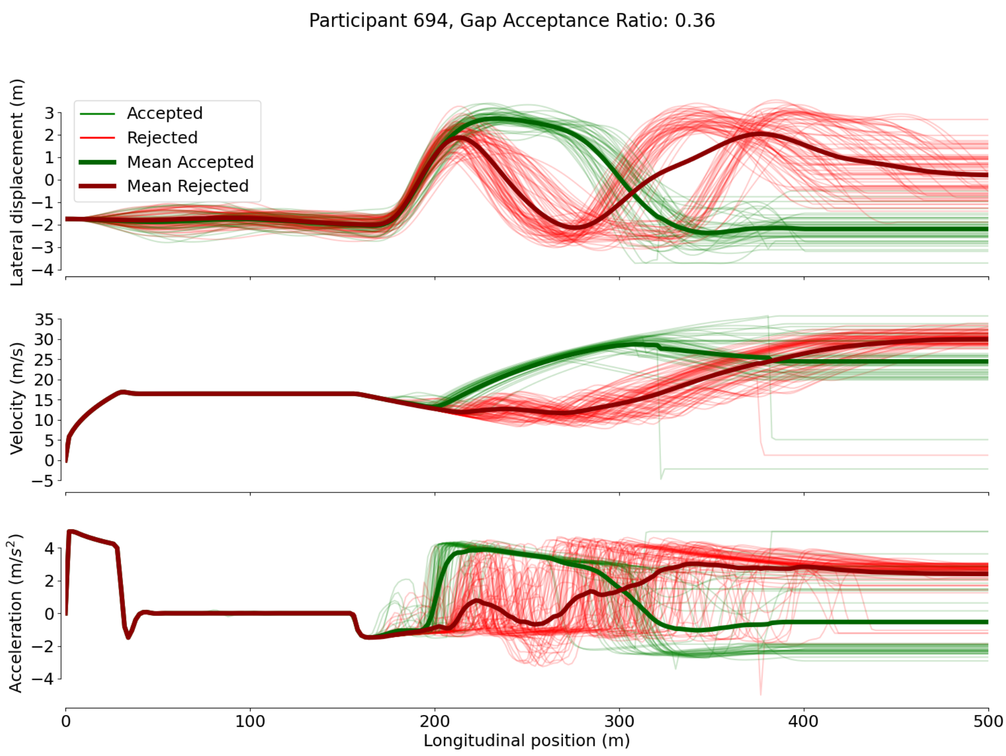
Participant 541, Gap Acceptance Ratio: 0.62

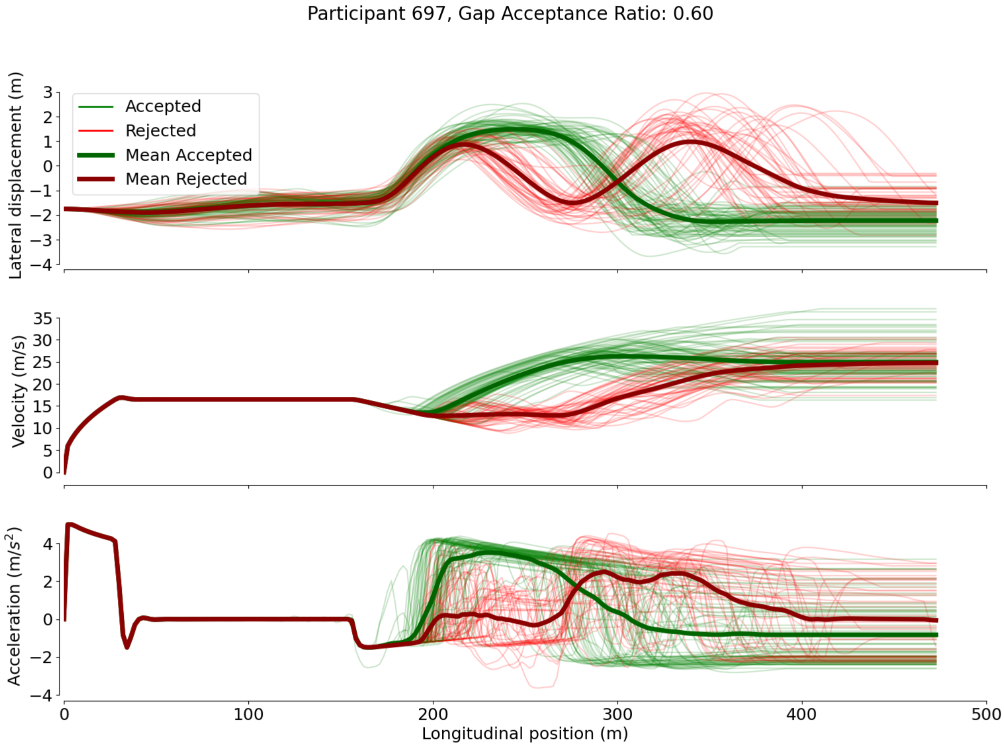


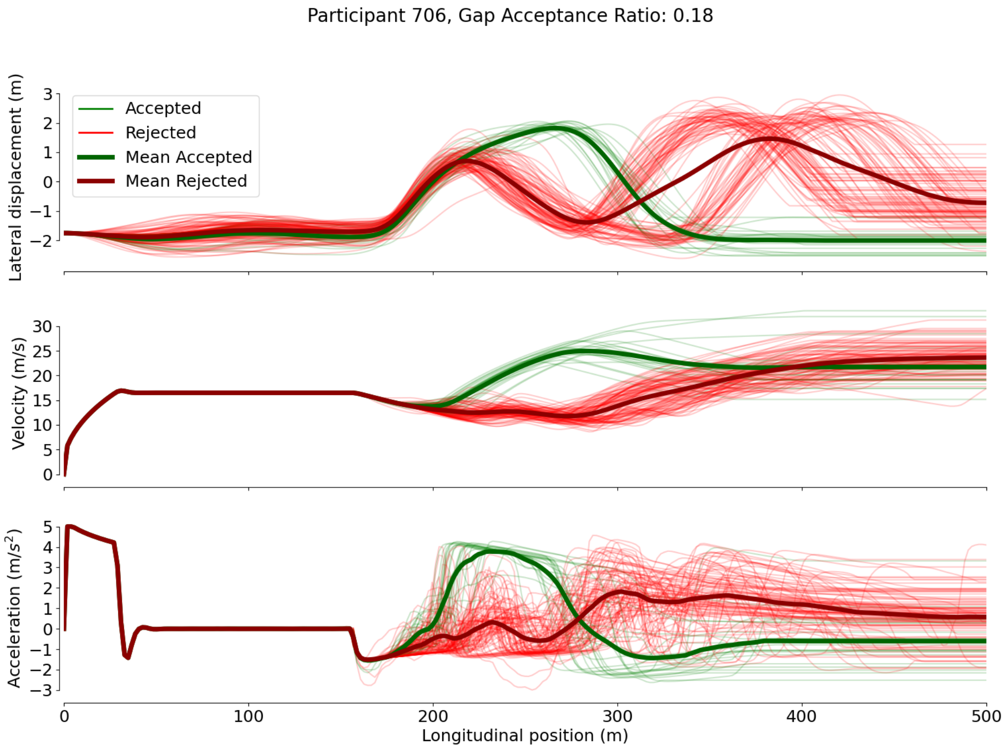
Participant 687, Gap Acceptance Ratio: 0.42



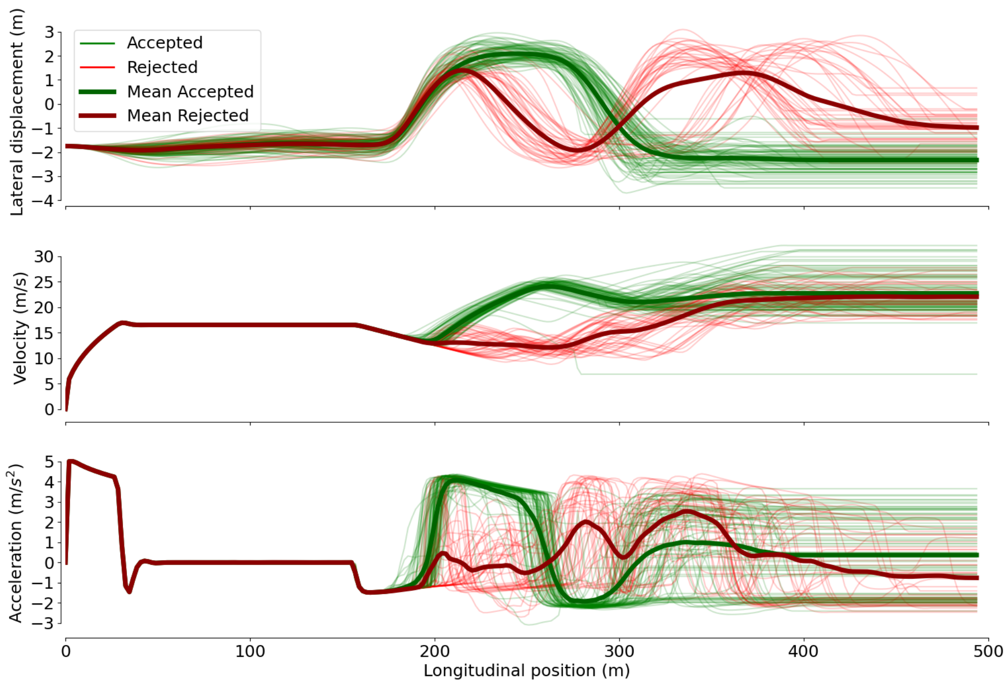

Participant 693, Gap Acceptance Ratio: 0.52
Lateral displacement (m)
Accepted
Rejected
Mean Accepted
Mean Rejected
Velocity (m/s)
Acceleration (m/s²)
0
100
200
300
400
500
Longitudinal position (m)


Participant 694, Gap Acceptance Ratio: 0.36
Lateral displacement (m)
Accepted
Rejected
Mean Accepted
Mean Rejected
Velocity (m/s)
Acceleration (m/s²)
0
100
200
300
400
500
Longitudinal position (m)

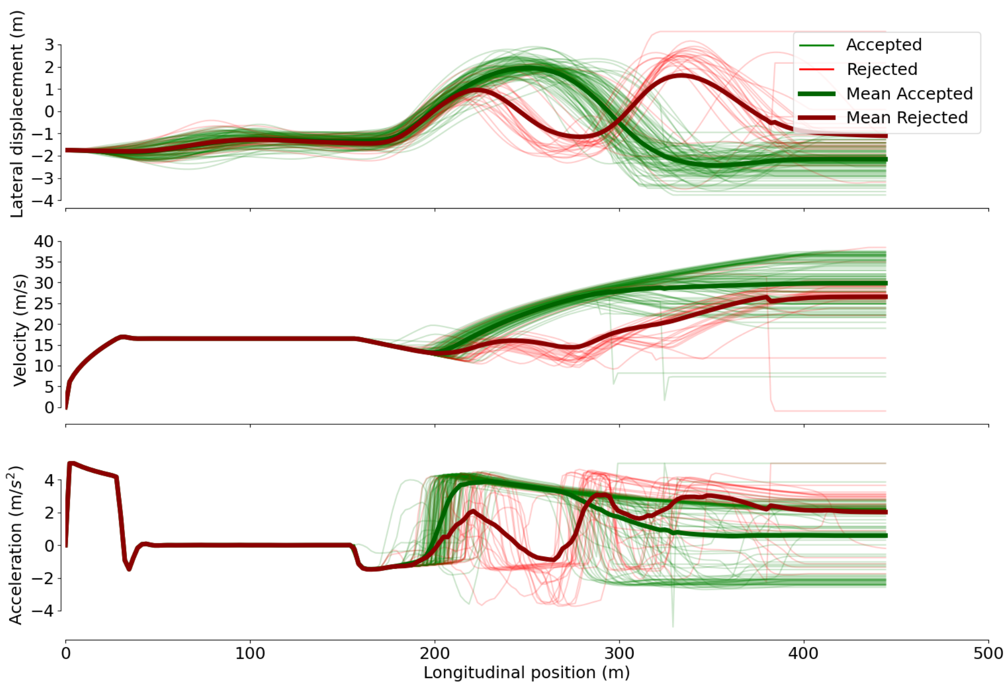

Participant 697, Gap Acceptance Ratio: 0.60
Accepted
Rejected
Mean Accepted
Mean Rejected
Lateral displacement (m)
Velocity (m/s)
Acceleration (m/s^2)
Longitudinal position (m)


Participant 706, Gap Acceptance Ratio: 0.18
Accepted
Rejected
Mean Accepted
Mean Rejected
Lateral displacement (m)
Velocity (m/s)
Acceleration (m/s^2)
Longitudinal position (m)

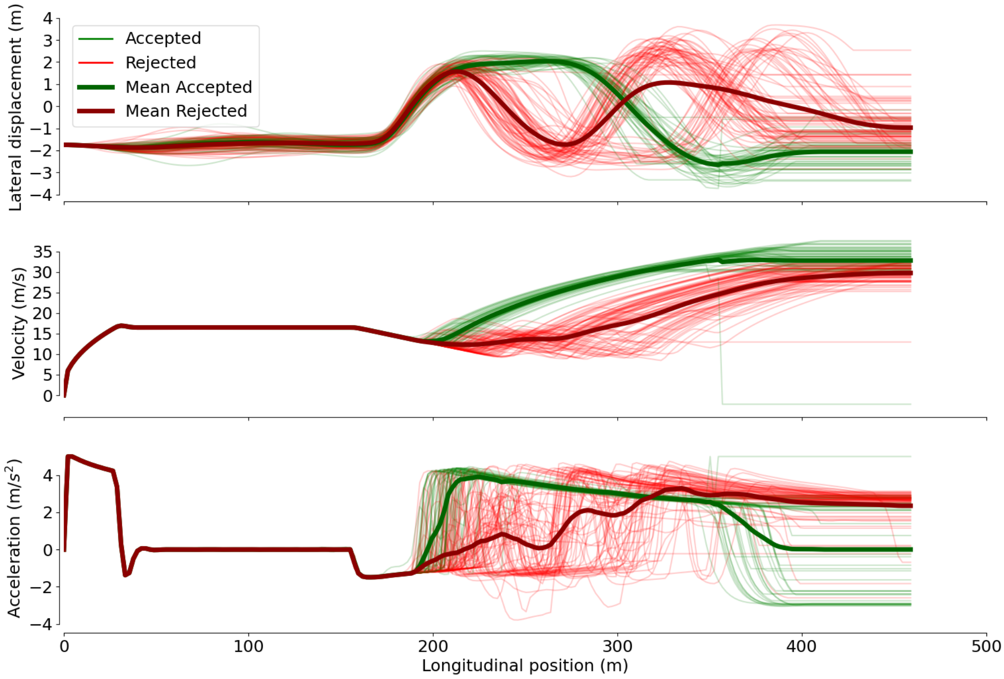
Participant 723, Gap Acceptance Ratio: 0.66



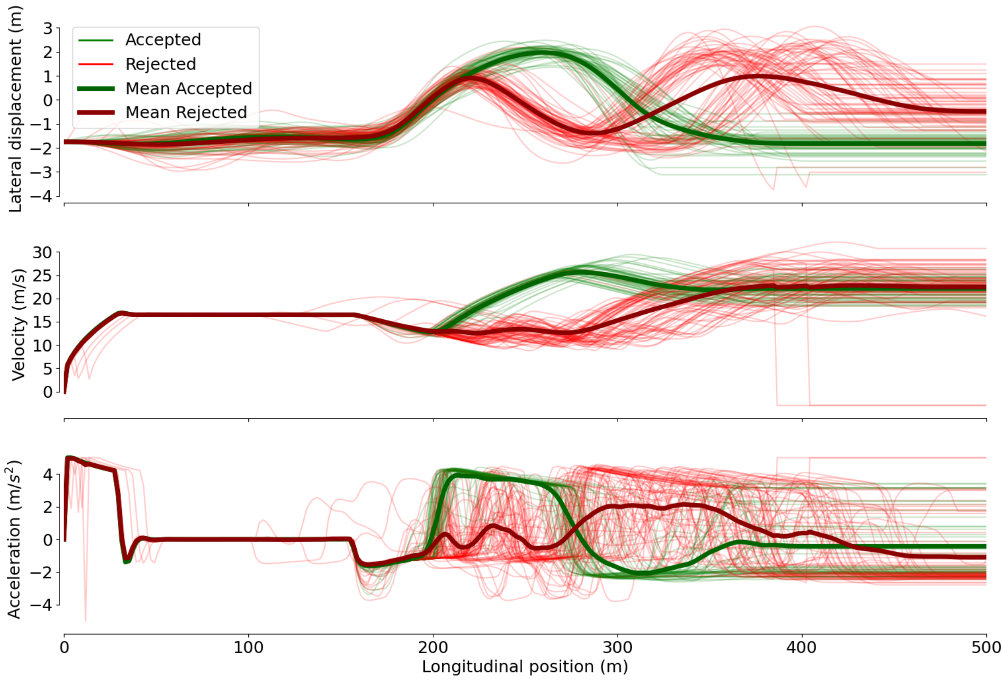
Participant 740, Gap Acceptance Ratio: 0.78

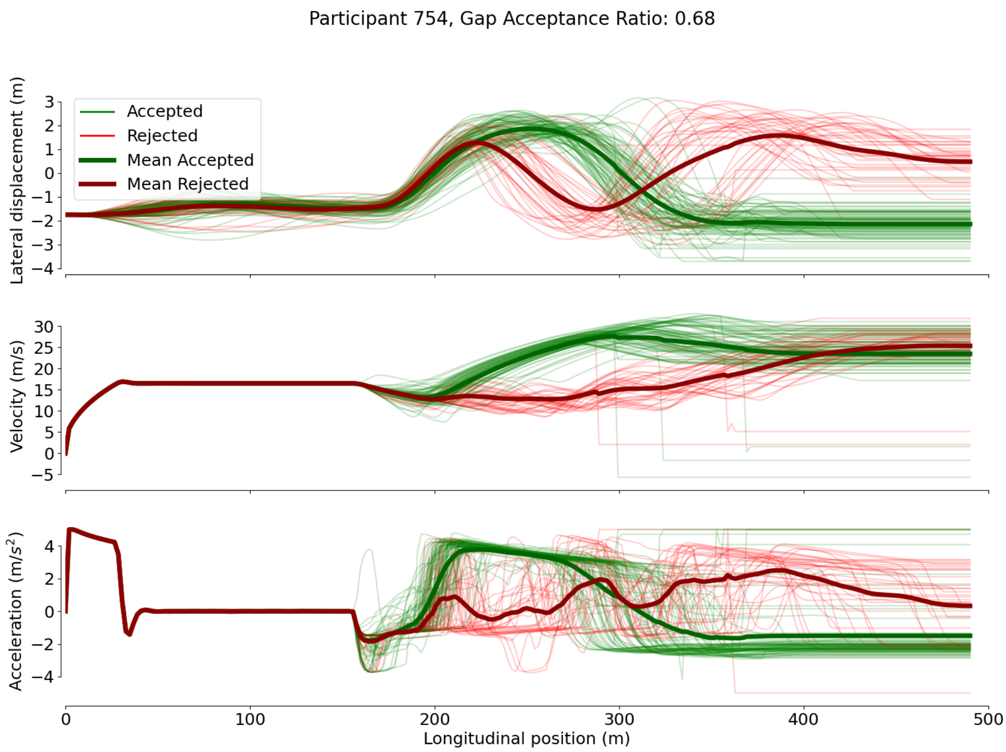


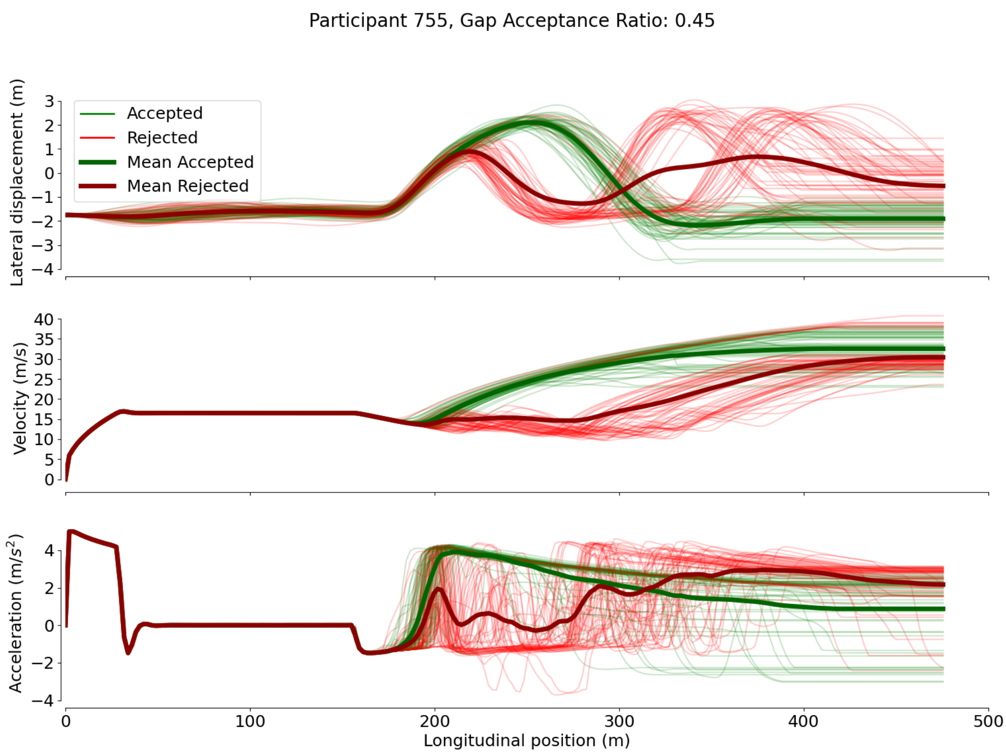
Participant 751, Gap Acceptance Ratio: 0.37

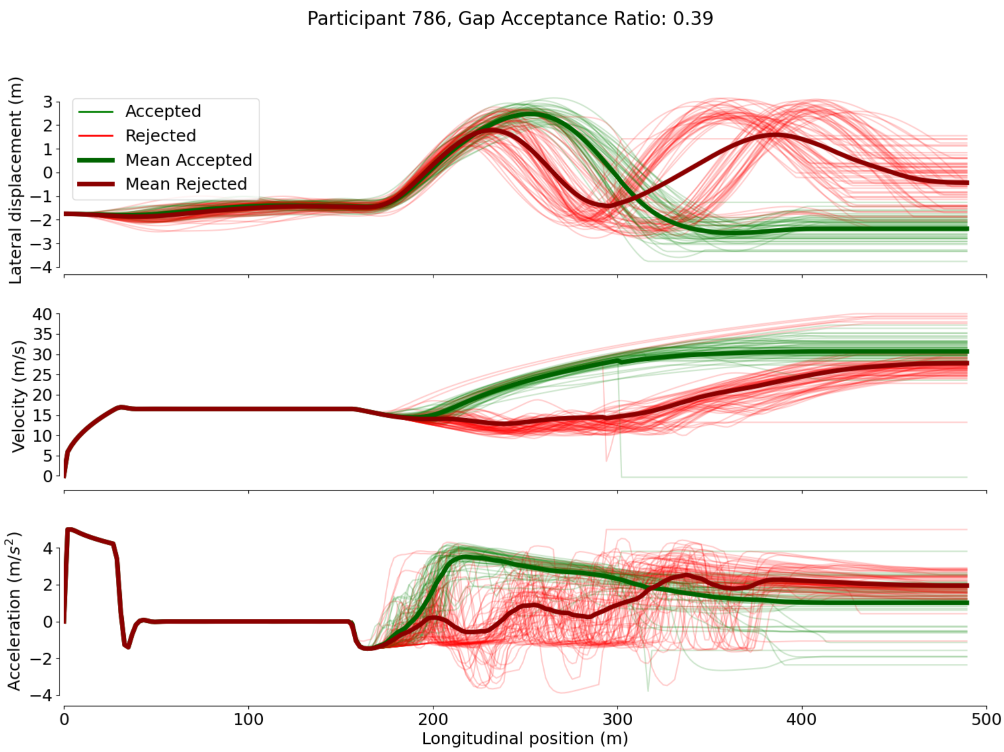


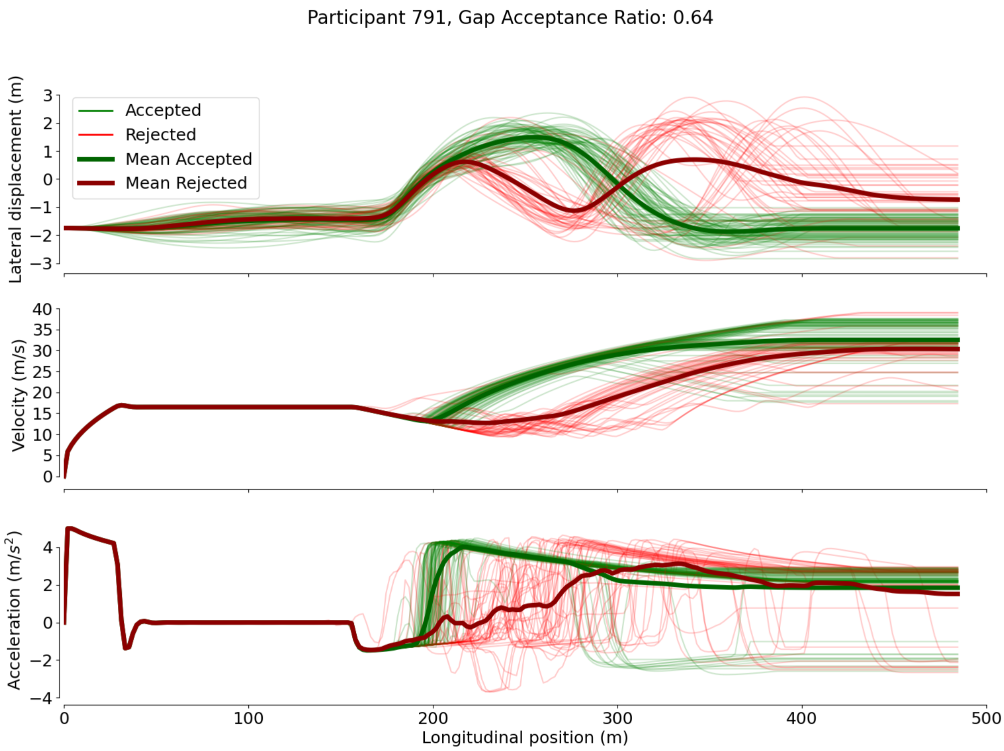
Participant 752, Gap Acceptance Ratio: 0.39

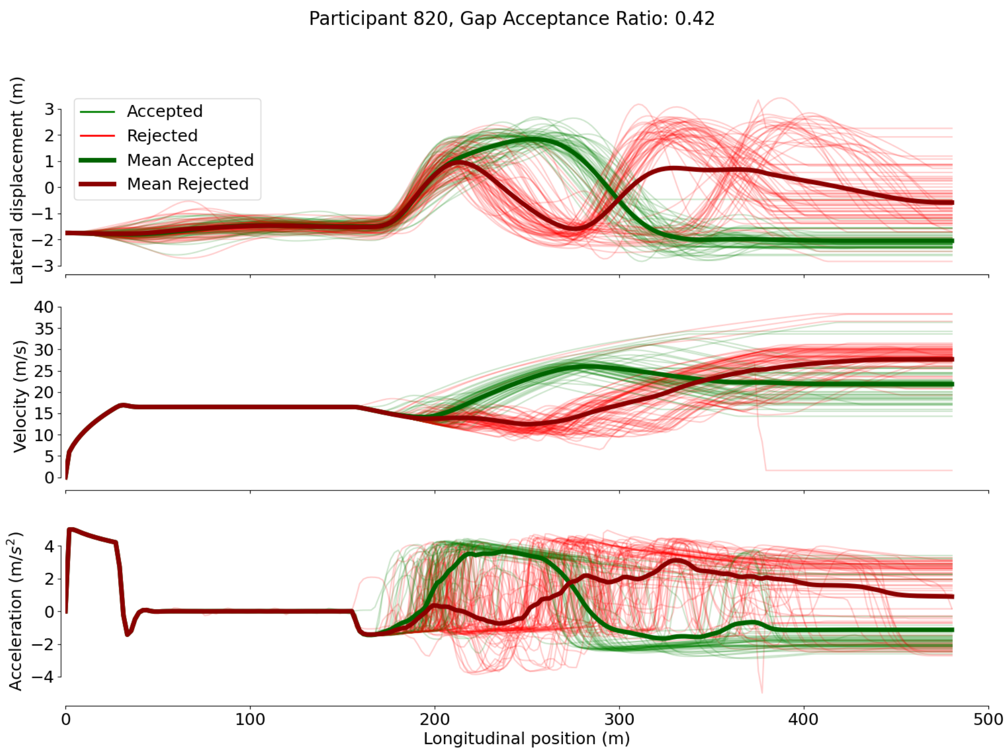



Participant 754, Gap Acceptance Ratio: 0.68
Accepted
Rejected
Mean Accepted
Mean Rejected
Lateral displacement (m)
Velocity (m/s)
Acceleration (m/s²)
Longitudinal position (m)


Participant 755, Gap Acceptance Ratio: 0.45
Accepted
Rejected
Mean Accepted
Mean Rejected
Lateral displacement (m)
Velocity (m/s)
Acceleration (m/s²)
Longitudinal position (m)


Participant 786, Gap Acceptance Ratio: 0.39
Accepted
Rejected
Mean Accepted
Mean Rejected
Lateral displacement (m)
Velocity (m/s)
Acceleration (m/s^2)
Longitudinal position (m)


Participant 791, Gap Acceptance Ratio: 0.64
Accepted
Rejected
Mean Accepted
Mean Rejected
Lateral displacement (m)
Velocity (m/s)
Acceleration (m/s^2)
Longitudinal position (m)


Participant 820, Gap Acceptance Ratio: 0.42
Accepted
Rejected
Mean Accepted
Mean Rejected
Lateral displacement (m)
Velocity (m/s)
Acceleration (m/s^2)
Longitudinal position (m)
0
100
200
300
400
500

Bibliography

[1] Annemartijne Sevenster et al. “Response times in drivers’ gap acceptance decisions during overtaking”. In: *Transportation research part F: traffic psychology and behaviour* 94 (2023), pp. 329–340.

[2] Samir H.A Mohammad, Haneen Farah, and Arkady Zgonnikov. “A cognitive process approach to modeling gap acceptance in overtaking”. In: *IEEE Transactions on Intelligent Transportation Systems* (2023 in press).