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In the driver's mind: Modeling the dynamics of human overtaking decisions in interactions with oncoming automated vehicles

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ABSTRACT

Understanding human behavior in overtaking scenarios is crucial for enhancing road safety in mixed traffic with automated vehicles (AVs). Computational models of behavior play a pivotal role in advancing this understanding, as they can provide insight into human behavior generalizing beyond empirical studies. However, existing studies and models of human overtaking behavior have mostly focused on scenarios with simplistic, constant-speed dynamics of oncoming vehicles, disregarding the potential of AVs to proactively influence the decision-making process of the human drivers via implicit communication. Furthermore, despite numerous studies in other scenarios, so far it remained unknown whether overtaking decisions of human drivers are affected by whether they are interacting with an AV or a human-driven vehicle (HDV). To address these gaps, we conducted a "reverse Wizard-of-Oz" driving simulator experiment with 30 participants who repeatedly interacted with oncoming AVs and HDVs, measuring the drivers' gap acceptance decisions and response times. The oncoming vehicles featured time-varying dynamics designed to influence the overtaking decisions of the participants by briefly decelerating and then recovering to their initial speed. We found no evidence of differences in participants' overtaking behavior when interacting with oncoming AVs compared to HDVs. Furthermore, we did not find any evidence of brief decelerations of the oncoming vehicle affecting the decisions or response times of the participants. Cognitive modeling of the obtained data revealed that a generalized drift-diffusion model with dynamic drift rate and velocity-dependent decision bias best explained the gap acceptance outcomes and response times observed in the experiment. Overall, our findings highlight that cognitive models of the kind considered here can provide a generalizable description of human overtaking decisions and their timing. Such models can thus help further advance the ongoing development of safer interactions between human drivers and AVs during overtaking maneuvers.

1. Introduction

While driving automation promises improved traffic safety (Milakis et al., 2017), successfully managing interactions between automated vehicles (AVs) and human drivers in mixed traffic scenarios remains a substantial challenge (Schieben et al., 2019; Brown

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et al., 2023). Overtaking maneuvers on two-lane rural roads, in particular, pose significant risks of head-on collisions at high speeds. As a part of these maneuvers, human drivers need to make a gap acceptance decision, i.e. estimate the available space between their vehicle and other vehicles and choose whether they can accept the gap (perform the maneuver) or reject the gap (wait for another opportunity). However, human drivers' inconsistent judgments of these gaps (Gray & Regan, 2005; Lerner et al., 2000; Gordon & Mast, 1970) require a comprehensive understanding of human overtaking behavior to enhance road safety.

Advanced overtaking behavior models can enhance our understanding of human gap acceptance, consequently playing a pivotal role in enhancing road safety and the development of AV technology. These models can simulate realistic human behavior in overtaking scenarios, improving the accuracy of testing and validation of AVs (Markkula et al., 2018). Furthermore, AVs can utilize such models to predict gap acceptance in real time and anticipate overtaking maneuvers by human drivers, contributing to overall safety (Sadigh et al., 2016; Schumann et al., 2023). More specifically, AVs can use implicit communication aimed to influence human driving behavior (Markkula et al., 2020), and advanced human behavior models can help design such implicit communication (Zgonnikov, Beckers, et al., 2024).

While existing studies and models of overtaking gap acceptance contributed to our understanding of human overtaking behavior (e.g., (Gray & Regan, 2005; Farah & Toledo, 2010; Llorca et al., 2013; Hegeman et al., 2005; Polus et al., 2000; Farah, 2016; Farah et al., 2009; Stefansson et al., 2020; Vlahogianni, 2013)), they predominantly approach gap acceptance as an instantaneous process. In other words, the traditional approaches to studying overtaking gap acceptance overlook the fact that decision making takes time. This is in contrast with the dynamic nature of traffic interactions more generally: these interactions evolve over time (Markkula et al., 2020), influenced by factors such as relative speeds, distances between vehicles, and the behavior of other road users (e.g., negotiations in bottleneck scenarios (Rettenmaier & Bengler, 2020; Miller et al., 2022) or simulated highway merging (Siebinga et al., 2024)). Therefore, models of human overtaking behavior that neglect these dynamic aspects are limited in their applications for human-AV interactions.

Recent research has started addressing the dynamic aspect of traffic interactions by modeling the dynamics of the decision-making processes across various traffic situations, including pedestrian crossing (Pekkanen et al., 2021), unprotected left turns (Zgonnikov, Beckers, et al., 2024; Zgonnikov, Abbink, et al., 2024; Bontje & Zgonnikov, 2024), and overtaking maneuvers (Mohammad et al., 2023) using *cognitive process models*, in particular, drift-diffusion models (DDMs). These models assume that drivers integrate visual cues (such as distance and time-to-arrival to oncoming vehicles) over time until sufficient evidence is accumulated. DDMs have effectively incorporated dynamic aspects of interactions, such as an AV signaling yielding intent through deceleration or external human-machine interface signals (Pekkanen et al., 2021; Markkula et al., 2023). Furthermore, DDMs have demonstrated potential in describing how time-varying dynamics of oncoming AVs influence gap acceptance decisions and response times (Zgonnikov, Beckers, et al., 2024).

Despite their success in multiple traffic interactions scenarios, DDMs have yet to prove their worth in the context of overtaking interactions. The studies of overtaking have only recently started incorporating advanced measures of human decisions such as response times (Sevenster et al., 2023); these measures have also informed first attempts to model overtaking using drift-diffusion models (Mohammad et al., 2023). However, these initial efforts have been limited by their focus on human gap acceptance decisions in response to an oncoming vehicle with trivial, constant-acceleration dynamics. Consequently, human overtaking decisions have yet to be systematically investigated and modeled in the context of dynamic interactions with time-varying kinematics.

Furthermore, it is currently unknown whether overtaking decisions of human drivers are affected by whether they interact with an AV or an HDV. In the context of other traffic interactions, recent studies have presented mixed results on the influence of vehicle type on gap acceptance. Soni et al. (2022) and Trende et al. (2019) reported that drivers were willing to accept smaller gaps when interacting with AVs compared to HDVs. However, these studies influenced their participants' perceptions of AVs before the experiment by providing information on expected AV behavior, potentially impacting their results. In contrast, studies that refrained from doing so (e.g., (Reddy et al., 2022; Velasco et al., 2019; Palmeiro et al., 2018)) did not find differences between AVs and HDVs in terms of their effect on gap acceptance. These mixed findings underscore the need for a comprehensive investigation into the potential influence of oncoming vehicle type (AV vs HDV) on human overtaking behavior.

This study aimed to address the above research gaps through cognitive process modeling of data obtained in a driving simulator experiment involving interactions with oncoming AVs and HDVs with time-varying dynamics. Specifically, we investigated whether AVs can utilize brief decelerations (referred to as "nudges" (Zgonnikov, Beckers, et al., 2024)) as a form of implicit communication to signal their intention and affect the overtaking decisions of human drivers. The oncoming AV was preprogrammed to perform one of the three behaviors: 1) maintaining a constant speed; 2) decelerating with 2.5 m/s^2 for 2 s soon after appearing in participants' field of view and then accelerating back to its original speed ("weak nudge"); 3) "strong nudge" — similar to the weak nudge but with deceleration magnitude of 5 m/s^2. To investigate the effect of interacting with AV compared to HDV, we manipulated participants' belief of the type of oncoming vehicle they interacted with. To this end, we used a "reverse Wizard-of-Oz" setup: the participants were made to believe that in HDV trials they would interact with the experimenter, while the actual oncoming vehicle was still AV with the same pre-programmed behaviors.

We hypothesized that a) participants' overtaking behavior (as measured by gap acceptance probability and response time) would remain the same when interacting with AVs compared to HDVs, and b) participants' gap acceptance likelihood in response to deceleration nudges of the oncoming vehicle would be higher, compared to the constant-speed condition. Finally, we fitted two versions of a drift-diffusion model to the collected data to investigate the cognitive mechanisms underlying participants' decisions in dynamic overtaking interactions.

Fig. 1. "Reverse Wizard-of-Oz" experimental setup of the driving simulator. During the sessions involving oncoming "human-driven" vehicles, the experimenter (on the right-hand side) was not visible to the participant (who also could not see the movements of the experimenter's steering wheel) and pretended to operate an unconnected driving simulator. The participant wore a noise-canceling headset to avoid hearing the experimenter's control inputs.

2. Methods

2.1. 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 (15 male, 15 female), 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 automated vehicles averaged 2.4 ± 1.3 on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). Their self-reported perceived safety of automated vehicles averaged 2.9 ± 0.8. In return for their participation, each participant received a €20 gift voucher.

2.2. Setup

The experiment utilized a fixed-base driving simulator (Fig. 1). The simulator featured a 65-inch screen and was equipped with a Logitech G923 steering wheel, which included a gas pedal and a brake pedal. The experiment was configured using open-source software frameworks JOAN (Beckers et al., 2023) and CARLA (Dosovitskiy et al., 2017). The experimental environment, comprising a straight two-lane rural road, was designed in MathWorks RoadRunner.

2.3. Experimental design

Participants were instructed to drive in the simulator as they normally would on a typical Dutch rural road in real life. They were explicitly told that the speed limit was 80 km/h, but there would be no penalty for exceeding it. Participants were informed that oncoming traffic would be present in the opposite lane. Each trial started with three oncoming vehicles with small distances between each other (i.e., a platoon) passing on the opposite lane to block premature overtaking maneuvers. The ego vehicle was set to cruise control until the platoon of vehicles in the opposite lane passed it. After the last vehicle in the platoon passed the ego vehicle, an auditory signal (beep) was delivered through headphones, indicating the start of an overtaking situation (Fig. 2). At this point, participants gained full control over the ego vehicle, which had a headway of approximately 1.5 seconds behind the lead vehicle. Subsequently, to induce a desire to overtake, the lead vehicle speed was gradually reduced from 60 km/h to 45 km/h over 4 seconds. Following a methodology akin to Sevenster et al. (2023) where the lead vehicle blocked the ego vehicle driver's view of oncoming traffic, at the time the participant started veering out of their lane, the oncoming vehicle appeared at a given distance (D_0) and time-to-arrival (TTA_0), executing one of the three longitudinal maneuvers (Fig. 3). As a result, the participant then had to assess the gap to the oncoming vehicle and make a decision whether to overtake the lead vehicle.

In our experiment, we kept the lead vehicle's velocity during the overtaking maneuver constant at 45 km/h, while the initial gap to the oncoming vehicle was varied through adjustments in the initial distance D_0 (240 and 280 meters) and initial time-to-arrival TTA_0 (6 seconds and 10 seconds) (Fig. 3). Here the time-to-arrival denotes the time needed for the vehicles (more specifically, their front bumpers) to arrive to the same longitudinal position from their current positions if they continue moving with their current speed.

Given the initial conditions D_0, TTA_0, and the initial speed of the ego vehicle v_0^{ego}, the oncoming vehicle's initial speed for each trial was determined as

Fig. 2. Participants' perspective while performing the task in the driving simulator. The lead vehicle blocks the view of oncoming traffic. As the participant moves to the opposing lane to assess the road situation a decision has to be made to either overtake the lead vehicle (accepting the gap) or stay behind the lead vehicle until the oncoming car passes (rejecting the gap). The inset depicting an oncoming vehicle is for illustrative purposes only and was not present in participants' view during the experiment.

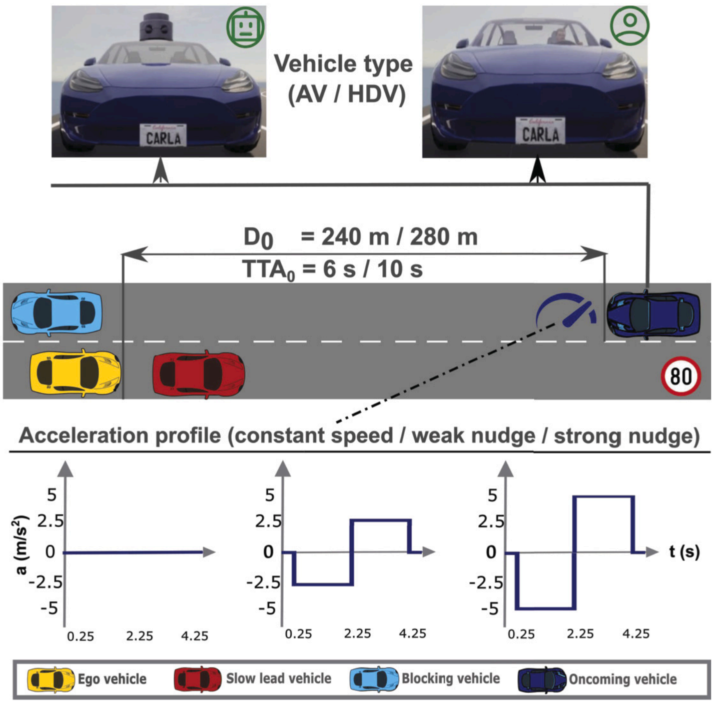

Fig. 3. Independent variables manipulated in the experiment: vehicle type, initial distance (D_0), initial time-to-arrival (TTA_0), and acceleration profile of the oncoming vehicle.

$$v_0^{\text{oncoming}} = D_0/TTA_0 - v_0^{\text{ego}}.$$

As an example, for the ego vehicle with an initial speed of 45 km/h, the initial velocity of the oncoming vehicle would range between 40 km/h (low distance, high TTA) and 120 km/h (high distance, low TTA). This setup was chosen to mimic the conditions reasonably encountered on rural roads (Polus et al., 2000; Llorca & Farah, 2016).

Not only the initial conditions but also the behavior of the oncoming vehicle during interactions was manipulated. The oncoming vehicle maintained a constant speed or executed a deceleration of 2.5 m/s^2 (weak nudge) or 5 m/s^2 (strong nudge) for 2 seconds, after which it accelerated back to its original speed over another 2 seconds. These acceleration profiles were designed to investigate the potential of using brief decelerations as a means of implicit communication by the oncoming AV (Tian et al., 2023). Similar nudging maneuvers have previously shown their effectiveness in interactions at intersection crossing (Zgonnikov, Beckers, et al., 2024), but have not been investigated in the context of overtaking. We posited that varying dynamics over 4 seconds might influence the overtaking decision-making process, considering that such decisions typically span 1 to 3 seconds (Sevenster et al., 2023). The exact deceleration values of 2.5 m/s^2 and 5 m/s^2 were selected based on pilot experiments.

Additionally, we manipulated the oncoming vehicle type (AV and HDV) over two sessions throughout the experiment. In the session featuring an oncoming HDV, we employed a "reverse Wizard-of-Oz" setup where the experimenter was pretending to operate another driving simulator (Fig. 1). This setup created the illusion that the oncoming HDV was human-controlled. To further visualize the differences between HDV and AV, the HDV had an animated driver inside, and AV had no driver but had a LiDAR sensor on top of it (Fig. 3). Before each session, participants were explicitly told which vehicle type they will be interacting with during that session. The order of sessions (AV first/HDV first) was randomized between participants.

The experiment thus followed a within-participant design with a 2 x 2 x 2 x 3 factorial structure, with four independent variables: the initial distance between the ego vehicle and the oncoming vehicle (240 m or 280 m), the initial TTA (6 s or 10 s), the oncoming vehicle type (AV or HDV), and the acceleration profile of the oncoming vehicle (constant speed, weak nudge, or strong nudge) (Fig. 3). In total, there were 24 unique conditions. Two additional conditions were included in which the gap was very small ($D_0 \in \{70, 150\} m$, $\mathrm{TTA}_0 = 2$ s, constant speed). These conditions were added to encourage participants to perform a careful assessment of the road situation and not simply overtake in every trial. The data from these conditions was excluded from the analysis.

To familiarize themselves with the driving equipment and task, participants were asked to perform 5 to 10 practice trials before the start of the experiment, ensuring their comfort with the experimental procedure. Then, 26 conditions were repeated five times, randomly shuffled 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 task followed after every 13 trials. Each session lasted approximately 45 minutes, with a 15-minute break between the sessions. After the second session, participants answered questions regarding perceived safety and the behavior of the oncoming vehicle in a post-experiment questionnaire. Overall, the experiment recorded a total of about 3600 overtaking gap acceptance decisions.

2.4. Recorded data and metrics

The data, including trajectories and velocities of the ego vehicle and the oncoming vehicle, was captured at a rate of 100 Hz. From this data, we extracted the two main dependent variables: the decision outcome (Overtake (gap accepted) or Stay (gap rejected)) and response time (the duration of the gap acceptance decision-making process).

The decision was determined by checking whether the ego vehicle returned to its lane behind the lead vehicle (indicating gap rejection) or not (indicating gap acceptance). The response time was determined as the difference between t_{end} (the timestamp corresponding to the end of the decision-making process) and t_{start} (the time the decision-making process started).

The start of the decision-making process was determined as the moment the oncoming vehicle appeared in the field of view of the ego vehicle. The moment the decision-making process ended was quantified differently depending on whether the gap was rejected or accepted (Fig. 4).

For rejected gaps, the decision was considered finalized (t_{end}) at the peak of the lateral swerve, indicating the moment the ego vehicle began to return to its original lane after veering into the opposite lane to assess the gap, following the method proposed by Sevenster et al. (2023) (Fig. 4).

For accepted gaps, we denoted the end of the decision-making process as the point where the acceleration of the ego vehicle surpassed a predetermined threshold of 3 m/s^2 (Fig. 4). 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.

2.5. Exclusion criteria

We excluded trials in which the overtaking decision could not be determined due to vehicle collisions ($n = 19$) 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.

In total, our analyses were based on 3438 overtaking maneuvers to assess decision outcomes and 3109 decisions for analyzing response times and cognitive modeling.

2.6. Data analysis

We conducted statistical analyses using mixed-effect regressions for decision outcomes (logistic) and response times (linear) in *pymer4* (Jolly, 2018). Dummy coding was employed for vehicle type and acceleration profile, 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 as a random slope as well as random intercept per participant in all regression models.

For statistical analyses, we standardized all continuous variables (initial distance D_0, initial time-to-arrival TTA_0, and initial ego vehicle velocity v_0^{ego}) as well as trial number through z-scoring. This standardization allowed us to interpret the coefficients for each independent variable in terms of their relative contributions to the dependent variable. Additionally, we dichotomized the values of

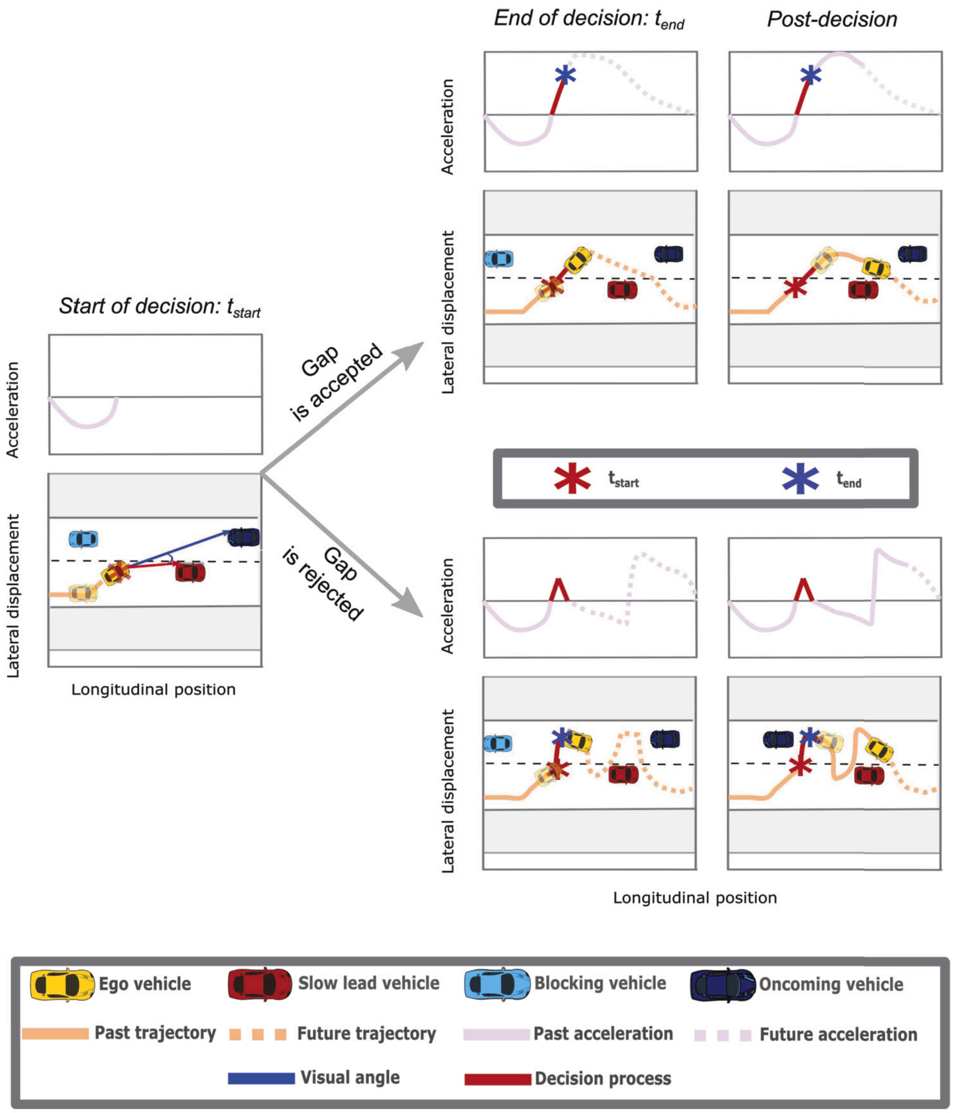

Fig. 4. Response time measurement in rejected gaps (Sevenster et al., 2023) and our proposed measurement method in accepted gaps. The moment the oncoming vehicle appeared in participants' field of view was denoted as the start of the decision-making process (t_{start}). The end of the decision-making process (t_{end}) was defined as the moment the ego vehicle acceleration reached a pre-defined threshold of 3 m/s^2 (in accepted gaps) or the peak of the lateral swerve, indicating when the ego vehicle began to return to its original lane after veering into the opposite lane to assess the gap (in rejected gaps).

initial ego vehicle velocities into two equally-sized clusters: low (v_0^{ego} < 13.8 m/s) and high (v_0^{ego} > 13.8 m/s) velocities. This was done for visualization and to enable inclusion of the initial velocity as a factor in the drift-diffusion models; for statistical analyses, the original values of v_0 were used.

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.

2.7. Implementation and fitting of cognitive models

Cognitive models were implemented using *pyddm* (Shinn et al., 2020) and fitted to the data using the differential evolution optimization technique with Bayesian information criterion as a loss function.

We aimed to assess whether our models effectively captured the general trends in the behavior of our participants, rather than explaining individual differences. Hence, we fitted the models to the "average" participant by aggregating all the data. Furthermore, since there was no evidence for differences in participants' overtaking behavior between oncoming AVs and HDVs, as well as no order effects, we excluded vehicle type and session order factors from all cognitive models.

Table 1
Fixed-effect coefficients of the mixed-effect logistic regression describing the final decision as a function of z-scored variables D_0, TTA_0, v_0^{ego} and trial number, acceleration profile, vehicle type, and session order. The vehicle type per participant ID was included as a random slope.

	Estimate	SE	z	p
(Intercept)	-0.10	0.26	-0.36	0.72
D_0	0.96	0.04	21.7	< 0.001
TTA_0	0.58	0.04	13.6	< 0.001
v_0^{ego}	0.52	0.06	9.23	< 0.001
Acceleration profile “weak nudge”	0.06	0.10	0.58	0.56
Acceleration profile “strong nudge”	0.07	0.10	0.66	0.51
Vehicle type HDV	0.009	0.16	0.06	0.96
Session order HDV first	-0.42	0.37	-1.13	0.26
Trial number (within session)	-0.13	0.04	-3.0	0.003
Vehicle type HDV:Session order HDV first	0.22	0.23	0.93	0.35

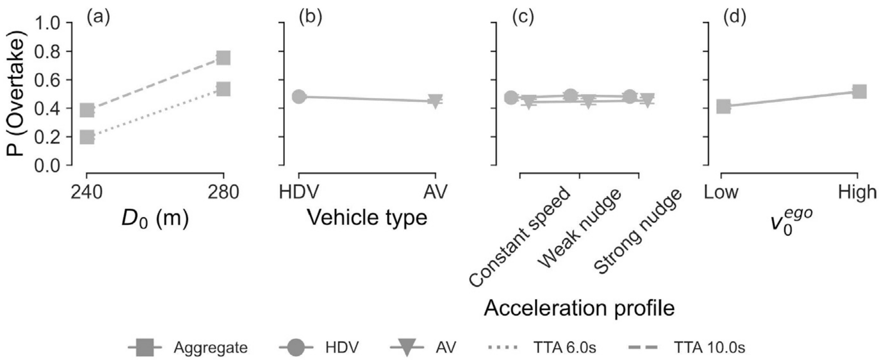

Fig. 5. Overview of the average participant’s behavior in overtaking decisions. Panel (a) shows that initial distance D_0 positively affected the overtaking probability, in both initial time-to-arrival TTA_0 conditions. Panel (b) shows that the vehicle type of the oncoming vehicle had a marginal effect. Panel (c) also shows that the deceleration nudges did not substantially affect the overtaking probability. Panel (d) shows that this probability is positively affected by the initial velocity of the ego vehicle v_0^{ego}. For visualization purposes, v_0^{ego} was dichotomized into low and high groups (with the cutoff value of $13.8 m/s$). Error bars denoting 95% confidence intervals are narrower than the marker size in some panels and therefore not visible.

3. Results

3.1. Decision outcomes

The probability of accepting the gap (i.e., the Overtake decision) for each condition is defined as the ratio of the number of overtake decisions to the total number of decisions (Overtake and Stay) in that condition. This probability was positively affected by the initial distance D_0 and initial time-to-arrival TTA_0 to the oncoming vehicle, as well as the initial velocity of the ego vehicle v_0^{ego} (Table 1, Fig. 5).

In line with our hypothesis, we found no evidence that the probability of overtaking differed between vehicle types AV vs. HDV ($p = 0.96$); neither the interaction between vehicle type and session order had a significant effect ($p = 0.35$). Despite no evidence of the overall effect of vehicle type on decision outcome on the group level however, we did observe substantial individual differences where a few participants decided to overtake more frequently in the presence of an oncoming HDV and vice versa in the case of an oncoming AV (see online supplementary information). Furthermore, there was a negative effect of trial number on gap acceptance probability ($p = 0.003$), indicating that participants became more conservative in their gap acceptance over the course of the experiment.

Contrary to our hypothesis, there was no evidence of differences in overtaking probability across different acceleration profiles: “constant speed” vs “weak nudge” ($p = 0.56$), “constant speed” vs “strong nudge” ($p = 0.51$).

3.2. Response times

We observed significant influences of the decision outcome, initial distance D_0, and initial time-to-arrival TTA_0 on response times (Table 2, Fig. 6). Post-hoc comparisons showed that Overtake responses were faster than Stay responses (Δ = -1.15 s, t = -59.9, $p < 0.001$). Initial distance D_0 positively affected Stay response times ($b = 0.13$, $t = 11.5$, $p < 0.001$), but not Overtake response times ($b = -0.02$, $t = -1.61$, $p = 0.053$). Both Overtake and Stay response times increased with TTA_0; Overtake: $b = 0.057$, $t = 4.38$, $p < 0.001$, and Stay: $b = 0.085$, $t = 7.73$, $p < 0.001$. Response times in rejected gaps increased with initial ego velocity ($b = 0.04$, $t = 3.5$, $p < 0.001$) while response times in accepted gaps decreased with v_0^{ego} ($b = -0.02$, $t = -1.8$, $p = 0.032$), although both effects were small (Fig. 6). Furthermore, there was no evidence of either Overtake and Stay response times changing systematically with the trial number; Overtake: $b = 0.018$, $t = 1.5$, $p = 0.07$, and Stay: $b = 0.002$, $t = 0.2$, $p = 0.42$.

Table 2
ANOVA table based on the mixed-effect linear regression describing response time as a function of decision, acceleration profile, vehicle type, session order, and z-scored variables D_0, TTA_0, v_0^{ego} and trial number.

	SS	MS	df	F	p
Decision	638	638	1	3526	< 0.001
D_0	6.64	6.64	1	36.7	< 0.001
TTA_0	13.8	13.8	1	76.4	< 0.001
v_0^{ego}	0.14	0.14	1	0.79	0.37
Acceleration profile	0.37	0.19	2	1.04	0.36
Vehicle type	0.09	0.09	1	0.50	0.48
Session order	0.02	0.02	1	0.12	0.73
Trial number (within session)	0.30	0.30	1	1.63	0.20
Decision:D_0	13.2	13.2	1	72.7	< 0.001
Decision:TTA_0	0.53	0.53	1	2.92	0.08
Decision:v_0^{ego}	2.96	2.96	1	16.4	< 0.001
Decision:Acceleration profile	0.18	0.09	2	0.49	0.61
Decision:Vehicle type	0.84	0.84	1	4.64	0.031
Decision:Session order	1.44	1.44	1	7.96	0.005
Decision:Trial number (within session)	0.20	0.20	1	1.12	0.29

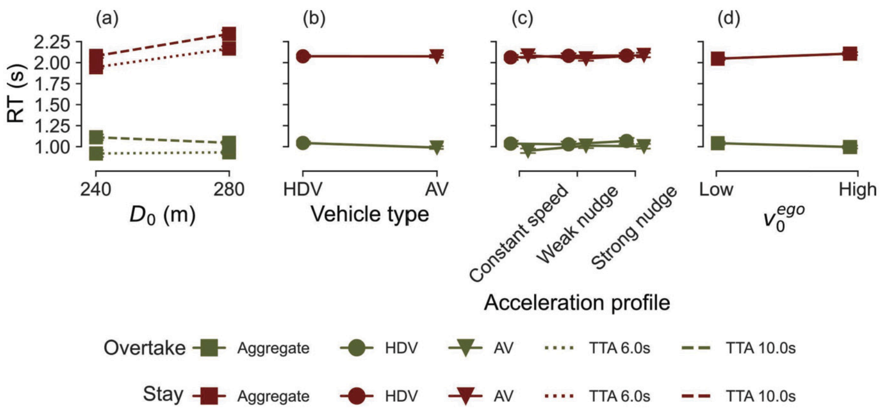

Fig. 6. Overview of the average participant's behavior in overtaking response times. Panels (a)-(d) show that Stay (rejected gap) response times are higher than Overtake (accepted gap) response times. Panel (a) shows that initial distance D_0 positively affected the response times in Stay decisions, in both initial time-to-arrival TTA_0 conditions. D_0 does not substantially affect response times in Overtake decisions. Panel (b) shows that the vehicle type of the oncoming vehicle had a marginal effect on both Stay and Overtake response times. Panel (c) also shows that the deceleration nudges did not substantially affect these responses. Panel (d) shows that the initial velocity of the ego vehicle v_0^{ego} did not substantially affect response times as well. For visualization purposes, v_0^{ego} was dichotomized into low and high groups (with the cutoff value of $13.8 m/s$). Error bars denoting 95% confidence intervals are narrower than the marker size in some panels and therefore not visible.

Our analysis of response times did not reveal evidence for main effects of vehicle type ($p = 0.48$) or acceleration profile ($p = 0.36$). However, we observed a marginally significant interaction between vehicle type and decision ($p = 0.031$), as well as between session order and decision ($p = 0.005$). However, post-hoc analyses showed no significant differences between vehicle type conditions "AV" vs "HDV" in Overtake response times (Δ = -0.06 s, t = -1.5, $p = 0.13$) or Stay response times (Δ = 0.01 s, t = 0.29, $p = 0.77$). Similarly, no significant differences were found between session order conditions "AV first" vs "HDV first" in Overtake response times (Δ = 0.02 s, t = 0.27, $p = 0.79$) or Stay response times (Δ = -0.07 s, t = -0.97, $p = 0.34$).

Further post-hoc tests revealed no evidence for differences in Overtake response times between conditions "constant speed" vs "weak nudge" (Δ = -0.01 s, t = -0.29, $p = 0.95$), "constant speed" vs "strong nudge" (Δ = -0.044 s, t = -1.27, $p = 0.41$), and "weak nudge" vs "strong nudge" (Δ = 0.034 s, t = 1.01, $p = 0.57$). Likewise, no evidence for differences was found in Stay response times: "constant speed" vs "weak nudge" (Δ = -0.002 s, t = -0.064, $p \approx 1.0$), "constant speed" vs "strong nudge" (Δ = -0.02 s, t = -0.76, $p = 0.73$), and "weak nudge" vs "strong nudge" (Δ = 0.02 s, t = 0.69, $p = 0.77$) conditions.

3.3. Post-experiment questionnaire

In the post-experiment questionnaire, using a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree), participants reported a similar sense of safe interactions in the two sessions (AV: mean = 3.9, SD = 0.76 vs HDV: mean = 3.9, SD = 0.64, t = -0.25, p = 0.83). Lastly, despite the lack of differences in the actual behavior of AVs and HDVs, participants were moderately certain that the AV and the HDV behaved differently (mean = 3.1, SD = 1.3).

3.4. Summary

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

- Initial distance, initial TTA, and initial ego vehicle velocity positively affected overtaking probability.
- Initial TTA positively affected the response times for both decisions, while initial distance positively affected response times for Stay but not Overtake decisions.
- No evidence of a difference in overtaking probability between the oncoming vehicle types AV and HDV was found.
- There was no evidence that weak and strong nudges impact overtaking probability compared to the constant-speed oncoming vehicle.
- There was no evidence that the oncoming vehicle type or its acceleration profile affected the response times.

4. Cognitive process modeling

4.1. Basic drift-diffusion model and its applications to traffic

We utilized the drift-diffusion modeling (DDM) framework (Ratcliff, 1978) to describe participants' decision-making processes in our experiment. According to the DDM, decision making is an ongoing process of accumulating relevant perceptual information over time. This process is noisy (reflecting the assumption that the perceived information is perceived and processed imperfectly) and bounded, such that a decision is made when a certain amount of evidence is accumulated.

Mathematically, the rate of evidence accumulation is denoted as the drift rate $s(t)$, while the random factor (diffusion) is characterized as a stochastic variable $\varepsilon(t)$ (white noise). The momentary evidence x favoring one alternative emerges from integrating both drift and diffusion:

$$\frac{dx}{dt} = s(t) + \varepsilon(t), \quad x(t_0) = Z. \tag{1}$$

This continuous process, beginning at position Z, is bounded and concludes when the evidence favoring one alternative reaches a predetermined boundary ($x = \pm b(t)$). Finally, DDM also incorporates non-decision time, which accounts for the duration of cognitive processes not directly related to decision-making, such as perceptual and motor delays.

Despite its computational simplicity, DDMs have proven highly effective in modeling and comprehending a wide array of decision-making processes, encompassing choice behavior and response times in experimental investigations (Ratcliff et al., 2016; Evans & Wagenmakers, 2020). More recently, DDMs have also been successfully applied to traffic-related decision processes in the presence of dynamically changing evidence such as gap acceptance in pedestrian crossings (Pekkanen et al., 2021) and left turns at unprotected intersections (Zgonnikov, Beckers, et al., 2024; Zgonnikov, Abbink, et al., 2024; Bontje & Zgonnikov, 2024). These studies emphasized that the drift rate $s(t)$ and possibly boundaries $b(t)$ need to be contingent on dynamically evolving gap sizes.

However, in contrast to pedestrian crossing and left-turn decisions, in overtaking maneuvers the decision maker is moving with a high velocity while making the decision. The influence of this initial velocity on decision outcomes was evident in the overtaking experiment conducted by Sevenster et al. (2023). In particular, they found that initial velocity positively influenced gap acceptance probability while negatively affecting response times in accepted gaps. Drawing upon the data from Sevenster et al. (2023), Mohammad et al. (2023) explored various versions of the DDM where the initial velocity was integrated into different components of the model: drift rate, decision boundary, and the starting point Z. The simplest model capable of effectively capturing all qualitative patterns in the data of Sevenster et al. (2023) included a drift rate dependent on both distance and TTA, the boundaries collapsing as distance and TTA decreased, and, importantly, the starting point Z dependent on the initial velocity of the ego vehicle (Mohammad et al., 2023).

4.2. Candidate drift-diffusion models for dynamic overtaking scenarios

Although previous studies provided early evidence that DDMs can be applied to overtaking decisions, these studies were limited to situations with a constant-acceleration oncoming vehicle (Sevenster et al., 2023; Mohammad et al., 2023). Furthermore, our experiment differed substantially from the one conducted by Sevenster et al. (2023) in other aspects, with variations in the initial distance (160 m and 220 m vs. 240 m and 280 m) and additional controlled variable (initial TTA). Thus, to shed light on cognitive processes underlying the overtaking decisions and response times of our participants, we explored multiple models to find the one that fits our dataset best. To do this, we re-evaluated the four main components of the DDM framework (Fig. 7) used by Mohammad et al. (2023) and proposed two potential models to explain our experimental results (Table 3).

Non-decision time

For both models, the non-decision time is assumed to vary randomly across trials, following a normal distribution:

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

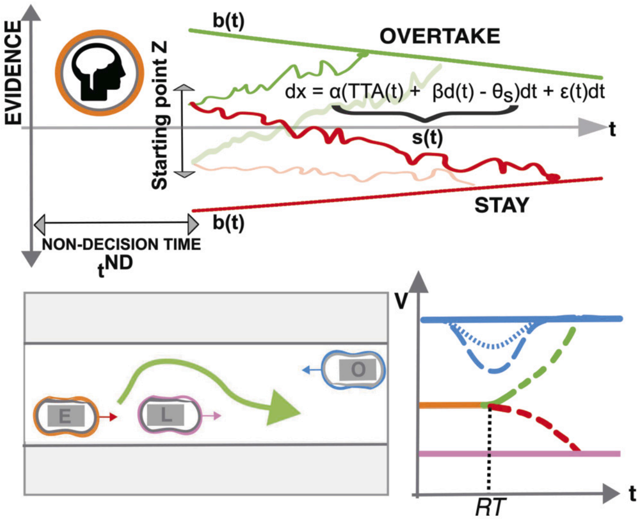

Fig. 7. Drift-diffusion model of gap acceptance in an overtaking scenario. Pink represents the lead vehicle, blue is the oncoming vehicle, and orange is the human-driven ego vehicle. Red indicates staying in the lane, and green represents overtaking, while blue velocity curves depict different dynamics of the oncoming vehicle. The outputs of the model are the decision outcome (Overtake or Stay) and the response time (i.e. the timing of the decision). (For interpretation of the colors in the figure(s), the reader is referred to the web version of this article.)

Drift rate

The drift rate $s(t)$ in both 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:

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

where $d(t)$ is the distance between the ego vehicle and the oncoming vehicle at time t, and $TTA(t)$ is an approximation of the current time-to-arrival

$$TTA(t) = \frac{d(t)}{v^{\text{ego}}(t) + v^{\text{oncoming}}(t)}. \tag{4}$$

As the speed of the ego vehicle varied from trial to trial in our data but the model components need to be specified as a function of time and experimental conditions, we used a constant-speed approximation of v^{ego} based on its initial velocity: $v^{ego}(t) \equiv v_0^{ego}$. During model fitting, v^{ego} was then dichotomized and treated as an experimental condition.

The size of the time and distance gap (combined with the weighting factor β) between the ego vehicle and the oncoming vehicle, relative to the critical gap value θ_s determines the drift rate's direction. Specifically, if the combined gap is larger than θ_s, the drift rate is positive, suggesting a higher likelihood of the decision-maker leaning towards the Overtake decision. Conversely, a gap smaller than θ_s leads to a negative drift rate, indicating a greater probability of choosing the Stay decision. The gap itself is dynamic and can increase during the decision-making process, for example, when the oncoming vehicle decelerates. This change in gap size directly impacts the drift rate by affecting how the current gap compares to the critical threshold θ_s.

Decision boundary

The accumulation 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. Previously, constant (Zgonnikov, Beckers, et al., 2024) or collapsing (Zgonnikov, Abbink, et al., 2024; Bontje & Zgonnikov, 2024) boundaries have been used in the literature, with more recent evidence pointing towards constant boundaries providing a better description of gap acceptance decisions (Zgonnikov, Beckers, et al., 2024; Mohammad et al., 2023). Hence, here we used constant decision boundaries for both models[1]:

$$b(t) = \pm B. \tag{5}$$

Starting point

Similar to Sevenster et al. (2023), our experimental results highlighted an effect of the initial velocity of the ego vehicle on decision outcomes and response times (Fig. 8). Therefore, similar to Mohammad et al. (2023), we tested two possible variations: fixed starting point

[1] Here we tested variants of our models with collapsing boundaries as well, and found that they are either reduced to the constant-boundary models or yield poorer fits compared to constant-boundary versions (see online supplementary information).

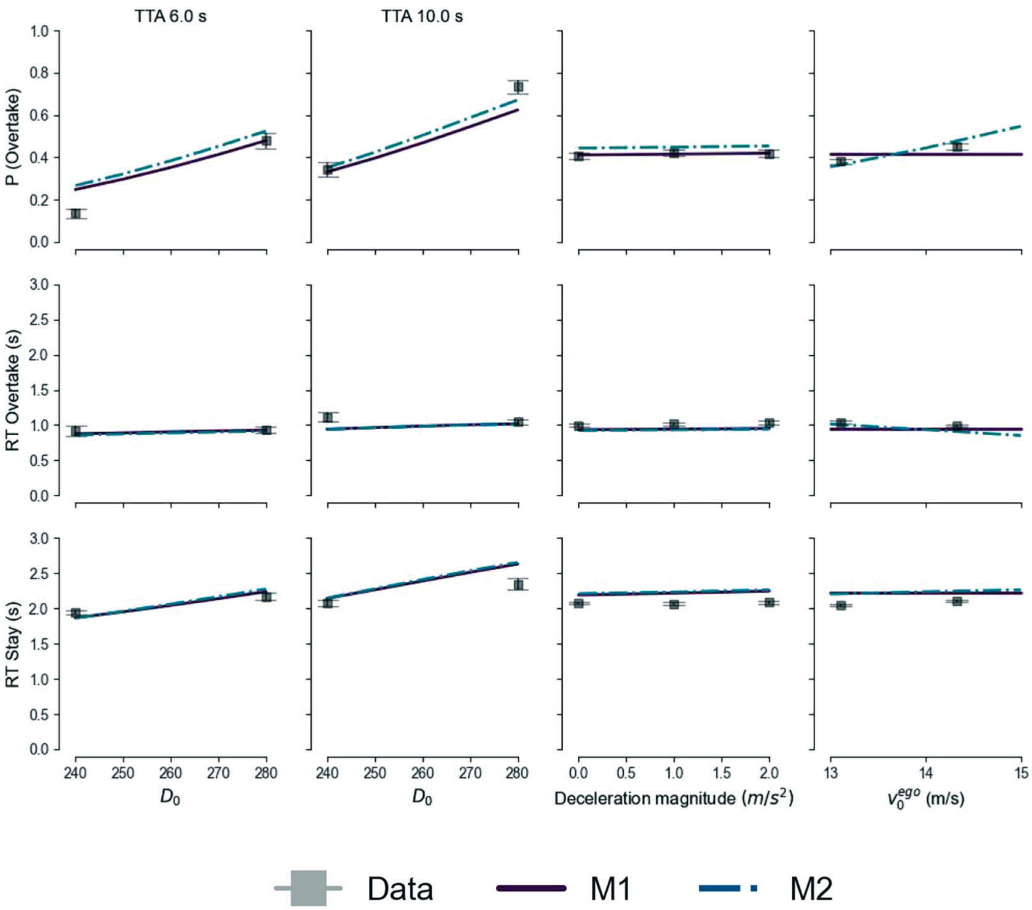

Fig. 8. Simulated model results compared to the experimental data to show the effect of distance and TTA, deceleration magnitudes of acceleration profiles, and the initial ego vehicle velocity on gap acceptance behavior. The lines represent the model simulations across the conditions indicated by the ticks on the x-axis. The error bars represent the 95% confidence intervals of the mean.

Table 3
Two tested variations of the generalized drift-diffusion model (1) with varying starting point functions (Eq. (6) (7)). Both models used the same drift rate (Eq. (3)), decision boundary (Eq. (5)), and non-decision time (Eq. (2)). The number of parameters in the last column thus includes not only the decision boundary and starting point parameters, but also the drift rate parameters α, β, θ_s, decision boundary parameter B, and the non-decision time parameters μ_{ND}, σ_{ND}.

Model	Initial bias $-b(t_0) < Z < b(t_0)$	Eq.	# parameters
M1: fixed starting point	C_z	(6)	7
M2: velocity-dependent starting point	$\frac{2B}{1+e^{-b_z(v_0^{\text{ego}}-\theta_z)}} - B$	(7)	8

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

and the starting point dependent on the initial velocity of the ego vehicle

$$Z = \frac{2B}{1 + e^{-b_z(v_0^{\text{ego}}-\theta_z)}} - B. \tag{7}$$

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_0^{ego} in relation to a critical parameter θ_z. In the latter case, relatively higher and lower initial speeds correspond to a bias toward the Overtake and Stay decisions, respectively. The parameter b_z quantifies the strength of this speed-related effect on the starting point. Furthermore, the starting point is constrained within the initial limits of the boundaries $\pm b_{t_0}$ i.e. $\pm B$ since $b(t)$ is a constant function (Eq (5)).

The two model variants we tested all have the same non-decision time, drift rate and decision boundary components, but differ in their assumptions on starting point (Table 3).

Table 4
Qualitative assessment of candidate drift-diffusion models according to the experimental findings.

Finding	M1	M2
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 TTA to the oncoming vehicle.	✓	✓
The probability of accepting the gap increases with the initial velocity of the ego vehicle.	X	✓
The probability of accepting the gap is not substantially affected by the acceleration profile of the oncoming vehicle.	✓	✓
Response times in rejected gaps are higher than in accepted gaps	✓	✓
Response times in accepted gaps are not substantially affected by the initial distance to the oncoming vehicle.	✓	✓
Response times in rejected gaps increase with the initial distance to the oncoming vehicle.	✓	✓
Response times increase with the initial TTA to the oncoming vehicle.	✓	✓
Response times are not substantially affected by the initial velocity of the ego vehicle.	✓	✓
Response times are not substantially affected by the acceleration profile of the oncoming vehicle.	✓	✓
Total	**9/10**	**10/10**

4.3. Model fitting results

We found that the two tested models were similar in their qualitative alignment with the observed behavior of the average participant (Fig. 8, Table 4). Both models exhibited consistent behavior regarding the probability of overtaking not varying across various acceleration profiles with magnitudes of deceleration nudges ranging from 0 (constant speed) to 5 m/s^2 (strong nudge). However, M1 (constant starting point) failed to account for the effect of initial velocity on gap acceptance probability. Conversely, M2 (initial velocity-dependent initial bias) successfully captured this effect.

Both models, featuring a constant boundary over time, adequately described the relationship between kinematic conditions and response time. This suggests that there might not be a substantial urgency effect under these experimental conditions. The simplest model that comprehensively described all qualitative patterns we observed is M2, which includes a velocity-dependent initial bias. The fitted parameters for M2 were $\alpha = 0.05$, $\beta = 0.52$, $\theta_s = 148$, $B = 1.4$, $b_z = 0.11$, $\theta_z = 8.48$, $\mu_{ND} = 0.53$, $\sigma_{ND} = 0.10$.

5. Discussion

We conducted a driving simulator experiment to determine the effect of the oncoming vehicle type (automated vs. human-driven vehicle) and the dynamic changes in the oncoming vehicle's acceleration on human drivers' overtaking behavior. Subsequently, we used the drift-diffusion modeling framework to describe gap acceptance during these overtaking interactions. Our experimental results revealed that gap acceptance in overtaking depends on the initial distance and time-to-arrival to the oncoming vehicle, and on the ego vehicle's initial velocity. These findings resonate with other gap acceptance studies in overtaking (Farah & Toledo, 2010; Sevenster et al., 2023; Farah et al., 2009). Most importantly, our study reveals two new empirical findings and one advancement in cognitive modeling: Firstly, we found no evidence of changes in participants' gap acceptance when interacting with an AV as opposed to an HDV. This finding implies that future overtaking behavior models do not necessarily need to increase their complexity by incorporating vehicle type. Secondly, the oncoming vehicle's acceleration profile did not affect overtaking behavior. Potentially, this limits the effectiveness of implicit longitudinal communication cues by AVs to show yielding behavior to human-driven vehicles during overtaking maneuvers. Finally, we showed that a version of a drift-diffusion model proposed earlier for simple overtaking scenarios can adequately describe human overtaking behavior in interactions with oncoming vehicles with varying longitudinal dynamics.

5.1. 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. (2022) and Trende et al. (2019) found that drivers were willing to accept shorter gaps at unsignalized intersections with approaching AVs, i.e., drivers decreased their critical gaps when they interacted with AVs as opposed to HDVs. However, in both studies, participants were given information about the AV's (strategic) behavior with the intention of influencing their perception of AVs. Studies that did not inform their participants about the AV's behavior showed no significant difference in gap acceptance behavior (Reddy et al., 2022; Velasco et al., 2019; Palmeiro et al., 2018). Similar to these studies, we did not inform participants beforehand about the AV's behavior, and found that participants did not change their overtaking behavior between sessions with an oncoming AV and an oncoming HDV. Taken together with the previous literature, this suggests that differences in human drivers' gap acceptance behavior could be attributed to the presence of bias in participants' perception of AVs; this hypothesis should be investigated in future work. However, participants in our experiment were aware of the oncoming vehicle type (AV or HDV) before each trial due to grouping of all AV/HDV trials in a single block (which was done to streamline the experimental procedure). This prior knowledge could have restricted our ability to capture any potential bias *during* the decision-making process. Future studies should consider randomizing the oncoming vehicle type across trials to mimic the uncertainty encountered in real mixed-traffic scenarios. However, this approach introduces a new potential challenge: the difficulty of visually distinguishing AVs from HDVs at large distances.

5.2. Human overtaking behavior: insensitive to nudging?

Perhaps the most unexpected finding is that we observed no evidence for differences in participants' behavior across the acceleration profiles of the oncoming vehicle. This outcome is contrary to Rettenmaier and Bengler (2020) who found that human drivers adapted their behavior when interacting with an oncoming vehicle with varying dynamics at a narrow passage. Consistent with this, Zgonnikov, Beckers, et al. (2024) reported higher gap acceptance rates in left-turn interactions with an oncoming vehicle exhibiting a deceleration nudge profile (similar to the ones considered here) compared to a constant-speed profile. The difference between these studies and our results could be potentially attributed to much larger distances investigated here (240 m to 280 m vs 50 m (Rettenmaier & Bengler, 2020) or 80 m (Zgonnikov, Beckers, et al., 2024)).

This leads us to consider two possible explanations of our findings. The first possibility focuses on human perception at the distances we examined. Despite our considered distances falling within a realistic range (e.g., (Polus et al., 2000; Llorca & Farah, 2016)), and being comparable to those used in other simulated overtaking studies (e.g., (Farah & Toledo, 2010; Leitner et al., 2023; Piccinini et al., 2018)), it may be that overtaking human drivers are inherently not sensitive to the kinds of nudges we tested. This insensitivity could be attributed to human perceptual limitations at long ranges (Schiff & Oldak, 1990). Indeed, the finding that even strong nudges (deceleration rate of $5m/s^2$ over 2 seconds) had no significant effect on gap acceptance and response times suggests that our participants might not have perceived any dynamic change in TTA during the interaction.

Alternatively, the lack of observed behavioral differences might stem from the limitations inherent to the simulator technology used in our experiment (Caird & Horrey, 2011). While participants did perceive initial TTA discriminately, the visual resolution of our driving simulator might not have been fine enough for them to also capture subtle changes in spatial and temporal information (Kemeny & Panerai, 2003). 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 (Stinchcombe et al., 2017). 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.

5.3. Simpler drift-diffusion models for more complex overtaking scenarios?

Cognitive process models offer distinct advantages over purely statistical models when analyzing human behavioral data: they provide a structured framework for comprehending the underlying cognitive mechanisms and causal relationships that drive observed behaviors. While statistical models (including machine-learned models) can depict data correlations, cognitive models go a step further, allowing exploration into *why* drivers accept gaps, rather than merely describing *what* factors they take into account. Furthermore, cognitive 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 human decision-making processes during overtaking interactions with oncoming vehicles with time-varying dynamics. This contributes to the existing modeling literature, which until now either considered overtaking interactions without time-varying dynamics (Mohammad et al., 2023) or modeled time-varying dynamics in interactions other than overtaking (Zgonnikov, Beckers, et al., 2024; Pekkanen et al., 2021). Similar to our work, these studies also considered DDMs with time-varying drift rates, highlighting the need to include dynamic information on distance and time-to-arrival.

Out of the two tested DDMs, only M2 (initial velocity-dependent initial bias) was capable of describing all the qualitative patterns in our overtaking dataset. One aspect of our models that differed from the models tested before by Mohammad et al. (2023) was the constant decision boundaries (as opposed to collapsing boundaries). However, the best-fitting model reported by Mohammad et al. (2023) for the dataset of Sevenster et al. (2023) had a very low boundary collapse rate, indicating that time-varying boundaries might be redundant. To further clarify this point, we fitted our best-fitting model M2 to the dataset (Sevenster et al., 2023) and found that M2 provided a qualitatively comparable fit to the model proposed by Mohammad et al. (2023) (see online supplementary information). This suggests that the constant-boundary model offers a more parsimonious yet equally effective description of overtaking gap decisions.

Secondly, the longitudinal movement profiles of the oncoming vehicle previously modeled by Mohammad et al. had constant *acceleration*, as opposed to (time-varying) *deceleration* modeled here; this could have led to a stronger urgency effect in the dataset they used, something that can be associated with collapsing boundaries (Zgonnikov, Abbink, et al., 2024). Although our findings regarding the decision boundary diverge from Mohammad et al. (2023), our results reinforced their other insights into the dynamics of the decision-making process during overtaking. Specifically, they emphasized the dynamic dependence of drift rate on both distance and time-to-arrival, as well as a velocity-dependent starting point. The fact that these conclusions persisted across studies despite differences in the experimental setup (varying TTA values, larger distances, smaller variation in the initial speed of the ego vehicle) suggests that the DDMs of the kind considered here can provide a generalizable description of human overtaking decisions and their timing.

An important limitation of our model is that it is limited to decisions and response times of only the *final* decision, and in its current state cannot capture "changes-of-mind" (Resulaj et al., 2009): the situations in which a driver initially rejected a gap but then decided to accept it after all. In our analyses, we counted these decisions as accepted gaps, disregarding participants' potential initial inclination to reject the gap. The cognitive models we analyzed here are not readily able to account for these too. Similarly, aborted overtaking maneuvers were not accounted for in our models: such aborted maneuvers represent scenarios where participants initially accepted a gap and start executing an overtaking maneuver but subsequently decided to reject it.

Only considering final decisions restricts the predictive power of the model in regards to the decision-making *process* and (to a lesser extent) the decision *outcome* (Atiya et al., 2020). For example, the decision-making process could continue even after rejecting a gap when there is late-arriving evidence in favor of accepting the gap (Resulaj et al., 2009). Although aborted gaps have been measured before and factors (e.g., individual driver's age and gender) affecting the probability of aborting an overtaking maneuver have been studied (Polus et al., 2000; Farah, 2016), this is not the case for changes-of-mind (reverting from rejecting to accepting a gap). Therefore understanding and modeling these types of overtaking decisions requires further research, including extensions of models like DDM and corresponding fitting tools to incorporate changed decisions.

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

Understanding and modeling human behavior in dynamic interactions between AVs and human drivers is essential for safe transportation systems of the future (Schieben et al., 2019). For instance, AVs can improve their own decision-making and planning by incorporating predictions of human road user behavior (Schumann et al., 2023). Here, an AV can adopt the perspective of human-driven vehicles and employ perceptual cues such as distance and TTA in the simulated human drivers' evidence accumulation process to predict the likelihood and timing of their gap acceptance, to adjust its behavior accordingly. 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.

The goal of our work was to explain the cognitive processes underlying overtaking gap acceptance. At the same time, recent studies have started investigating the potential of evidence accumulation models for behavior prediction in traffic. For instance, Schumann et al. (2023) compared a traffic interaction model which incorporates evidence accumulation among other components (Markkula et al., 2023) to simple logistic regression as well as state-of-the-art neural network models on a range of gap acceptance scenarios (including roundabouts and lane-changes) based on real-world and driving simulator datasets. They found that the cognitive model is often on par with the models developed specifically for behavior prediction and can even outperform them under some conditions. Zgonnikov, Abbink, et al. (2024) investigated predictive power of a DDM model that is similar to ours, and found that their DDM could predict decision probabilities of humans in a left-turn gap acceptance based on initial kinematic conditions with the accuracy close to an oracle predictor (knowing the exact probabilities observed in the data). Their accuracy of predicting response times however varied substantially across participants. We believe overtaking is an even more challenging scenario for evidence accumulation models, with multiple kinematic variables to take into account; investigating their predictive power is an important avenue for future research.

Finally, cognitive models like DDMs can contribute to more realistic simulations of human-AV interactions (Guido et al., 2019; Markkula et al., 2018). These models can be embedded in the trajectory control of human-driven vehicles in microscopic traffic simulations, allowing for rigorous training and testing of AV performance within highly realistic simulated environments. 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, which can often be the case for overtaking (Trafton et al., 2020). Such restrictions can negate the benefits of data-driven models commonly used for simulating human agents for virtual AV testing (Montali et al., 2023), but can potentially be overcome by cognitive process models that incorporate generative mechanisms underlying human behavior. However, a major challenge in portraying realistic scenarios is simulating the impact of individual differences and how parameters of the cognitive model change over time, potentially influenced by humans' perception of AVs in emerging mixed traffic. In our study, participants on average did not change their overtaking behavior when interacting with an AV (as compared to interactions with an HDV), although we did find evidence of individual differences (see online supplementary information). However, as human drivers become increasingly exposed to human-AV interactions on the road in the future, new behavioral patterns may evolve. Therefore, continued empirical and modeling research is essential to ultimately unlock the full potential of cognitive process models for automated vehicle development.

CRediT authorship contribution statement

Samir H.A. Mohammad: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Haneen Farah:** Writing – review & editing, Supervision, Resources, Methodology, Conceptualization. **Arkady Zgonnikov:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Conceptualization.

Data availability

All the data and code produced in this study, as well as online supplementary information are available at https://osf.io/p2wme.

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References

Atiya, N. A., Zgonnikov, A., O'Hora, D., Schoemann, M., Scherbaum, S., & Wong-Lin, K. (2020). Changes-of-mind in the absence of new post-decision evidence. *PLoS Computational Biology*, *16*(2), Article e1007149.

Beckers, N., Siebinga, O., Giltay, J., & van der Kraan, A. (2023). Joan: A framework for human-automated vehicle interaction experiments in a virtual reality driving simulator. *The Journal of Open Source Software*, *8*(82), 4250.

Bontje, F., & Zgonnikov, A. (2024). How sure is the driver? Modelling drivers' confidence in left-turn gap acceptance decisions. *Computational Brain and Behavior*, 1–20.

Brown, B., Broth, M., & Vinkhuyzen, E. (2023). The halting problem: Video analysis of self-driving cars in traffic. In *Proceedings of the 2023 CHI conference on human factors in computing systems, CHI '23*. New York, NY, USA: Association for Computing Machinery.

Caird, J. K., & Horrey, W. J. (2011). Twelve practical and useful questions about driving simulation. In *Handbook of driving simulation for engineering, medicine, and psychology, Vol. 2*.

Dosovitskiy, A., Ros, G., Codevilla, F., Lopez, A., & Koltun, V. (2017). Carla: An open urban driving simulator. In *Conference on robot learning, PMLR* (pp. 1–16).

Evans, N. J., & Wagenmakers, E.-J. (2020). Evidence accumulation models: Current limitations and future directions. *The Quantitative Methods for Psychology*, *16*(2), 73–90. https://doi.org/10.20982/tqmp.16.2.p073. http://www.tqmp.org/RegularArticles/vol16-2/p073/p073.pdf.

Farah, H. (2016). When do drivers abort an overtaking maneuver on two-lane rural roads? *Transportation Research Record*, *2602*(1), 16–25.

Farah, H., & Toledo, T. (2010). Passing behavior on two-lane highways. *Transportation Research. Part F, Traffic Psychology and Behaviour*, *13*(6), 355–364.

Farah, H., Bekhor, S., Polus, A., & Toledo, T. (2009). A passing gap acceptance model for two-lane rural highways. *Transportmetrica*, *5*(3), 159–172.

Gordon, D. A., & Mast, T. M. (1970). Drivers' judgments in overtaking and passing. *Human Factors*, *12*(3), 341–346.

Gray, R., & Regan, D. (2005). Perceptual processes used by drivers during overtaking in a driving simulator. *Human Factors*, *47*, 394–417. https://doi.org/10.1518/0018720054679443.

Guido, G., Giofrè, V. P., Astarita, V., & Vitale, A. (2019). Using traffic microsimulation to evaluate potential crashes: Some results. In *2019 IEEE/ACM 23rd international symposium on distributed simulation and real time applications (DS-RT)* (pp. 1–4). IEEE.

Hegeman, G., Brookhuis, K., & Hoogendoorn, S. (2005). Opportunities of advanced driver assistance systems towards overtaking. *European Journal of Transport and Infrastructure Research*, *5*(4).

Jolly, E. (2018). Pymer4: Connecting r and python for linear mixed modeling. *The Journal of Open Source Software*, *3*(31), 862.

Kemeny, A., & Panerai, F. (2003). Evaluating perception in driving simulation experiments. *Trends in Cognitive Sciences*, *7*(1), 31–37.

Leitner, J., Miller, L., Stoll, T., & Baumann, M. (2023). Overtake or not–a computer-based driving simulation experiment on drivers' decisions during transitions in automated driving. *Transportation Research. Part F, Traffic Psychology and Behaviour*, *96*, 285–300.

Lerner, N. D., Steinberg, G., Huey, R., & Hanscom, F. (2000). Driver misperception of maneuver opportunities and requirements. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *44*. 3–255–3–258.

Llorca, C., & Farah, H. (2016). Passing behavior on two-lane roads in real and simulated environments. *Transportation Research Record*, *2556*(1), 29–38.

Llorca, C., García, A., Moreno, A. T., & Pérez-Zuriaga, A. M. (2013). Influence of age, gender and delay on overtaking dynamics. *IET Intelligent Transport Systems*, *7*(2), 174–181.

Markkula, G., Romano, R., Madigan, R., Fox, C. W., Giles, O. T., & Merat, N. (2018). Models of human decision-making as tools for estimating and optimizing impacts of vehicle automation. *Transportation Research Record*, *2672*(37), 153–163. https://doi.org/10.1177/0361198118792131. http://journals.sagepub.com/doi/10.1177/0361198118792131.

Markkula, G., Madigan, R., Nathanael, D., Portouli, E., Lee, Y. M., Dietrich, A., Billington, J., Schieben, A., & Merat, N. (2020). Defining interactions: A conceptual framework for understanding interactive behaviour in human and automated road traffic. *Theoretical Issues in Ergonomics Science*, 1–24. https://doi.org/10.1080/1463922X.2020.1736686. https://www.tandfonline.com/doi/full/10.1080/1463922X.2020.1736686.

Markkula, G., Lin, Y.-S., Srinivasan, A. R., Billington, J., Leonetti, M., Kalantari, A. H., Yang, Y., Lee, Y. M., Madigan, R., & Merat, N. (2023). Explaining human interactions on the road by large-scale integration of computational psychological theory. *PNAS nexus*, *2*(6), Article pgad163.

Milakis, D., Van Arem, B., & Van Wee, B. (2017). Policy and society related implications of automated driving: A review of literature and directions for future research. *Journal of Intelligent Transportation Systems*, *21*(4), 324–348.

Miller, L., Leitner, J., Kraus, J., & Baumann, M. (2022). Implicit intention communication as a design opportunity for automated vehicles: Understanding drivers' interpretation of vehicle trajectory at narrow passages. *Accident Analysis and Prevention*, *173*, Article 106691.

Mohammad, S. H., Farah, H., & Zgonnikov, A. (2023). Modeling gap acceptance in overtaking: A cognitive process approach. In *2023 IEEE 26th international conference on intelligent transportation systems (ITSC)* (pp. 5925–5931). IEEE.

Montali, N., Lambert, J., Mougin, P., Kuefler, A., Rhinehart, N., Li, M., Gulino, C., Emrich, T., Yang, Z., Whiteson, S., White, B., & Anguelov, D. (2023). The waymo open sim agents challenge. arXiv:2305.12032 [cs]. http://arxiv.org/abs/2305.12032.

Palmeiro, A. R., van der Kint, S., Vissers, L., Farah, H., de Winter, J. C., & Hagenzieker, M. (2018). Interaction between pedestrians and automated vehicles: A wizard of oz experiment. *Transportation Research. Part F, Traffic Psychology and Behaviour*, *58*, 1005–1020.

Pekkanen, J., Giles, O. T., Lee, Y. M., Madigan, R., Daimon, T., Merat, N., & Markkula, G. (2021). Variable-drift diffusion models of pedestrian road-crossing decisions. *Computational Brain and Behavior*, 1–21.

Piccinini, G. F. B., Moretto, C., Zhou, H., & Itoh, M. (2018). Influence of oncoming traffic on drivers' overtaking of cyclists. *Transportation Research. Part F, Traffic Psychology and Behaviour*, *59*, 378–388.

Polus, A., Livneh, M., & Frischer, B. (2000). Evaluation of the passing process on two-lane rural highways. *Transportation Research Record*, *1701*(1), 53–60.

Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review*, *85*(2), 59.

Ratcliff, R., Smith, P. L., Brown, S. D., & McKoon, G. (2016). Diffusion decision model: Current issues and history. *Trends in Cognitive Sciences*, *20*(4), 260–281.

Reddy, N., Hoogendoorn, S., & Farah, H. (2022). How do the recognizability and driving styles of automated vehicles affect human drivers' gap acceptance at t-intersections? *Transportation Research. Part F, Traffic Psychology and Behaviour*, *90*, 451–465.

Resulaj, A., Kiani, R., Wolpert, D. M., & Shadlen, M. N. (2009). Changes of mind in decision-making. *Nature*, *461*(7261), 263–266. https://doi.org/10.1038/nature08275. http://www.nature.com/articles/nature08275.

Rettenmaier, M., & Bengler, K. (2020). *Modeling the interaction with automated vehicles in road bottleneck scenarios*. *Proceedings of the human factors and ergonomics society annual meeting: Vol. 64*. Los Angeles, CA: SAGE Publications Sage CA (pp. 1615–1619).

Sadigh, D., Sastry, S., Seshia, S. A., & Dragan, A. D. (2016). Planning for autonomous cars that leverage effects on human actions. In *Robotics: Science and systems, Vol. 2, Ann Arbor, MI, USA* (pp. 1–9).

Schieben, A., Wilbrink, M., Kettwich, C., Madigan, R., Louw, T., & Merat, N. (2019). Designing the interaction of automated vehicles with other traffic participants: Design considerations based on human needs and expectations. *Cognition Technology & Work*, *21*, 69–85.

Schiff, W., & Oldak, R. (1990). Accuracy of judging time to arrival: Effects of modality, trajectory, and gender. *Journal of Experimental Psychology. Human Perception and Performance*, *16*(2), 303.

Schumann, J. F., Srinivasan, A. R., Kober, J., Markkula, G., & Zgonnikov, A. (2023). Using models based on cognitive theory to predict human behavior in traffic: A case study. In *2023 IEEE 26th international conference on intelligent transportation systems (ITSC)* (pp. 5870–5875). IEEE.

Sevenster, A., Farah, H., Abbink, D., & Zgonnikov, A. (2023). Response times in drivers' gap acceptance decisions during overtaking. *Transportation Research. Part F, Traffic Psychology and Behaviour*, *94*, 329–340.

Shinn, M., Lam, N. H., & Murray, J. D. (2020). A flexible framework for simulating and fitting generalized drift-diffusion models. *eLife*, *9*, Article e56938.

Siebinga, O., Zgonnikov, A., & Abbink, D. A. (2024). Human merging behavior in a coupled driving simulator: How do we resolve conflicts? *IEEE Open Journal of Intelligent Transportation Systems*, *5*, 103–114. https://doi.org/10.1109/OJITS.2024.3349635. conference Name: IEEE Open Journal of Intelligent Transportation Systems, https://ieeexplore.ieee.org/abstract/document/10380755.

Soni, S., Reddy, N., Tsapi, A., van Arem, B., & Farah, H. (2022). Behavioral adaptations of human drivers interacting with automated vehicles. *Transportation Research. Part F, Traffic Psychology and Behaviour*, *86*, 48–64.

Stefansson, E., Jiang, F. J., Nekouei, E., Nilsson, H., & Johansson, K. H. (2020). Modeling the decision-making in human driver overtaking. *IFAC-PapersOnLine*, *53*(2), 15338–15345.

Stinchcombe, A., Kadulina, Y., Lemieux, C., Aljied, R., & Gagnon, S. (2017). Driving is not a game: Video game experience is associated with risk-taking behaviours in the driving simulator. *Computers in Human Behavior*, *69*, 415–420.

Tian, K., Tzigieras, A., Wei, C., Lee, Y. M., Holmes, C., Leonetti, M., Merat, N., Romano, R., & Markkula, G. (2023). Deceleration parameters as implicit communication signals for pedestrians' crossing decisions and estimations of automated vehicle behaviour. *Accident Analysis and Prevention*, *190*, Article 107173. https://doi.org/10.1016/j.aap.2023.107173. https://www.sciencedirect.com/science/article/pii/S0001457523002208.

Trafton, J. G., Hiatt, L. M., Brumback, B., & McCurry, J. M. (2020). Using cognitive models to train big data models with small data. In *Proceedings of the 19th international conference on autonomous agents and MultiAgent systems* (pp. 1413–1421).

Trende, A., Unni, A., Weber, L., Rieger, J. W., & Luedtke, A. (2019). An investigation into human-autonomous vs. human-human vehicle interaction in time-critical situations. In *Proceedings of the 12th ACM international conference on PErvasive technologies related to assistive environments* (pp. 303–304).

Velasco, J. P. N., Farah, H., van Arem, B., & Hagenzieker, M. P. (2019). Studying pedestrians' crossing behavior when interacting with automated vehicles using virtual reality. *Transportation Research. Part F, Traffic Psychology and Behaviour*, *66*, 1–14.

Vlahogianni, E. I. (2013). Modeling duration of overtaking in two lane highways. *Transportation Research. Part F, Traffic Psychology and Behaviour*, *20*, 135–146.

Zgonnikov, A., Abbink, D., & Markkula, G. (2024). Should I stay or should I go? Cognitive modeling of left-turn gap acceptance decisions in human drivers. *Human Factors*, *66*(5), 1399–1413.

Zgonnikov, A., Beckers, N., George, A., Abbink, D., & Jonker, C. (2024). Nudging human drivers via implicit communication by automated vehicles: Empirical evidence and computational cognitive modeling. *International Journal of Human-Computer Studies*, *185*, Article 103224.