Designing Multi-Driver Interaction Scenarios in Connected Driving Simulators: Technical Challenges and Solutions for Naturalistic Driving Behaviors

Tianyu Tang* Adan Moreno* Niklas Grabbe* Klaus Bengler*

Abstract: Connected driving simulators are effective tools for collecting driving behavior data. This work proposes an experimental design to create natural driver interaction scenarios, verified through a pilot and main study. The results, showing an 88% interaction success rate, demonstrate the framework's effectiveness and offer practical insights for researchers in driving behavior and human factors research.

Keywords: driver-driver interaction, connected driving simulators, social interaction

1 Introduction

Incorporating social interaction capabilities into autonomous vehicles is vital for them to exist together with human-driven vehicles in future shared traffic environments. Without these skills, autonomous vehicles might misunderstand what other drivers intend to do. This misunderstanding could lead to traffic jams or even accidents [1]. However, in real traffic, rich interactions between drivers do not always happen. Most human drivers drive alone, responding to the physical environment instead of directly interacting with other road users in most tasks, like keeping lanes on highways or making protected left turns at traffic lights [2]. Moreover, as current data sets provide few examples of driver interaction behaviors [1], capturing these implicit interactions becomes a major challenge. Connected driving simulators have proven to be an effective and rapid tool for collecting driving data, as they offer repeatable conditions and subjective driver information compared to traditional traffic observation data [3]. However, additional resources, equipment, and personnel, including multiple experimenters and participants, are required to conduct a connected driving simulator study, adding complexity to the experimental design. This research aims to address these challenges by introducing methods that ensure natural interactions between drivers in simulation environments and by focusing on the following research questions:

- RQ1: What methods can be applied to achieve synchronous arrival and naturalistic interaction between both drivers in multi-driver simulations as planned?
- RQ2: What are the advantages and disadvantages of different methods, and how effective are they in practical applications?
- RQ3: How to determine driver-driver interactions existence in road traffic?

*Chair of Ergonomics, Technical University of Munich, 85748 Garching, (e-mail: tianyu.tang@tum.de).

2 Related Work

2.1 Related Work on Multi-Driver Simulation

Some research has explored how a driver's behavior influences other road users or traffic flow by connecting multiple simulators, creating multi-driver simulations. Mühlbacher et al. [3] offered methodological advice on multi-driver simulations, while Abdelgawad et al. [4] reviewed the state-of-the-art in networked driving simulations, focusing on design considerations and platform evaluations. Houtenobos [5] used two simulators to examine how uncertainty affects driving behavior. Feierle et al. [6] implemented a multi-agent simulation to analyze interactions between autonomous and human-driven vehicles. While these studies demonstrate the broad potential of multi-driver systems, most research focuses on testing new technologies or evaluating conditions' effects on human behavior. Few studies use multi-driver simulations to specifically gather data on driver-to-driver interactions, leaving a gap in literature regarding detailed analysis of such interactions.

2.2 Approaches to determine interaction existence

Determining whether observable interactions truly exist between drivers constitutes a foundational step before conducting quantitative analysis. Wang et al. [2] systematically compared three identification approaches in transportation research: 1) Potential Conflict Detection, 2) Task-based Agent Selection, and 3) Region of Interest (RoI) Setting. While the first two methods face limitations in capturing continuous multi-agent interactions, the RoI-based approach is discussed in detail below.

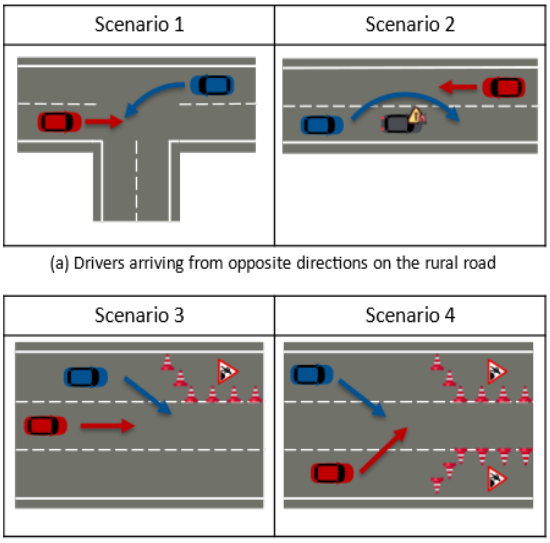
Defining a specific Region of Interest (RoI) in the driving environment has been shown to be an effective method for detecting interactions between an ego agent and surrounding agents [7]. An interaction is considered to occur when two or more agents simultaneously occupy the RoI, while no interaction is recorded once any agent exits the region. This method has two variations: Scenario-centric and Agent-centric. In the Scenario-centric approach, the RoI is fixed at a specific location on the map, treating all vehicles within this area as interactive agents. In contrast, the Agent-centric approach assigns the RoI to a particular agent of interest, commonly referred to as the ego agent [2]. The RoI-based method relies on predefined rules, making the evaluation sensitive to how the RoI is configured [7]. In general, a larger RoI may include more agents, potentially leading to an overestimation of interaction occurrences, whereas a smaller RoI could exclude relevant agents, possibly underestimating the frequency of interactions [2].

3 Methodology

The methodology begins with selecting driving situations where interactions occur frequently. Through thoughtful experimental and map design, all potential interactive driving situations are connected. This method enables efficient collection of interactive behaviors while heightening participant immersion through naturalistic scenario integration. In each specific scenario where an interaction is needed, the physical elements of the environment are used to guide and control the drivers' behavior. This ensures that the interactions happen as intended.

3.1 Selected Scenarios

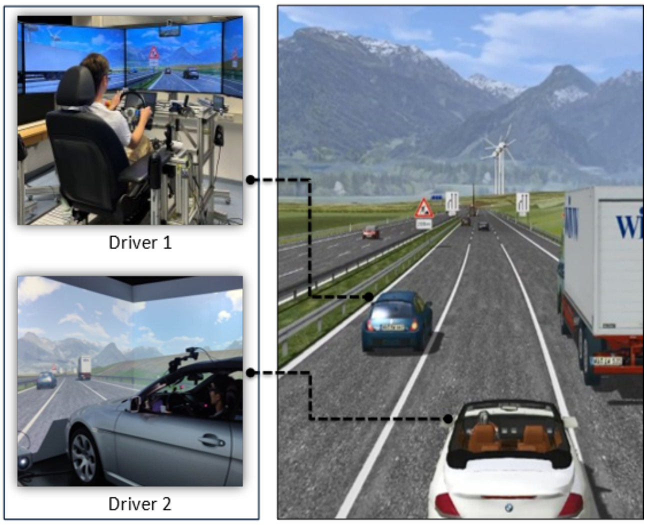
The first key criterion for selecting the scenarios was to identify situations where driver interactions are essential and occur frequently. We refer to these as **highly interactive driving scenarios** [1]. The second criterion was based on the overall goal of studying social interactions between drivers, which is to help autonomous vehicles smoothly being integrated into future mixed traffic without causing accidents or congestion. Therefore, we focused on scenarios that are currently complex and challenging for human drivers, where mistakes or accidents are more likely to occur [8]. The third criterion was to identify situations where autonomous vehicles are prone to difficulties due to current technological limitations.



(a) Drivers arriving from opposite directions on the rural road

(b) Drivers driving in the same direction on the highway

Figure 1: Selected Scenarios



(a) Drivers controlling the cars in the driving simulators

(b) Simulated lane-changing driving situation in the virtual environment

Figure 2: Experimental Set-up

To select scenarios that meet these criteria, we organized an expert workshop with ten participants. To focus on driver-to-driver social interactions and exclude interactions with vulnerable road users, the workshop only considered scenarios on highways and rural roads. Through brainstorming sessions and voting, the experts prioritized the most relevant scenarios. As shown in the Figure1, the selected scenarios include (1) lane changes on a three-lane highway when the leftmost lane is closed due to construction and (2) lane changes when both the left and right lanes are closed simultaneously. For rural roads, the selected scenarios involved an unprotected left turn at a T-junction and overtaking a broken-down vehicle by borrowing the opposite lane.

3.2 Map design

Designing a route that ensures all scenarios are connected without interruption is a significant challenge. Our solution was to decouple the entire driving journey by dividing it into repeatable modules, such as relevant modules and free driving modules. Each relevant module consists of an entry, exit, and interaction zone (i.e., the scenario), ensuring consistency across modules. In this work, the implementation is illustrated in the figure 3, where symmetric driving routes were strategically applied in scenarios like left turns and overtakes. Since the two interactive agents follow the same driving direction, implementing scenarios on highways was relatively straightforward. This approach maintains continuity between scenarios while also allowing for controlled interactions. This modular design allows us to randomize the sequence of the scenarios to prevent learning effects while also minimizing the time and effort required to create entirely new routes. Instead of designing multiple distinct routes, we can simply rearrange the order of the modules to present participants with a new and complete driving path. We used the characteristics of different road types to design how participants would be guided into and out of each module. This ensured that the transitions between modules were smooth and that the interaction zones within each module remained the focus of the experiment.

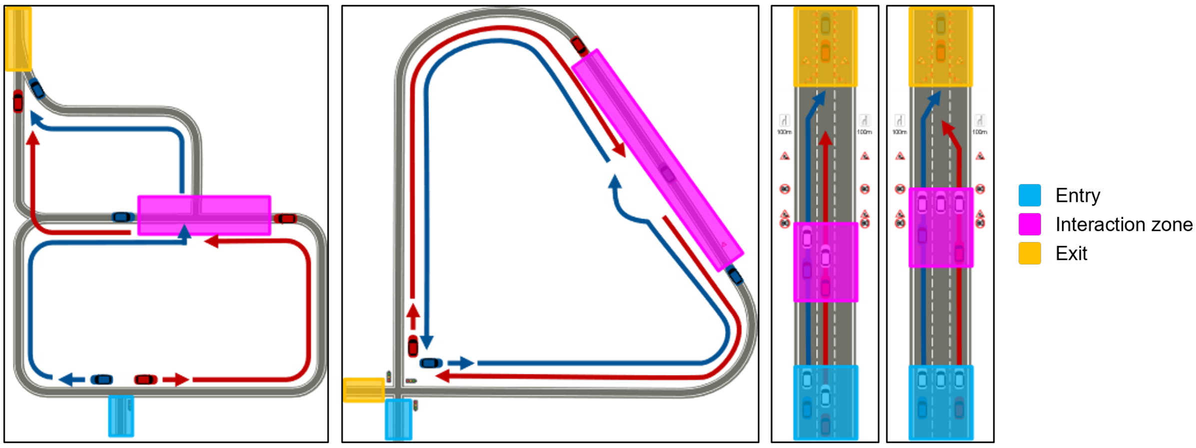


Figure 3: Technical implementation of each scenario module: Illustration of entry, exit, and interaction zones with blue line representing the blue car's route and red line representing the red car's route

3.3 Synchronization of Participants

The next challenge was to synchronize the participants' arrival at the entry, exit, and interaction zones. After thoroughly reviewing related experimental designs and assessing their feasibility, we categorized the synchronization methods into two types: fuzzy synchronization and precise synchronization.

Fuzzy synchronization included:

- Speed signs, which provided a designated speed for participants. The advantage was that they could limit speed, but the drawback was that they couldn't accurately control speed. If participants drove too fast or too slow, it was impossible to restrict their maneuvers.

- Symmetrical road geometries, which ensured equal driving distances for both participants from a road environment perspective. However, it shared the same drawback as speed signs.

- Traffic regulations, such as solid and dashed lines indicating when lane changes were allowed or not.

Precise synchronization included:

- Traffic signals, which accurately controlled vehicle stopping and waiting times.
- Manipulation of surrounding vehicles, such as placing slower vehicles to slow down participants.
- Message instructions, which provided participants with prompts to adjust their speed if they were driving too slowly.

Table 1 shows the specific measures used for each scenario in this work. We combined various approaches. For instance, in the overtaking scenario, we used traffic signals to ensure that both participants entered the module simultaneously. The module was designed with a triangular shape to maintain symmetry. This design required both drivers to travel the same distance to reach the interaction zone. To prevent either driver from arriving too early or too late, participants were instructed to maintain the speed indicated by the traffic signs, set at 80 km/h. The traffic signals also ensured that both participants exited the module at the same time. The bolded measures represent adjustments made based on the pilot study results and participant feedback.

	Left Turn	Overtake	Single & Double Lane change
Measures in the pilot study	- Traffic light - Speed limit	- Traffic light - Speed limit - Symmetric road geometries	- Speed limit - Overhead highway signs indicating lane destinations - Manipulated slow vehicles
Measures in the main study	- Traffic light - Speed limit - **Symmetric road geometries**	- Traffic light - Speed limit - Symmetric road geometries	- Speed limit - Overhead highway signs indicating lane destinations - Manipulated slow vehicles - **Solid lines meaning lane changing not allowed**

Table 1: Implemented measures in the experiments of this work

4 Experimental Verification and Results

4.1 Experimental Verification

To verify how effective the proposed methods are, we conducted studies connecting two driving simulators provided by the chair of ergonomics at the Technical University of Munich. The simulators were placed in separate rooms and linked via LAN to ensure the lowest possible network latency. The verification process involved two studies: a pilot study and a main study. Both studies used the same hardware setup, as illustrated in Figure 2.

4.1.1 Experimental Design

The goal of both studies was to collect as much interaction-driving behavior data as possible in an experiment while also testing whether our method could ensure natural driver encounters and interactions in a simulated environment.

Each multi-driver study followed a 3 (scenario type) × 2 (perspective) repeated-measures design. The first factor, scenario type (within-subject), represented different types of road interactions and included three levels: left turn, overtaking, and lane change. The second factor, perspective (within-subject), referred to the role of the participant in each scenario. When a participant actively initiated a scenario (e.g., making a left turn in Scenario 1), they were in the active perspective. In contrast, when they simply responded to the situation (e.g., going straight in Scenario 1), they were in the passive perspective. Additionally, in Scenario 4, the interaction structure required both participants to take an active role. Each participant experienced Use Cases 1–7 once in a permuted order within a simulated drive and completed two full driving sessions in the experiment (see Table 2). To ensure that participants did not make a trip in vain, an experimenter acted as a confederate and took the missing participant's place when necessary.

	Left Turn	Overtake	Single Lane Change	Double Lane Change
Active Perspective	Use Case 1 (Turning Left)	Use Case 3 (Overtaking)	Use Case 5 (Changing Lane Mandatorily)	Use Case 7 (Changing Lane Mandatorily)
Passive Perspective	Use Case 2 (Going Straight)	Use Case 4 (Going Straight)	Use Case 6 (Going Straight, Changing Lane If Necessary)	-

Table 2: Seven different use cases each participant experienced

4.1.2 Procedure

Both studies followed the same procedure. Two experimenters conducted the experiments, each responsible for one participant. The welcoming and introduction were carried out together to ensure that both participants knew another person was present in the simulation. However, they were not informed which vehicles were controlled by a computer and which by the other participant. After the introduction, the experimenters guided them to separate laboratories to begin the experiments. After reading the safety instructions and participant information, both participants provided their consent to take part in the experiment. The experiment consisted of three parts: a demographic questionnaire, two simulated drives, and a post-experiment interview.

Once the questionnaire was completed, participants received their driving task. They were instructed to navigate to a specific destination while following their usual driving habits and obeying traffic rules, relying only on road signs and traffic indicators. Next, both participants underwent validation for the eye-tracking glasses and completed an introductory drive lasting about 10 minutes. It allowed them to get used to the simulator's driving behavior and the road's navigation signs.

The main experiment involved two driving sessions. Participants completed Use Cases 1-7, arranged in a permuted order to minimize learning effects. To prevent fatigue, each driving session was kept under 20 minutes. Finally, participants took part in a post-experiment interview by experimenters. The main study took place one week later after we refined the scenario implementation based on feedback from the pilot study.

4.1.3 Sample Characteristics

Eight participants took part in the pilot study resulting in four pairs, including one female and seven males. The average age of the participants was M = 23.88 years, with a standard deviation of SD = 4.40 years. For the main study, 23 participant pairs were recruited, resulting in a total of 46 participants. Among them, 39% were women and 61% were men, with an average age of M = 26.8 years (SD = 10.0 years). The pairing distribution was as follows: 22% female-female, 43% male-male, and 35% female-male. All participants were required to hold a valid driver's license in Europe.

4.1.4 Measures and Analysis

We adopted the agent-centric setting ROI method described in Section 2.2 to assess the synchronicity and interaction events. The definition of ROI varies across different scenarios due to road geometries and traffic regulations. We assume that the two participant vehicles are considered as our interactive agents, and only encounters between these two vehicles are regarded as interactions. Interactions between the participant vehicles and other programmed surrounding vehicles are not considered for the purpose of this study.

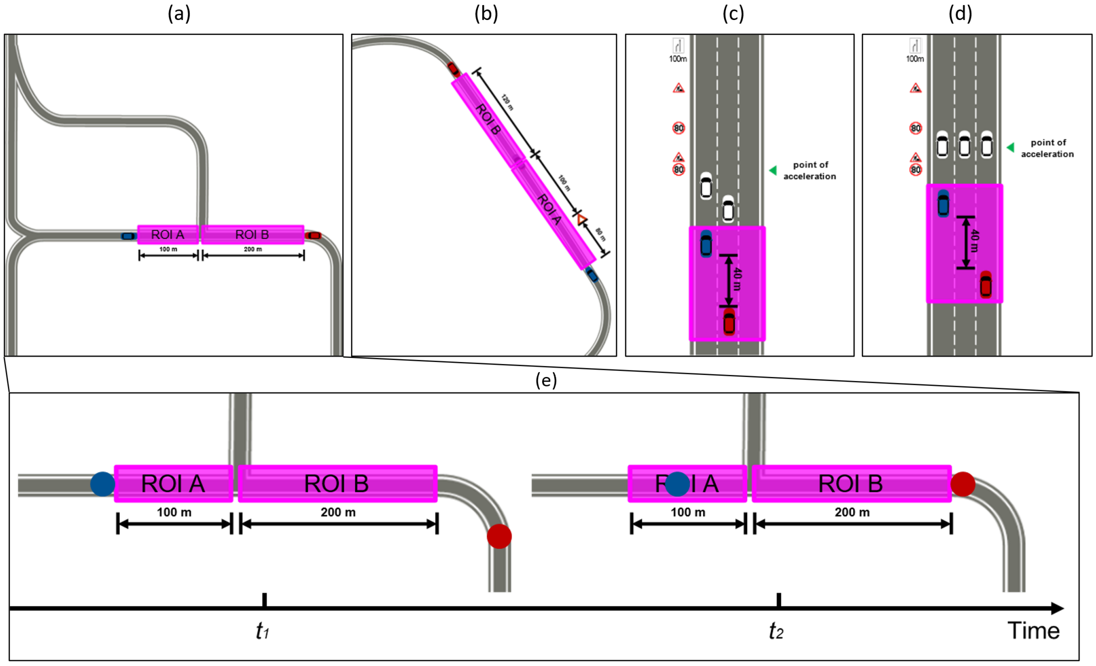


Figure 4: Definition of ROIs in scenarios showed in (a)-(d) and an example of explanation of start time of interaction in Scenario 1

In the Left Turn and Overtake scenarios, the visibility range of the driving simulator is 300 m and also verified by eye-tracking data, so the total length of the ROI is 300 m. As shown in the figure, the ROI in these two scenarios is divided into two regions: ROI A and ROI B. Interaction is considered to occur when the blue car appears in the ROI A and the red car appears in the ROI B area simultaneously (as defined by $\text{Position}_{\text{blue car}} \in \text{Area}_{\text{ROI A}} \;\;\&\;\; \text{Position}_{\text{red car}} \in \text{Area}_{\text{ROI B}}$). For example, in the Left Turn scenario, at time t_1, the blue car is in the ROI A, but the red car is not present, so no interaction occurs at that time. At time t_2, the red car enters the ROI B region, both cars can see each other, and we assume they have interacted. Time t_2 is thus considered the start of the interaction (Figure 4 (e)).

For the single and double lane change scenarios on the highway, the drivers can only see each other through mirrors, with a visibility range limited to 40 m verified by eye-tracking data. As shown in the figure 4, when the white cars (the manipulated slow cars) are still in front of both vehicles, neither can change lanes, and no interaction occurs. When the white cars accelerate and increase the distance from the following vehicle, it indicates that lane change is possible. Therefore, the time when the white cars start to accelerate is considered the start time for a potential interaction. To determine if an interaction has occurred, the distance between the two cars must be less than 40 m, meaning they are within each other's visibility range, which is when we consider the interaction to have taken place.

4.2 Results

Study	Scenarios	Planed Attempts	Disrupted Attempts	Occurred Attempts	No Interaction	Successful Attempts	Successful Rate
Pilot Stuy	Left Turn	16	1	15	7	8	53.33%
	Overtake	16	2	14	1	13	92.86%
	Single Lane Change	16	0	16	4	12	75.00%
	Double Lane Change	8	0	8	5	3	37.50%
	Sum	56	3	53	17	36	67.92%
Main Study	Left Turn	92	7	85	14	71	83.53%
	Overtake	92	10	82	2	80	97.56%
	Single Lane Change	92	5	87	14	73	83.91%
	Double Lane Change	46	7	39	5	34	87.18%
	Sum	322	29	293	35	258	88.04%

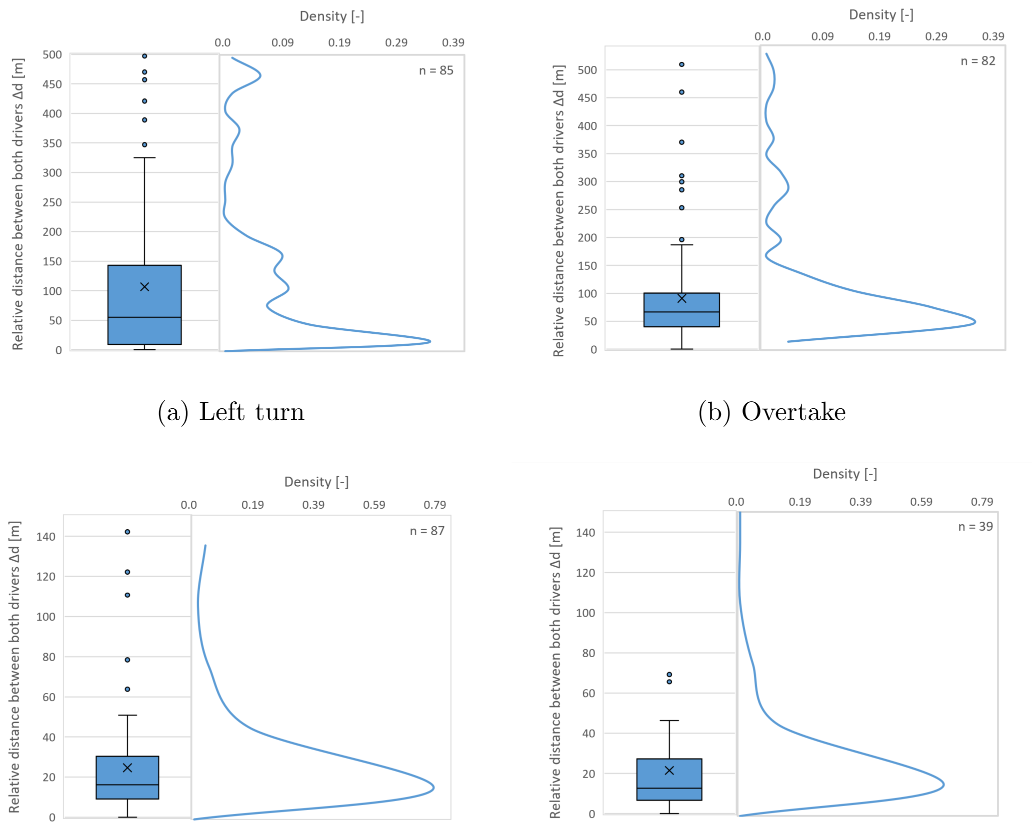
Table 3: Overview of interaction attempts and successful rate of each scenario

Table 3 presents the results of the Interaction Event Existence Analysis. Disrupted attempts, caused by technical failures or participants terminating the experiment due to motion sickness, were excluded from the calculation of the success rate.

In both studies, the overtake scenario had the highest success rate, reaching 92.86% in the pilot study and 97.56% in the main study. However, in the pilot study, the double lane change scenario had a success rate of less than 50%, falling significantly below expectations. In contrast, the main study showed a notable improvement, with an overall success rate of 88% and each scenario achieving over 80%. Notably, the double lane change scenario increased by nearly 50%.

The relative distance (Δd) between both vehicles at the start of interaction is shown in Figure 5. In the Left Turn scenario, the mean distance was $M = 114.09$ m (SD = 131.32 m), while in the Overtake scenario, it was $M = 101.95$ m (SD = 95.20 m). In both cases, an interaction was considered to have occurred when $\Delta d \leq 300$ m.

For the two highway scenarios, the mean relative distances and standard deviations were $M = 26.02$ m (SD = 27.99 m) and $M = 25.38$ m (SD = 36.10 m), respectively. Here, an interaction was defined by $\Delta d \leq 40$ m. Outlier values indicate cases where no interaction occurred.



(a) Left turn

(b) Overtake

(c) Single lane change

(d) Double lane change

Figure 5: Relative distance of both vehicles at the interaction start time in the main study. Outliers indicate that no interaction occurred.

5 Discussion and Conclusion

The results of the pilot study indicated that designing symmetrical routes and assigning specific speeds were the most effective methods to ensure both vehicles met as intended. In contrast, simply using speed limit signs was not sufficient to control participants' driving behavior. The primary reason for failed interactions was the significant speed differences caused by variations in participants' driving styles.

However, implementing traffic lights and surrounding vehicles to slow down participants proved to be highly effective. Additionally, during the pilot study, we observed that some participants on the highway overtook the manipulated slow vehicle and continued driving forward. As a result, they ended up outside the intended lane and moved further away from the other participant. To prevent this issue, we used solid lane markings, ensuring that lane changes only occurred within the designated area. Findings from the main study showed that this adjustment significantly improved the success rate of interactions.

To minimize driving behavior differences caused by experimental setup inconsistencies, each participant experienced Use Cases 1–7, meaning they took on both roles within each scenario. However, due to equipment limitations, traffic light activation could only be controlled by one vehicle, increasing the technical complexity of the implementation. Additionally, inconsistencies between the two simulation labs may have contributed to variations in participants' driving behavior. While this work focuses on four specific interaction scenarios, future research can expand upon these findings by incorporating additional scenarios, such as urban bottlenecks, intersections, and roundabouts, to further enhance research on driver social behavior.

This work presents a systematic experimental design to create natural driver interaction scenarios, providing a new way to collect driver-social behavioral data. Two studies were conducted to evaluate the effectiveness of the proposed measures in the methodology. Our experiments confirmed that this approach successfully ensured interactions in most cases. Additionally, we developed specific metrics to assess whether interactions occurred in different scenarios and provided several methodological recommendations for study design.

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