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Interaction Patterns of Motorists and Cyclists at Intersections: Insight from a Vehicle–Bicycle Simulator Study

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Abstract: At intersections, road users need to comprehend the intentions of others while also implicitly expressing their own intentions using dynamic information. Identifying patterns of this implicit communication between human drivers and vulnerable road users (VRUs) at intersections could enhance automated driving functions (ADFs), enabling more human-like communication with VRUs. To this end, we conducted a coupled vehicle–bicycle simulator study to investigate interactions between right-turning motorists and crossing cyclists. This involved 34 participants (17 pairs of motorists and cyclists) encountering each other in a virtual intersection. The analysis focused on identifying interaction patterns between motorists and cyclists, specifically aiming to discern which patterns were more likely to be accepted by both parties. We found that in CM (vehicles overtaking), the post-encroachment time (PET) and the average speed of vehicles were higher than in the other two interaction patterns: C (bicycles always in front) and CMC (bicycles overtake). However, subjective ratings indicated that CM was viewed as more critical and less cooperative. Furthermore, this study unveiled the influence of crossing order and overtaking position on subjective ratings through ordered logistic regressions, suggesting that earlier overtaking could improve cyclists' acceptance of the interaction. These findings may contribute to the optimization of communication strategies for ADF, thereby ensuring safety in interactions with VRUs.

Keywords: VRU; implicit communication; intersection; multiple driving simulator cyclists

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Citation: Zhang, M.; Quante, L.; Gröne, K.; Schießl, C. Interaction Patterns of Motorists and Cyclists at Intersections: Insight from a Vehicle–Bicycle Simulator Study. *Sustainability* **2023**, *15*, 11692. https://doi.org/10.3390/su151511692

Academic Editor: Rosolino Vaiana

Received: 19 June 2023
Revised: 25 July 2023
Accepted: 27 July 2023
Published: 28 July 2023

1. Introduction

1.1. Motivation

In daily life, implicit communication often refers to non-verbal forms of communication, such as gestures and facial expressions. Similarly, implicit communication plays a significant role in the field of transportation. In traffic, "verbal" forms of communication typically involve explicit signals produced for conveying specific messages, such as turn signals and brake lights. On the other hand, "non-verbal" signals may not be intended for communication purposes but still convey information implicitly, such as speed and position. Effective communication is essential as road users may need to occupy the same region of space simultaneously in the near future [1]. Road users may communicate through both explicit and implicit cues. However, recent research suggests that implicit communication is the primary strategy for communication between motorists and vulnerable road users (VRUs) [2]. For example, cyclists can predict whether a vehicle will pass through an intersection upon observing its current speed and subsequently decide whether or not to continue crossing. This form of implicit communication applies to motorists as well.

This phenomenon poses a challenge for high-level automated driving functions (ADFs). Understanding and replicating implicit communication between motorists and VRUs is vital for developing effective and safe ADFs. On the one hand, the prediction of VRU intentions primarily relies on implicit signals. Properly functioning ADFs should

be able to interpret and respond to subtle cues from other road users. On the other hand, ADFs must express their intentions through implicit signals, ensuring seamless integration with existing traffic patterns and minimizing the risks associated with miscommunication. Both aspects need to be based on the interaction patterns accomplished through implicit communication that already exists between humans. A human-like ADF should neither be more aggressive, increasing the risk of collision, nor more conservative, leading VRUs to over-trust that the ADF will always yield to them. Therefore, determining the existing interaction patterns between motorists and VRUs is essential for ADF development.

1.2. Implicit Signals and Interaction Patterns

The accurate interpretation of implicit signals can help ADFs anticipate and avoid potential conflicts. This capability depends on both advanced sensing technology and a comprehensive understanding of human interaction models on the road. The Wiedemann Car-Following Model [3] is a good example that investigates interaction models between human drivers. This model provides insight into the dynamic interactions between following and leading vehicles, considering implicit signals such as distance and speed differences between vehicles. In terms of implicit communication between motorists and VRUs, kinematic information and spatiotemporal relationships are also considered. In a field study of a shared space, Fuest et al. [4] observed VRUs determined whether they cross a road based on a vehicle's speed. For VRUs, a vehicle's deceleration often implies yielding, while maintaining speed or accelerating may suggest the vehicle is not giving right-of-way [5–8]. This aligns with common sense. However, on an operational level, it is not immediately clear at what distance from the VRU the vehicle should decelerate and by how much in order to reassure the VRU that they are safe to proceed. Such tacit interaction patterns may already exist among human road users.

Taking crossing interactions as an example, the straightforward interaction patterns can be categorized based on the order of access; either the vehicle crosses first, or the VRU crosses first [8–10]. Alternatively, these patterns can also be classified according to motorists' braking behavior, such as no braking, ideal initial braking, and provoked braking caused by competition [11]. Furthermore, based on the process of transferring priority, four types of interaction patterns have been defined, which include the prioritized road user going first with or without forcing the right-of-way, the prioritized road user actively giving away the right-of-way and the road user who should yield not slowing down, forcing the prioritized road user to stop [12]. Investigating interaction patterns between VRUs and motorists requires a large amount of real-world data to offset the influence of context factors (e.g., traffic density, time of day) and individual differences (e.g., desired speed). For example, Zhang et al. [13] collected the trajectories of over 200 interactions using video-based traffic observation, based on which three interaction patterns were identified: The motorist does not yield to the cyclist, the motorist actively yields to the cyclist, and the motorist passively yields to the cyclist.

It is not only essential to identify specific interaction patterns but also to evaluate them to determine which patterns are more widely accepted and which ones pose safety risks. Evaluations can be approached from a performance perspective by estimating relevant dimensions such as safety and efficiency. For instance, PET and predicted PET could be used to assess the risk at the time of crossing (e.g., [14]), while average speed or passing time could be used to indicate traffic efficiency (e.g., [15]). It could be imagined that an interaction pattern with high safety and efficiency for both interaction partners may be more likely to be accepted and should thus be adopted by ADFs. In addition to the performance perspective, the subjective feelings of drivers and other road participants are also crucial in evaluations. Subjective feelings in the field of traffic could refer to subjective risk, which has been involved in driving studies since the 1960s [16]. Some scholars have included subjective risk in the category of mental workload, arguing that so-called high subjective risk is caused by a mismatch between task difficulty and individual capabilities [17]. In addition to subjective risk, the quality of communication, namely the recognizability

of the other party's signals and whether people feel a sense of cooperation during the process, also form part of the subjective evaluation. However, in traffic observation studies, subjective indicators are not easily obtained, as the object of measurement is often randomly encountered road users. The emergence of driving and cycling simulators has compensated for the shortcomings of traffic observation. On the one hand, they allow participants to engage in realistic scenarios and obtain objective data without exposing them to physical danger (e.g., [18]). On the other hand, other measurement methods targeting psychological indicators, such as physiological measurements and questionnaires, can be implemented under laboratory conditions.

1.3. The State of the Art

Motorist–cyclist interactions have always been an important topic in the field of transportation. Previous studies focused on the behavioral choices of observers when facing oncoming vehicles in different manners, using the subjective perspective video of cyclists [8]. Some studies have built models for the yielding behavior during motorist–cyclist interactions through traffic observation using performance parameters [19]. However, these methods lack the integration of subjective ratings and performance parameters. Driving simulators provide a platform that can record driving data and the subjective ratings of the participants simultaneously during the experiment. Such simulation experimental designs are usually formulated in the form of "human–machine interaction." That is, either the participant interacts as a motorist with a programmed bicycle [20,21] or as a cyclist with a programmed self-driving vehicle [22]. To achieve a "human–human interaction" simulation, coupling of different simulators is required. The concept of a coupled simulator has already been applied to study motorist–motorist [23,24] and motorist–pedestrian interactions [25]. However, to our knowledge, it has not been used to study motorist–cyclist interactions.

1.4. Current Study

This study investigated the interaction between right-turning motorists and bicyclists traveling straight in the same direction using a coupled vehicle and bicycle simulator, which allowed participants to interact freely in the same virtual environment. The aim of this study was to explore how human road users accomplish cooperation at intersections through implicit communication. It was hypothesized that there exist interaction patterns based on implicit communication between motorists and cyclists. These interaction patterns may reflect the tacit understanding and unspoken rules that human road users follow to achieve cooperation on the road. These patterns were evaluated using performance and subjective indicators in terms of criticality, cooperation, and certainty. Additionally, the effect of the widely-discussed factors, crossing order and overtaking position, on subjective evaluations was examined. The results may not only help in establishing more complex interaction patterns, thereby enhancing the accuracy of predicting VRU (vulnerable road users) behaviors, but also contribute to the application of ADFs by providing valuable insights into the evaluation of these interaction patterns.

2. Methods

2.1. Participants

Seventeen pairs of participants (randomly paired) took part in this study. Of the 34 participants, 18 were male and 16 were female. Participants aged between 18 and 59 years (mean (*M*) age = 27.6 years; standard deviation (*SD*) of age = 10.0 years). All participants held a valid driver's license for 9.7 years on average (*SD* = 9.6 years, range = [1; 40]), with 16 participants owning a private vehicle. Participants were invited via the institute's database for recruiting participants as well as via online advertisement. Participants were compensated with 10 €/h. The study protocol (experimental design, assessed data, used methods, etc.) was approved by the DLR ethics committee.

2.2. Set-Up and Design

2.2.1. Study Design

The study design was a 2 × 2 within-subject design with role (motorist, cyclist), and driving mode (manual, autonomous) (see Figure 1). It should be noted that this study covered the evaluation of all types of human–machine interfaces (HMI), including external HMI (eHMI), internal HMI (iHMI), and dynamic HMI (dHMI). Manual driving involves dHMI, while autonomous driving involves eHMI and iHMI. Every session consisted of four experimental blocks: In the first two blocks, Participant A drove, and Participant B cycled. In the last two blocks, Participant A cycled, and Participant B drove. Within the first two blocks (last two blocks), Participant A (B) drove manually in one block and was driven autonomously in the other block. The order of blocks was counterbalanced with respect to driving mode. Within a block, trials were performed in a randomized order. In the "manual driving" blocks, three unique trials (variation of the vehicle's starting position: 0, 5, or 10 m behind the bicycle) were each repeated once (= six trials per block). The two "autonomous driving" blocks are not reported in this paper.

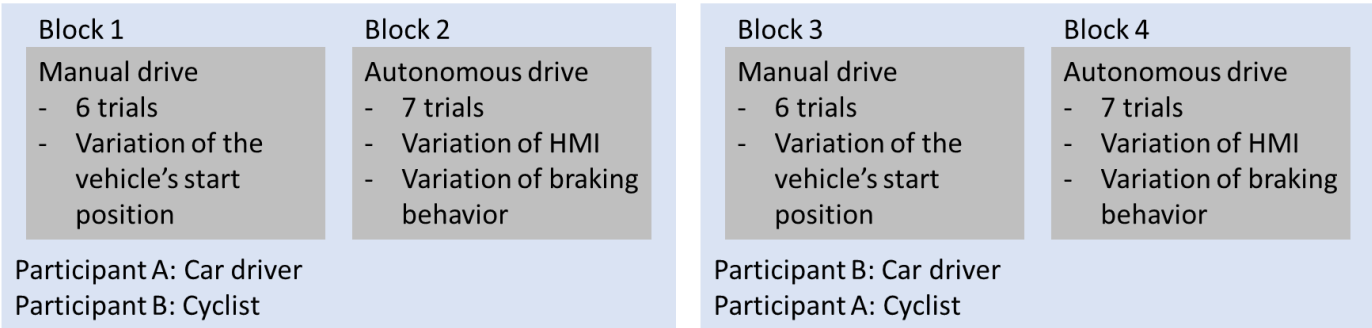

Figure 1. Design of this study and sequence of experimental blocks.

2.2.2. Coupled Simulator

This study was completed in a coupled vehicle and bicycle simulator (see Figure 2). The vehicle simulator consisted of three screens and a steering wheel as well as gas and brake pedals to control a virtual car in a simulated environment. The bicycle simulator consisted of a break force sensor, a steering resistance motor, a force bike trainer, and a motion platform. Additionally, the simulated environment was presented through VR glasses. The visualization of environmental 3D models and scenarios was accomplished using Unreal Engine 4. The two simulation systems were synchronized during the experiment, allowing the participants to see each other in real time at the simulated intersection.

2.2.3. Scenario

In every trial, the cyclist was supposed to cross an intersection going straight, and the motorist (coming from the same direction) was supposed to turn right at the intersection and cross the cyclist's path (Figure 3). The traffic lights for both the cyclist and the motorist were set to green. No dynamic surrounding traffic was present. The cyclist initiated the trial by starting to cycle. When arriving at a specific distance, the vehicle was triggered and started driving autonomously. In the "manual driving" blocks, the driver had to take over vehicle control, which was signaled using a color change in an LED light band within the vehicle. The simulated intersection was based on the DLR AIM Research Intersection in Braunschweig, Germany (Hans-Sommer-Straße/Brucknerstraße).

2.3. Procedure

Every session started with a short introduction, including information about the general scope and procedure of this study as well as information about the potential risks and data protection. Participants then gave their informed consent. Afterward,

participants filled out questionnaires regarding demographic information, technical affinity, and simulation sickness.

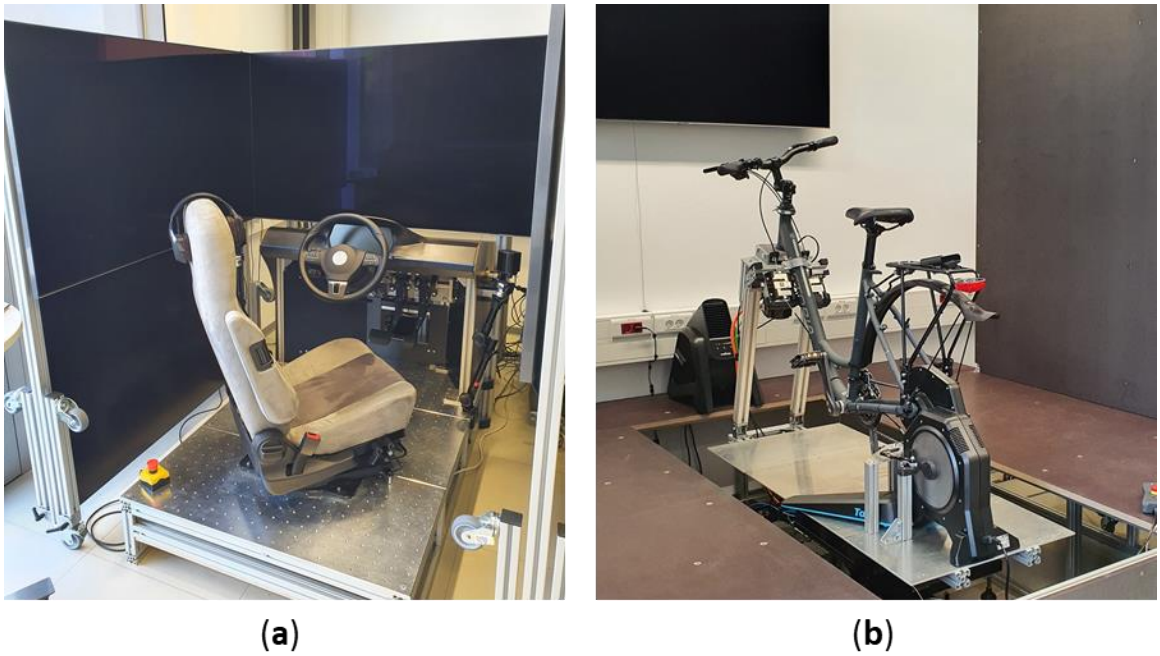

Figure 2. Coupled simulator: stationary driving simulator (**a**) and bicycle simulator (**b**).

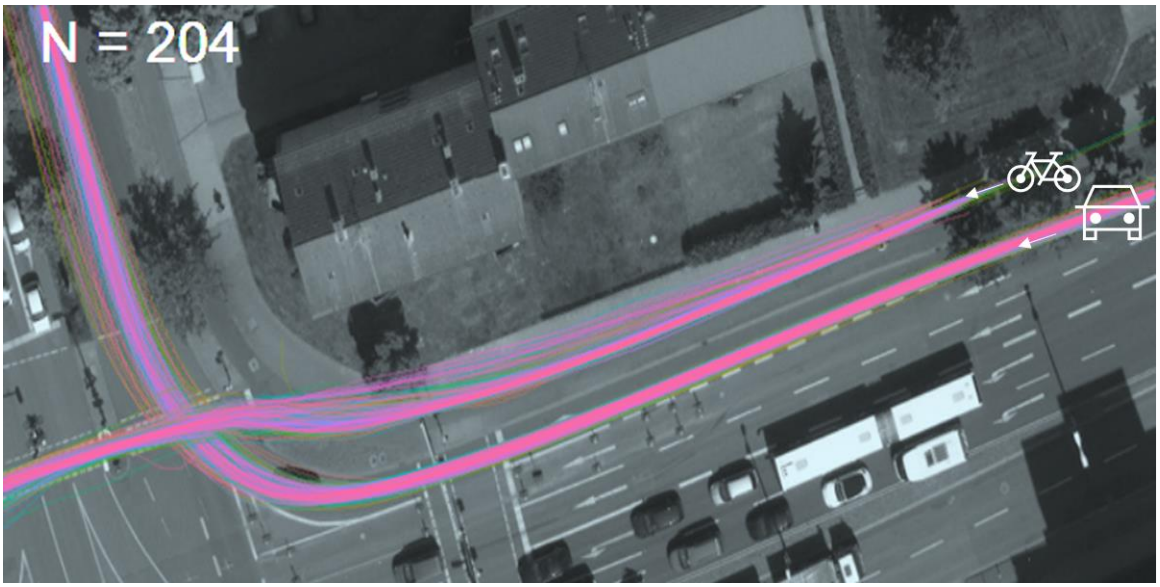

Figure 3. Trajectories (204 pairs) and moving directions of cyclists and motorists in the simulators with the background of the aerial view of Hans–Sommer–Straße/Brucknerstraße in Braunschweig, Germany.

In terms of familiarization with the simulators before the experimental drive, participants were trained on the bicycle simulator and in the driving simulator for approximately 15 min each. In training sessions, the motorist first followed a predefined route through a simulated city and was instructed to familiarize him-/herself with the vehicle and its communication signals (indicator, headlights, horn). After this drive, every motorist practiced the experimental scenario, including the take-over, three times (without the cyclist being present). The cyclist also first followed a predefined route, once without and once with VR glasses. Afterward, s/he practiced the experimental scenario three times without

the motorist being present. If the cyclist was still not comfortable handling the bicycle simulator, the experimental scenario was practiced more often.

After the training, both participants filled out a simulator sickness questionnaire (SSQ; [26]). Then the first two experimental blocks started: The "manual driving" block consisted of six trials with a short questionnaire after every trial and a post-questionnaire after the block for both the participant cycling and the participant driving. After the first two blocks, participants again filled out the SSQ and paused for at least 10 min. For the third and fourth experimental blocks, participants switched roles, and the procedure of the first two blocks was repeated. Afterward, participants were informed about the exact details of this study and left. An experimental block lasted around 20 min; the complete session took about three hours.

2.4. Questionnaires

After every trial, participants were asked four questions about the experienced encounter (see Table 1).

Table 1. Questions asked after every trial of the "manual driving" blocks.

Addressee	Question	Response Scale
Cyclist	How critical would you rate the driving situation you just experienced? [1]	totally not critical (1)–extremely critical (6)
	How confident were you that the vehicle would respond appropriately to you? [2]	totally not confident (1)–extremely confident (6)
	How cooperative would you rate the driving situation you just experienced? [3]	totally not cooperative (1)–extremely cooperative (7)
	Did you cross the road before or after the vehicle? [4]	before/after
Motorist	How critical would you rate the driving situation you just experienced? [1]	totally not critical (1)–extremely critical (6)
	How confident were you that you could turn in front of the cyclist? [2]	totally not confident (1)–extremely confident (6)
	How cooperative would you rate the driving situation you just experienced? [3]	totally not cooperative (1)–extremely cooperative (7)
	Did you turn before or after the bicycle? [4]	before/after

[1] criticality; [2] certainty; [3] cooperation; [4] control question. Note that an additional neutral option was included in the cooperation scale, resulting in a total of seven levels for this scale.

2.5. Analyses

First, interaction patterns were classified. Then these patterns were evaluated with respect to participants' subjective ratings regarding criticality, certainty, and cooperation (see Table 1) and performance parameters based on participants' driving/cycling behavior. In terms of objective measures, the position, kinematic information, and the spatiotemporal relationships of vehicles and bicycles were focused. Table 2 describes the objective variables considered in the analysis.

Table 2. Description of performance parameters.

Parameter	Unit	Description
distance to conflict point	m	the longitudinal distance between the current position and the conflict point, where two trajectories intersect.
average speed	m/s	the mean value of the speeds of the bicycle or vehicle from the starting point until they reach the intersection
speed difference	m/s	the difference between the speeds of the vehicle and the bicycle at a given moment
PET	s	post encroachment time, an observed time, which describes the time interval by which two road users miss each other
pPET	s	predicted PET, the time at which the vehicle and bicycle would intersect if they maintain their current speeds at a given moment

According to the results of Shapiro–Wilk normality tests, the performance parameters (average bicycle speed: $W = 0.90$, $p < 0.001$; average vehicle speed: $W = 0.88$, $p < 0.001$; PET: $W = 0.90$, $p < 0.001$) and the subjective ratings (criticality (cyclists: $W = 0.66$, $p < 0.001$, motorists: $W = 0.73$, $p < 0.001$), cooperation (cyclists: $W = 0.85$, $p < 0.001$, motorists: $W = 0.85$, $p < 0.001$), certainty (cyclists: $W = 0.77$, $p < 0.001$, motorists: $W = 0.88$, $p < 0.001$)) were not normally distributed. Therefore, we used Kruskal–Wallis tests as well as pairwise Wilcoxon–Tests (using the Holm method for adjusting p values) to reveal the effect of the interaction patterns on the performance parameters and subjective ratings. The results of the Kruskal–Wallis tests were converted into Z-scores. We used η^2, recommended by Tomczak and Tomczak [27], to indicate the effect size of the Kruskal–Wallis tests. The effect size is considered low when η^2 is less than 0.06, medium when η^2 is less than 0.14, and large when η^2 is greater than 0.14.

In addition, we investigated the effect of crossing order and overtaking position on the subjective ratings of criticality, cooperation, and certainty from the perspective of both road users. The categorical parameter "order" with motorist first as default was used to indicate the crossing order, while the continuous parameter "distance," meaning the longitudinal distance between the overtaking position and the conflict point, was used to indicate the overtaking position. Subjective ratings were considered ordered parameters with a range of one to six (criticality and certainty) and one to seven (cooperation). One cyclist did not report the subjective ratings and was therefore excluded. We employed an ordered logistic regression as implemented in the package MASS (version: 7.3–53.1; [28]) for the R programming language, building a regression model and reporting coefficient (r), the results of t-Tests (t) and p-value (p) for criticality, cooperation and certainty from the cyclists' and the motorists' perspective separately. A significance level of $\alpha = 0.05$ was used for all tests.

3. Results

3.1. Interaction Patterns

Two hundred four interactions between right-turning motorists and crossing cyclists were clustered. According to the crossing order (cyclist first vs. motorist first) and whether the motorist has overtaken the cyclist, three interaction patterns were defined (see Table 3). The naming of the patterns reflects the leading interaction partner at each stage. It has to be noted that, due to the experimental design, the vehicle always appeared behind the bicycle, so the bicycle leads in the first stage in all three patterns.

Table 3. Description of interaction patterns.

Patterns	N (%)	Description
CM	49 (24%)	cyclists are first in front of motorists but cross the intersection after motorists
CMC	57 (28%)	cyclists are first in front of, then behind motorists, and cross the intersection before motorists
C	98 (48%)	cyclists are always in front of motorists and cross the intersection before motorists

3.1.1. Performance Parameters

- Speed difference

In CM, the vehicle maintains a speed difference of at least 2 m/s throughout the interaction. However, in CMC and C, this speed difference is smaller, and within a 30 m range, the speed advantage gradually shifts to the cyclist (see Figure 4a). Compared to C, the transition in CMC is more abrupt.

- Average speed

With respect to cycling speed, a significant difference was observed among the patterns CM, CMC, and C ($Z = 6.26$, $p < 0.001$, $\eta^2 = 0.21$). According to the results of the Wilcoxon tests ($\alpha = 0.05$), the average speed of the bicycle in C ($Md = 4.46$ m/s) was significantly greater than in CMC ($Md = 4.05$ m/s, $Z = 5.11$, $p < 0.001$) and in CM ($Md = 4.09$ m/s,

$Z = 5.1$, $p < 0.001$). There was no difference between CMC and CM ($Z = 0.27$, $p = 0.61$). A significant difference was observed in the driving speed among the patterns CM, CMC, and C according to the Kruskal–Wallis tests ($Z = 10.77$, $p < 0.001$, $\eta^2 = 0.59$). The average speed of the vehicle was greater in CM ($Md = 9.25$ m/s) than in CMC ($Md = 4.93$ m/s, $Z = 8.66$, $p < 0.001$) and C ($Md = 5.55$ m/s, $Z = 9.35$, $p < 0.001$). The average speed of the vehicle in C was greater than in CMC ($Z = 4.83$, $p < 0.001$). The difference in average speed from both perspectives is shown in Figure 4b.

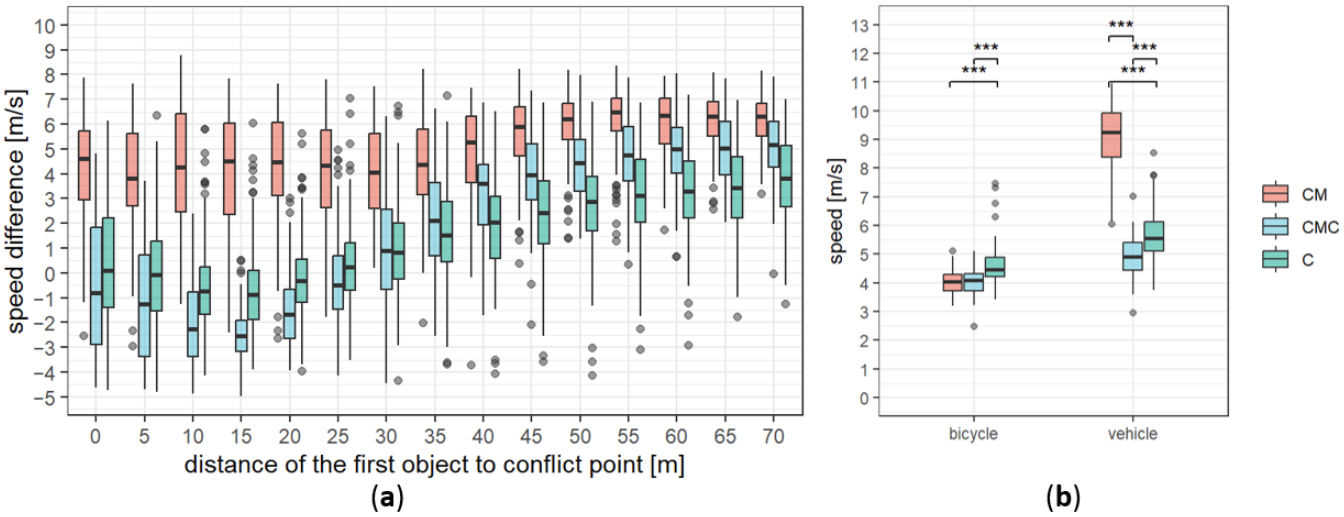

Figure 4. (**a**) Boxplots of the speed difference (+: vehicle faster, −: bicycle faster) over the distance of the first object to the conflict point in interaction patterns CM (red), CMC (blue), and C (green); (**b**) Boxplots of average cycling speed and driving speed in interaction patterns CM (red), CMC (blue) and C (green) and significant difference (***: $p < 0.001$).

- pPET

In CM and CMC, either the vehicle or the bicycle demonstrated a clear advantage during the initial stage (55–70 m), meaning that one interaction partner would clearly cross in front of the other if both would have continued with the present speed, whereas in C, the advantage holder had less pPET. In CMC and C, the temporal gap between the advantaged party reached its minimum at around 25–30 m, while in CM, the advantaged party maintained a lead of approximately 4 s or more throughout. Finally, as they approached the conflict point, the temporal gap between vehicles and bicycles in CM, CMC, and C became similar, with all of them exceeding 3 s (see Figure 5a).

- PET

The median PET of interaction patterns CM, CMC, and C was 5.57 s, 3.36 s, and 3.73 s, respectively (see Figure 5b). The Kruskal–Wallis test indicated a significant difference in PET among the interaction patterns ($Z = 5.8$, $p < 0.001$, $\eta^2 = 0.18$). According to the pairwise comparisons using Wilcoxon tests ($\alpha = 0.05$), the PET in CM was significantly greater than in CMC ($Z = 5.32$, $p < 0.001$) and in C ($Z = 4.83$, $p < 0.001$). There was no difference between the PET of CMC and C ($Z = 1.38$, $p = 0.08$).

3.1.2. Subjective Ratings

- Criticality

The Kruskal–Wallis test indicated significant differences among the patterns CM, CMC, and C from the perspective of both road users (cyclists: $Z = 2.36$, $p < 0.05$, $\eta^2 = 0.03$, motorists: $Z = 6.52$, $p < 0.01$, $\eta^2 = 0.22$). The cyclists' rating of criticality was higher in CM ($M = 2.29$) than in C ($M = 1.42$, $Z = 2.09$, $p < 0.05$) (see Figure 6). There was no difference between CM and CMC ($M = 1.6$, $Z = 0.97$, $p = 0.17$) as well as between CMC and C ($Z = 0.97$,

$p = 0.17$). With regard to the motorists, the rating in CM ($M = 2.76$) was higher than in CMC ($M = 1.82$, $Z = 3.19$, $p < 0.01$) and C ($M = 1.36$, $Z = 6.38$, $p < 0.001$). The rating in CMC was higher than in C ($Z = 3.19$, $p < 0.01$).

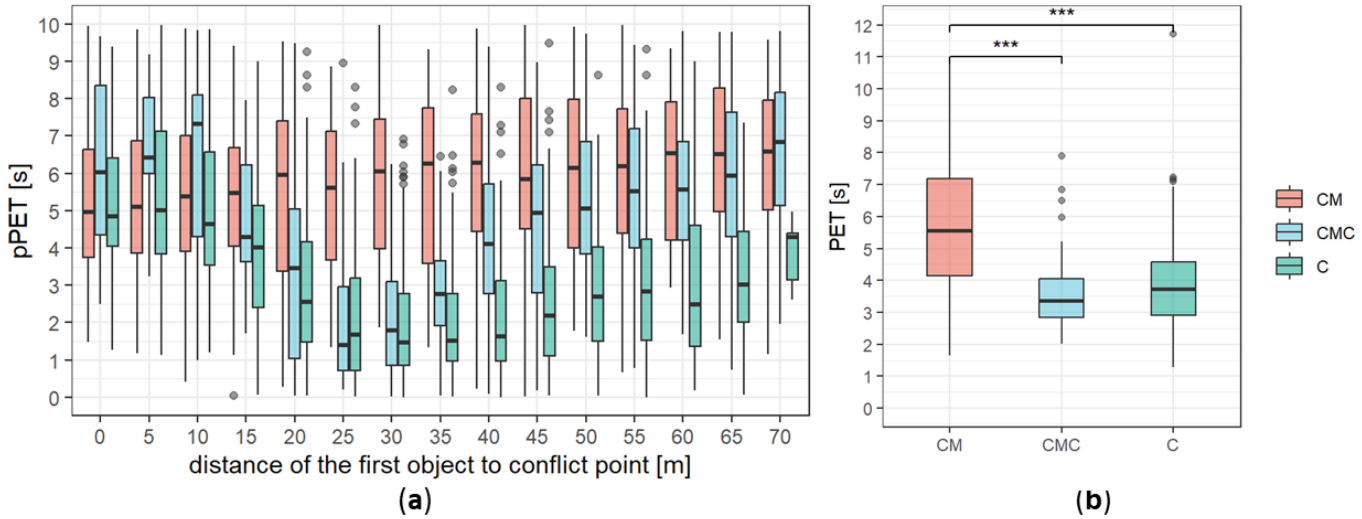

Figure 5. (**a**) Boxplots of the pPET over the distance of the first object to the conflict point in interaction patterns CM (red), CMC (blue), and C (green); (**b**) Boxplots of PET in interaction patterns CM (red), CMC (blue) and C (green) and significant difference (***: $p < 0.001$).

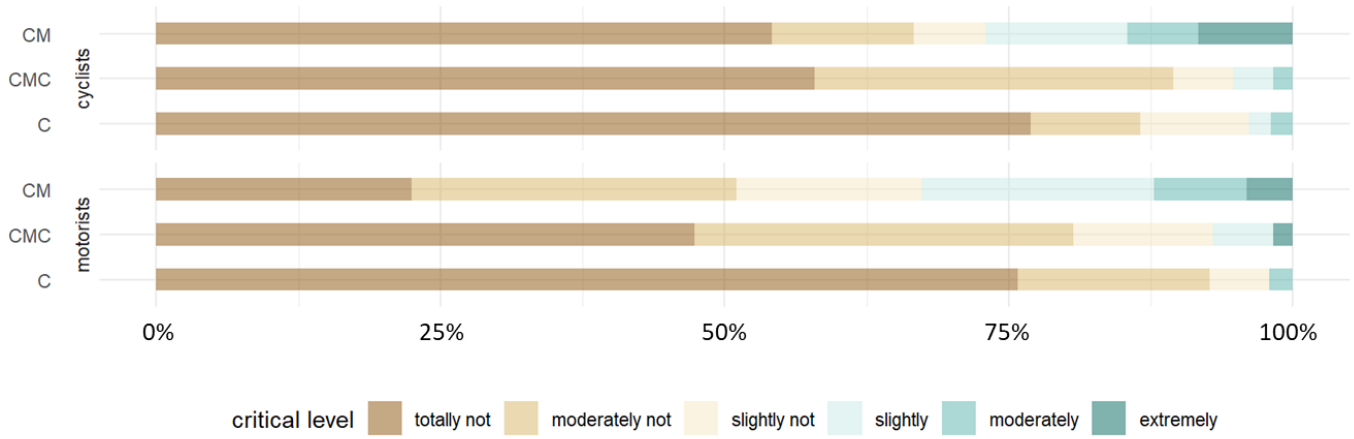

Figure 6. Cyclists' and motorists' ratings of criticality (not critical at all (1) to very critical (6)) in interaction patterns CM, CMC, and C.

- Cooperation

Significant differences were observed among the patterns CM, CMC, and C from the perspective of both road users based on the Kruskal–Wallis test (cyclists: $Z = 5.55$, $p < 0.001$, $\eta^2 = 0.16$, motorists: $Z = 5.92$, $p < 0.001$, $\eta^2 = 0.19$). The cyclists' rating in CM ($M = 3.88$) was lower than in CMC ($M = 5.96$, $Z = 5.2$, $p < 0.001$) and C ($M = 5.62$, $Z = 4.11$, $p < 0.001$) (see Figure 7). There was no difference between CMC and C ($Z = 0.97$, $p = 0.17$). The motorists' rating in CM ($M = 3.92$) was lower than in CMC ($M = 5.61$, $Z = 4.51$, $p < 0.001$) and C ($M = 5.83$, $Z = 5.77$, $p < 0.001$). There was no difference between CMC and C ($Z = 0.83$, $p = 0.80$).

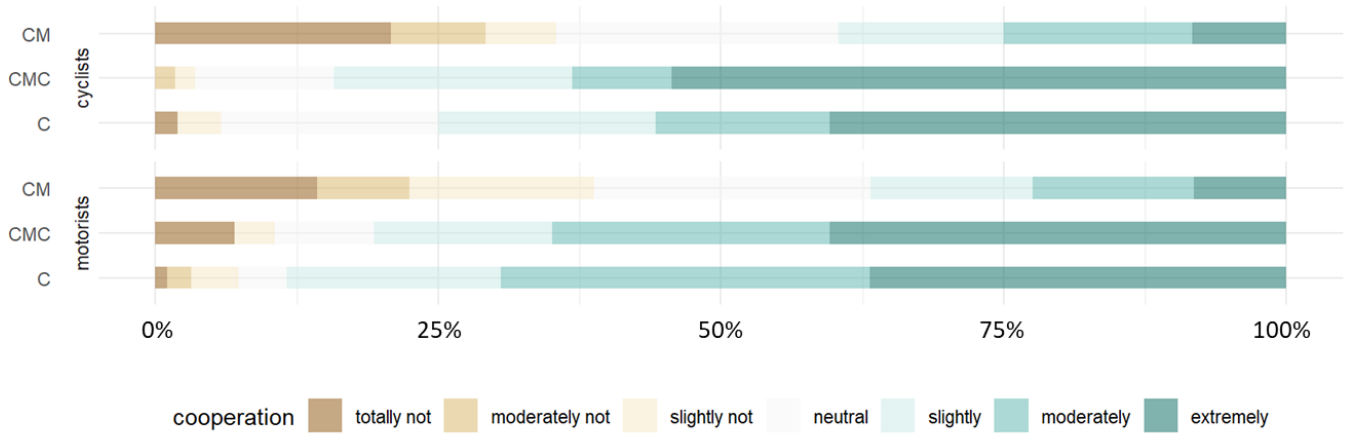

Figure 7. Cyclists' and motorists' ratings of cooperation (very uncooperative (1) to very cooperative (7)) in interaction patterns CM, CMC, and C.

- Certainty

The Kruskal–Wallis test indicated significant differences among the patterns CM, CMC, and C from the perspective of both road users (cyclists: $Z = 2.27$, $p < 0.05$, $\eta^2 = 0.03$, motorists: $Z = 7.7$, $p < 0.01$, $\eta^2 = 0.29$). The cyclists' rating of certainty was lower in CM ($M = 4.33$) than in C ($M = 5.24$, $Z = 1.98$, $p < 0.05$) (see Figure 8). There was no difference between CM and CMC ($M = 4.98$, $Z = 0.77$, $p = 0.22$) as well as between CMC and C ($Z = 0.77$, $p = 0.22$). The motorists' rating in CM ($M = 4.57$) was higher than in CMC ($M = 2.72$, $Z = 5.89$, $p < 0.001$) and C ($M = 2.21$, $Z = 7.04$, $p < 0.001$). The motorists' rating in CMC was higher than in C ($Z = 2.9$, $p < 0.01$).

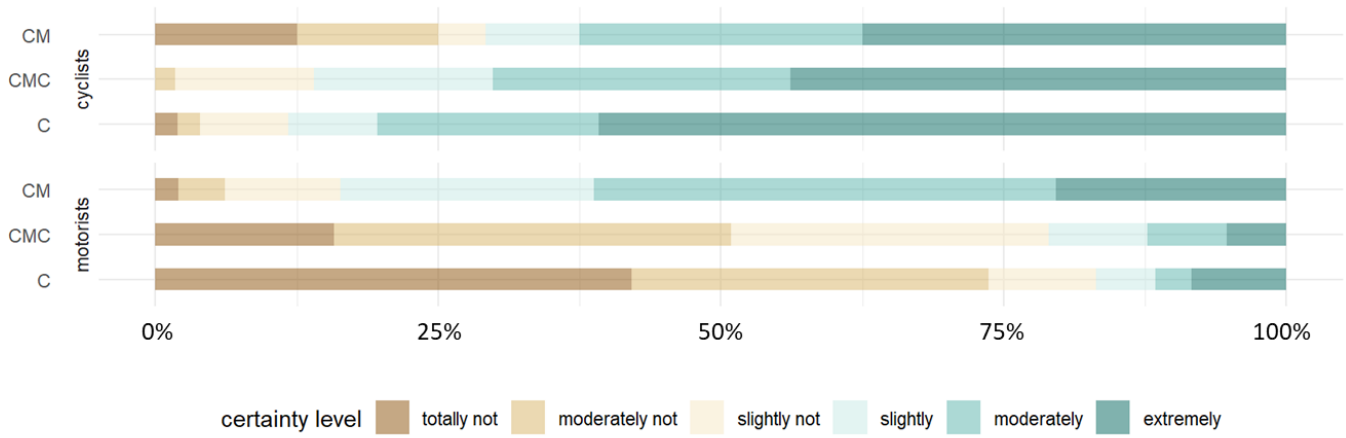

Figure 8. Cyclists' and motorists' ratings of certainty (very unconfident (1) to very confident (6)) in interaction patterns CM, CMC, and C.

3.2. Effect of Crossing Order and Overtaking Position

C was excluded, as there was no overtaking position in this interaction pattern. Namely, 106 interactions (CM and CMC) were considered in this analysis session. Table 4 presents the results of the ordered logistic regressions estimated for the cyclists' ratings on criticality, cooperation, and certainty. The results indicate that cyclists' ratings on criticality and cooperation were correlated with the crossing order and overtaking position: 1. when motorists crossed before cyclists, the cyclists' ratings on criticality were higher (more critical), and the cyclists' ratings on cooperation were lower (less cooperative); 2. when the overtaking position was closer to the conflict point, the cyclists' ratings on criticality were higher (more critical) and the cyclists' ratings on cooperation were lower (less cooperative). A small effect was found for crossing order cyclists' rating of certainty, indicating a lower

rating of certainty if the motorists crossed before the cyclists. However, no significant effect of overtaking position was found on the cyclists' rating of certainty.

Table 4. Results of ordered logistic regressions for cyclists' and motorists' ratings on criticality, cooperation, and certainty.

		Criticality		Cooperation		Certainty	
		Coeff.	*t*	*Coeff.*	*t*	*Coeff.*	*t*
Cyclist	crossing order [1]	0.92	2.25 *	−2.4	−5.7 ***	−0.6	−1.7 ˉ
	overtaking position [2]	−0.1	−3 **	0.04	1.88 ˉ	0.02	1.27
Motorist	crossing order [1]	1.46	3.8 ***	−1.84	−4.76 ***	2.53	5.80 ***
	overtaking position	−0.02	−1.4	0	0.03	0.02	1.08

[1]: positive value = motorist first, [2]: distance to the conflict point, ˉ: $p < 0.1$, *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.

Table 4 also presents the results of the ordered logistic regressions estimated for the motorists' ratings on criticality, cooperation, and certainty. The results indicate that motorists' ratings on criticality, cooperation, and certainty were only correlated with the crossing order: when the motorists crossed before the cyclists, the motorists' ratings on criticality were higher (more critical), on cooperation were lower (less cooperative) and on certainty were higher (more certain). The overtaking position had no effect on these ratings from the perspective of the motorists.

4. Discussion

The aim of this study was to investigate how motorists and cyclists cooperatively interact with each other at intersections through implicit communication. To achieve this, a coupled vehicle and bicycle simulator experiment was conducted, in which the interaction behavior of right-turning motorists and crossing cyclists was recorded. Three interaction patterns were classified and evaluated with respect to criticality, efficiency, certainty, and cooperation using both performance and subjective indicators.

The analyses presented were guided by the question of what kind of interaction pattern is more likely to be accepted by the interaction partners in this specific scenario. Theoretically, based on the experimental set-up, motorists could overtake cyclists and pass through the intersection first in all interactions. However, this only happened in 24% of cases. In another 28% of cases, motorists overtook cyclists but chose to control their speed or wait, allowing cyclists to go first. In the remaining cases (nearly half of all cases), motorists were always behind the cyclists. This distribution may reflect certain social expectations among the interacting participants, suggesting that motorists are likely to yield to cyclists in most situations. Furthermore, in these situations, motorists may prefer not to appear in the cyclists' field of vision to avoid influencing their behavior. The effects of this approach were reflected in the efficiency of cyclists: Compared to CM and CMC, cyclists in C had a higher average speed. At the same time, motorists did not lose efficiency, as their average speed was also higher than in CMC, where they yielded as well. Therefore, from the perspective of combined efficiency for both parties, the performance of C is better. From the perspective of proximity, the PET in CM is significantly higher than in the other two modes, with cyclists catching up to the motorists about 5.6 s after the motorists have passed through the intersection, while in the other two modes, it takes the motorists a maximum of 3.7 s. This gap in PETs may be partly due to the difference in acceleration between vehicles and bicycles, and on the other hand, it could imply that motorists will only choose not to yield when there is a sufficiently safe distance.

The subjective evaluations of the participants might provide a direct answer to which interaction pattern is more acceptable. As shown in Figures 6–8, compared to the other two

patterns, cyclists rated the pattern CM as a more critical, less cooperative, and less certain interaction pattern. Interestingly, motorists in CM gave similar ratings, even though they actively overtook the cyclists in this pattern. However, it is worth noting that this does not imply that the CM is unacceptable, as the absolute values of the ratings can be described as low risk, neutral cooperation, and neutral certainty. Compared to CM, both CMC and C are more likely to be accepted, as they might meet road users' expectations for the scenario in which the motorist should yield to the cyclist. However, the difference between CMC and C is not significant.

Interaction patterns can be understood as several fixed tactical-level modes formed by the interacting parties through implicit communication. As previously analyzed, interaction patterns can be evaluated through their frequency as well as performance and subjective indicators. The following question arises: at the operational level, which specific behaviors can improve the acceptance of road users, particularly cyclists? We incorporated the two indicators we focused on, crossing order and overtaking position, into the regression model for subjective evaluations. In terms of crossing order, the ratings of both road users tend to be more critical and less cooperative when motorists cross first. Regarding the overtaking position, results imply a shift from uncertainty (one party is not within the field of view) to certainty (both parties are within each other's field of view). The farther this transition point is from the conflict point, the more time road users may have to assess the situation, adapt, or adjust through communication. Conversely, the overtaken road user may not be able to cope, especially when s/he expects to be ahead for most of the journey. Thus, the results lead to the conclusion that if right-turning motorists decide to overtake the cyclist traveling alongside them (in CM or CMC), overtaking earlier can increase the acceptance of the cyclists in terms of criticality and cooperation.

One limitation of this study comes from the questionnaire. Firstly, the questions posed to cyclists and motorists on the dimension of certainty were different and, therefore, cannot be directly compared. Additionally, the question posed to motorists, "how confident were you that you could turn in front of the cyclist?" may rise a unidirectional bias, which may cause confusion when the driver is certain not to turn in front of the cyclist. As a result, motorists rated the certainty of CMC and C lower (see Figure 8), even though the situation might be under their control. Therefore, the certainty ratings of motorists for CMC and C may not be reliable for reference.

The validity is one of the ongoing challenges with simulator driving studies, namely, to what extent they capture real-world traffic behavior. The consistency of kinematic information recorded in vehicle and bicycle simulators, such as speed and acceleration, with data from real-world scenarios may need to be validated through traffic observations or research vehicles and bicycles equipped with sensors on actual roads. Recently, a study has already explored the validation of the used bicycle simulator based on real-world data (e.g., [29]). As mentioned previously, the intersection simulated in this study is a 1:1 reproduction of a research intersection in Braunschweig, Germany. This provides the possibility of comparing the results with real data in the same infrastructure context. This will be considered in future work. In addition, so far, it is unclear what influence the social situation in a coupled simulator study has on traffic behavior [23,30]. In this study, the two participants were in the same room and deliberately encountered each other repeatedly in the same situation, which is rather rare in real road traffic.

5. Conclusions

The current study investigated interaction patterns based on implicit communication between motorists and cyclists through a coupled vehicle–bicycle simulator experiment. In the selected scenario, a right-turning vehicle encounters a crossing bicycle, and three interaction patterns were identified. In nearly half of all cases, motorists stayed behind cyclists, reflecting a societal expectation for motorists to yield to cyclists. In the other half of cases, it was found that the earlier overtaking may improve cyclists' acceptance of the interaction in terms of subjective criticality and cooperation. The results of this

research study allow autonomous driving to effectively distinguish the interaction patterns that people form on the road with other road users, especially VRUs, and to adopt more acceptable maneuver plans during interactions.

Author Contributions: Conceptualization, M.Z. and L.Q.; methodology, M.Z., L.Q. and K.G.; software, K.G.; investigation, L.Q.; data curation, M.Z. and L.Q.; writing—original draft preparation, M.Z. and L.Q.; writing—review and editing, M.Z., L.Q. and C.S.; visualization, M.Z.; supervision, C.S.; project administration, C.S.; funding acquisition, C.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the former German Federal Ministry of Economic Affairs and Energy (BMWi, grant number 19A18003I).

Institutional Review Board Statement: This study was approved by the Institutional Ethics Committee of the German Aerospace Center (8 March 2021).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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