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What will the car driver do? A video-based questionnaire study on cyclists' anticipation during safety-critical situations

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ABSTRACT

Introduction: Many bicycle–car crashes are caused by the fact that the driver fails to give right of way to the cyclist. Although the car driver is to blame, the cyclist may have been able to prevent the crash by anticipating the safety-critical event and slowing-down. This study aimed to understand how accurate cyclists are in predicting a driver's right-of-way violation, which cues contribute to cyclists' predictions, and which factors contribute to their self-reported slowing-down behavior as a function of the temporal proximity to the conflict. *Method*: 1030 participants were presented with video clips of nine safety-critical intersection situations, with five different video freezing moments in a between-subjects design. After each video clip, participants completed a questionnaire to indicate what the car driver will do next, which bottom-up and top-down cues they think they used, as well as their intended slowing-down behavior and perceived risk. *Results and conclusions*: The results showed that participants' predictions of the driver's behavior develop over time, with more accurate predictions (i.e., reporting that the driver will not let the cyclist cross first) at later freezing moments. A regression analysis showed that perceived high speed and acceleration of the car were associated with correctly predicting that the driver will not let the cyclist cross first. Incorrect predictions were associated with believing that the car has a low speed or is decelerating, and with reporting that the cyclist has right of way. Correctly predicting that the driver will not let the cyclist cross first and perceived risk were significant predictors of intending to slow down in safety-critical intersection situations. *Practical applications*: Our findings add to the existing knowledge on cyclists' hazard anticipation and could be used for the development of training programs as well as for cycling support systems.

1. Introduction

A crucial skill for safe performance in traffic is the ability to anticipate future events quickly and accurately, in order to have sufficient time for decision-making and performing an appropriate action (Allen, Lunenfeld, & Alexander, 1971; Cumming, 1964; Horswill, 2016a). An in-depth crash analysis suggests that both cyclists and drivers make anticipation errors that result in emergency events on the road (Räsänen & Summala, 1998). Although several researchers have investigated the mechanisms that underlie drivers' errors in cyclist–driver conflicts (e.g., Herslund & Jørgensen, 2003; Räsänen & Summala, 2000; Summala, Pasanen, Räsänen, & Sievänen, 1996), knowledge on cyclists' errors is sparse. Thus far, research indicates that a large proportion of crashes happen in situations where the cyclist does see the oncoming car but wrongly expects that the car driver will yield in accordance with traffic rules (Räsänen & Summala, 1998).

A cyclist processes top-down and bottom-up cues to determine what the driver on a collision course is going to do next (see Endsley, 1995; Summala & Räsänen, 2000). Top-down or "conceptually driven" cues consist of procedural knowledge and expectancies based on formal/informal traffic rules and previous experience (Allen et al., 1971; Shor, 1964; Summala & Räsänen, 2000; Theeuwes, 2000). Knowledge and expectancies create prototypical representations of intersection situations, called schemas or scripts (Minsky, 1975; Rumelhart, 2018; Schank & Abelson, 1977). Bottom-up or "data-driven" cues consist of perceptual features in the situation that a road user can perceive directly (see Gibson, 2015). A cyclist can extract the driver's intentions from the car speed and position on the road, the indicator lights, and the driver's head orientation and hand signals (e.g., Drury & Pietraszewski, 1979; Lee & Sheppard, 2016; Sun, Zhuang, Wu, Zhao, & Zhang, 2015; Walker, 2005). In the situation where a car driver inappropriately takes right of way (such as observed in Räsänen & Summala, 1998), the cyclist

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has to deviate from the expected sequence of events (top-down cues) and extracts relevant visual information (bottom-up cues) to prevent a collision.

Recently, Lee and Sheppard (2016) conducted a study in which participants were asked to predict the intentions (i.e., continuing straight or turning) of cars and motorcycles at three-way intersections. The authors found that drivers were more accurate in judging turning maneuvers when the vehicle was indicating the turn compared to when the indicator was off. However, participants were also able to predict the vehicle's maneuver based on vehicle motion in the indicator-off condition. A previous interview study on safety-critical events in everyday cycling indicated that a high speed of the car is a cue that cyclists pick up before the potential conflict (Werneke, Dozza, & Karlsson, 2015).

In bicycle–car conflicts, responding quickly can make the difference between crashing or not crashing. Despite the highly dynamic nature of such conflicts, the existing studies do not address the temporal aspect of how road users anticipate upcoming safety-critical events. For example, in Lee and Sheppard's (2016) and Westerhuis and De Waard's (2017) studies, participants were presented with video clips of an approaching or leading road user that ended just before the road user made a maneuver. In this way, only information until a single temporal moment was obtained, without providing an insight into the development of anticipation as a function of time.

Being able to anticipate other road users' intentions accurately is a critical precursor of successful decision-making in traffic. However, having excellent anticipatory skills is not enough for safe performance in traffic; safe performance also depends on the amount of risk one perceives and is willing to take in traffic (e.g., Brown & Groeger, 1988; Deery, 1999; Näätänen & Summala, 1974). Cyclists' perceived risk is known to be high in situations where cyclists interact with cars, when not having control over the outcome of the traffic situation, or when the predictability of traffic situation is low (Chaurand & Delhomme, 2013; Møller & Hels, 2008), such as in situations where a car driver fails to give right of way. Road users who perceive a relatively low level of risk are more likely to show risky behaviors in traffic (see Deery, 1999, for a review).

In the present study, participants were asked to watch video clips from a cyclist's perspective. Each video included a safety-critical intersection situation in which a car driver violated the formal traffic rules. To examine how the accuracy of cyclists' anticipation develops as a function of the temporal proximity to the collision, participants were presented with five clip freezing moments of each intersection situation in a between-subjects design. After each video clip, participants completed a questionnaire to indicate what the car driver will do next, which bottom-up and top-down cues they think they used, as well as their intended slowing-down behavior and perceived risk. To summarize, this study addressed the following three research questions:

1. How do cyclists' predictions of what a car driver will do next at an intersection develop prior to a near miss or a crash with that car?

The temporally closer the person is to the critical event, the more relevant visual information is available (see Farrow, Abernethy, & Jackson, 2005, for a temporal occlusion paradigm). Based on this presumption, we expected that the accuracy of cyclists' predictions of whether the car driver will let the cyclist cross first or not increases as a function of the temporal proximity to the conflict, with the highest accuracy when the cyclist is temporally closest to the conflict.

2. How do bottom-up and top-down cues guide cyclists' predictions of what a car driver will do next at an intersection in near-miss and crash intersection situations?

We expected that cyclists use both bottom-up cues (e.g., the speed and turn indicator of the car) and top-down (e.g., the right-of-way rule, previous experience) to predict a car driver's behavior at an intersection. Based on Räsänen and Summala (1998) and Summala and Räsänen (2000), we expected that relying on the right-of-way rules and thinking that the car has a low speed or is decelerating are related to incorrect predictions (i.e., predicting that the driver will yield to the cyclist).

3. How are the prediction of the car driver's behavior, subjectively perceived risk, participants' age, and cycling experience associated with self-reported slowing-down behavior in near-miss and crash intersection situations?

We expected that correctly predicting the car driver's behavior as well as a high level of perceived risk are predictive of the cyclist's self-reported slowing-down behavior. Lastly, in line with studies that have used objective measures of riding behavior (e.g., Crundall, Stedmon, Saikayasit, & Crundall, 2013; Liu, Hosking, & Lenné, 2009), we expected that age and cycling experience would be positively associated with self-reported slowing-down behavior in near-miss and crash intersection situations.

2. Method

2.1. Participants

A total of 1384 participants from 65 countries completed the study online using SurveyMonkey (the five most frequently reported countries of residence were United States, Venezuela, Italy, Canada, and the UK). Participants were recruited through the crowdsourcing service CrowdFlower and through the social networking service Facebook between February 27 and August 21, 2017. 1030 individuals (374 females, 653 males, 3 unknown) who met eligibility and quality control criteria (i.e., older than 18 years, provided consent to the instructions, correctly answered the quality control items), and who did not indicate 'never' on the cycling frequency item were included in this study. The mean age of the remaining participants was 34.09 ($SD = 10.45$), ranging between 18 and 70 years.

Table 1
Reported cycling experience in the summertime and driving experience in the last 12 months.

Cycling frequency	Never	Less than once a month	Once a month to once a week	1–3 days a week	4–6 days a week	Every day	N/A
Number of participants	0	121	127	508	172	102	0
Weekly cycling mileage	0–5 km	6–10 km	11–30 km	31–90 km	91–150 km	More than 151 km	N/A
Number of participants	221	223	219	228	88	39	12
Driving frequency	Never	Less than once a month	Once a month to once a week	1–3 days a week	4–6 days a week	Every day	N/A
Number of participants	154	87	65	233	248	237	6
Yearly driving mileage	0 km	1–5000 km	5001–15,000 km	15,001–25,000 km	25,001–50,000 km	More than 50,001 km	N/A
Number of participants	130	316	227	194	106	40	17

Table 2
Overview of the 10 intersection situations, estimated cycling speed, estimated time required to come to a full stop, and times between very early and very late clip freezing moments and the moment of conflict/collision. Note that the very late freezing moment was created by removing 5 frames (0.17 s) from the moment the car entered the bike path.

No.	Intersection situation	Bicycle facility	Estimated cycling speed[a] (km/h)	Estimated time to stop based on cycling speed (s)		Time between freezing moment and the conflict/collision point[b] (s)	
				Deceleration rate 3.1 m/s^2	Deceleration rate 4.6 m/s^2	Very early	Very late
1	Crash	Yes	20.4	1.83	1.23	1.57	0.50
2	Near miss	Yes	23.0	2.07	1.39	1.60	0.53
3	Near miss	Yes	29.1	2.61	1.76	1.73	0.67
4	Near miss	Yes	28.2	2.53	1.70	1.37	0.30
5	Safe	Yes	30.2	–	–	–	–
6	Crash	Yes	31.5	2.82	1.90	1.30	0.23
7	Crash	Yes	42.0	3.76	2.54	2.53	1.47
8	Crash	No	29.3	2.63	1.77	1.77	0.70
9	Near miss	Yes	30.0	2.69	1.81	1.27	0.20
10	Crash	Yes	36.3	3.26	2.19	1.77	0.70

[a] The estimated cycling speed in the video clips was calculated by measuring the distance between the position reached 2 s prior to conflict/collision point and 34–35 m before this position in Google[TM] Earth (see Supplementary material), and dividing this distance by the duration of the moving video clip between these two points.
[b] For near-miss situations, a conflict point was defined as the moment when the car entered the cyclist's bike lane. For crash situations, a collision point was defined as the moment when the cyclist collided with the car (see Supplementary material for the video frames of these points).

On average, participants started to cycle at the age of 8.32 years (*SD* = 4.58), and 76.0% of the participants reported driving a car at least once a month (see Table 1 for an overview of participants' cycling and driving experience). The majority of participants (58.1%) indicated that the car is their primary mode of transport, followed by the bicycle (17.6%), public transport (13.8%), walking (7.8%), and other (2.7%). The majority of participants owned a city bike (52.8%) or mountain bike (42.4%). 254 participants (24.7%) reported to have been involved in an accident as a cyclist at least once during the last three years, and 44 participants reported that some of the reported accidents happened with a motorized vehicle at an intersection. The Human Research Ethics Committee of university (Ethics application no. 151, 2017) approved the study.

2.2. Materials

Video clips from a cyclist's point of view were collected from publicly available YouTube postings. Clip segments in which the car was crossing a cyclist's path and was visible for at least 2 s prior to this crossing were selected. Nine safety-critical and one safe intersection situation were selected. Safety-critical situations were defined as situations that included an approaching car that was not giving right of way to the cyclist, resulting in a crash (five situations) or a near miss if a car crossed the bike path without giving a right of way and the cyclist braked (four situations). In a safe situation, an approaching car stopped in front of the bike path. The safe situation was included to assess whether participants could discriminate between safety-critical and safe intersection situations. In addition, one extra video clip of a safe situation was extracted from YouTube postings, which was used as a practice video clip to familiarize participants with the task.

The intersection situations were recorded during daylight in real traffic on Dutch (intersection situations 1–5), Northern American (intersection situations 6–8), and Australian roads (intersection situations 9–10); see Table 2 for an overview of the 10 intersection situations. The video clips of two situations recorded on the Australian roads were horizontally flipped to follow right-hand traffic rules in all intersection situations. Cyclists formally had right of way in all 10 situations and were cycling on a bike path/lane in 9 of the 10 situations.

All downloaded video clips were stored at a frame rate of 29.97 fps. Using a video editing method proposed by Westerhuis and De Waard (2017), each video clip started with a frozen frame containing a 3 s countdown at the right bottom of the screen, after which the clip was played. Five clip freezing conditions of each clip were created using Adobe Premiere Pro CC 2017. First, a very late freezing moment was created by removing 5 frames (=0.17 s) from the moment the car either entered the bike path/lane in near-miss and crash situations or the moment the car stopped in the safe situation. From this point of each video clip, eight additional frames were removed four times to create four additional versions of each clip: late (=0.43 s), intermediate (=0.70 s), early (=0.97 s), and very early (=1.24 s) freezing moments (see Fig. 1). The time between the very late freezing moment and the conflict/collision varied between clips from 0.20 to 1.47 s (Table 2). After the video clip had played, the last frame was frozen. From the moment of the freeze, the relevant car was encircled for 2 s, after which the same static image without the circle remained visible for another 2 s. Clips with very late freezing moments were between 13.75 and 21.42 s long (including frozen frames). A total of 50 video clips (10 intersection situations * 5 clip freezing moment conditions) were created.[1]

The estimated approach speeds of the cyclists differed between the 10 intersection situations, ranging from 20 km/h in Situation 1 to 42 km/h in Situation 7 (Table 2). These speeds are generally higher than the cruising speeds observed among conventional bicycle users (e.g., De Waard, Lewis-Evans, Jelijs, Tucha, & Brookhuis, 2014; Kircher, Ihlström, Nygårdhs, & Ahlstrom, 2018). However, the speeds are in line with cruising speeds collected during naturalistic cycling studies among e-bike users (e.g., Rotthier et al., 2017; Stelling-Konczak et al., 2017) and with average speeds reported by users of racing bicycles (Hendriksen et al., 2008).

Taylor (1993) computed that the maximum attainable deceleration of cyclists is 5.5 m/s^2. However, braking tests using various types of bicycles suggest that cyclists decelerate at a somewhat lower rate of 3.5 to 4.5 m/s^2 (Beck, 2004). Data from a braking task text (ref) were used to estimate the cyclists' average deceleration (3.1 m/s^2) and the 90th percentile value (4.6 m/s^2). Using these values, it was computed that the cyclist had insufficient time to avoid a (potential) collision by means of braking, for each of the nine 'very late' safety-critical situations (Table 2).

2.3. Survey design

The online video-clip survey consisted of 14 web pages written in the English language. On the first page, participants provided their consent for participating in this study. Second, participants completed an introduction questionnaire with items on demographic characteristics, cycling, and driving experience. Weekly cycling mileage in the summertime was indicated on a 6-point scale ranging from *never* (1) to *every day* (6). As mentioned above, participants who indicated 'never' were

[1] The video clips can be found in the Supplementary material. For review: https://www.dropbox.com/sh/zq553x80cskyukg/AADI6o-7PY69oHsj6p45LLYfa?dl=0

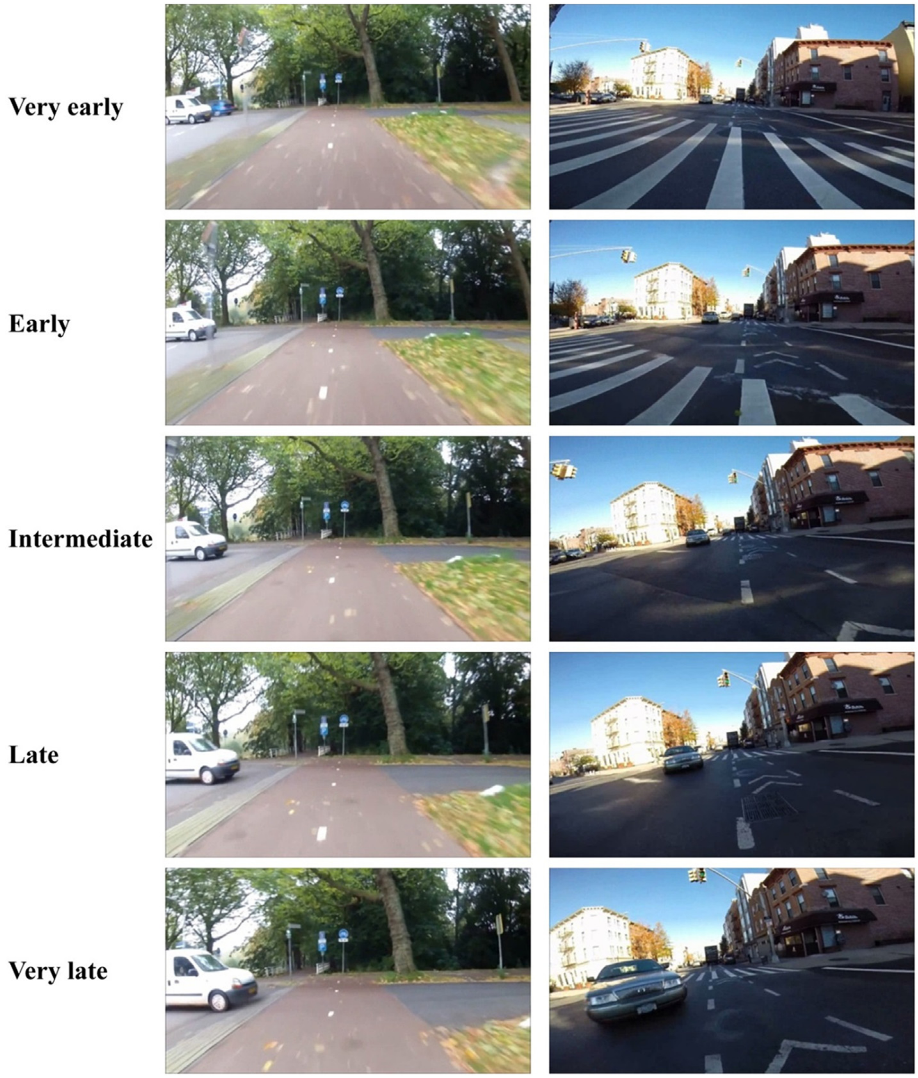

Fig. 1. The five freezing moments of a near-miss situation (Situation 3; left) and a crash situation (Situation 6; right). See Supplementary material for the final frames of all 10 intersection situations.

excluded. The weekly cycling frequency in the summertime was indicated on a 10-point scale ranging from *0 km/mi* (1) to *more than 201 km (more than 125 mi)* (10).

The next 11 pages consisted of 1 practice and 10 experimental video clips and an 8-item questionnaire after each video clip. In this questionnaire, participants were asked to indicate their responses to the following items:

(1) Perceived risk ("The situation was risky.") – participants indicated their response on a 7-point Likert scale from *strongly disagree* to *strongly agree*.
(2) Cyclist's slowing-down behavior ("Imagine that you are the cyclist in the video. Would you slow down?") – participants were asked to choose between *yes, I would slow down* and *no, I would continue cycling at this speed*.
(3) Prediction of the driver's behavior ("Imagine that the cyclist in the video will continue cycling at this speed. Will the car driver let the cyclist cross first?") – participants were asked to choose between *yes, the car driver will slow down and let the cyclist cross first* and *no*.
(4) Certainty about the driver's behavior ("I am certain about my previous answer.") –participants indicated their response on a 7-point Likert scale from *strongly disagree* to *strongly agree*.
(5) Factors that contributed to the prediction of the driver's behavior ("Which factors contributed to your prediction?") – this was a checkbox item where participants could select from seven bottom-up cues (including the speed of the car, turn signals, and road markings) and two top-down cues (priority rules and prior experience), see Fig. 3, for all nine options. Participants could also report other factors in a textbox.
(6) Priority rules ("The encircled car has priority in this situation.") – participants indicated their response using the following three options: *yes*, *no*, *unsure*.
(7) Number of times the video was played ("How many times did you watch the video?") – participants indicated their response using a numerical scale ranging from *0* to *more than 5*.
(8) Color of the encircled car ("What was the color of the encircled car?") – participants could choose one of the four colors where only one option was correct (e.g., *silver*, *red*, *green*, *black*).

Item 7 was included to verify whether the number of video replays affected participants' prediction correctness. Item 8 was a quality control item used to select only participants who watched the video clips prior to answering the questionnaire.

On the first of the 11 video-clip pages, participants read the instructions, watched a practice video clip, and reported their answers to the eight questions mentioned above. The task instruction was as follows: "*You will now look at videos taken from a cyclist's perspective. In each* *video, you will have to pay attention to a particular car. After each video, you will answer questions about a car that is encircled at the end of the video. In each video, the cyclist is going straight ahead. When traffic lights are present in the video, the cyclist always has a green light. Please watch the videos and complete the questions in the order they appear. Please watch each video only once. In case you did not notice the car about which we ask you questions, you may replay the video once again. However, we kindly ask you to pay attention during the first viewing.*"

On the last questionnaire page, participants completed the Cycling Skill Inventory (CSI) and items on accident involvement during the last three years as a cyclist and as a car driver. The psychometric analysis of the CSI data has been reported elsewhere (ref).

2.4. Procedure

The study was of mixed between-within subjects design. The 50 experimental video clips were divided into five sets (i.e., fibe different forms of the SurveyMonkey online survey). Each participant was presented with 10 video clips; they saw each of the 10 intersection situations once and encountered each of the five clip freezing conditions twice. The order of the clip freezing conditions and the order of the intersection situations were counterbalanced across participants. All video clips were uploaded to YouTube and embedded into the online survey. Because of this, we could not control how many times each participant played the video clips.

Participants recruited through CrowdFlower were randomly allocated to one of the five sets. Participants recruited through Facebook were redirected to the survey via the posts with an Internet link to one of the five sets of the survey. Randomly selected Internet links to the survey were posted on the cycling-related Facebook groups based in the Netherlands (e.g., Bikes in Groningen). It took on average 20 min to complete the survey.

2.5. Analysis

First, a data check of responses from 1030 participants who met the eligibility and quality control criteria was performed. Participants had the option to respond *I prefer to not respond* to the items in the introduction and final questionnaire (i.e., background, cycling, driving-related, and accident-related items). These responses were considered as missing values in the analysis. Text responses to the other cue option were coded as "other" in case they were different from the nine predefined cues (e.g., "The driver might not be able to see the cyclist."). In some cases, participants mentioned road markings or experience in their comments while they did not select these predefined checkboxes. Therefore, these responses were edited accordingly (e.g., "Bad experience with vans being in a hurry." was coded as the "I have experience as a cyclist at a similar intersection" cue).

We first calculated participants' predictions of the car driver's behavior and self-reported slowing-down behavior as a function of video clip freezing moments. The remaining analyses were conducted without the safe situation, as the safe situation was included only for method validation purposes.

We proceeded with an analysis of the reported bottom-up and top-down cues. The frequencies of the reported cues were calculated for correct (i.e., the car driver will not let the cyclist cross first) and incorrect (i.e., the car driver will let the cyclist cross first) predictions of the driver's behavior. In this analysis, the percentages of reported cues were first calculated per clip freezing moment for each video clip, and then the percentages of each cue were averaged across clip freezing moment and the nine intersection situations. In addition, percentages of reported cues and average perceived risk levels were plotted as a function of video clip freezing moment.

Finally, Spearman's rank-order correlations, linear regressions, and linear hierarchical regressions were conducted at the level of individual participants. Prior to these statistical analyses, participants responses on "prediction of the driver's behavior," "cyclist's slowing-down behavior," and "perceived risk" items were averaged across: (a) the four near-miss situations and clip freezing moments, and (b) the five crash situations and clip freezing moments. Similarly, the 10 cue-related responses were averaged across the five clip freezing moments of the four near-miss or the five crash intersection situations. Except for the "perceived risk" item, participants indicated their responses using binary options. The averaged scores of these binary items ranged between 0% and 100% (e.g., 0%, 25%, 50%, 75%, 100% for near-miss situations), where 100% refers to perfect accuracy in predicting the driver's behavior (i.e., a participant correctly predicted that the car would not stop in all four near-miss situations), always slowing-down, or always reporting a particular cue.

A linear regression analysis was conducted with predictions of the driver's behavior as the dependent variable and the 10 cues as predictors. Next, a hierarchical linear regression analysis was conducted with self-reported slowing-down behavior as the dependent variable. In the hierarchical regression models, background and cycling variables (i.e., gender, age, weekly cycling mileage, and cycling frequency) were entered in Step 1, prediction of the driver's behavior in Step 2, and perceived risk in Step 3. The regression analyses were conducted for near-miss and crash situations separately. As shown by Hellevik (2009), linear regression analysis can safely be used instead of logistic regression analysis. Linear and logistic regression analyses yield highly correlated regression coefficients and p-values, while an important advantage of linear regression analysis is the "intuitive meaningfulness of the linear measures as differences in probabilities" (Hellevik, 2009, p. 59).

Additionally, we analyzed cross-cultural differences in participants' predictions of the car driver's behavior, self-reported slowing-down behavior, and perceived risk in the near-miss and crash situations. Ten countries that were represented by more than 30 participants were included in this analysis. The percentages were calculated for each of the five clip freezing moments and subsequently averaged across the four near-miss or five crash situations. Due to the relatively small sample sizes per freeze frame conditions, the results should be interpreted with appropriate caution (see Supplementary material).

3. Results

3.1. Predictions of the car drivers' behaviors and participants' self-reported slowing-down behaviors

As can be seen in Fig. 2 (left), the percentage of participants who predicted that the car driver would not let the cyclist cross first increased as a function of elapsed time in the four near-miss situations (blue lines) and the five crash situations (black lines), and decreased in the safe situation (green line). In other words, the accuracy of participants' predictions increased with elapsed time in all 10 intersection situations, being the most accurate in the very late clip freezing moment. However, as shown in Table 2, for the late clip freezing moment, there was not enough time to come to a full stop. Participants' predictions of the driver's behavior were more accurate in the near-miss situations than in crash situations (Table 3).

Fig. 2 (right) shows that similar to the predictions of the drivers' behaviors, participants' self-reported slowing-down behaviors increased with elapsed time in the safety-critical situations (blue and black lines) and decreased with elapsed time in the safe situation (green line). Participants reported to slow down more in the near-miss situations compared to the crash situations, especially for the early clip freezing moments (Table 3).

On average, participants reported playing the video clips 1.40 times ($SD = 0.61$). There was no statistically significant correlation between the number of times the video was played and correctly predicting the car driver's behavior ($\rho = 0.02$, $p = .454$, $N = 1030$) nor with the correctness of the reported slowing-down behavior (i.e., *yes, I would slow*

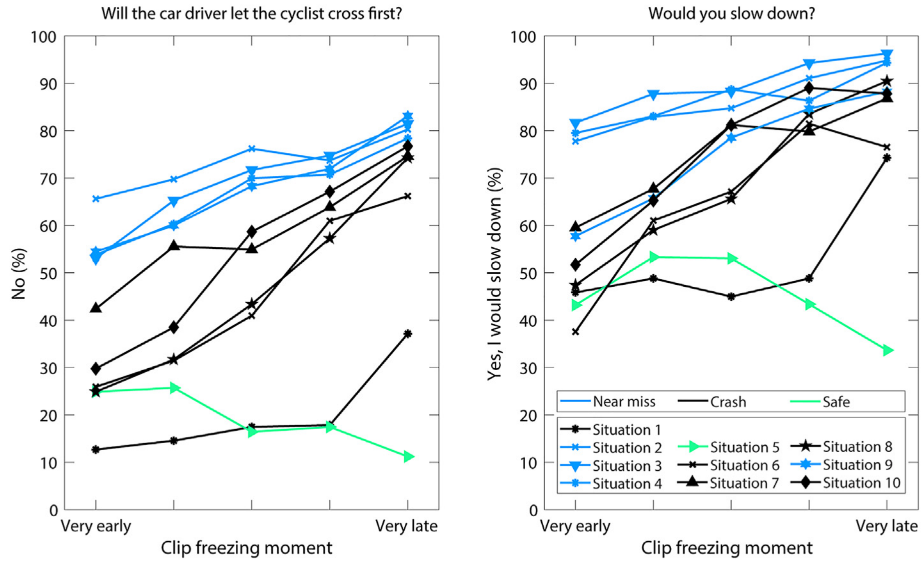

Fig. 2. Left: Percentage of participants who reported *no* to the question "Imagine that the cyclist in the video will continue cycling at this speed. Will the car driver let the cyclist cross first?" as a function of intersection situation and clip freezing moment. Right: Percentage of participants who reported *yes, I would slow down* to the question "Imagine that you are the cyclist in the video. Would you slow down?" as a function of intersection situation and clip freezing moment. The values of the markers are based on the responses of 189–213 participants.

down) ($\rho = 0.01$, $p = .780$, $N = 1030$). Overall, participants were certain about their prediction of the car driver's behavior (mean = 5.33, $SD = 1.05$, on the scale from 1 to 7), and their average certainty was similar across the five clip freezing moments (5.21 in the very early to 5.58 in the very late condition). Correctly predicting the car driver's behavior was positively associated with reported level of certainty ($\rho = 0.11$, $p < .001$, $N = 1030$).

3.2. Reported bottom-up and top-down cues

In the safety-critical situations (i.e., near-miss and crash), participants selected on average 1.60 cues per video clip ($SD = 0.68$). Fig. 3 shows that the cues concerning the car speed (cues 1–4) and priority rules (cue 8) were reported most frequently among the available options. As can be seen in Fig. 3, there were differences between the reported cues for correct and incorrect predictions: participants who correctly predicted that the car would not slow down typically reported that the car's high speed (cue 1) or the car's acceleration (cue 2) contributed to their prediction. On the other hand, participants who falsely believed that the car would slow down typically reported that the car's low speed (cue 3), or car's braking (cue 4), or priority rules (cue 8) contributed to their prediction. Further, participants more frequently reported their cycling experience (cue 9) when making correct predictions. Frequently mentioned cues in the other category (cue 10) were the distance between the cyclist and the car, the car's initiation or non-initiation of the turn, the driver's looking behavior, the position of the car at the intersection (e.g., the car is halfway through the intersection), a blind spot, and the presence of other road users (e.g., pedestrian, leading car). Overall, similar results for percentages of all reported cues were found for near-miss and crash situations (Fig. 3).

An examination of the car speed cues across the five clip freezing moments (Fig. 4) showed that high speed and acceleration of the car (cues 1 & 2) were selected more frequently when being temporally closer to the conflict, whereas low speed and deceleration of the car (cues 3 & 4) were selected more frequently in the early clip freezing moments. The percentage of "I have priority according to the traffic rules" responses was similar across the five clip freezing moments (Fig. 4).

The percentages of participants who correctly reported that the car driver did not have right of way ranged between 43.0% in Situation 2 and 76.2% in Situation 5 (see Supplementary material for the results of all 10 situations). Participants were more likely to know that the cyclist had right of way in situations where priority road markings were visible or in situations where the cyclist rode in a bike lane. However, approximately half of the participants incorrectly reported or were not aware of the priority rules in situations where the cyclist rode on a physically separated bike path (Situations 2, 3, and 4).

Table 4 shows linear regression analyses for participants' correct predictions of the car driver's behavior in near-miss (left) and crash (right) situations. In both models, high speed and acceleration (cues 1 & 2) as well as "I have experience as a cyclist at a similar intersection" (cue 9) and other cues (cue 10) were positively associated with making correct predictions of the driver's behavior. Low speed and deceleration (cues 3 & 4) and "I have priority according to the traffic rules" (cue 8) were negatively associated with making correct predictions of the driver's behavior, meaning that the probability that a participant made a correct prediction was lower if a participant had selected these cues. Turn signals and lines/markers on the road did not have a statistically significant relationship with the predicted driver's behavior in neither

Table 3
Mean percentages of correct predictions of the car drivers' behavior (top), mean percentages of self-reported slowing-down behavior (center), and mean scores of perceived risk (bottom) for the three intersection situation types and the five clip freezing moments.

Will the car driver let the cyclist cross first?	% of *No* responses				
	Very early	Early	Intermediate	Late	Very late
Near miss	56.7	63.8	71.5	72.8	80.8
Crash	27.1	34.4	43.1	53.4	65.8
Safe	24.9	25.7	16.4	17.5	11.2
Would you slow down?	% of *Yes, I would slow down* responses				
	Very early	Early	Intermediate	Late	Very late
Near miss	74.2	79.9	85.1	89.1	93.4
Crash	48.4	60.4	68.0	76.5	83.2
Safe	43.2	53.3	53.1	43.4	33.7
The situation was risky.	*Mean (1 = Strongly disagree; 7 = Strongly agree)*				
	Very early	Early	Intermediate	Late	Very late
Near miss	3.71	4.16	4.33	4.73	5.07
Crash	3.45	3.89	4.45	4.94	5.61
Safe	3.08	3.46	3.66	3.62	3.26

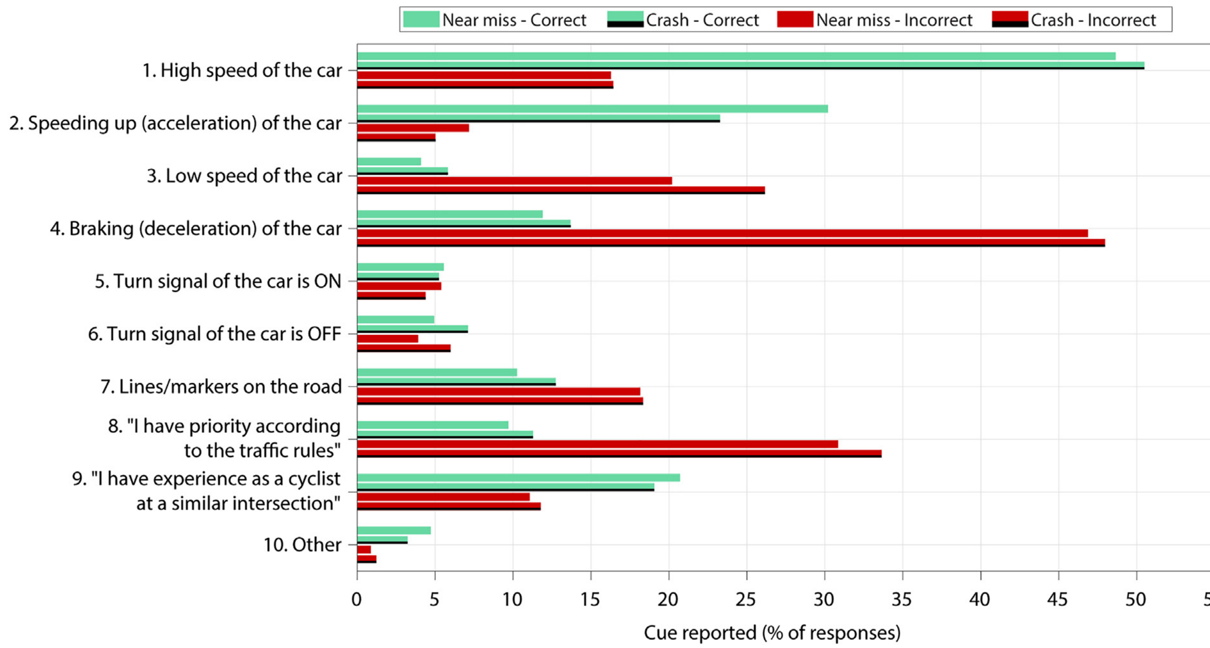

Fig. 3. Percentage of participants who reported bottom-up cues (cues 1–7) and top-down cues (cues 8 & 9) for correct (green) and incorrect (red) predictions of the car driver's behavior averaged across five clip freezing moments in near-miss and crash situations. Participants indicated their responses using a checkbox item "Which factors contributed to your prediction (of the driver's behavior)?" (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

of the two models ($p > .01$). The explained variance was higher for near-miss situations ($R^2 = 0.33$) than for crash situations ($R^2 = 0.25$).

3.3. Factors predicting self-reported cyclists' behavior

As can be seen in Table 5, participants were more likely to report to slow down when they correctly predicted the driver's behavior ($\rho = 0.25$ and $\rho = 0.19$ in near-miss and crash situations, respectively) and when they perceived higher risk ($\rho = 0.27$ and $\rho = 0.32$ in near-miss and crash situations, respectively). Age was positively correlated with slowing-down ($\rho = 0.06$ and $\rho = 0.10$ in near-miss and crash situations, respectively). Correlations between cycling experience (i.e., weekly cycling mileage and cycling frequency), on the one hand, and participants' slowing-down behavior, correctly predicting the driver's behavior, and perceived risk, on the other, were all non-significant ($p > .01$). Finally, self-reported accident involvement as a cyclist was not significantly associated with participant's slowing-down behavior, correctly predicting the driver's behavior, or perceived risk ($p > .01$).

The results of linear hierarchical regression analyses for predicting the cyclists' self-reported slowing-down behavior are shown in Table 6 (near-miss situations) and Table 7 (crash situations). At Step 1, only age was significantly associated with slowing-down ($\beta = 0.08$ and 0.09, for near-miss and crash situations, respectively). At Step 2, correctly predicting that the driver will not slow down contributed to the cyclists' slowing-down ($\beta = 0.25$ and 0.21 for near-miss and crash situations, respectively). At Step 3, perceived risk also contributed significantly to cyclists' slowing-down behavior in near-miss ($\beta = 0.25$) as well as in crash situations ($\beta = 0.32$). In near-miss situations, the relationship between the prediction of driver's behavior and cyclists'

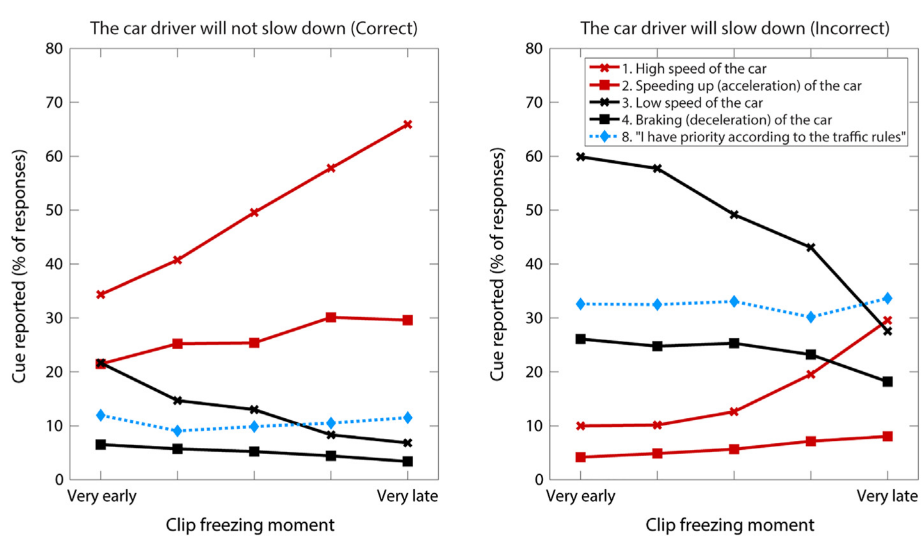

Fig. 4. Percentage of participants who reported a particular cue as a function of the clip freezing moment. Left: results for video clips where participants made a correct prediction about the car driver's behavior; Right: results for video clips where participants made an incorrect prediction about the car driver's behavior.

Table 4
Linear regression analysis for participants' correct predictions of the driver's behavior in near-miss and crash situations. Statistically significant predictors are shown in boldface.

Predictor (cue)[a]	Near-miss (4 situations)				Crash (5 situations)			
	B	*SE B*	β	*p*	*B*	*SE B*	β	*p*
(Constant)	62.667	2.362		<**0.001**	42.562	2.175		<**0.001**
1. High speed of the car	0.198	0.028	0.20	<**0.001**	0.245	0.030	0.24	<**0.001**
2. Speeding up (acceleration) of the car	0.278	0.030	0.25	<**0.001**	0.283	0.037	0.21	<**0.001**
3. Low speed of the car	−0.218	0.034	−0.19	<**0.001**	−0.151	0.030	−0.15	<**0.001**
4. Braking (deceleration) of the car	−0.239	0.048	−0.13	<**0.001**	−0.098	0.033	−0.08	**0.003**
5. Turn signals of the car are ON	−0.085	0.055	−0.04	0.123	0.032	0.058	0.02	0.584
6. Turn signals of the car are OFF	0.095	0.058	0.04	0.103	−0.027	0.045	−0.02	0.558
7. Lines/markers on the road	−0.011	0.036	−0.01	0.747	−0.045	0.032	−0.04	0.156
8. "I have priority according to the traffic rules"	−0.250	0.031	−0.22	<**0.001**	−0.167	0.025	−0.19	<**0.001**
9. "I have experience as a cyclist at a similar intersection"	0.168	0.028	0.16	<**0.001**	0.101	0.028	0.10	<**0.001**
10. Other	0.240	0.064	0.10	<**0.001**	0.185	0.077	0.07	**0.016**
R^2	0.33				0.25			
Adj. R^2	0.32				0.24			
F ($df1$, $df2$), p	49.97 (10, 1019), <**0.001**				33.27 (10, 1019), <**0.001**			

[a] Responses were averaged across the 4 near-miss situations, or across the 5 crash situations. The average scores per cue ranged from 0% to 100%, where 100% refers to always reporting the particular cue.

slowing-down remained essentially unchanged once perceived risk was entered into the model (β = 0.23). In crash situations, this relationship was reduced but remained statistically significant after controlling for perceived risk (β = 0.15).

Lastly, as shown in Fig. 5, participants' perceived risk increased as a function of time in the safety-critical situations (blue and black lines). For the (very) early freezing moments, participants perceived slightly higher risk in near-miss situations than in crash situations; the opposite effect was observed for the later three freezing moments (Table 3).

4. Discussion

The majority of bicycle–car collisions happen at intersections in urban areas (Schepers, Kroeze, Sweers, & Wüst, 2011; Wang & Nihan, 2004). So far, crash analyses have indicated that these collisions occur even when the cyclist must have seen the approaching car (Räsänen & Summala, 1998). In the present study, we examined how cyclists' hazard anticipation develops as a function of time in safety-critical intersection situations where a car on a collision course is already detected by the cyclist. Second, we investigated which bottom-up and top-down cues guide cyclists' predictions of car drivers' right-of-way violations. Lastly, we examined how predicting that the driver will not let the cyclist cross first, perceived risk, and cycling experience contribute to the cyclists' self-reported slowing-down behavior in near-miss and crash situations.

As expected, the accuracy of cyclists' prediction of whether a car driver will let the cyclist cross first developed as a function of video clip freezing moment, with the prediction being the most accurate when the cyclist was closest to the conflict point. Although the nine safety-critical situations differed from each other in terms of location, cyclist's approach speed, and visual features, participants showed similar patterns of correct predictions as a function of the freezing moment. Two situation-specific findings should be pointed out. First, differences in the accuracy of predicting the driver's right-of-way violation were observed between near-miss and crash situations, with overall higher accuracies in the near-miss situations. A plausible explanation for this finding is that, in near-miss situations, the car drove onto the cyclist's path relatively early; it could be therefore more obvious to the cyclist that the car driver would not let the cyclist cross first as compared to the crash situations. Second, participants showed poor accuracy in predicting the crash in Situation 1 as compared to the crashes in the other four situations. This difference can be attributed to features of the particular situation: the car driver in Situation 1 was driving slowly onto the bike path whereas drivers in the other four crash situations were driving fast while making a turn. This finding is congruent with Summala and Räsänen (2000), who observed that cyclists might interpret a low speed of a car as yielding behavior.

Participants reported various bottom-up and top-down cues when predicting drivers' behaviors. Overall, bottom-up cues were reported more often than top-down cues, suggesting that cyclists update their expectancies with perceptual features of the current situation. The

Table 5
Spearman rank-order correlations among background variables, crash involvement, prediction of the car driver's behavior, self-reported slowing-down behavior, and perceived risk.

		1	2	3	4	5	6	7	8	9	10	11
1	Gender (1 = female, 2 = male)	–										
2	Age (years)	−0.15***	–									
3	Weekly cycling mileage[a]	0.12***	−0.06*	–								
4	Cycling frequency[b]	0.02	−0.03	0.53***	–							
5	Accident involvement (#)	0.13***	−0.18***	0.15***	0.19***	–						
6	Accident with a motor vehicle at an intersection (0 = no, 1 = yes)	0.03	−0.13***	0.07*	0.04	0.38***	–					
7	Near miss: Correctly predicting the driver's behavior[c]	−0.02	0.03	−0.04	−0.04	−0.02	0.02	–				
8	Near miss: Cyclist's slowing-down[c]	0.01	0.06*	−0.05	−0.03	0.02	0.05	0.25***	–			
9	Near miss: Perceived risk[c]	0.04	0.12***	0.04	0.01	−0.05	0.01	0.08**	0.27***	–		
10	Crash: Correctly prediction the driver's behavior[d]	−0.02	−0.05	−0.03	−0.03	−0.02	0.01	0.38***	0.01	0.01	–	
11	Crash: Cyclist's slowing-down[d]	0.00	0.10**	−0.05	−0.06	0.03	0.04	−0.02	0.32***	0.07*	0.19***	–
12	Crash: Perceived risk[d]	0.13***	0.01	0.01	−0.04	0.03	0.06*	0.03	0.17***	0.54***	0.18***	0.32***

Samples size differed between 1016 and 1030 for the 66 pairs of variables listed. *$p < .05$, **$p < .01$, ***$p < .001$.
[a] Weekly cycling mileage in the summertime was indicated on a 10-point scale (from 1 = 0 km/mi to 10 = more than 201 km /more than 125 mi).
[b] Weekly cycling frequency in the summertime was indicated on a 6-point scale (from 1 = never to 6 = every day; participants who indicated never were excluded).
[c] Responses were averaged across the four near-miss situations.
[d] Responses were averaged across the five crash situations.

Table 6
Linear hierarchical regression analysis for predicting cyclists' self-reported slowing-down behavior in the near-miss situations. Statistically significant predictors are depicted in boldface.

Predictor	Near-miss (4 situations)							
	B	*SE B*	β	*p*	R^2	Adj. R^2	*F* (*df*1, *df*2)	*p*
Step 1					0.01	0.00	1.89 (4, 1011)	0.110
(Constant)	78.166	4.494		<**0.001**				
Gender (1 = female, 2 = male)	1.323	1.471	0.03	0.369				
Age (years)	0.167	0.067	0.08	**0.013**				
Weekly cycling mileage[a]	−0.324	0.406	−0.03	0.426				
Cycling frequency[b]	−0.116	0.748	−0.01	0.877				
Step 2					0.07	0.06	14.69 (5, 1010)	<**0.001**
(Constant)	65.361	4.636		<**0.001**				
Gender (1 = female, 2 = male)	1.375	1.426	0.03	0.335				
Age (years)	0.160	0.065	0.08	**0.014**				
Weekly cycling mileage[a]	−0.204	0.394	−0.02	0.605				
Cycling frequency[b]	−0.019	0.725	0.00	0.979				
Prediction of the driver's behavior[c]	0.175	0.022	0.25	<**0.001**				
Step 3					0.13	0.12	24.96 (6, 1009)	<**0.001**
(Constant)	50.321	4.824		<**0.001**				
Gender (1 = female, 2 = male)	0.757	1.381	0.02	0.584				
Age (years)	0.105	0.063	0.05	0.099				
Weekly cycling mileage[a]	−0.339	0.381	−0.03	0.375				
Cycling frequency[b]	0.047	0.701	0.00	0.947				
Prediction of the driver's behavior[c]	0.161	0.021	0.23	<**0.001**				
Perceived risk[d]	4.368	0.518	0.25	<**0.001**				

[a] Weekly cycling mileage in the summertime was indicated on a 10-point scale (from 1 = 0 km/mi to 10 = more than 201 km /more than 125 mi).
[b] Weekly cycling frequency in the summertime was indicated on a 6-point scale (from 1 = never to 6 = every day; participants who indicated never were excluded).
[c] The scores were averaged over the four near-miss situations and expressed on a scale from 0% to 100%, where 100% refers to perfect accuracy in predicting the driver's behavior (i.e., the car driver will not let the cyclist cross first).
[d] Perceived risk was indicated on a 7-point scale (from 1 = strongly disagree to 7 = strongly agree) and averaged over the four near-miss situations.

most frequently reported visual bottom-up cues that contributed to the cyclists' predictions were car speed and the car's acceleration/deceleration. There appear to be two groups of cyclists, those who interpreted the car's speed as high or that the car was accelerating and those who interpreted the speed as low or that the car was decelerating. Reporting that the car drives slowly or is decelerating was associated with failing to recognize that the car driver will not let the cyclist cross first. Regarding top-down cues, participants who followed the idea that they had right of way were more likely to predict incorrectly that the car driver will yield to them, a finding which is in line with Räsänen and Summala (1998).

Cyclists reported to slow down at overall higher percentages than they reported that the car driver would not let the cyclist cross first (Fig. 2). This difference suggests that besides hazard anticipation, there are other factors that made the cyclists want to slow down. As safety-critical situations involve some element of risk that individuals

Table 7
Linear hierarchical regression analysis for predicting cyclists' self-reported slowing-down behavior in the crash situations. Statistically significant predictors are depicted in boldface.

Predictor	Crash (5 situations)							
	B	*SE B*	β	*p*	R^2	Adj. R^2	*F* (*df*1, *df*2)	*p*
Step 1					0.01	0.01	3.36 (4, 1011)	**0.010**
(Constant)	62.798	5.256		<**0.001**				
Gender (1 = female, 2 = male)	1.845	1.721	0.03	0.284				
Age (years)	0.228	0.079	0.09	**0.004**				
Weekly cycling mileage[a]	−0.380	0.475	−0.03	0.424				
Cycling frequency[b]	−1.129	0.875	−0.05	0.197				
Step 2					0.06	0.05	12.39 (5, 1010)	<**0.001**
(Constant)	51.421	5.395		<**0.001**				
Gender (1 = female, 2 = male)	2.095	1.682	0.04	0.213				
Age (years)	0.261	0.077	0.10	**0.001**				
Weekly cycling mileage[a]	−0.292	0.465	−0.02	0.529				
Cycling frequency[b]	−1.060	0.855	−0.04	0.215				
Prediction of the driver's behavior[c]	0.207	0.030	0.21	<**0.001**				
Step 3					0.15	0.15	30.22 (6, 1009)	<**0.001**
(Constant)	24.982	5.694		<**0.001**				
Gender (1 = female, 2 = male)	−0.443	1.614	−0.01	0.784				
Age (years)	0.239	0.073	0.10	**0.001**				
Weekly cycling mileage[a]	−0.461	0.441	−0.04	0.296				
Cycling frequency[b]	−0.748	0.812	−0.03	0.357				
Prediction of the driver's behavior[c]	0.147	0.029	0.15	<**0.001**				
Perceived risk[d]	7.480	0.705	0.32	<**0.001**				

[a] Weekly cycling mileage in the summertime was indicated on a 10-point scale (from 1 = 0 km/mi to 10 = more than 201 km /more than 125 mi).
[b] Weekly cycling frequency in the summertime was indicated on a 6-point scale (from 1 = never to 6 = every day; participants who indicated never were excluded).
[c] The scores were averaged over the five crash situations and expressed on a scale from 0% to 100%, where 100% refers to perfect accuracy in predicting the driver's behavior (i.e., the car driver will not let the cyclist cross first).
[d] Perceived risk was indicated on a 7-point scale (from 1– strongly disagree to 7 – strongly agree) and averaged over the five crash situations.

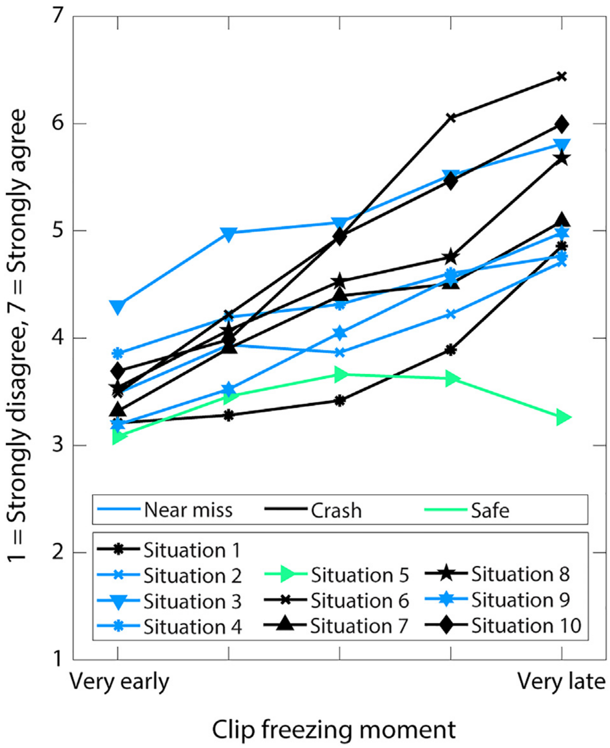

Fig. 5. Mean scores of perceived risk (item "The situation was risky.") as a function of intersection situation and clip freezing moment. The values of the markers are based on the responses of 189–213 participants.

might want to reduce (Näätänen & Summala, 1974), the subjectively perceived risk was investigated as a contributing factor to cyclists' slowing-down intentions. The results showed that a high level of perceived risk was a significant predictor of slowing-down behavior. The level of perceived risk was higher when the temporal proximity to the collision was smaller.

Cycling experience was not significantly associated with correctly predicting the driver's behavior, slowing-down, or perceived risk. Previous research showed that hazard detection skills can be improved through experience and training (e.g., Crundall et al., 2012; Horswill, 2016b), but little is known about the relationship between cycling experience and the ability to predict other road users' behaviors. It is possible that cycling experience is not a unique predictor, and that other types of experiences (e.g., driving, walking in traffic) as well as perceptual skills (e.g., speed estimation, interception skill) are predictive of whether one is able to anticipate what a car driver will do next.

The estimated time to stop based on the cyclist's speed in the video clips showed that the cyclist would have to initiate braking at, or before, the very early clip freezing moment to avoid a collision (Situations 1, 6–8, 10). Accordingly, more than half of the participants would get involved in the crash if they braked at the moment of the freeze. Even when taking into account that participants may cycle at lower speeds than the cyclists in the video clips (for example when using conventional bicycles), cyclists might not have been able to avoid these crashes (Table 2). More research should be conducted to examine under which conditions cyclists have sufficient time to avoid a potential collision, preferably using objective measures of cycling behavior.

Our study has several limitations. First, the video clips were taken in real traffic, which means that we had no control over the exact timing of the events. Further, participants were not actively in control of the bicycle and they could not influence the level of risk they were willing to take by cycling slower or faster (Näätänen & Summala, 1974). On the other hand, the ecological validity of the safety-critical situations can be considered a strength of this study. Second, the selection of intersection situations was dependent on the availability of publicly available video postings. Although the situations in the video clips capture a common crash scenario where a car driver fails to give way to an oncoming cyclist, the features of the intersection environment might not be representative for all kind of cyclists–car crashes. Third, the data collection was conducted online using self-reports. To address the main concern of online surveys that participants provide meaningless responses, stringent inclusion criteria were applied and quality control questions were included. Participants completed the survey on their own computers so that the field of view was smaller than in real cycling (see Pretto, Ogier, & Bulthoff, 2009, showing that a small field-of-view causes an underestimation of ego-speed). Furthermore, participants had different Internet connections that could influence the quality with which the video clips were played. Lastly, there was a large variety in the participants' countries of residence but the sample sizes from each country were too small to allow us to draw conclusions on cross-cultural differences in cyclists' hazard anticipation, slowing-down behavior, or perceived risk (see Supplementary material for the descriptive results).

5. Conclusions and practical applications

Crash analyses have shown that hazard anticipation is a contributing factor to bicycle–car collisions, but limited research exists on how cyclists anticipate drivers' right-of-way violations. Using video clips of safety-critical events, we demonstrated that cyclists' predictions of whether a car driver will yield to a cyclist or not develop as a function of time, being the most accurate temporary closest to the conflict. Participants who indicated that the car's speed or acceleration was high were more likely to correctly predict that the driver will not yield to the cyclist, whereas participants who thought that the car was driving slowly or decelerating often falsely believed that the car would let the cyclist cross first. Furthermore, participants who reported the right-of-way rule as a contributory factor to their predictions were more likely to incorrectly predict the driver's behavior at the intersection. Lastly, this study showed that correct predictions of the driver's behavior and high perceived risk are associated with self-reported slowing-down behavior.

One recommendation would be to address these issues in cycling training programs. For example, cyclists could be taught that if one sees a car slowing-down, it does not mean that the car will stop for you. Next, taking other road users' unsafe behaviors or errors (i.e., not seeing an oncoming cyclist and making a turn) into account and performing a forgiving reaction can be addressed in the training programs as an important traffic safety principle that can prevent crashes or limit injuries (SWOV, 2010). Furthermore, the road infrastructure could be redesigned so that cars do not have to brake in a way that is confusing for cyclists. Supporting cyclists' predictions by means of warning systems may represent a promising future application. Prototypes of cooperative cyclist–car applications have already been designed (Gustafsson, Muñoz, Lindgren, Boda, & Dozza, 2013; Segata, Vijeikis, & Cigno, 2017). Finally, it remains to be investigated to what extent the frequently reported cues contribute to cyclists' predictions in a real traffic environment, and to what extent cyclists are capable of avoiding a crash in situations where the driver has not seen the approaching cyclist.

Acknowledgments

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jsr.2019.01.002.

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