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# Reading cyclist intentions: can a lead cyclist's behaviour be predicted?

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**ABSTRACT**

As a cyclist, it is essential to make inferences about the intentions of other road users in order to anticipate their behaviour. There are official ways for cyclists to communicate their intentions to other road users, such as using their arms to point in the intended direction of travel. However, in everyday traffic cyclists often do not use such active forms of communication. Therefore, other visual cues have to be used to anticipate (critical) encounters or events. During this study, 108 participants completed a video internet survey in which they predicted the intentions of a lead cyclist based on visible behaviour preceding a turning manoeuvre. When the lead cyclist approached the intersection, each video was stopped just before the cyclist initiated turning. Based on visual cues, the participants had to select which direction they thought the cyclist would go. After entering their prediction, they were asked how certain they were about their prediction and on which visible behaviour(s) each prediction was based. The results show that it is very hard to predict the direction of a turning cyclist based on visual cues before the turning manoeuvre is initiated. Exploratory regression analyses revealed that observable behaviours such as head movements and cycling speed were related to prediction accuracy. These results may be used to support cyclists in traffic interactions.

**Keywords:** bicycling, intention, turning, prediction, survey, observation.

## 1 INTRODUCTION

Although the health benefits of cycling (Oja et al., 2011) and its positive effects on the environment are well-known, cyclists are very vulnerable in case of accidents. In the Netherlands, 32% of all fatal traffic accidents concerned cyclists (CBS, 2014). Non-fatal cycling accidents typically lead to injuries to the head, face or neck, traumatic brain injuries, spine and back injuries, damage to the torso and injuries to the upper- and lower extremities (Siman-Tov et al., 2012; Juhra et al., 2012; De Geus et al., 2012). Personal factors associated with accident involvement are age (Bíl et al., 2010; Boufous et al., 2012; Schepers, 2012; Siman-Tov et al., 2012; Kaplan et al., 2014; Martínez-Ruiz et al., 2014; Martínez-Ruiz et al., 2015), experience (Schepers, 2012; Poulos et al., 2015) and alcohol and drug use (Twisk and Reurings, 2013; Kaplan et al., 2014). Furthermore, environmental factors related to increased risk and injuries include sharing the road with motorised traffic (Kaplan et al., 2014), involvement of other road users (Heesch et al., 2011), high speed limits (Boufous et al., 2012; Kaplan et al., 2014), cycling in the dark (Boufous et al., 2012; Twisk and Reurings, 2013) slippery roads or paths (Kaplan et al., 2014), curves (Boufous et al., 2012) and poorly visible road elements (Schepers and Den Brinker, 2011). Cyclists are especially at risk in rural areas (Boufous et al., 2012), near intersections (Dozza and Werneke, 2014) and on designated cycling infrastructure (Schleinitz et al., 2015).

In the Netherlands, the majority of cycling accidents are cyclist-only accidents (Schepers, 2013), although conclusive statistical evidence is lacking due to an underreporting of bicycle crashes (Wegman et al., 2012; Schepers, 2013). Frequent types of cyclist-only accidents are a loss of balance, colliding with an obstacle, or entering the verge (Schepers and Klein Wolt, 2012). However, a considerable amount of cyclist-only accidents are preceded by interaction with another road user (Davidse et al., 2014a). For example, a cyclist misjudging the intentions of another cyclist can lead to a crash (Davidse et al., 2014a; Davidse et al., 2014b), suggesting a lack of situation awareness (Endsley, 1995). To limit or prevent these accidents, it is important that cyclists are aware of the presence of other road users and able to make accurate inferences about their intentions. The goal of this study is therefore to assess whether cyclists are indeed capable of predicting the intentions of other cyclists, or whether they would benefit from external support such as technical support systems.

### 1.2 Intentions, expectations and situation awareness

According to the Situation Awareness (SA) theory, one cannot reach its destination through traffic safely by merely perceiving the current state of the environment (Endsley, 1995). In order to prevent accidents, it is crucial to make inferences about oncoming events. SA is achieved in three levels, each describing a different step from perceiving individual elements (level 1), combining these into one holistic representation (level 2) to predicting oncoming events involving these elements (level 3) (Endsley, 1995).

Cyclists are supposed to use their arms to communicate their intention, as these cues are easily perceived by other road users (Walker, 2005). Informal signals of intention, such as maintaining a certain position on the road, trailing a foot, or seeking eye contact can be used for SA assessment level 1as well. Furthermore, car drivers may infer whether a cyclist will behave predictably from the cyclist's physical appearance, and adjust their overtaking accordingly (Walker, 2007). For example, Walker (2007) found that car drivers maintain a greater overtaking distance to cyclists who seem inexperienced, and therefore unpredictable (e.g. children), compared to cyclists who seem experienced. Directing the attention to the cyclists' face first might not always be possible nor be the most efficient strategy to assess their intentions, and it may result in a prolonged processing and reaction time (Walker and Brosnan, 2007). Car drivers respond more quickly and accurately when they expect a car in front to make a turn based on the indicator (Muhrer and Volrath, 2010). These are merely a few examples of different cues which can be used during SA assessment level 1 (Endsley, 1995). Apart from perceived behaviour by other road users, locational cues are used for predictions in traffic as well. For example, road users' expectation of the category of rural road they are facing is based on  how far apart both driving directions physically are (Stelling-Konczak et al., 2011). Martens and Fox (2007) found that the more familiar car drivers were with the location they were passing, the less they looked at relevant traffic signs.  However, these experiences can also have negative effects, as drivers tend not to look for signs at locations where they do not expect any, potentially leading to missing critical information (Borowsky et al., 2008).

During the second level of SA, all perceived and (rated as) relevant cues are combined into one holistic comprehension of the current situation (Endsley, 1995). Cognitive processing time is required to form this holistic image. The third level of SA assessment concerns making inferences about the future state of the current situation (Endsley, 1995). In other words: a car driver, cyclist or pedestrian (or any other) will predict the intentions of other traffic participants, in order to make a decision on how to anticipate and possibly evade a potential conflict. Therefore, correct expectations facilitate a quick response, but incorrect expectations are potentially hazardous. For example, an important factor leading to bicycle-car collisions is a cyclist having the incorrect expectation that a car driver will yield (Räsänen and Summala, 1998).

### 1.3 Cyclist intention prediction

In the current study it was assessed whether cyclists are able to predict the direction a preceding cyclist is going to choose, based on perceived informal signals (i.e. absence of the formal arm indication). As SA is not a continuous concept, it is the question whether cyclists are able to predict other cyclists' intention based on behaviour preceding the actual turning manoeuvre. Hemeren et al. (2014) found that the oncoming direction a cyclist will choose can be predicted by looking at the lateral position, head turns and speed, for two directions on a T section, i.e. cyclists going straight or turning left.

It was hypothesized that predictions for any intended direction of travel are more accurate than chance, in accordance to the results by Hemeren et al. (2014). As anticipating the intentions of other cyclists is essential, it was argued that models for driver behaviour might also (partially) explain cyclist behaviour. According to the Task-Capability Interface model, the amount of success for the prediction task depends on the cyclists' capability and the demands of the task (Fuller, 2011; Fuller et al., 2008). The cyclists' capability is determined by their physiological characteristics, cycling experience, cycling competence, and human factor variables (Fuller, 2011; Fuller et al., 2008). The current physical environment, behaviour of other road users, properties of the bicycle and current cycling speed contribute to the overall task demand (Fuller, 2011; Fuller et al., 2008). The second hypothesis was that experienced cyclists are better able to predict the intentions of other cyclists than less experienced cyclists.

## 2 METHOD

An online survey was created using Qualtrics, in which 24 trials were presented in which participants were asked to predict the oncoming turn of a cyclist, based on a video made in real traffic from the perspective of a cyclist. All questions were asked in Dutch. All participants were offered a financial compensation by using a lottery system: among all submissions, two gift vouchers (€15 value) were randomly allotted. This study has been approved by The Ethical Committee of Psychology, University of Groningen.

### 2.1 Participants

A total of 158 participants started the survey, of which 108 answered all questions (68% completion rate). The mean age of all participants was 39.7 years (SD: 16.0), 63% were female and the majority was living in the Netherlands (N = 104). A small number came from Germany (N = 4). The most used type of bicycle was the regular bicycle (N = 87), followed by the electric bicycle (N = 11) and the touring bicycle (N = 6). A racing bicycle, a mountain bike, a carrier cycle and a fixed gear bicycle were used by one participant each.

### 2.2 Design

The study was designed as a within subjects questionnaire containing 24 trials, in which the independent variable was defined as the correct direction of travel of a lead cyclist (three levels: left, straight and right directions) and the three dependent variables were defined as prediction correctness, prediction certainty and selected cues on which each prediction was based.

## 2.3 Materials

A total of 24 video stimuli trials were created, plus one practice trial. These video stimuli consisted of video fragments recorded using a Contour+2™ digital action camera with GPS, mounted on the front of a bicycle. The camera was set at 720p quality video settings (170° range of vision). The videos were recorded in real traffic; cyclists were followed until they reached a crossing and either turned left, right, or continued cycling straight on. The filmed cyclists were recorded inconspicuously and were unaware of the fact that they were being recorded, not to influence their cycling behaviour in terms of (over)acting. On four locations in the city of Groningen, footage was selected where cyclists did not use their arms to show their intentions to other road users. Furthermore, care was taken that the filmed cyclists did not have to give right of way to other road users and that no cars were present during the turning manoeuvre. Additional selections based on cue presence were not performed, as these would bias the availability of cues against real life. During filming, an estimated following distance of 4-8 metres was attained between the filming and the filmed cyclist. Three trials were filmed on a cycle path and contained two choice options (either left or right; location 1), and 21 trials were filmed on roads shared with motorised traffic, and contained three choice options (left, straight or right; locations 2, 3 and 4, respectively).

Following the recording and selection phase, the individual trials were created using Adobe Premiere Pro CS6. Per trial, each video had a total duration of 16 seconds, in which the first four seconds contained a frozen starting image in which a 3 second countdown timer was initiated, in order for the participants to shortly grasp the overall situation. After the countdown, each video was played for 10 seconds after which the image froze again, shortly before the cyclist initiated the turning manoeuvre (see figure 1). After freezing, the static image remained visible for two seconds after which it completely disappeared and the overall video screen turned black. This way, each participant had the same amount of visual information available to make a prediction. For practical reasons, the black screen remained in place for 44 seconds: this gave the impression the video had completely stopped, even though the video automatically would restart after these 44 seconds due to an ‘auto start’ feature of the video in the trials that could not be disabled. For this reason, the prediction submission time for each trial was recorded and only submission times below 60 seconds were included to ensure that each video had been seen once only, as the participants had no control over the video and they were not able to restart them manually.


*Figure 1: Two examples of the questionnaire’s video trials. First, a frozen image was shown and a 3-second countdown timer was initiated (left picture). Subsequently, a 10 second cycling video clip was played, until it was frozen again on the moment the cyclist starts to steer into a direction (right picture). After two seconds of freezing in front of the crossing, the entire image went black. For cyclists going straight on, similar distances from the crossings as cyclists who did turn into a direction were used to freeze the videos.*

**2.4 Procedure**

The participants were mainly recruited via word of mouth through the (informal) network of the researchers. After participants showed an interest, they were given an internet link (URL) to start the survey. Participants were asked not to spread the link to the study on the internet or social media. Upon loading the URL, instructions were given concerning the goal of the study (are you able to predict the upcoming turn of a lead cyclist?) and participants were informed that they automatically gave their informed consent if they chose to proceed to the actual start of the survey.

2.4.1. Personal details

After opening the survey, participants were asked to provide personal details such as age, gender, home country, average weekly cycling distance and their most frequently used type of bicycle. Mainly cycling experience was used as an indication of cyclist competence (Fuller, 2011; Fuller et al., 2008). The last question enquired about to what extent the participants were familiar with the city of Groningen. This question was asked in order to distinguish between participants who may recognise the traffic situations from real life and those who were not familiar with these particular locations. It was argued that participants who pass these locations regularly might make inferences about other cyclists' intentions, based on normal traffic flow or common destinations nearby. This could influence their perceived chance of cyclists making a certain turn.

2.4.2. Trials

After completing the personal details questions, the experimental trials were introduced. The first trial was a practice trial, which contained explanations on how the videos were shown and how the questions could be submitted. The remaining 24 trials were presented after the instructions and practice trial were completed. The first question in each trial involved the expected intended direction of travel, in other words: which direction would the cyclist choose after the video had stopped. After submitting an answer to this question, the participants were asked to provide additional information on their prediction. First, they were asked to report how certain they were about their prediction on a 7-point Likert scale, ranging from "completely uncertain" to "100% certain". Second, they were asked about significant factors or behaviour that contributed to their prediction. These factors were mainly related to 'task demand', according to the Task-Capability Interface model (Fuller, 2011; Fuller et al, 2008). Five factors were already presented for each trial, of which the first four were 'position on the road', 'speed', 'head movements', and 'change in speed', identical to the factors used in the study by Hemeren et al. (2014). However, for the fifth factor presented in this study the researchers chose to present 'body posture' as a broader term for the factors 'leaning' and 'pedalling' by Hemeren et al. (2014). Lastly, there were three empty text fields available per trial for the participants to fill in other factors, not covered by any of the presented options.

2.4.3. End of questionnaire

After completing all trials, the participants were asked how well they knew the locations that were used to film the trials on a seven-point Likert scale. They were also given the opportunity to provide their e-mail address if they wished to be informed about the study results, and/or to sign up for the lottery prize.

### 2.5 Statistical analyses

Basic data processing and explorative statistical analyses were performed using IBM SPSS Statistics 22 for Windows. MLwiN v.2.33 for Windows (Rasbash et al., 2015a) was used to compute Odds Ratios and Multilevel Models (Rasbash et al., 2015b) in which the observed factors were included. Additionally, post hoc content analyses were performed for all trials.

## 3 RESULTS

The survey was open for participation during six weeks, after being launched on January 12th 2015. The majority of the participants rated themselves as being familiar with the city of Groningen (M = 4.42, SD = 2) on a 7 point Likert scale. However, after exploring the values for each location, the participants were strongly divided into two groups, namely participants who knew the individual locations either hardly, or very well. As expected, the overall best known location was Location 1, as this was the at the city's main railway station.

### 3.1 Prediction success

To assess whether the participants were able to correctly predict the direction being chosen by the cyclists in the videos, the trials were divided according to their level of chance. As for Location 1, the amount of possible directions was limited to turning either left or right (50% chance), this location was analysed separately. Out of all 2592 responses, 41 were rejected as these exceeded the maximum submission time. The remaining mean response time for the trials was 6.5 seconds (SD = 6) after the stimuli ended and the screen turned black.

For Location 1, a total of 44% of all trials were predicted correctly, which was not significantly different from 50% chance level (T (df = 2) = -0.760, NS). However, out of the three-choice trials for the remaining locations, 49.4% were predicted correctly, which is significantly above 33% chance level (T (df = 20) = 2.932, p = 0.008). For these three-choice trials, the overall results per direction are displayed in Table 1.

*Table 1. Overall results per correct cyclist direction, for the three-choice trials. The rows represent the reactions given by the participants (the predictions), the columns represent the true direction the cyclist went. The bold printed counts are correct predictions (hits).*

| | | True direction (trial) | | | |
|---|---|---|---|---|---|
| Response direction (prediction) | | Left | Straight | Right | Total |
| Left | Count | **314** | 81 | 113 | 508 |
| | Expected Count | 169.0 | 145.5 | 193.5 | 508 |
| | % hits(left)/misses (straight, right) within predictions | **61.8%** | 15.9% | 22.2% | 100% |
| | % hits/misses for true direction | **42.3%** | 12.7% | 13.3% | 22.7% |
| Straight | Count | 284 | **465** | 410 | 1159 |
| | Expected Count | 385.5 | 332.0 | 441.5 | 1159 |
| | % hits (straight)/misses (left, right)within predictions | 24.5% | **40.1%** | 35.4% | 100% |
| | % hits/misses for true direction | 38.2% | **72.7%** | 48.2% | 51.9% |
| Right | Count | 145 | 94 | **328** | 567 |
| | Expected Count | 188.6 | 162.4 | 216.0 | 567 |
| | % hits (right)/misses(left, straight) within predictions | 25.6% | 16.6% | **57.8%** | 100% |
| | % hits/misses for true direction | 19.5% | 14.7% | **38.5%** | 25.4% |

First, it should be noted that on trial level the predictions for the trials in which cyclists turned left (T (df = 6) = 0.896, p = NS) as well as right (T (df = 7) = 0.686, p = NS) did not differ from chance level, as 42.3% and 38.5% of the trials were correctly predicted. However, 72.5% of the trials containing cyclists going straight were predicted correctly, which is above chance (T (df = 5) = 7.232, p = 0.001). Odds ratios were computed using the true direction as predictor variable for prediction success (see table 2).

*Table 2. Overall results per true cyclist direction, for the three-choice trials. The true directions left or right were included as predictors, using 'straight' as reference.*

| Predictor: True Direction | β | S.E. | Z=β/S.E. | $e^{\beta}$ |
|---|---|---|---|---|
| Constant | 0.977 | 0.089 | | 1 |
| Left | -1.286 | 0.116 | -11.09 | 0.28 |
| Right | -1.444 | 0.113 | -12.78 | 0.24 |

Considering the percentages and odds ratios presented in Table 2, it can be concluded that a correct prediction is unlikely when the cyclist is going to make a turn, compared to when the cyclist goes straight on, based on visual cues before an actual turning manoeuvre is initiated. Predicting either direction of a turning cyclist is equally hard, as a Wald Test showed no significant differences between left or right turning cyclists ($\chi^2$ (1) = 2.279, p = NS). However, there are indications for a bias towards selecting the category "straight" as the amount of given predictions for this direction are relatively high (51.9%), compared to the other directions (22.7% for left and 25.4% for right, respectively). Therefore, the resulting values concerning prediction success for 'cyclist going straight' should be interpreted with care, as one could argue that these predictions are an indication of perceived absence of salient cues to infer that a cyclist is going to make a turn. This could effectively result in this category being treated as a forced choice residual category as well, as one could say that if a cyclist is not going to make a turn, he or she will presumably continue cycling straight. Of all participants who predicted that the cyclist was going to make a turn, 60% of these predictions were correct (61.9% and 57.9% correct for left and right predictions, respectively). For all predictions that the cyclist was going straight, 40.1% were correct. Odds ratios were computed, although for this equation the responded directions (participants' predictions) were used as predictor variable as a measure of prediction accuracy (see Table 3). Considering these odds ratios, it is more likely that a prediction is correct if the performed prediction is a turn, as opposed to continuing straight on. A Wald Test yielded no significant differences between response directions left or right ($\chi^2$ (1) = 1.748, p = NS). However, it should be kept in mind that the overall prediction success for making a turn was not above chance level.

*Table 3. Overall results per responded prediction, for the three-choice trials. The responded predictions left or right were included as predictors, using 'straight' as reference.*

| Predictor: Response Direction | β | S.E. | Z=β/S.E. | $e^{\beta}$ |
|---|---|---|---|---|
| Constant | -0.400 | 0.060 | | 1 |
| Left | 0.882 | 0.109 | 8.09 | 2.42 |
| Right | 0.717 | 0.104 | 6.89 | 2.05 |

**3.2 Predictive factors**

As all participants were free to choose any factor they felt of importance for their predictions, there was no limit in selecting factors. As a consequence, several participants selected all of the five presented factors they could choose, which resulted in high inter-correlations between subjective predictive behaviour(s). In essence, selecting all factors also meant that the participants took all possible factors into account for all possible trials and manoeuvres, and did therefore not make any specific choice during the study. This could have been due to not having understood the instructions properly, however, the exact reason cannot be assessed in hindsight. Therefore, to limit multicollinearity and to create more reliable estimations, a conservative approach was used in order to prevent statistical inflation of factor relevance. For this reason, the nine participants who selected all five factors on all 21 trials were rejected from this analysis.

<u>3.2.1. True direction 1: cyclist turning left</u>

In Figure 2, the proportions of all selected factors per trial in which the cyclist would turn left (true direction) are displayed. For all trials in which the cyclist turns left, 52% of all correct predictions were justified by taking head movements into account, which was significantly different from all incorrect predictions, as 16% of the participants who gave incorrect predictions took 'head movements' into account ($T(671) = 10.8$, $p = < 0.001$). Therefore, it seems that taking head movements into account increases the chance of making a right prediction, when a cyclist is going to turn left. This also seems to be the case for the factor ‘change in speed’, as the group that made correct predictions based their decision significantly more often on this factor compared to the group that made incorrect predictions (T (671) = 4.04, $p < 0.001$). However, relatively more incorrect predictions were made when the factor ‘speed’ was taken into account, compared to the group that made correct predictions (T (671) = -7.4, $p < 0.001$).

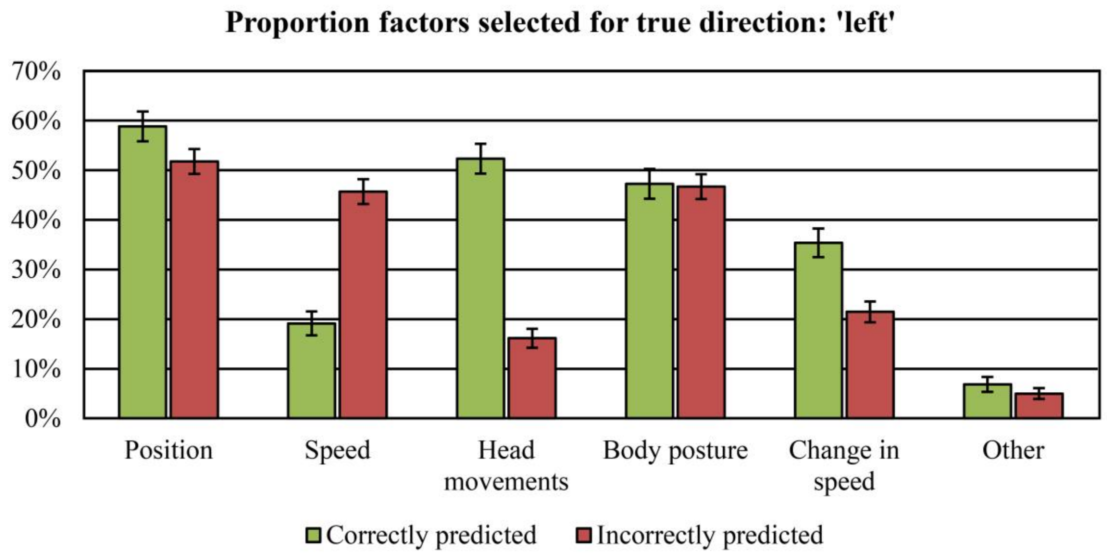


*Figure 2: The proportion of factors selected by the participants for all trials in which the cyclist would turn left (true direction). The error bars represent the standard error of the mean.*

3.2.2. True direction 2: cyclist going straight

The proportions of all selected factors per trial in which the cyclist would go straight (true direction) are displayed in Figure 3. As opposed to turning left, taking the speed of a cyclist into account seems to be the only factor positively related to prediction success for a cyclist going straight, as more correct predictions were based on speed compared to incorrect predictions (T (579) = 10.14, $p < 0.001$). Remaining factors such as head movements (T (579) = -3.36, $p < 0.001$), body posture (T (579) = -2.47, $p < 0.014$) and a change in speed (T (579) = -4.75, p <

0.001) were selected more often in incorrect predictions, compared to correct predictions. No differences in prediction success were found for the factor position on the road.

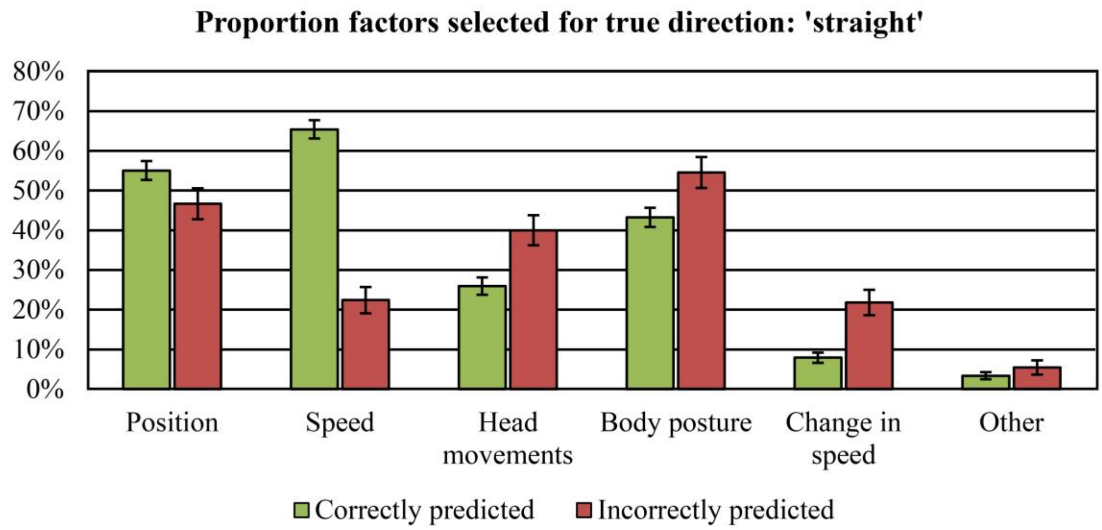


*Figure 3: The proportion of factors selected by the participants for all trials in which the cyclist would go straight on (true direction). The error bars represent the standard error of the mean.*

<u>3.2.3. True direction 3: cyclist turning right</u>

Lastly, the proportions of all selected factors per trial in which the cyclist would turn right (true direction) are displayed in Figure 4. For this direction, speed seems negatively related to prediction success ($T(769) = -5.795$, $p < 0.001$) when a cyclist is turning right. Changes in speed seem positively related to prediction success, however ($T(769) = 5.19$, $p < 0.001$).

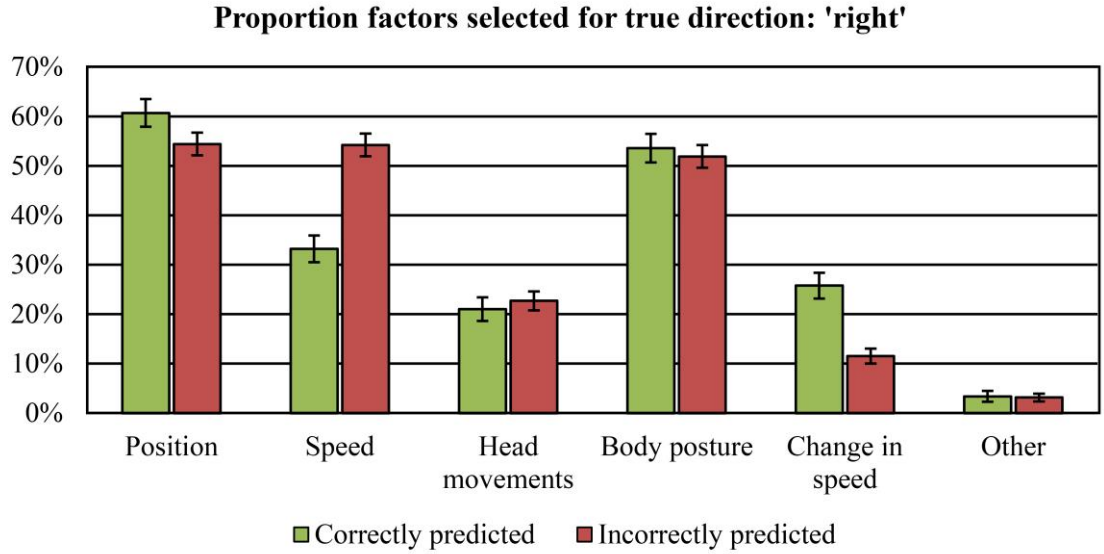


*Figure 4: The proportion of factors selected by the participants for all trials in which the cyclist would turn right (true direction). The error bars represent the standard error of the mean.*

### 3.3 Multilevel Logistic Regression Model

As during the exploring phase it was found that for each direction different predictors seemed either positively or negatively related to prediction success, three different multilevel models were designed using MLWiN (Rasbash et al., 2015a). Goal was to explore the role of all different variables assessed during the survey, for each direction. The trials were treated as a level 1 variable, which were technically nested within the participants group (level 2), as all participants answered all items (Rasbash et al., 2015a). These models and their corresponding predictors are presented in Table 4. For each predictor Wald Tests were performed to assess significance.

For all three trial directions, certainty is a significant predictor for response success (see Table 4). However, the most predictive impact is gained by the selection of speed and head movements. Remarkable, however, is that detecting a certain speed only has a positive influence on predictive accuracy when the cyclist continues cycling forward ($\beta$ = 1.687, p = <0.001). If the cyclist makes a turn (in either direction), the $\beta$ values for speed as a predictor for turning left ($\beta$

= -1.244, p = <0.001) or right (β = -0.816, p = <0.001) are both negative, decreasing the probabilities for making correct predictions. The opposite is found for the factor head movements, as the detection of head movements is only a significant positive predictor when the cyclist makes a left turn (β = 1.551, p = <0.001), and is negatively related to prediction accuracy for lead cyclists going straight on (β = -0.593, p = <0.009). Head movements did not have any predictive value for cyclists turning to the right in the corresponding model. The detection of a change in speed is a significant predictor that the lead cyclist will make a turn to the right (β = 0.838, p = <0.001), however. Lastly, the factor 'body posture' was only a negative predictor for the lead cyclist going straight on (β = -0.495, p = 0.028). The remaining factors such as participant age, gender, cycling experience, observed position on the road and other factors did not have any predictive value for any direction in the models.

*Table 4. An overview of all predictors included in separate logistic regression models for each direction of travel. All significant predictors (Beta values) are printed in bold.*

| True direction | Left | | | Straight | | | Right | | |
|---|---|---|---|---|---|---|---|---|---|
| Predictor | β | S.E. | p | β | S.E. | p | β | S.E. | p |
| Constant (i) | **-1.781** | **0.499** | **<0.001** | 0.427 | 0.521 | NS | -0.556 | 0.393 | NS |
| Constant (j) | 0.166 | 0.138 | NS | 0.000 | 0.000 | NS | 0.004 | 0.084 | NS |
| Certainty | **0.257** | **0.059** | **<0.001** | **0.258** | **0.069** | **<0.001** | **0.114** | **0.051** | **0.024** |
| Familiarity | 0.061 | 0.042 | NS | -0.073 | 0.045 | NS | 0.003 | 0.033 | NS |
| Age | 0.000 | 0.007 | NS | -0.012 | 0.007 | NS | -0.006 | 0.005 | NS |
| Gender | -0.272 | 0.224 | NS | -0.092 | 0.235 | NS | 0.014 | 0.174 | NS |
| Experience | 0.002 | 0.002 | NS | -0.000 | 0.002 | NS | -0.001 | 0.001 | NS |
| Position | 0.189 | 0.191 | NS | 0.209 | 0.211 | NS | 0.169 | 0.161 | NS |
| Speed | **-1.244** | **0.216** | **<0.001** | **1.687** | **0.225** | **<0.001** | **-0.816** | **0.164** | **<0.001** |
| Head | **1.551** | **0.205** | **<0.001** | **-0.593** | **0.228** | **0.009** | -0.188 | 0.193 | NS |
| Body Posture | -0.203 | 0.199 | NS | **-0.495** | **0.225** | **0.028** | -0.018 | 0.164 | NS |
| Speed Diff. | 0.326 | 0.209 | NS | -0.511 | 0.295 | NS | **0.838** | **0.209** | **<0.001** |
| Other | 0.469 | 0.388 | NS | -0.508 | 0.498 | NS | 0.033 | 0.436 | NS |
| | N=666 | | | N=575 | | | N=764 | | |

### 3.4. Post hoc trial content analyses

As no prior selection was performed on cue availability, post hoc content analyses were performed concerning the availability of the preselected factors (position, speed, head movements, body posture and changes in speed). Lateral position was measured in Kinovea™ for Windows™. For each measurement, a perspective grid was placed over the road or path which divided it in 16 equally sized sections. Two samples were scored, one at the start and one at the end of the video. A shift in position was calculated by subtracting the beginning position from the ending position. Average speeds were calculated by measuring the distance between start- and ending points in Google™ Earth, and dividing this by the total duration of the moving video. Speed change, head movements and body posture adjustments were scored visually. The results of the analyses are depicted in Table 5,6 and 7.

*Table 5. Content analyses for all trials in which true direction = left. Lower lateral position value = to the right. Values for speed change are as follows: -1 = decelerating, 0 = constant speed, +1 = accelerating.*

| Trial | Lateral position | | | Speed | | Head movements | | Body posture | |
|---|---|---|---|---|---|---|---|---|---|
| | Start | End | Shift | Mean | Change | Left | Right | Freq. | *Movement* |
| 3 | 4 | 3 | -1 | 15 | -1 | 1 | 0 | 1 | *BR, SP* |
| 9 | 2 | 4 | +2 | 19 | 0 | 2 | 1 | 1 | *RH* |
| 10 | 2 | 2 | 0 | 17 | 0 | 1 | 0 | 2 | *LF, BL* |
| 11 | 4 | 2 | -2 | 21 | -1 | 1 | 1 | 1 | *SP* |
| 15 | 5 | 4 | -1 | 13 | -1 | 1 | 0 | 0 | |
| 16 | 5 | 8 | +3 | 14 | 0 | 1 | 1 | 1 | *LH* |
| 22 | 8 | 4 | -4 | 20 | 0 | 0 | 0 | 0 | |
| M | 4.3 | 3.9 | -0.4 | 16.8 | -0.43 | 1 | 0.43 | 0.86 | |

*BR = Brakes*
*SP = Stops pedalling*
*RH = Right hand off handlebar*
*LF = Leans Forward*
*BL = Balance loss (shortly)*
*LH = Left hand off handlebar*

*Table 6. Content analyses for all trials in which true direction = straight. Lower lateral position value = to the right. Values for speed change are as follows: -1 = decelerating, 0 = constant speed, +1 = accelerating.*

| Trial | Lateral position | | | Speed | | Head movements | | Body posture | |
|---|---|---|---|---|---|---|---|---|---|
| | Start | End | Shift | Mean | Change | Left | Right | Freq. | *Movement* |
| 4 | 4 | 2 | -2 | 19 | 0 | 0 | 0 | 1 | *SP* |
| 7 | 6 | 4 | -2 | 16 | 0 | 0 | 0 | 0 | |
| 12 | 1 | 2 | +1 | 15 | 0 | 0 | 0 | 2 | *LH, RH* |
| 13 | 2 | 3 | +1 | 19 | 0 | 0 | 0 | 1 | *RH* |
| 17 | 3 | 3 | 0 | 13 | -1 | 0 | 0 | 0 | |
| 23 | 3 | 3 | 0 | 13 | 0 | 2 | 2 | 0 | |
| M | 3.2 | 2.8 | -0.3 | 15.9 | -0.17 | 0.33 | 0.33 | 0.67 | |

*SP = Stops pedalling*
*LH = Left hand off handlebar*
*RH = Right hand off handlebar*

*Table 7. Content analyses for all trials in which true direction = right. Lower lateral position value = to the right. Values for speed change are as follows: -1 = decelerating, 0 = constant speed, +1 = accelerating.*

| Trial | Lateral position | | | Speed | | Head movements | | Body posture | |
|---|---|---|---|---|---|---|---|---|---|
| | Start | End | Shift | Mean | Change | Left | Right | Freq. | *Movement* |
| 5 | 3 | 4 | +1 | 15 | 0 | 0 | 0 | 0 | |
| 6 | 5 | 2 | -3 | 16 | 0 | 0 | 1 | 0 | |
| 8 | 3 | 3 | 0 | 17 | 0 | 1 | 0 | 0 | |
| 14 | 7 | 4 | -3 | 19 | -1 | 0 | 0 | 2 | *SP, RH* |
| 18 | 5 | 5 | 0 | 14 | 0 | 0 | 0 | 0 | |
| 19 | 5 | 1 | -4 | 16 | 0 | 0 | 1 | 0 | |
| 20 | 4 | 3 | -1 | 15 | 0 | 0 | 0 | 0 | |
| 24 | 2 | 2 | 0 | 18 | 0 | 1 | 0 | 0 | |
| M | 4.3 | 3.0 | -1.3 | 16.5 | -0.13 | 0.25 | 0.25 | 0.25 | |

*SP = Stops pedalling*
*RH = Right hand off handlebar*

There were no large differences between cyclists turning left or right on mean lateral position, however, cyclists going straight seem to be positioned slightly more to the right compared to turning cyclists. Furthermore, an overall slight trajectory shift towards the right was observed for cyclists who were about to make a right turn. The average speed for cyclists were observably different between clips. Overall, the cyclists most frequently showed head movements when they were about to turn left, and these were more often head movements to the left than to the right. Cyclists also performed most body posture adjustments when they were about to turn left, compared to the other conditions.

# 4 DISCUSSION

## 4.1 Prediction success

In a real traffic situation, cyclists have to make inferences about the expected future behaviour of other cyclists in order to prevent conflicts. To form these predictions and act accordingly, cyclists first have to perceive all relevant cues and create one holistic image of the current situation, according to the first two levels of the situation awareness theory (Endsley, 1995). During this study, participants predicted the potential manoeuvres of a lead cyclist approaching an intersection based on video clips.

The intended directions of lead cyclists were predicted more accurately than on chance level when the cyclist was going straight, i.e. not making a turn. In case the cyclist would make either a left or right turn, the average prediction scores were not significantly above chance level. Therefore it is concluded that cyclists cannot predict that a cyclist ahead is going to make a turn *before a cyclist actually starts a turning manoeuvre*, and are therefore most likely to predict that a cyclist is continuing to cycle straight on and is not going to alter its course. Nevertheless, the high percentage of correct predictions for those cases in which cyclists went straight do reveal that the expectation that a cyclist will go straight are more often correct than on chance level.

However, after perceiving certain cues, cyclists do seem able to predict the direction a lead cyclist is going to choose more accurately. Within the given predictions, it was found that 60% of all predictions that a cyclist would make a turn, were correct. There were no differences found between prediction accuracy for all left or right responses. Furthermore, 40% of the predictions that a cyclist would go straight were correct, which is above chance.

To assess whether certain observable behaviours contribute to making a correct prediction of which direction the leading cyclist will take, three multilevel models were created in which several predictors were analysed. For each direction, trial certainty was related to prediction success. For a cyclist turning left, cyclist speed and head movements were predictors for prediction success, although taking speed into account negatively influenced a correct prediction. For a cyclist going straight, cycling speed was a significant factor which positively contributed to prediction success, as opposed to head movements and body posture, which negatively contributed to the prediction being correct. For a cyclist turning right, the results were ambiguous, as the speed negatively contributed to a correct prediction and a change in speed contributed positively. In summary: if a high cyclist speed is detected, it is more likely that the cyclist will continue straight and less likely that he or she will make a turn. If head movements are detected, it is more likely that the lead cyclist will make a left turn and less likely to continue cycling forward. Overall, it can be concluded that mainly perceived speed and head movements potentially can contribute to all three levels of situation awareness sufficiently, in order to make inferences about a future turn of a lead cyclists (SA level three) (Endsley, 1995). However, these findings are indicative, as the resulting Beta values are related to prediction success, no causal relationship between these variables can be inferred. Participant characteristics, including age, gender and cycling experience, did not add predictive value to any of the models.

## 4.2 Strengths and weaknesses of the research

### 4.2.1. Computer based survey

As with every study, there are several strengths and limitations worthy of mentioning. The first issue concerns the use of an open access internet survey protocol, as anyone with internet access could have participated and influenced the results. However, as the participants were mainly recruited by word of mouth, they were asked not to spread the link on the internet or social media. Furthermore, additional information to classify cyclists (Dill and McNeil, 2013) was not assessed, which limits the insights in the cyclist sample characteristics. Lastly, as the survey was performed online in its entirety, it was not possible to fully standardize the environment. Although it was recommended to perform the survey on a computer and not on a smartphone or tablet, different devices, screen sizes or even viewing distances from the screen could have influenced perception, and thus the results. Also, participants had more time to give their prediction compared to real traffic, as the mean response time was 6.5 seconds. This may influence the generalizability to real world situations.

#### 4.2.2. Trial content

There were some limitations resulting from the selection and design of the trials. The first limitation concerns location of the recordings. As the main scope of the study was to assess whether cyclists are able to predict the intentions of another cyclist in real traffic, trials were randomly recorded in real traffic in the city of Groningen. Therefore, all cyclists and locations filmed for the trials were sampled within the specific cycling infrastructure and culture of the Netherlands, potentially limiting generalizability to other countries. However, as the three locations used in the analyses were roads shared with motorised traffic, the influence of specific cycle path layouts was limited. Furthermore, no motorised traffic was present at the moments the cyclists were about to make their turns. Another limitation originates from the contents of the trial videos. As all trials were taken from real traffic, no a priori selection was performed to assess whether certain cues were available or visible, as any prior selection based on cue availability would undermine the naturalistic basis of the study and would not represent real traffic. Post hoc content analyses revealed that there were indeed differences in cue availability between trials, and this may have influenced the results overall to a limited extent.

For every video clip the moment of freezing was carefully selected by watching each one using a very slow playback speed. However, it cannot be ruled out that the selection of these moments were influential on the perceived predictability for each trial. This approach was used, however, as one could reason that a prediction by definition has to take place before the *actual* manoeuvre is initiated, as it would otherwise have been a test of observing movements. Additionally, during the recording of the trials, the researchers carefully tried to maintain a consistent constant following distance to the filmed cyclist ahead. However, the following distances were still variable and therefore these distances were not standardized to a high degree. This could have made certain cues such as body movements more or less visible as well.

#### 4.2.3. Naturalistic content

Many of the above mentioned study limitations are due to the fact that all trials were recorded in real traffic, partly resulting in a lack of standardization and limited influence on the content of the trials. At the same time this is a major strength of the study as the ecological validity of the real world situations from the cyclists' perspective, and the random presentation of 24 trials to a 100+ sample of participants, resulted in a highly suitable combination of ecological valid trials and digital measurement accuracy. Moreover, as the content analyses revealed that there were differences between stimuli, any selection of clips based on cue appearance would have influenced the naturalistic content and was therefore not performed.

### 4.3 Contribution to the knowledge and to the theory in the field

The findings of the current study contradict previous findings by Hemeren et al. (2014), who indicated that observers were relatively good at predicting that cyclists would either turn left (78%) or go straight (75%). The difference between the study by Hemeren et al. (2014) and the current study is the recording perspective, as the video stimuli used by Hemeren et al. (2014) were recorded from a fixed perspective 6 meters high and 20 metres away from the crossing. Therefore, it could be that participants are more accurate at predicting the intentions of a cyclist when they observe them from a "helicopter view", compared to the perspective of a cyclist in real traffic. This has clear implications for the relevance of studying intention prediction in ecologically valid settings, as the perspective of a cyclist is the actual perspective in which the predictions have to take place.

### 4.4 Practical implications of the results

As in this study it is concluded that making inferences concerning future turns of lead cyclists are difficult, it remains important to explicitly communicate intentions while cycling in traffic. Therefore, it is essential to use cues which are easy to interpret, for example by pointing in the intended direction of movement by using the arms (Walker, 2005) and to do this sufficiently early, i.e. before a turn is initiated. As the cues related to prediction success have to be considered exploratory, more research has to be performed to find out which cues are actually performed in real life cycling traffic, and whether these cues are sufficiently visible to be perceived and used by other cyclists (or road users) for assessing intentions.

### 4.5 Future research

The results concerning the ability to predict the intentions of cyclists from this study and work by Walker and Brosnan (2007) and Hemeren (2014) are mixed, it therefore remains difficult to draw definite conclusions about the ability of observers to predict intentions in real traffic. Future research could include eye movement measurements and should be aimed at further identifying which cues are potentially critical for predicting cyclists' behaviour, and whether technical devices may be able to read intentions, as opposed to human observers, based on sophisticated measurement devices. In this area of research, Schmidt and Färber (2009) found that multiple sources of pedestrian information (i.e. head and leg movements; "body language") and traffic parameters (i.e. speed and density) can be used to predict whether pedestrians are going to cross the road. For car drivers' intentions, Ohn-Bar et al. (2015) found that observations from multiple visual perspectives and modalities can be used to make inferences about the intentions of a car driver. Also, Bi et al. (2015) found that the intention of car drivers to change lanes in a driving simulator can be predicted by monitoring the drivers' steering angle sequences. Although these current techniques are not yet suitable to be used safely in real traffic, these results may contribute to the development of predictive driver assistance systems. These systems might be capable of providing critical information, assistance or even intervene, once critical driver intentions or potential conflicts are detected. Future studies should aim at using comparable techniques for cyclists.

## 5 CONCLUSIONS

One hundred and eight participants predicted the direction of travel of 24 cyclists that approached a crossroad up to the moment a movement in the direction of travel was initiated. The cyclists would either turn left, turn right or continue cycling straight on. On an overall level, the participants were not able to predict the direction a cyclist would take more accurately than on chance level. However, certain factors such as head movements and the speed of the cyclist ahead increased reliability of predictions for cyclist turning either left or straight.

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## REFERENCES


Bi, L., Wang, C., Yang, X., Wang, M., Liu, Y., 2015. Detecting Driver Normal and Emergency Lane-Changing Intentions With Queuing Network-Based Driver Models. Intl. Journal of Human–Computer Interaction 31, 139-145.

Bíl, M., Bílova, M., Muller, I., 2010. Critical factors in fatal collisions of adults with automobiles. Accid. Anal. Prev. 42, 1632-1636.

Borowsky, A., Shinar, D., Parmet, Y., 2008. Sign location, sign recognition, and driver expectancies. Transport. Res. Part F 11, 459-465.

Boufous, S., De Rome, L., Senserrick, T., Ivers, R., 2012. Risk factors for severe injury in cyclists involved in traffic crashes in Victoria, Australia. Accid. Anal. Prev. 49, 404-409.

CBS, 2014. Fors minder verkeersdoden in 2013 [Large decrease in traffic fatalities in 2013]. Retrieved 23.03.2016 from http://www.cbs.nl/NR/rdonlyres/FAC6EA11-7889-4DF4-8AC8-1EADFA3119E8/0/pb14n025.pdf.

Davidse, R.J., Van Duijvenvoorde, K., Boele, M.J., Doumen, M.J.A., Duivenvoorden, C.W.A.E., Louwerse, W.J.R., 2014a. Fietsongevallen van 50-plussers: karakteristieken en ongevalsscenario's van enkelvoudige ongevallen en botsingen met overig langzaam verkeer [Cycling accidents of cyclists aged 50 years or older: characteristics and accident scenarios of single-sided crashes and collisions with other slow traffic]. Institute for Road Safety Research The Hague, The Netherlands. Retrieved 23.03.2016 from https://www.swov.nl/rapport/R-2014-03A.pdf.

Davidse, R.J., Van Duijvenvoorde, K., Boele, M.J., Duivenvoorden, C.W.A.E., Louwerse, W.J.R., 2014b. Fietsongevallen met 50-plussers in Zeeland: hoe ontstaan ze en welke mogelijkheden zijn er om ze te voorkomen? [Cycling accidents of cyclists aged 50 years or older in the province of Zeeland: how do they emerge and what are the possibilities to prevent these?] Institute for Road Safety Research The Hague, The Netherlands. Retrieved 23.03.2016 from https://www.swov.nl/rapport/R-2014-16A.pdf.

De Geus, B., Vandenbulcke, G., Int Panis, L., Thomas, I., Degraeuwe, B., Cumps, E., Aertsens, J., Torfs, R., Meeusen, R., 2012. A prospective cohort study on minor accidents involving commuter cyclists in Belgium. Accid. Anal. Prev., 45, 683- 693.

Dill, J., McNeil, N., 2013. Four types of cyclists? Examination of typology for better understanding of bicycling behaviour and potential. Transport. Res. Rec. 2387, 129-138.

Dozza, M., Werneke, J., 2014. Introducing naturalistic cycling data: What factors influence bicyclists' safety in the real world? Tranport. Res. Part F 24, 83-91.

Endsley, M.R., 1995. Toward a Theory of Situation Awareness in Dynamic Systems. Human Factors 37, 32-64.

Fuller, R., 2011. Driver control theory: from task difficulty homeostasis to risk allostasis. In: B. Porter (ed.), Handb. of Traffic Psychology, Acadamic Press, London, p.14.

Fuller, R., Bates, H., Gormley, M., Hannigan, B., Stradling, S., Broughton, P., Kinnear, N., O'Dolan, C., 2008. The Conditions for Inappropriate High Speed: A Review of the Research Literature from 1995 to 2006. London: Department for Transport.

Heesch, K.C., Garrard, J., Sahlqvist, S., 2011. Incidence, severity and correlates of bicycling injuries in a sample of cyclists in Queensland, Australia. Accid. Anal. Prev. 43, 2085-2092.

Hemeren, P.E., Johannesson, M., Lebram, M., Eriksson, F., Ekman K., Veto, P., 2014. The use of Visual Cues to Determine the Intent of Cyclists in Traffic. IEEE International Inter-Disciplinary Conference on Cognitive Methods in Situation Awareness and Decision Support (CogSIMA), 47-51.

Juhra, C., Wieskötter, B., Chu, K., Trost, L., Weiss, U., Messerschmidt, M., Malczyk, A., Heckwolf, M., Raschke, M., 2012. Bicycle accidents - Do we only see the tip of the iceberg? A prospective multi-centre study in a large German city combining medical and police data. Injury 43, 2026-2034.

Kaplan, S., Vavatsoulas, K., Prato, C.G., 2014. Aggravating and mitigating factors associated with cyclist injury severity in Denmark. Journal of Safety Research 50, 75-82.

Martens, M.H., Fox, M.R.J., 2007. Do familiarity and expectations change perception? Drivers' glances and response to changes. Transport. Res. Part F 10, 476- 492.

Martínez-Ruiz, V., Jiménez-Mejías, E., De Dios Luna-del-Castillo, J., García-Martín, M., Jiménez-Moleón, J.J., Lardelli-Claret, P., 2014. Association of cyclists' age and sex with risk of involvement in a crash before and after adjustment for cycling exposure. Accid. Anal. Prev. 62, 259-267.

Martínez-Ruiz, V., Jiménez-Mejías, E., Amezcua-Prieto, C., Olmedo-Requena, R., De Dios Luna-del-Castillo, J., Lardelli-Claret, P., 2015. Contribution of exposure, risk of crash and fatality to explain age- and sex-related differences in traffic-related cyclist mortality rates. Accid. Anal. Prev. 76, 152-158.

Muhrer, E., Volrath, M., 2010. Expectations while car following - The consequences for driving behaviour in a simulated driving task. Accid. Anal. Prev. 42, 2158-2164.

Ohn-Bar, E., Tawari, A., Martin, S., Trivedi, M.M., 2015. On surveillance for safety critical events: In-vehicle video networks for predictive driver assistance systems. Computer Vision and Image Understanding 134, 130-140.

Oja, P., Titze, S., Bauman, A., de Geus, B., Krenn, P., Reger-Nash, B., Kohlberger, T., 2011. Health benefits of cycling: a systematic review. Scandinavian Journal of Medicine & Science in Sports. 21, 496-509.

Poulos, R.G., Hatfield, J., Rissel, C., Flack, L.K., Murphy, S., Grzebieta, R., McIntosh, A.S., 2015. An exposure based study of crash and injury rates in a cohort of transport and recreational cyclists in New South Wales, Australia. Accid. Anal. Prev. 78, 29-38.

Rasbash, J., Charlton, C., Browne, W.J., Healy, M., Cameron, B., 2015a. MLwiN Version 2.33. Centre for Multilevel Modelling, University of Bristol.

Rasbash, J., Steele, F., Browne, W.J., Goldstein, H., 2015b. A User's Guide to MLwiN, v2.33. Centre for Multilevel Modelling, University of Bristol, 119-146.

Räsänen, M., Summala, H., 1998. Attention and expectation problems in bicycle-car collisions: an in-depth study. Accid. Anal. Prev. 30, 657-666.

Schepers, P., 2012. Does more cycling also reduce the risk of singe-bicycle crashes? Injury Prev. 18, 240-245.

Schepers, P., 2013. A safer road environment for cyclists. PhD thesis Technical University Delft. Delft, The Netherlands. Retrieved 23.03.2016 from http://www.swov.nl/rapport/Proefschriften/Paul_Schepers.pdf.

Schepers, J.P., Den Brinker, B.P.L., 2011. What do cyclists need to see to avoid single-bicycle crashes? Ergonomics 54, 315-327.

Schepers, J.P., Klein Wolt, K., 2012. Single-bicycle crash types and characteristics. Cycling Res. Int. 2, 119-135.

Schleinitz, K., Petzoldt, T., Franke-Barthold, L., Krems, J.F., Gehlert, T., 2015. Conflict partners and infrastructure use in safety critical events in cycling – Results from a naturalistic cycling study. Transport. Res. Part F 31, 99-111.

Schmidt, S., Färber, B., 2009. Pedestrians at the kerb – Recognizing the action intentions of Humans. Transport. Res. Part F 12, 300-310.

Siman-Tov, M., Jaffe, D.H., Peleg, K., Isreal Trauma Group, 2012. Bicycle injuries: A matter of mechanism and age. Accid. Anal. Prev. 44, 135-139.

Stelling-Konczak, A., Aarts, L., Duivenvoorden, K., Goldenbeld, C., 2011. Supporting drivers in forming correct expectations about transitions between rural road categories. Accid. Anal. Prev. 43, 101-111.

Twisk, D.A.M., Reurings, M., 2013. An epidemiological study of the risk of cycling in the dark: The role of visual perception, conspicuity and alcohol use. Accid. Anal. Prev. 60, 134-140.

Walker, I., 2005. Signals are informative but slow down responses when drivers meet bicyclists at road junctions. Accid. Anal. Prev. 37, 1074-1085.

Walker, I., 2007. Drivers overtaking bicyclists: Objective data on the effects of riding position, helmet use, vehicle type and apparent gender. Accid. Anal. Prev. 39, 417-425.

Walker, I., Brosnan, M., 2007. Drivers' gaze fixations during judgements about a bicyclist's intentions. Transport. Res. Part F 10, 90-98.

Wegman, F., Zhang, F., Dijkstra, A., 2012. How to make more cycling good for road safety? Accid. Anal. Prev. 44, 19-29.